

Cross-country elasticity of intertemporal substitution and common monetary policy in the eurozone

A study of consumption choice heterogeneities in response to changes in the interest rate set by the ECB

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ABSTRACT

In analysing the effectiveness of monetary policy, it is important to understand to what extent and why there may exist differences in how sensitive consumers' intertemporal consumption choice is to changes in the monetary policy rate. This paper estimates the elasticity of intertemporal substitution (EIS) across the eurozone and uses the results to discuss the effectiveness of the eurozone from a monetary policy perspective. We find evidence of EIS heterogeneity in the sense that consumers around Europe differ greatly in willingness to rearrange their intertemporal consumption choice given a change in the short-term interest rate. These differences are structural and relate to differences in wealth, asset market participation and credit availability, as well as cultural differences. This suggests that common monetary policy as set by the ECB will have a dissimilar impact around the eurozone. In light of this finding, combined with a discussion on fiscal transfer programmes and initiatives to direct member countries towards more fiscal prudence, we discuss the effectiveness of the eurozone. We argue that while the eurozone is not an optimum currency area and EIS heterogeneity reduces monetary policy effectiveness, the individual member country is better served with staying within the eurozone.

Keywords: Elasticity of intertemporal substitution, common currency area, monetary policy, ECB, eurozone

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1. Introduction

This paper studies the elasticity of intertemporal substitution (EIS) at the macro level and its implications for common monetary policy. The EIS is a key element in understanding how consumers choose to spend their income across periods. For this reason, a broad research has been dedicated to the study of the EIS, both in terms of empirical estimation of the elasticity and in terms of analysis of the factors that drive its differences across time, countries and households.

The EIS is important from a theoretical perspective as its implications with respect to consumers' intertemporal preferences may be used in asset pricing as well as macroeconomic models. In practice, this field of study has implications for macroeconomic policies. One dimension of this broad scope is EIS's applicability when discussing the effectiveness of shared monetary policy. If it is a political aim to coordinate monetary policy to form a monetary union, it is important for policy makers and central bankers to understand to what extent and why there may exist cross-country differences in how sensitive consumers' intertemporal consumption choice is to changes in the monetary policy rate.

Our motivation for testing EIS heterogeneities in eurozone countries as well as countries outside the eurozone, originates from the prolonged debate concerning the effectiveness of common monetary policy. In this context, the EU and the eurozone are particular examples of high levels of political efforts to coordinate common solutions and overcome economic and cultural differences. However, the euro is a debated topic which has been hot since the European Central Bank in 2009 first took actions to stimulate the European economies, and it remains no less relevant in 2017. While some Europeans celebrate the 60-year anniversary of the signing of the Treaty of Rome, the British voted to leave the union by 52% to 48% in June last year and Theresa May has officially started the process of leaving in March this year. From having thus far only expanded, the EU collaboration is now again up for discussion and highly dependent on this year's national elections. With a shaking Union as backdrop, the eurozone stands out as an obvious weak point as high solidarity among member countries is vital to ensure a well-functioning common currency area.

A number of studies have estimated the EIS in different countries and tried to explain cross-country differences. Nonetheless, we do not know of any paper which has studied the EIS in a eurozone context. Furthermore, what makes our paper stand out is the adequacy of our dataset. We use a panel dataset of subjective country-specific expectations on different macroeconomic variables, made by financial professionals. The data is monthly, spans 11 years and refers to 14 countries. This provides us with a substantial amount of data points. Additionally, our dataset includes expectations on consumption growth so we do not need to proxy the dependent variable in our EIS estimation. Finally, we benefit from the expectational format of our data, which allows us to clear our regressions from noise in the estimates.

1.1. Research questions and objectives of the research

The objective of this paper is to (1) estimate the EIS across the eurozone and additional non-euro-countries to analyse whether and to what extent country-level EIS heterogeneity is present. Additionally, we (2) explain variations in EIS estimates across countries by means of both tests on different macroeconomic variables and reference to earlier academic findings. Finally, we (3) discuss the effectiveness of the eurozone from a monetary policy perspective in light of EIS heterogeneity.

Our paper is structured around three research questions. The first two concern the estimation and analysis of the EIS by means of panel data and time series regressions conducted in STATA, as well as through reference to past literature. The final research question concerns analysis and discussion based on our EIS findings and insights from market experts.

Our research questions are as follows:

- **RQ1:** Is EIS heterogeneity present amongst eurozone countries?
- **RQ2:** If evidence of heterogeneity is found amongst eurozone countries, what country differences can explain these variations?
- **RQ3:** What implications does EIS heterogeneity have for the effectiveness of the eurozone from a monetary policy perspective?

In research question 1 we estimate the EIS from our sample, obtaining 14 estimates in total, one for each country of our dataset. The analysis is split in two. We first estimate one elasticity across the whole sample to attain an EIS estimate benchmark, as well as to discuss whether our results are robust and the model we are using is solid. Secondly, we run the model on the countries one by one and obtain country-level elasticities. The results are discussed at the end of the chapter, in the context of the literature and previous findings.

In research question 2 we use the country estimates from research question 1 with the intension of explaining the EIS heterogeneities. For this purpose, we regress our EIS estimates on a number of macroeconomic factors that we argue could explain those differences. Although we extend our dataset with estimates from Havranek et al. (2015)'s meta study, many of our test results and correlations are inconclusive. Thus, this chapter conclusion partly relies on discussion of own findings with reference and comparison to earlier studies as well as a critique of our own model.

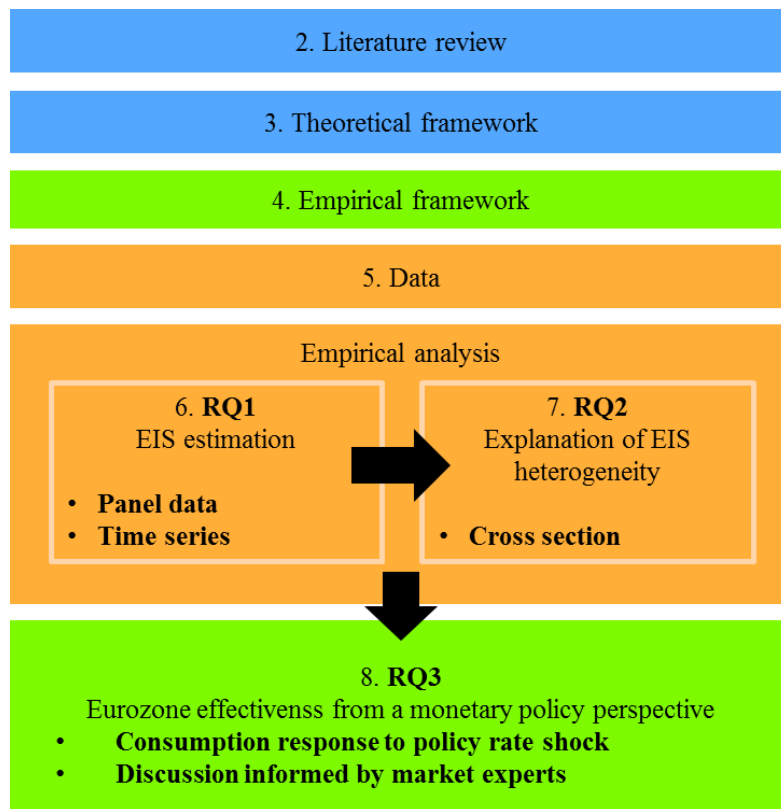
In research question 3 we discuss the effectiveness of the eurozone from a monetary policy perspective. The scope of this discussion primarily relies on an analysis of the dissimilar consumption effect between eurozone member countries from a shock to the short-term interest rate, given EIS heterogeneity. This analysis

is supported by discussions on the eurozone from an optimum currency area perspective as well as whether it is realistic to assume that the individual member state could achieve greater monetary policy independence outside the eurozone.

1.2. Thesis structure

The thesis is structured as outlined in [Figure 1.1](#).

Figure 1.1: Outline of the thesis structure



Chapter 2 reviews the literature regarding both the EIS estimation and the research that aims to explain EIS heterogeneity. This chapter gives an overview of where the research is at, as well as where our paper fits in and stands apart. Chapter 3 outlines the theoretical framework we base our research on. We introduce the concept of the EIS and define theoretical assumptions with respect to the utility function. Chapter 4 outlines the empirical framework in which we conduct our research. We introduce the eurozone and the European Monetary System, as well as explain how the European Central Bank conducts monetary policy in theory and practise – by means of the policy rate and beyond. Chapter 5 provides an overview of the data we use; our dataset, the study estimates from Havranek et al. (2015) and the macro variables we use in answering research question 2. Chapters 6 to 8 answer our research questions. Chapter 9 concludes on our findings.

1.3. Problem area limitations

The ideal approach to estimate the EIS in the eurozone and discuss the common monetary policy would be to do so for each eurozone country and with information at the household-level. This kind of data is unfortunately not available to us. We use instead a dataset with information at the macro-level for five eurozone countries and nine outside the euro area.

Concerning the assumptions on consumer preferences, it is beyond the scope of this paper to comment on the relative risk aversion and implications with respect to risk premia and asset pricing apart from the theoretical overview provided.

Furthermore, it is beyond the scope of this paper to reflect on long term monetary neutrality in relation to the real economy. We will also not discuss whether we deem it best to conduct an active monetary policy in the Keynesian sense versus the monetaristic perspective. This also implies that we will not attempt to evaluate how the ECB and related institutions have tackled recent years' crises. Our focus is exclusively on how certain steps towards greater coordination may provide better conditions for common monetary policy.

Finally, it would be more accurate to look at the eurozone as a whole and within its historical and political context. However, that is beyond the scope of this paper. We will not conclude on overall eurozone effectiveness, but limit ourselves to a discussion of eurozone effectiveness from a monetary policy perspective, given our findings in the EIS analyses.

1.4. Abbreviations

We introduce here the most used abbreviations in our paper, listed in [Table 1.1](#).

Table 1.1: List of abbreviations

10y	The ten-year government bond yield
3m	The three-month interest rate
ECB	European Central Bank
EFSM	European Financial Stabilisation Mechanism
EIS	Elasticity of intertemporal substitution
EONIA	Euro Overnight Index Average
ESM	European Stability Fund
LHS	Left-hand-side
OCA	Optimum Currency Area
QE	Quantitative Easing
RHS	Right-hand-side
RQ	Research question
RRA	Relative risk aversion

2. Literature review

2.1. Chapter outline

There are a number of important reference points within existing literature on the elasticity of intertemporal substitution. Although there is some consensus on the assumptions and techniques to be used, the estimates can differ greatly from study to study, as shown in [Figure 2.1](#). This broad topic can be divided in two main branches: (1) the estimation of the EIS and (2) the analysis of the factors that lead to differences in EIS. As our paper deals with both of these branches, this literature review follows this split. Specifically, in section 2.2 we give an overview of key papers that estimate the EIS and their findings, focusing in particular on which (a) theoretical model the research is based on, (b) the econometric techniques and how frequent issues are avoided, and finally (c) the data used in terms of use of expectations and survey data. We then move on in 2.3 to outline papers that deal with explaining the EIS differences and the possible causes of these differences. In each section we compare our paper to the literature highlighting how we take inspiration from earlier research as well as how we distinguish ourselves. Since the literature on the topic is very broad, we aim to limit this overview so as to not go into details in explaining models and methods that are not directly related to our research.

2.2. Estimation of the EIS

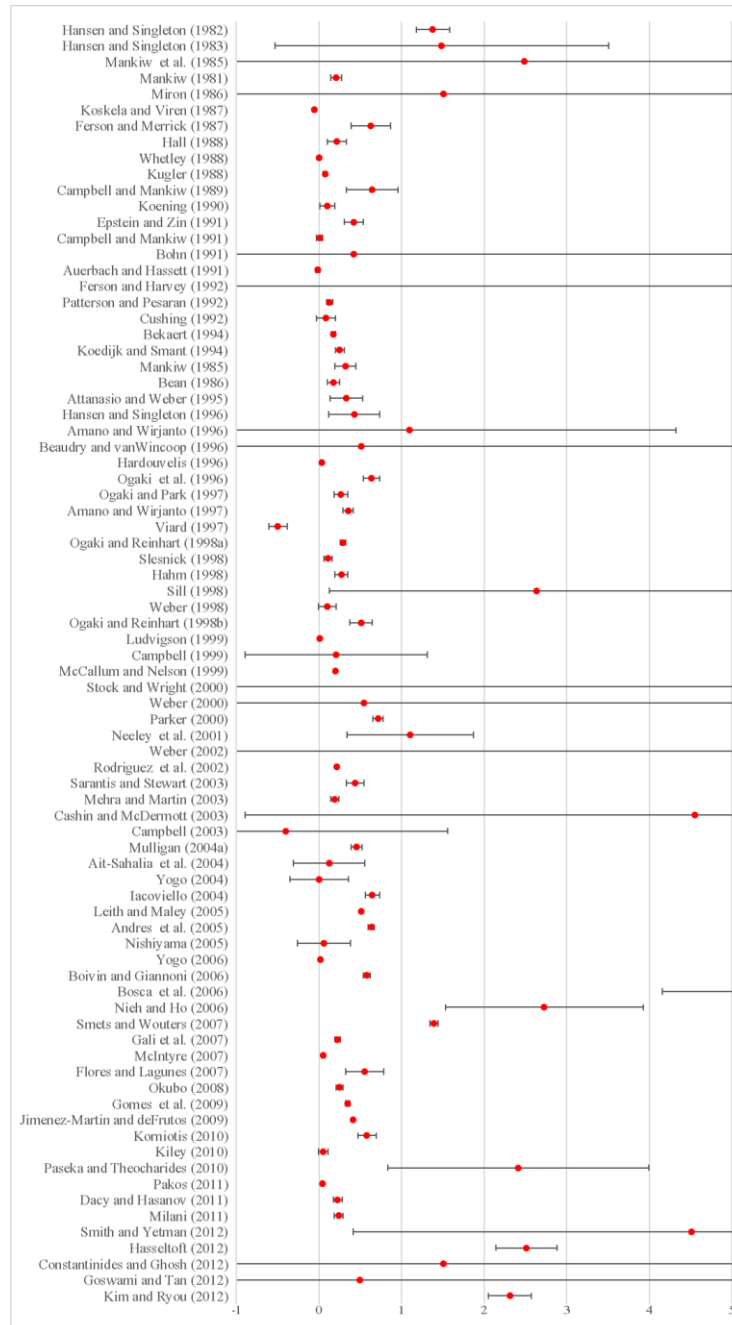
One of the most important reference points within this area of study is Hall (1988). Hall takes inspiration from Lucas (1976) as he argues that there may not be a *true* or *single* consumption or investment function which best explains the relationship between interest rates, income and consumption. On the contrary this relationship may best be defined and understood as highly dependable on the macroeconomic context and thus less stable over time than a fixed utility function test approach would suggest. This perspective makes up the foundation for testing the EIS in the manner which has prevailed since Hall's influential paper almost 40 years ago.

2.2.1. Assumptions about utility function and theoretic models used

The assumptions about consumer preferences are fundamental to estimate the EIS as they are essential in determining the econometrics approach to be used and the results that can be achieved. The majority of studies assumes discrete time, even though the same models could be carried out in continuous time. Furthermore, it is highly popular to assume recursive utility, proposed by Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990). This model is also known as recursive preferences or Epstein-Zin

preferences. Recursive utility is an intertemporal utility theory where the utility $U(C_t)$ of time t is a function of both the consumption at time t and the next period utility, $U(C_{t+1})$.

Figure 2.1: EIS estimates for the US from different studies using macro data



Source: Havranek et al. (2015) and own analysis.

The intra-temporal utility function, i.e. the utility function of the consumer in each period, is often assumed to be a constant relative risk aversion (CRRA) or iso-elastic utility. This assumption was originally proposed by Hall (1978), Lucas (1978), Grossman and Shiller (1981) and Grossman and Shiller (1982) and has developed into the norm when estimating the EIS.

A special case of the CRRA utility is when the EIS is set equal to the reciprocal of the relative risk aversion (RRA). This utility is time-separable, which means that consumption in a given time period does not influence preferences about consumption in the future and it is not influenced by past consumption.

We follow the literature in assuming a CRRA time-separable utility in our estimations, but we do not make any explicit conclusions concerning the RRA factor: we do not assume a direct link between EIS and RRA and we deem it beyond the scope of this paper to explore this dimension of the EIS.

Lucas (1990) uses the consumption Euler equation under certainty, derived from the maximization problem of a CRRA utility function, and analyses the risk-free rate as a function of the subjective discount factor and consumption growth, i.e. he uses the inverse of the usual Euler equation. Here the coefficient of consumption growth is the reciprocal of the EIS. Both Attanasio and Weber (1989) and Yogo (2004) run regressions based on the classic Euler equation, having the risk-free rate on the RHS. They estimate EIS values that range from 0.2 to 2. The log-linearised consumption Euler equation that is derived from the assumptions outlined above is considered the preferred framework with respect to the estimation of the EIS (Havranek et al., 2015). Hansen and Singleton (1983) define the following expression for EIS in the CRRA case, assuming conditional joint lognormal distribution of returns and next period consumption:

$$EIS = \frac{dE_t[\ln(C_{t+1}/C_t)]}{dE_t[\ln(1 + R_t)]}$$

We use the same expression in our model, where we regress consumption growth on the interest rate, resulting in the EIS being the coefficient of the interest rate.

In the framework of the CRRA utility function, Epstein and Zin (1989) drop the restriction on EIS and RRA, such that $EIS \neq \frac{1}{RRA}$, to arrive at an Euler equation that includes both the risk-free return and the return on the wealth portfolio. Related to the divergence between assuming a link between the EIS and RRA, the EIS is often assumed to lie above 1 within finance literature, for practical reasons¹. However, this assumption stands in direct contrast to the existing estimates of the EIS (Schmidt, Toda, 2016), and while from an asset pricing point of view, the relative risk aversion is equal to the inverse of the EIS, this link is considered not to hold in practical studies of the EIS. In other words, EIS estimates should, according to the standard reading of EIS literature, not be used to conclude on relative risk aversion levels².

However very recent studies have tried to reconnect the two and thus potentially solve the equity premium puzzle. This new wave of papers have been introduced with the work of Bansal and Yaron (2004), among others, and later developed by Ai (2010) and Drechsler and Yaron (2011). These papers all conclude

¹ When this is the case the equity premium is larger, the risk free rate is lower and stable, and variance is associated with discounts in asset prices due to the associated increase in risk.

² This point will be elaborated further in the subsequent chapter.

on EIS estimates above 1 by means of long-run asset pricing models which then allows them to retain the link to risk aversion and explain a sizeable equity premium among other key concepts.

Thimme (2016), who conducts a literature review on papers related to the study of the EIS, finds that if authors move away from the CRRA assumption, they tend to arrive at EIS estimates close to or above 1.

2.2.2. Econometrics techniques and overcoming issues

The model described above can be estimated with different econometrics methods. The most popular are OLS, 2SLS and GMM. Even though OLS is used by some studies, the regression suffers from endogeneity, given by estimation error, simultaneity and possibly omitted variables, as we will explain in the following chapters. Shea (1995), Barsky et al. (1997) and Gorbachev (2011) use OLS to estimate the EIS with micro data on US consumers. They estimate elasticities that range from 0.02 to 4.7 with quite low standard errors. Because of endogeneity, the use of instruments is often preferred, as Mankiw (1981) does to estimate the EIS from the log-linearized Euler equation. Other studies using a 2SLS model are Hall (1988), Zeldes (1989), Koenig (1990), Lawrance (1991), Bean (1986) and Mulligan (2004), which estimate the EIS on US data, and Attanasio and Weber (1993) and Dynan (1993) that estimate the EIS for the UK. Dynan (1993) finds estimates which are quite high, from 8.6 to 10.2, with very large standard errors, using micro data from the Panel Study of Income Dynamics (PSID). Excluding Dynan, the elasticities estimated by the other studies range from -1.46 to 1.95. We rely on both OLS and 2SLS in our regressions.

Summers (1981) and Hansen and Singleton (1982) use instead the generalized method of moments (GMM) and find significant results for the EIS: 0.4 for Summers (1981) and around 1 for Hansen and Singleton (1982). Other studies that use the GMM are Epstein and Zin (1991), Constantinides and Ghosh (2012), Bansal et al. (2010), Colacito and Croce (2011) and Bansal and Shaliastovich (2013). They obtain EIS estimates that range from 0.4 to 2, resulting from different assumptions about the specifications of their models.

Other models have been used in the literature, such as the simulated method of moments (SMM)³, employed by Bansal et al. (2010) and Hasseltoft (2012) who estimates an EIS of 2.51, and the Bayesian Monte Carlo Markov Chain (MCMC). We want to provide the reader with an overview of the models that have been used by the literature, but we won't go in details in explaining the alternative methods employed by earlier studies.

Within the studies using instrumental variables, there are Hall (1988) and Vissing-Jørgensen (2002), which both use lagged variables as instruments. In particular, Vissing-Jørgensen instruments the rates of return by the log dividend-price ratio, the lagged log real value-weighted NYSE return, the lagged log real Treasury bill return, the lagged government bond horizon premium and the lagged corporate bond default premium.

³ This approach identifies model parameters that minimize (a function of) the distance between model-implied moments, generated by simulation, and empirical moments. (Thimme 2016)

Additionally, her observations are overlapping due to the nature of the survey data, so she needs to use lags that are outside the overlapped period. We encounter a very similar issue given by our dataset being monthly observations of annual values, and we refer to Vissing-Jørgensen when choosing our instruments, as we further explain in the methodology section of [research question 1](#).

Another common issue in the EIS estimation is the non-availability of the model's variables, in particular consumption growth and return rate. GDP and lagged consumption are often used as proxies for consumption. Summers (1981) and Hansen and Singleton (1982) use the first lag of consumption growth as proxy. Hall, on the other hand, discards the validity of using planned consumption growth as a valid instrument for consumption growth, as he writes: "*actual movements of consumption differ from planned movements by a completely unpredictable random variable that indexes all the information available next year that was not incorporated in the planning process the year before*" (Hall, 1988, p. 340, The Journal of Political Economy, Vol. 96, No. 2).

Concerning the rate of return, different proxies have been used. When using the Euler equation of Epstein and Zin (1989), the return on the wealth portfolio can be challenging to estimate and different papers have tried different approaches. Epstein and Zin (1991), Stock and Wright (2000), Weber (2000), Yogo (2006) and Kim and Ryou (2012), all use a stock index as proxy for the wealth portfolio. Gomes et al. (2009) use a proxy for the wealth return that comes from durable goods and private residential fixed assets. They estimate an EIS of 0.6. Others include in the wealth portfolio a proxy for human capital, as is the case for Thimme and Volkert (2015), who estimate an EIS of 1.78. These are just few examples on how to proxy the return on wealth and the estimation of the EIS in these settings is challenging. Majority of the literature finds EIS estimates above one, but these results strongly depend on the proxy used for the wealth portfolio. In our case, we have at our disposal both data on consumption growth and 3-month interest rate, so we won't use any proxy for these two⁴. Nevertheless, our dataset consists of country-level data, meaning that we do not distinguish between households. In the literature, the choice of the rate of return has often been a bigger issue when dealing with panel data at the micro level, i.e. panels with different households which are free to invest in very different assets – spanning from stock to the housing market. In these settings, the ideal would be to have an individual rate of return for each household, in order to capture the differences in the independent variable. Few studies try to do so by means of proxying the rate of return by household-specific tax rates (Thimme, 2016) or individual's 401(k) savings⁵ (Engelhardt and Kumar, 2009). Doing so, Engelhardt and Kumar estimate an EIS of 0.74. Most literature uses more aggregated rates. Some studies use the return on capital, like Gomes et al. (2009), who finds an EIS of 0.03 and 0.66 using US data. Others use the stock return as rate of return, as Hansen and Singleton (1982), Hall (1988), Koenig (1990), Attanasio et al. (2002) and Colacito and Croce (2011). Hansen and Singleton (1983), Epstein and Zin (1991), Stock and Wright (2000), Vissing-Jørgensen

⁴ We will though instrument the 3m rate, as we explain later.

⁵ The American tax-qualified, defined-contribution pension account defined in subsection **401(k)** of the Internal Revenue Code

(2002), Vissing-Jørgensen and Attanasio (2003) and Mulligan (2004) use both return on capital and on stock. They estimate EIS that range from -2.8 to 7.5, from US and UK data. Mulligan (2004) tries to calculate the return on the market portfolio, using the ratio between capital income and total capital, which leads to an EIS above one.

In general, the Euler equation holds with any asset's return, so the choice of the rate of return should have a small impact. If this assumption doesn't hold, i.e. the Euler equation is not valid for specific assets, then the results could be biased when the returns on these assets are used in the estimation (Thimme, 2016)

It may be relevant to end this section of our literature overview by referring to Hall as his findings are still a benchmark within the topic of EIS. Hall concludes on a very low EIS estimate – around 0.1 – and explains this via a very low growth rate of consumption during the sample period. However later studies have explained such low EIS estimations as due to attenuation bias in the results caused by estimation error. This is a common issue when relying on realized data. In our research, we try and avoid this using expectations of macroeconomic variables, which are therefore cleaned from noise and realized shocks.

Earlier studies by Working (1960) find that the error term in the equation used to estimate the EIS is not white noise but a first-order moving average process with serial correlation. After tests we find the same problem in our data. In fact our data presents a unit root. In the following chapters we explain in details the nature of our data and how we overcome the different issues. In this chapter we initiate this discussion by means of the next section's literature overview.

2.2.3. Data used, expectations and surveys

Concerning the data used for the estimation of the EIS, there have been discussions on whether the use of aggregated data, i.e. considering studying different types of households as an aggregate, biases the estimates. Attanasio and Weber (1993) find an EIS of 0.4 when considering aggregated data on households and of 0.8 when using cohorts of households. Beaudry and Wincoop (1996) perform a similar test on US data: when they use state-level consumption data they estimate an EIS of around 1, while with aggregated data the results are downward biased.

Additional ways of dis-aggregating data are explored by the literature. Ortu et al. (2013) run the basic EIS regression on different consumption growth and interest rate's components, separated on the base of their level of persistence. They estimate EIS between 2.09 and 5.54, depending on the sample they consider. Aggregation over time also leads to downward bias when using small samples, as argued by Bansal et al. (2010). We won't encounter this issue in the first part of our analysis, since we use a large sample and run time series regressions. Nevertheless, we do use macro data at the country level, which is therefore aggregated and does not consider within-country differences. We discuss this issue further together with our results in the discussion sections within each chapter.

Concerning the data used for the analysis, the use of expectational data has been exploited by different papers. Crump et al. (2015) is an example of recent use of an expectational dataset as basis for EIS estimation. The authors argue that the benefit from using expectations on both sides of the equal sign is that one avoids making assumptions about expectation formation. When on the contrary one uses realised variables, the error term will include the agents' consumption forecast errors, and these will be correlated with the independent variable, the change in the real interest rate. Thus, estimates would suffer from attenuation bias. Buraschi et al. (2017) deal with the debate concerning whether differences in subjective estimations of variables such as bond returns and short term rates as well as general macroeconomic variables are different and persistently so. Several academic studies have tried to disentangle whether this persistent difference in estimations are due to dogmatic beliefs, or some other behavioural bias, or whether it is simply due to information friction (Thimme, 2016). The authors of the Buraschi et al.'s study find that overall expectations, at least with respect to bond returns, display significant elements of rationality.

A final point within this section is that survey data is often used for the estimation of EIS, but one of the flaws is measurement error. In our case, we do use survey data, but the survey is submitted to economic and finance professionals and experts of the market for them to forecast a number of macro variables, as we will explain further in the [Data](#) chapter. Therefore, we distinguish ourselves from the literature in having both data in expectations and based on survey, that is believed to be consistently similar to realized data.

2.3. *Literature on why EIS differs*

Studies of the EIS yield quite different estimates as seen above and as exemplified by [Figure 2.1](#). Further given the circumstance that standard errors tend to be large (Havranek et al., 2015⁶) we underline that conclusions with respect to the magnitude of the EIS are highly mixed. Another paper by Havranek (2014) also finds a publication bias in the sense that authors tend to have a preference for publishing results which reflect significant and large, positive EIS estimates.

Given these mixed results, research has been dedicated to try and explain differences in the EIS. Havranek et al. (2015) perform a meta-study using a large sample of EIS estimates from earlier papers and regressing them on a number of variables, both macroeconomic factors as well as methodological variables that account for the methods used in the estimation. We conduct a similar analysis in trying to explain why the EIS that we estimate differs across our sample of countries.

Other papers find specific characteristics of the population that explain differences in the EIS, mainly at the micro level. Blundell et al. (1994) and Attanasio and Browning (1995) suggest that rich households tend to show a larger elasticity of intertemporal substitution. Mankiw and Zeldes (1991) and Vissing-Jørgensen (2002) find a larger elasticity for stockholders than for non-stockholders. Bayoumi (1993) and Wirjanto (1995),

⁶ The meta study concludes upon a standard error of 1.4 across 33 studies published in top journals, even after excluding outliers.

among others, indicate that liquidity constrained households show a smaller EIS. We explore these factors as well in our analysis to answer [research question 2](#), where we find similar proxies to account for these differences at the country level.

Havranek et al. (2015) make aggregate conclusions on a collection of 2,735 EIS estimates from 169 published articles and find that EIS estimates are highly influenced by estimation method and data used⁷. In particular they find that factors like wealth, asset market participation and liquidity constraints have a significant influence in differences of the EIS across countries.

⁷ We account for that in our analysis as we compare EIS estimates across multiple studies. More on this in a subsequent chapter

3. Theoretical framework

3.1. Chapter outline

The purpose of this section is to introduce the concept of elasticity of intertemporal substitution (EIS). We explain the concept of the EIS, put it into a theoretical context, and provide an overview of the assumptions we make concerning the utility function.

This chapter is divided into the following sub-parts. We start in section 3.2 by introducing the EIS, which is at the core of our research, and move on to defining its role in a theoretic context. In 3.3 we then take a step higher and introduce the utility function, which determines the individual's consumption choice. In this part, we discuss different utility types and then present the one that we will use as base for our empirical model. Within this topic, we explain the concept of consumption and the trade-off of consumption in different time periods, which is defined by the elasticity of intertemporal substitution. We close this chapter in 3.4 by means of explaining how the EIS is estimated in practice, given the assumptions we took with respect to the consumer's preferences.

3.2. The elasticity of intertemporal substitution

The elasticity of intertemporal substitution (EIS) defines the effect of a change in the interest rate on consumers' consumption allocation between periods. In other words, the EIS reveals a consumer's willingness to rearrange his consumption plan across time. The underlying assumption is that the consumer is rational and plans his intertemporal consumption pattern according to how his utility is maximized. When the interest rate increases by one percentage point, this increases the overall wealth of the individual and he can make two opposite, and still logic, choices:

1. Move some of the planned consumption of the current period into savings, and thus turn it into consumption in the coming period. Thereby he takes into account the rise in opportunity cost of consuming in the current period and takes advantage of the increased interest rate which allows him to increase utility across both periods, as his savings will now provide a higher return. This is called the **substitution effect**, because the agent substitutes consumption between periods.
2. Alternatively, consume more in the current period, i.e. spend part of the future wealth already today, as less savings are going to return the same amount in any case because of the increased interest. This is termed the **income effect**, because the agent feels richer already today, he chooses to consume more today and get the same consumption in the next period.

The EIS gives us information on the net effect between the two. An individual who saves more today if interest rates are high, and so postpones consumption to the next period, is characterized by a high EIS. Inversely, an individual with low EIS is not willing to relocate his consumption habits so easily. A negative EIS corresponds to a stronger income effect, as the individual would consume more today given an increase in the interest rate, and so he would register a decreasing consumption growth.

The EIS can be defined as:

$$EIS = - \frac{\partial \log\left(\frac{C_{t+1}}{C_t}\right)}{\partial \log\left(\frac{\partial U / \partial C_{t+1}}{\partial U / \partial C_t}\right)}$$

Which shows how consumption growth changes given changes in the real interest rate. This is not immediately intuitive, but can be explained one element at the time. Ignoring for a moment the derivative operators, at the numerator we see the percentage change in consumption from one period to the next, i.e. the consumption growth. At the denominator, we have information on how the utility changes given changes in the consumption of the two periods. This ratio is also expressed as percentage. In common dynamic choice models, the denominator is closely linked to real interest rates (Thimme 2016)⁸. So, the expression can be interpreted as the marginal change of consumption growth driven by changes in the interest rate.

3.3. *The utility function*

The EIS is a factor that appears in the utility function of the individual, as it connects changes in the rates of return in the economy (e.g. the interest rate) to changes in consumption, which in turn is the element that gives utility to the individual. Every individual chooses between two main allocations of his or her resources: consumption and savings. Savings is simply postponed consumption, i.e. consumption in the future. In each period, the individual will therefore face the problem of choosing optimally how much to consume and how much to save. For simplicity, we outline the problem of the agent in a two-period setting, i.e. two points in time, $t = \{0, 1\}$, but the same can be extended to multiple periods.

3.3.1. *A basic two-period problem and the Euler equation*

The lifetime utility of consumption is given by the sum of the utilities in the two points in time (at the beginning of the period and at the end of the period): $u(C_0) + \beta \cdot u(C_1)$. β is the subjective discount factor, which gives us information on the disutility of the individual from postponing consumption. In each period the individual gets an income, denoted with Y_t . Finally, it is possible to invest anything that is not consumed in

⁸ We show this with calculations below.

time 0 in the credit markets at a given interest rate r . So, in time 0 the individual receives income Y_0 , decides how much to consume and how much to save, and in time 1 he consumes the new income Y_1 and any return on the savings⁹.

The individual's problem is:

$$\max_{C_0} u(C_0) + \beta \cdot u(C_1)$$

Subject to the intertemporal budget constraint:

$$C_0 + \frac{C_1}{1+r} = Y_0 + \frac{Y_1}{1+r}$$

Which states that an individual's total intertemporal consumption equals his intertemporal income: the individual cannot consume more than what he earns, but will also consume all of his income.

The most important solution to this problem is the Euler equation:

$$u'(C_0) + \beta \cdot (1+r) \cdot u'(C_1)$$

Where the term $\beta \cdot (1+r)$ defines the slope of consumption over time.

The Euler equation shows how the individual maximizes the two utilities choosing consumption optimally in the two periods. It can be extended to a multiple periods model, where in each period we would have:

$$u'(C_t) + \beta \cdot (1+r) \cdot u'(C_{t+1})$$

3.3.2. Different utility functions

The problem we outlined above, holds with different types of utility functions. The most common ones are (a) the utility with constant absolute risk aversion (CARA), meaning that the individual's risk aversion does not change with changes in wealth. These utilities are monotone affine transformations of exponential utility, which can be represented as: $u(w) = -e^{-aw}$, where w is the level of wealth¹⁰ and a is the coefficient of absolute risk aversion. (b) The utility with constant relative risk aversion (CRRA), meaning that the risk aversion relative to the level of wealth is constant, so that the absolute risk aversion decreases with wealth.

⁹ Here we assume income during the period, but the same can be done without income and with initial wealth. There is no difference for the scope of what we want to show.

¹⁰ Again, wealth and income can be considered synonyms here.

These utilities are monotone affine transformations of the power utility, also called isoelastic utility, which can be represented as: $u(w) = c^{1-\gamma}/1 - \gamma$. The log utility is a special case of power utility, where $\gamma = 1$. Another important distinction when dealing with models over time, is whether the life-time utility is time-separable or not, i.e. whether the utilities of the single periods are independent from each other or not. A time-separable utility can be represented as: $U = u(c_0) + \beta \cdot u(c_1) + \beta^2 \cdot u(c_2) + \dots$, where β is the subjective discount factor that denotes the individual's impatience. To quote Barro and King (1984) "*Time-separability of utility means that past work and consumption do not influence current and future tastes. This form of preferences does not restrict the size of intertemporal-substitution effects, but does place constraints on the relative responses of leisure and consumption to changes in relative prices and in permanent income*".

3.3.3. Our choice of utility and the updated problem

To outline the consumption-savings decision, we will use the most simplistic case of time-separable isoelastic utility model. Our utility function in each period is:

$$u(C) = \frac{C^{1-\gamma} - 1}{1 - \gamma}$$

Where γ is a positive factor giving information on the willingness of the individual to rearrange consumption over periods of time.

The EIS can be calculated as:

$$EIS = - \frac{u'(C)}{C \cdot u''(C)}$$

As it is clear from the formula above, the EIS gives information on the shape and curvature of the utility function, which is precisely what determines the allocation of consumption of an individual across periods. In the case of the isoelastic utility function, the EIS is:

$$EIS = - \frac{C^{-\gamma}}{C \cdot (-\gamma \cdot C^{-\gamma-1})} = \frac{1}{\gamma}$$

For simplicity during the calculations, we name the $EIS = \frac{1}{\gamma} = \psi$.

The individual's problem with isoelastic utility function, across two periods of time, then becomes:

$$U(C_t, C_{t+1}) = \max_{C_t} \frac{C_t^{1-\gamma} - 1}{1-\gamma} + \beta \cdot \frac{C_{t+1}^{1-\gamma} - 1}{1-\gamma}$$

Subject to the intertemporal budget constraint:

$$C_t + \frac{C_{t+1}}{1+r} = Y_t + \frac{Y_{t+1}}{1+r}$$

The resulting Euler equation is:

$$C_t^{-\gamma} = \beta \cdot (1+r) \cdot C_{t+1}^{-\gamma}$$

Which can be re-written as:

$$C_t = [\beta \cdot (1+r)]^{-1/\gamma} \cdot C_{t+1}$$

Where

$$C_{t+1} = (1+r) \cdot (Y_t - C_t) + Y_{t+1}$$

We can replace the expression for C_{t+1} into the one of C_t to see how consumption in the first period changes with changes in the interest rate, computing $\frac{dC_t}{dr}$:

$$\begin{aligned} dC_t = & -\psi \cdot \beta \cdot [\beta \cdot (1+r)]^{-\psi-1} \cdot dr \cdot [(1+r) \cdot (Y_t - C_t) + Y_{t+1}] + [\beta \cdot (1+r)]^{-\psi} \\ & \cdot [dr \cdot (Y_t - C_t) - (1+r) \cdot dC_t] \end{aligned}$$

The final result is:

$$\frac{dC_t}{dr} = \frac{(Y_t - C_t) - \psi \cdot \frac{C_{t+1}}{(1+r)}}{[\beta \cdot (1+r)]^\psi + 1 + r}$$

Where $\psi = \frac{1}{\gamma} = EIS$.

The denominator is always positive, while the sign of the numerator is ambiguous: it includes both the income effect $(Y_t - C_t)$ and the substitution effect $\left(-\psi \cdot \frac{C_{t+1}}{(1+r)}\right)$ and the sign depends on which of the two effects is bigger. As we can immediately see, the EIS amplifies the substitution effect. When γ is high the individual is not willing to reallocate his consumption easily, and the EIS is small. In this second case, the

income effect wins over the substitution effect. Finally, we could have that $C_t > Y_t$, in which case the individual is a borrower.

Until now, we assumed that the individual was not facing uncertainty over the future state of the economy. In a stochastic environment, where the individual maximizes his expected life-time utility, we obtain the following Euler equation:

$$u'(C_t) = \beta \cdot (1 + r) \cdot E_t[u'(C_{t+1})]$$

If we consider the subjective discount factor, β , as continuously compounded, we can rewrite it as $\beta = e^{-\delta}$, where δ is the individual's discount rate. Additionally, we can write $(1 + r) = R_f$, which is the gross risk-free rate. With these changes, we obtain the following Euler equation:

$$u'(C_t) = e^{-\delta} \cdot R_f \cdot E_t[u'(C_{t+1})]$$

Rearranging:

$$R_f = e^{\delta} \cdot \frac{u'(C_t)}{E_t[u'(C_{t+1})]}$$

Taking logs on both sides:

$$r_f = \delta - \log\left(\frac{E_t[u'(C_{t+1})]}{u'(C_t)}\right)$$

Where the last term is the same as $\log\left(\frac{\partial U / \partial C_{t+1}}{\partial U / \partial C_t}\right)$, which proves the close link of the EIS denominator to real interest rates, as we stated at the beginning of this section.

From the expression for R_f , where we re-substitute $e^{-\delta} = \beta$, and apply the isoelastic utility, we obtain:

$$R_f = \frac{1}{\beta} \cdot C_t^{-\gamma} \cdot E_t[C_{t+1}^{\gamma}] = \frac{1}{\beta} \cdot E_t\left[\left(\frac{C_t}{C_{t+1}}\right)^{-\gamma}\right]$$

We raise both side of the expression to -1

$$\frac{1}{R_f} = \beta \cdot E_t\left[\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\right]$$

Applying the logarithm to the right-hand-side, we obtain:

$$\frac{1}{R_f} = \ln(\beta) - \gamma \ln \left(E_t \left(\frac{C_{t+1}}{C_t} \right) \right)$$

Where $\ln \left(E_t \left(\frac{C_{t+1}}{C_t} \right) \right) = E_t[\ln(C_{t+1}) - \ln(C_t)]$ and $\ln(C_{t+1}) - \ln(C_t) = c_{t+1} - c_t = \Delta c_{t+1}$, so

$$\frac{1}{R_f} = \ln(\beta) - \gamma \cdot E_t[\Delta c_{t+1}]$$

Applying the exponential to the right-hand-side will make the expression equivalent to the initial ones:

$$\frac{1}{R_f} = \beta \cdot e^{-\gamma E_t[\Delta c_{t+1}]}$$

Assuming conditional normality, we have the following:

$$\frac{1}{R_f} = \beta \cdot e^{-\gamma E_t \Delta c_{t+1} + \frac{1}{2} \gamma^2 \text{Var}_t[\Delta c_{t+1}]}$$

Applying the natural logarithm on both sides, and multiplying by -1 , we can rewrite as:

$$r_f = \ln R_f = -\ln \beta + \gamma E_t \Delta c_{t+1} - \frac{1}{2} \gamma^2 \text{Var}_t[\Delta c_{t+1}]$$

And finally rearranging we obtain:

$$E_t \Delta c_{t+1} = \frac{1}{\gamma} \left[r_f + \ln \beta + \frac{1}{2} \gamma^2 \text{Var}_t[\Delta c_{t+1}] \right]$$

Where $\frac{1}{\gamma}$ is again the elasticity of intertemporal substitution. This final expression defines the expected change in consumption from one period to the next one, i.e. the expected consumption growth, which depends on the elasticity of intertemporal substitution, the risk-free interest rate, the subjective discount rate and the variance of the consumption growth. This expression holds for multiple periods. One can show this iterating the expression one period ahead.

From the above expressions, we can see that:

- when impatience ($-\ln\beta$) is high, the interest rate is high;
- when consumption growth is high, the interest rate is high;
- when factor γ is high, the interest rate is more sensitive to consumption growth;
- the term $Var_t[\Delta c_{t+1}]$ captures precautionary savings. When consumption is more volatile, people with power utility are more worried about the low consumption states than they are pleased by the high consumption states. Therefore, people want to save more, driving down interest rates.

From the last expression:

- consumption growth is high when real interest rates are high, meaning that people save more today and consume their savings in the future, consuming more as a consequence;
- consumption is less sensitive to interest rates as the desire for a smooth consumption stream, captured by γ , rises, or when the elasticity of intertemporal substitution is small.

Similarly, the above relationship holds with Epstein Zin utilities. Kreps and Porteus (1978) and Epstein and Zin (1989) introduced recursive preferences, or recursive utility, which allow to break the link between EIS and relative risk aversion. Usually in the theory the EIS equals the reciprocal of the relative risk aversion factor (RRA): $EIS = \frac{1}{RRA}$. With recursive preferences, time t utility $U(C_t)$ is a function that depends on time t consumption, C_t , and utility at time $t+1$, $U(C_{t+1})$. Epstein and Zin generalize this with a certainty equivalent of $t+1$'s consumption: $U_t = F(c_t, R_t(U_{t+1}))$. If there is no uncertainty, $R_t(U_{t+1}) = U_{t+1}$. Dropping the restriction of $EIS = \frac{1}{RRA}$ leads to the following Euler equation:

$$1 = E_t \left[e^{-\delta \cdot \theta} \cdot \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} \cdot R_{w,t+1}^{\theta-1} \cdot R_{t+1} \right]$$

Where:

$$\theta = \frac{1-\gamma}{1-\psi^{-1}}.$$

R_w is the return on the wealth portfolio that pays dividends and is not observable.

δ is the subjective discount factor.

ψ is the EIS.

γ is the relative risk aversion (RRA).

It is easy to see that when $\psi = \frac{1}{\gamma}$, i.e. when there is the link between EIS and RRA, $\theta = 1$ and the

$$\text{Euler equation is back to } 1 = E_t \left[e^{-\delta} \cdot \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \cdot R_{t+1} \right].$$

Epstein and Zin (1989) deal with a sub-class of utility functions which (a) adheres to the von Neumann-Morgenstein properties, (b) have an infinite horizon extension as presented by Kreps and Porteus, and (c) have

properties which belong to the a-temporal non-expected utility theory of Chew (1989) and Dekel (1986), extended into a multiperiod framework. The utility functions considered in their paper are all recursive and thus intertemporally consistent. However, the manner in which their choice of utility function stands out is for instance due to the circumstance that they discard the general assumption that consumers are indifferent between spending today and in the next period. Epstein and Zin argue that uncertainty about the future affects the consumption choice. The model the authors present takes into account both the current macroeconomic conditions reflected by the consumption index and the deviation hereof, as well as the rate of return on the asset being considered¹¹.

3.4. *The EIS in practice*

As stated by Thimme (2016), *assumptions on consumers' preferences have a great impact on estimates of the EIS*. The tradition of Hall (1988) assumes a log-linearized consumption Euler equation with constant relative risk aversion (CRRA). This is also what we assume in our analysis. Different studies have used log growth in consumption of non-durable goods and services and the 3-month real government bond rate, to estimate the EIS from the recursive preferences' Euler equation. We use the same variables, even though our data on consumption includes also durable goods.

Popular ways to measure variations of the correlation of consumption growth and short-term interest rate have been to use GDP as proxy for consumption and stock market returns as a way to capture a change in the expected rate of return on an investment. In our case, we have data on both consumption growth and real short-term rate, so we do not need any proxy.

The classic equation to estimate the EIS is the following:

$$\Delta c_{t+1} = \alpha_i + EIS \cdot r_{i,t+1} + \epsilon_{i,t+1}$$

Δc_{t+1} denotes the consumption growth at time $t+1$, i.e. in the next period, $r_{i,t+1}$ is the real return on asset i at time $t+1$, and $\epsilon_{i,t+1}$ is the error term. The error term is most of the time correlated with $r_{i,t+1}$. For this reason, multiple studies add control variables and instrument the short-term interest rate. We try both approaches as well. We assume discrete time, but the theory holds in continuous time as well. As a final note, researches have, since the work of Hall, moved away from seeing the EIS as the inverse of relative risk aversion. This is because this relationship does not hold when we measure the EIS in isolation as demonstrated above. Thus, it is beneficial not to make assumption on RRA from the measured EIS.

¹¹ they explain that in this sense the framework is a combination of the static CAPM and the consumption CAPM, p. 957

4. Empirical framework: the eurozone and the ECB rates

4.1. *Chapter outline*

In this chapter we set the framework for the subsequent analyses and discussions. Namely we will raise attention to the development of the eurozone, a group of European countries that adopted the euro in 2002, and the operations of the European Central Bank (ECB).

The chapter covers the following subjects. Section 4.2 presents the eurozone, in terms of its development and current scope. Section 4.3 deals with the European Monetary System and the launch of the euro, while section 4.4 presents the ECB's mandate. Sections 4.5 and 4.6 explain the link between monetary policy rate and short term market rates, in theory and practice respectively. The last section includes a practical case that shows how a country outside the eurozone, namely Denmark, implements the ECB's monetary policy rate.

4.2. *The eurozone – development and current scope*

The European Union was originally formed on the back of World War II which had torn apart Intereuropean relationships and set many of the largest economies in Europe decades back in time. In 1957, the Treaty of Rome was signed, forming the European Economic Community by France, West Germany, Italy, Belgium, the Netherlands and Luxembourg. They adopted common import tariffs on non-member imports, promised free labour mobility, capital market integration, free trade in services and a range of common policies, and as a response, 11 outsiders led by the UK formed EFTA in 1960. However, the following year, the UK applied for EEC membership and by 1973 the structure we know today had taken shape. In other words, a closely tied EEC core and a broader EFTA periphery consisting of e.g. Norway and Sweden. In the early 1970s, the currency peg that most West European countries had sustained against the dollar became unviable, and a need for exchange rate stability was seen as key to ensure future growth and prosperity in Europe. In 1971 the EEC adopted the Werner plan which designed a step-by-step plan for a European monetary union by 1980, but integration slowed due to instability in relation to oil crises and stagflation¹². This put monetary integration on hold until the establishment of The European Monetary System (EMS) in 1978¹³ in which currencies were fixed against the precursor to the euro.

An important step to turn monetary integration into reality was the Delors report which outlined three steps to a single currency in Europe: (1) Complete the internal market and remove restrictions on further financial integration; (2) Establish the European Monetary Institute to strengthen central bank cooperation and

¹² High unemployment and high inflation

¹³ Adopted the following year

prepare for the European System of Central Banks (ESCB). Hereunder plan the transition to the euro; define the future governance of the euro area and achieve economic convergence between the Member States; and finally (3) the fixation of exchange rates of willing member states and transition to the euro (Baldwin and Wyplosz, 2015). From the Delors report it follows that the ECB and ESCB would be responsible for independent monetary policy making – indirectly on behalf of the eurozone members. While Member States would remain in control of own fiscal policies, they would be required to implement binding budgetary rules.

By 1987 the members had adopted the Single European Act which in short was designed to enforce and broaden the four freedoms of the Treaty of Rome. With the fall of the Berlin wall in 1989, Helmut Kohl and Francois Mitterand guided the making of the Maastricht Treaty which proclaimed the intention to form a monetary union by 1999 and a single currency area by 2002 (Baldwin and Wyplosz, 2015).

Today the eurozone consists of 19 countries. Namely the original 12 countries: Belgium, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, the Netherlands, Austria, Portugal and Finland, and then subsequently Slovenia (since 2007), Cyprus and Malta (since 2008), Slovakia (since 2009), Estonia (since 2011), Latvia (since 2014) and Lithuania (joined in 2015) (Baldwin and Wyplosz, 2015).

4.3. The European Monetary System and the launch of the euro

With the adoption of the European Monetary System (EMS) in 1979 the intension of creating a union of monetary stability and economic cooperation was official. The member currencies were fixed against each other within a narrow band of fluctuation based on a central European Currency Unit (ECU) rate¹⁴. Early on it was realized that the countries needed to re-align fiscal policy as fiscal prudence has direct implications for inflation. Among other measures, it was required to support the exchange rate peg by means of raising interest rates and tightening up budgetary policy, however large inflation differences remained. As a result, currency realignments among member states were frequent. Eventually ERM I, the name of the first European Resolution Mechanism, was abandoned in 1993 following a number of speculative attacks and the uncertainty concerning the signing of the Maastricht Treaty. In 1999 the EMU was established with the launch of ERM II, and by 2002 the euro was introduced¹⁵.

The member states should adhere to a set of convergence criteria before being allowed to join the euro. These directed that a member should set guidelines with respect to low inflation and low interest rates. Furthermore, budget deficits should not be allowed to exceed 3% and public debt to GDP ratio should not exceed 60% (Baldwin and Wyplosz, 2015).

At the outset, the most unstable members did in fact fulfil the requirements of low inflation and interest rates, however this might be due to a ‘self-fulfilling prophecy’ in the sense that the market expected these

¹⁴ Spain, Portugal and Italy had a wider, 6%, band of fluctuation

¹⁵ One might say DK is the only current member of ERM II since it is the only country with a currency peg and without the euro

countries to commit to the EMU and thus keep inflation low in the long run. Such expectations would have direct effects on current rates. However, budget deficit rules and government debt to GDP rules were not strictly adhered; especially Italy and Greece had above 100% debt to GDP. This did create room for concerns at the time and for instance the inclusion of Greece was postponed one year, but as we know today, both countries were eventually allowed to become members of the common currency area (Baldwin and Wyplosz, 2015).

4.4. *The ECB's mandate*

Today the control of the ECB remains dominated by the five largest economies in the eurozone: Germany, France, Italy, Spain and the Netherlands. The current president of the ECB is an Italian economist, Mario Draghi, who has served since 2011 from the bank's headquarters in Frankfurt. The primary objective of the European System of Central Banks (ESCB) has been and remains to ensure price stability, specifically to limit CPI to below 2% in the medium term. Only thereafter might the ECB take action with the purpose of tackling economic fluctuations. An inflation target is by far the most common central bank target, but one might question that the target is not more clearly defined. However, a broad central bank target is arguably good in this context as the main objective of the central bank governor is to calm markets and not disappoint investors. On the contrary, the central bank should always adhere to set targets. This is what is referred to as 'signalling' (Cœuré, 2015).

The ECB also acts as 'lender of last resort' as is traditionally expected of a central bank. In other words, the ECB is expected to provide liquidity to the financial system in order to prevent lending markets from freezing and the interbank market from breaking down. Such operations may become necessary in a time the banks refuse to lend to each other as we observed recently during the financial crisis (Baldwin and Wyplosz, 2015).

4.5. *The monetary policy rate and short term market rates – in theory*

To see how ECB decisions translate into the real economy, we are now going to explain the link between the monetary policy rate as set by the ECB and the market rates we observe. When we refer to monetary policy changes, we no longer talk of the issuance of banknotes as large transactions are all handled electronically (Danmarks Nationalbank, 2009). We talk of how a central bank affects the short-term money market rates via monetary policy rates and related market operations. The monetary policy rate, I_t , consists of expected inflation, π_t^e , and the real interest rate, i_t , as set by the Governing Council of the European System of Central Banks (ESCB) (Baldwin and Wyplosz, 2015).

$$I_t = i_t - \pi_t^e$$

The interest rate that consumers and firms borrow and invest at is the nominal market rate, R_t , which is higher than the monetary policy rate by a risk premium, σ_t . The risk premia reflect credit and liquidity risk between borrower and lender on top of the monetary policy rate which reflects a risk-free return and may vary substantially across contexts (Blomquist et al., 2011). In general, the short-term real market rates, r_t , are linked to the monetary policy interest rates and inflation expectations as illustrated below:

$$R_t = I_t + \sigma_t \rightarrow r_t = i_t + \sigma_t$$

The real market rate is thus a direct sum of the real monetary policy rate and a risk premia, but also interest rates on assets with longer maturities are affected by the monetary policy rate as long-term yields are merely the average of the expected short-term interest rates over the relevant period of time plus a premium to compensate the lender for the uncertainty of changes in the real interest rate during the period. Such a premium is increasing in the maturity and the relationship is illustrated below. The fixed real market rate is denoted r_t^k and the term premium for interest rates in k periods of time is denoted t_τ^k (Blomquist et al., 2011).

$$r_t^k = \sum_{j=0}^k r_{t,t+j}^e + t_\tau^k$$

Here it is illustrated how the monetary policy rate directly affects the 3-month interest rate and thereby also the ten-year government bond yield as the short rates feed into the longer maturity bond. We employ both of these in our tests.

4.6. *The monetary policy rate and short term market rates – in practise*

4.6.1. *Key interest rates*

In the previous section, we assumed that the central bank only sets one monetary policy interest rate. This is not the case in practice. In fact the ECB sets three key interest rates (ECB, 2017): (1) the interest rate on the main refinancing operations at which the majority of liquidity is provided to the banking system; (2) the deposit facility rate; and (3) the marginal lending facility rate. These provide a floor and a ceiling respectively for interbank lending. In between is the rate of the main refinancing facility which is decided upon

given an auction process by the Eurosystem¹⁶ as well as the Euro Overnight Index Average (EONIA)¹⁷. The rate of the main refinancing facility translates into short term rates across the European banks via the European interbank market. In other words, by maintaining open lending and deposit facilities at pre-announced interest rates and steering the market in-between, the monetary policy rate as set by the ECB directs short term rates. This is why European banks' short term rates are almost identical while they may have very different long term interest rates depending on the national risk premium (Baldwin and Wyplosz, 2015).

Furthermore, besides open market operations – i.e. adjustments to the main refinancing rate – a central bank also has other tools to steer the economy in times of recession. In response to the recent crisis, we have observed the ECB's initiation of a quantitative easing (QE) programme with which the central bank creates money and buys government and corporate or mortgage backed bonds from financial institutions and market participants with the hope of raising their prices and thereby lowering the yields on such assets. This acts to increase the value of the banks' balance sheets and most importantly it increases their cash holdings which should encourage the banks to increase lending to consumers and businesses. Thus, the intension is that the economy should be encouraged to invest and spend itself out of a slump (Cœuré, 2015).

The ECB governing council announced in May 2009 that it would permit the ECB to purchase up to 60 billion euros of covered bonds, which is debt backed by pools of assets, on both the primary and secondary markets. This amount has since increased several times. In the beginning of 2017 the ECB had purchased assets worth more than 1.5 trillion euros. However, by the end of 2016 the ECB announced a reduction in monthly asset purchases from 80 billion euros to 60 billion (Hale, 2017).

4.6.2. Implications from a change in the interest rate

In the previous section, we outlined how the short-term interest rate – the main refinancing rate – has direct effect on longer term interest rates from a theoretical perspective. It follows that if the overnight rate is lowered, the rate on securities with longer term structures will also fall. Further, asset prices increase as the opportunity cost from an investment decreases. Intuitively it is less expensive to lend money which enables house buyers and stock investors alike to buy larger quantities and more expensively. This also works to put downward pressure on the euro as investors look for higher yields elsewhere and thus demand for the currency drops. Everything else equal, this should improve the eurozone's terms of trade. This is the classic text book relationship, however if we consider the role of signalling it may also be that a lowering of the monetary policy rate suggests that the central bank is assuming that inflation will stay depressed for the coming period. In other words, a lowering of the interest rate may make investors expect a less positive outlook for the economy. The

¹⁶ The monetary authority of the Eurozone. It is led by representatives of the national banks of the 19 eurozone members as well as the Executive Board of the ECB. This is the ESCB.

¹⁷The EONIA is the weighted average of overnight unsecured lending transactions in the euro interbank market.

opposite example is that a rise in the interest rate might encourage investors and thereby drive stock markets up, contrary to the relationship just described.

4.6.3. *The Danish case*

To best illustrate the effect of the ECB's policy changes on the individual eurozone and fixed currency regime countries, we have chosen to describe the line of dependency by means of the Danish example. This choice has two reasons: firstly, we want to illustrate the effect of the ECB's policy rate, and secondly, we introduce a case that is interesting to us, or rather how a country that does not belong to the eurozone has still chosen to tie its monetary policy to its interest rate as the Danish fixed exchange rate policy *vis-à-vis* the euro implies that Danmarks Nationalbank's lending rate as a general rule follows that of the ECB¹⁸.

Denmark has had a fixed-exchange rate policy, first against the D-mark and from 1999, towards to euro (Danmarks Nationalbank, 2009). As touched upon in previous sections, this implies that the Danish monetary policy rate as a general rule follows ECB rate setting. This property is best illustrated by means of the theory of the impossible trinity as introduced by Mundell-Flemming. The simple logic is that a national can only obtain two out of three of the following properties; full capital mobility, fixed exchange rate and autonomous monetary policy (Mundell, 1961). As financial markets are highly integrated, free capital mobility is arguably less of a choice than a necessity in order to have a well-functioning domestic financial market. Thus we observe that eurozone members have chosen a fixed exchange rate regime and thereby implicitly accepted that monetary policy be set by the ECB. This property is directly transferable to the Danish case as the Krona is irrevocably pegged to the euro.

Danmarks Nationalbank sets the following monetary policy rates: the discount rate, the current account rate, the lending rate and the rate of interest on certificates of deposit. These are determined by the Board of Governors of Danmarks Nationalbank and may be changed at any time. The monetary policy counterparties – i.e. for instance the Danish banks – have access to two facilities at Danmarks Nationalbank. These are via open market operations in which the counterparties have the option to borrow funds against securities by purchasing certificates of deposit. This occurs on the final banking day of each week and lasts for the next seven days. The other facility Danmarks Nationalbank provides is the current account where counterparties can place liquidity, but whose balance must not be negative at the end of the day. The Danish central bank is the sole supplier of the current account liquidity which is in demand by the banks as risk-free and safe means of interbank settlement. As in the inter-European market described above, the Danish banks' own interest rates lie very close as they all depend on the banks' own terms of lending. Just as is the case in the European

¹⁸Only in unusual events in which the Danish krone has been subject to a sustained strengthening or weakening against the euro may Danmarks Nationalbank be forced to adjust the interest rate unilaterally to protect its peg towards the euro.

interbank market in general. However, should short term or frequent changes in the monetary policy rate occur, the banks may be reluctant to implement these immediately due to menu costs (Danmarks Nationalbank, 2009).

The reader may question why are the interest rates across the eurozone are not all identical if all central banks set their national interbank lending and borrowing rates as illustrated by the Danish example. Here it is essential to recall that risk premia may differ substantially. Until the outbreak of the sovereign debt crisis in Europe, risk premia across the eurozone hardly differed. However, this changed alarmingly with the introduction of bankruptcy risk of Greece among other eurozone countries. Interest rates have again grown closer to each other, but the almost identical levels of perceived risk are not assumed to return in the near future (Baldwin and Wyplosz, 2015).

5. Data

5.1. Chapter outline

The purpose of this chapter is to provide an overview of the data we use. In section 5.2 we introduce our dataset, in 5.3 we present the study estimates that we select from Havranek et al. (2015), as well as, in 5.4, the macro variables we use in the analysis concerning [research question 2](#).

5.2. Our dataset

Our dataset originates from Consensus Economics which is a world leading international economic survey organization which attains forecasts and views on country-specific macro aspects from more than 250 economics across 85 countries each month (Consensus Economics, 2017). The respondents of the survey are prominent economic forecasters and financial institutions for each country. The United States' forecasters include Morgan Stanley, Goldman Sachs, Moody's Analytics and Oxford Economics, together with more than other 20 institutions.

Our data is a panel dataset which consists of country-specific variables in expectations for 14 countries. Specifically, we have data on the US, Canada, Japan, Australia, New Zealand (as outside-Europe benchmarks), Germany, France, , Italy, the Netherlands, Spain (as eurozone countries), the UK, Norway, Sweden and Switzerland (as rest of Europe outside the eurozone) as All data is monthly and runs from January 1993 until December 2014 with a few missing years for some countries. The data provides subjective estimates on expectations with respect to change in GDP, inflation and similar macroeconomic variables, some of which are beyond the relevance of this topic. All expectations are subjective estimations of values one year ahead, which also implies that we have a 11-month time overlap in estimates.

Specifically, we have data on economists' expectations of yearly real and nominal change, reported on a monthly basis, of the following variables:

- Gross domestic product
- Household consumption
- Gross fixed investment
- Corporate profits
- Manufacturing production
- Retail prices (rpix)
- Producer prices
- Wages

- Car sales
- Housing starts
- Unemployment rate
- Current account
- PSNCR (fiscal years)
- Three month interest rates (3m)
- 10 year government bond yield (10y)
- Consumer prices index (hicp)
- Money policy evaluation: probability of rate change in the next 30 days¹⁹

These different expectations are divided by the name of the financial or economic institution as well as by country. The variables we focus on for each country are expectations of change in consumption and forecasts of interest rates and government bond yields (3m and 10y in particular). Additionally, we will include in some of the models the expectations of change in wages, unemployment level and budget deficit. [Table 5.1](#) shows the summary statistics for these variables as well as information on the periods and total number of observations. Specifically, in order to estimate the EIS, we will use the expected yearly change in consumption for one period as the dependent variable and the expectation of the real cost of current consumption, measured in a number of different ways and subject to various test alternatives, as the explanatory variable.

Table 5.1: Summary statistics of our dataset

	count	mean	sd	min	max
E_cons	3,422	1.94	1.19	-2.67	4.42
E_m3	3,422	3.44	2.20	0.00	12.45
E_y10	3,422	4.77	1.85	0.70	12.95
E_wages	3,082	2.81	1.20	-2.19	6.00
E_unem	2,304	7.16	2.55	2.42	12.75
E_budget_def	2,565	-61.57	202.04	-1512.14	396.62
year	3,696	2003.5	6.35	1993	2014
month	3,696	6.5	3.45	1	12
N	3,696				

5.2.1. Data validity and reliability

We consider this dataset unique and very adequate to our purpose. We argue that this is the case since the ideal way to test the EIS is to detect the correlation between the real change in the cost of current consumption

¹⁹ These variables refer to the UK survey. Variables can change slightly from country to country, but the variables of interest that we are going to use in our analysis are consistent across countries.

and the actual change in future consumption (also called planned consumption) as stated by consumers. However (a) due to endogeneity issues²⁰, and (b) lack of access to a dataset of subjective consumer forecasts and expectations, this ideal EIS test is not possible in practice. Our dataset however, allows to test the EIS in a close-to-optimal manner. Also, consistent and reliable datasets of consumer expectations are highly rare and would potentially be less valid for comparison between countries as one might be worried that certain consumers have been questioned in one country and certain in another, leading to a problem of selection bias. In other words, the data would be very sensitive to method of measurement. In our case, the data is collected by the same institution across different countries, insuring consistency of questions and respondents. We consider this dataset a very close substitute for the ideal test, as described above, for a number of characteristics which we will explain below.

1. **Sample size and time length.** The dataset consists of country-specific expectations made by a large and varied group of experts from financial institutions. Furthermore, the dataset spans across a long period of time which results in a high amount of data points which make our test findings more robust. In total, we count 3,696 observations. Furthermore, the latest data points run up to 2014, a fairly recent year, which allows us to propose conclusions on current times.
2. **Source and consistency.** The dataset is from a highly trustworthy source. Consensus Economics has been providing macroeconomic forecast benchmarks since 1989, when the analytical institute was established in London (Consensus Economics, 2017). In addition, the survey is consistent in the manner of data collection as the forecasters are often recurrent and from identical financial institutions across borders. This makes the dataset well-suited for our purpose where we want to have a similar a survey approach in different countries and then still be able to estimate heterogeneity in the EIS estimates. The estimates are subjective but we test for significant difference between Consensus Economics forecast on GDP growth and inflation relative to their realised values and we get overall no significant difference between the two vectors. The conclusion that the expectations are very close to realised data is supported by the notion that the respondents are considered market makers – or at least very close market observers – and thus very aware of market development and price changes. Thus, their inflation forecasts and expectations of changes in consumption may be considered as close to realised numbers as would be possible to attain. Finally, Consensus Economics its-self also provides tests on an ongoing basis which illustrate the similarity between the forecasts and the realized data.
3. **Expectation on both sides and avoidance of noise.** The most important reason for why we consider this data set excellent is that it provides us with subjective measures on both sides of the equal sign; thus we

²⁰Due to simultaneity and omitted variable bias ect., which will be elaborated on in a subsequent chapter.

‘clear’ our correlation estimate from auxiliary assumptions on the expectation formation process (Crump et al., 2015). Earlier studies which have not had access to expectational data suffer from estimation error which results in attenuation bias and close to zero EIS estimates.

4. **Availability of consumption growth.** Finally, this dataset provides us with a very important variable: consumption growth, which is usually not available and therefore proxied by GDP in many studies of the EIS.

5.2.2. Data limitations

We realise our data is not without flaws. We would foremost have wished that the data sample consisted of more countries and it would have been ideal to have an even longer time period as well as more measures of the cost of current consumption – i.e. more bond yields and/or short term interest rates.

5.3. EIS estimates from other studies

For our second analysis, [research question 2](#), we use additional estimates of the elasticity of intertemporal substitution from Havranek et al. (2015). We download Havranek et al.’s dataset from meta-analysis.cz/substitution.

The initial Havranek’s dataset includes 2,736 EIS estimates. We clean this dataset eliminating:

- EIS estimates larger than 100 in absolute value²¹
- EIS estimates that refer to more than one country
- EIS estimates coming from samples older than 1973²²
- EIS estimates coming from non-OECD countries.

[Table 5.2](#) shows the summary statistics for the EIS.

Table 5.3: Summary statistics of Havranek et al.’s EIS dataset

	count	mean	sd	min	max
eis	1,236	0.86	3.98	-37.00	61.73

Our choice of cleaning the initial dataset is justified by the fact that Havranek et al. don’t explain in detail how they collect the macro variables for the different countries, so we do that and in order to have

²¹ Havranek et al. (2015) use a similar elimination of outliers, arguing: “For all the analyses in this paper we have excluded estimates of the EIS larger than 10 in absolute value. [...] The threshold of 10 is arbitrary, but we get very similar results with the threshold set to 1, 5, 20, and 100.” (Havranek et al., p. 111, Journal of International Economics 96, 2015). In the Appendix XX we show the results (1) using the whole sample and (2) eliminating EIS bigger than 10 in absolute value.

²² i.e. when the starting year of the analysis is older than 1973

reliable macro variables, i.e. from reliable sources²³, we cannot use studies that are too old and for some of the countries. We are left with 1,236 estimates for 28 countries, listed in [Table 5.3](#) below.

Table 5.4: List of countries included in our analysis

USA	Chile	Denmark
Switzerland	Korea, South	Finland
Germany	Turkey	Ireland
UK	Australia	Greece
Canada	Italy	Iceland
France	Mexico	Luxembourg
Japan	Spain	New Zealand
Sweden	Austria	Norway
Israel	Belgium	Portugal
Netherlands		

Out of these countries, we have 12 out of 19 countries belonging to the eurozone, with the corresponding number of studies estimating the EIS for that country, as listed in [Table 5.4](#):

Table 5.5: List of eurozone countries included in our analysis, with corresponding number of studies

Eurozone country	# studies
Austria	5
Belgium	5
Finland	44
France	43
Germany	39
Greece	3
Ireland	5
Italy	32
Luxembourg	3
Netherlands	31
Portugal	3
Spain	41

We therefore have 254 estimates when considering the eurozone.

²³ See the [Macroeconomic variable](#) section for the sources of our macro variables

5.3.1. Method variables

Because we use EIS estimates from other studies, we need to account for different study designs, as Havranek et al. do. In doing this, we focus on the methodology variables that form the optimal model resulting from a Bayesian Model Averaging (BMA) analysis. These are:

- Inverse estimation =1 if the rate of return is the response variable in the estimation
- Top journal =1 if the study was published in one of the top five journals in economics
- Stock return =1 if the rate of return is measured as the stock return
- Total consumption =1 if total consumption is used in the estimation
- OLS =1 if ordinary least squares are used for the estimation
- No. years = the logarithm of the number of years of the data period used in the estimation.
- Asset holders =1 if the estimate is related to the rich or asset holders
- Exact Euler =1 if the exact Euler equation is estimated
- Capital return =1 if the rate of return is measured as the return on capital
- Monthly data =1 if the data frequency is monthly

5.4. Macroeconomic variables

We have gathered data from the World Bank, The Worldwide Governance Indicators, Eurostat and World Happiness Report 2017. To further strengthen the basis for our conclusions, we have more than one measure for the same variable when it comes to estimates which may be highly affected by the manner in which the survey was performed. This is for instance the case when it comes to perception of level of corruption and national government efficiency. We have the variables on structural differences with respect to (1) wealth level; (2) stock market participation and indebtedness; (3) credit liquidity versus credit constraints and (4) trust in local institutions. The control variables we collect for our analysis are the following:

- Credit provided = Domestic credit to private sector (% of GDP)
- Tax rate = Taxes on income, profits and capital gains (% of revenue)
- GDP per capita = GDP per capita (current US\$)
- Stock participation = Stocks traded, total value (% of GDP)
- Listed market cap = Market capitalization of listed domestic companies (% of GDP per capita)
- Control of corruption = An indicator that reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests

- Government effectiveness = An indicator that reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.

Summary statistics for these variables are provided in [Table 5.5](#).

Table 5.6: Summary statistics of our macroeconomic variables

	count	mean	sd	min	max
credit	1,236	94.31	35.83	17.89	192.13
tax_rate	836	43.59	13.08	13.05	65.36
GDP	1,236	18,300	7,483	1,197	61,696
Stock_part	1,232	34.88	28.02	1.89	237.93
listmktcap	922	9.68E+09	7.42E+09	0	3.48E+10
corruption	588	1.66	0.45	0.28	2.44
gov_eff	588	1.71	0.29	0.54	2.11
N	1,236				

6. Empirical Analysis 1: RQ1: Is EIS heterogeneity present amongst eurozone countries?

6.1. Chapter outline

The objective of this section is to estimate to what extent there exists heterogeneity in the elasticity of intertemporal substitution amongst eurozone countries. To answer this question, we first estimate the EIS across the whole panel sample and get a benchmark estimate. Consequently, we run time series regressions for each country and get country-level EIS. Finally, we test whether the country-specific estimates are significantly different between each other before making our conclusions.

The panel EIS estimate enables us to discuss the optimal econometrics model to test for the EIS given the data we are using. It also allows us to compare our findings to earlier studies. The second part of the analysis provides us with country-level EIS estimates which we compare to evaluate whether heterogeneity is present and if yes, to what extent. Both the panel and the country-level analyses are done using a number of econometric models which are described below. Finally, the country-specific EIS estimates will serve as basis for the analyses performed under [research question 2](#).

In all the models, we regress the expected percentage change in consumption, i.e. expected consumption growth, one year from now on the expected three-months interest rate (expressed as percentage) one year from now, as based on the classic model.

$$E[\% \Delta cons] = \alpha + EIS \cdot E[\% r]$$

Depending on the regression model, we add controls, dummy variables, interaction terms and use instrumental variables.

This chapter is divided into the following sections. 6.2 gives an overview of the econometric considerations, which we base our models on. 6.3 lists the models that we are going to use with a brief description. 6.4 analyses and discuss the panel data results. 6.5 analyses and discuss the time series results. Finally, 6.6 concludes the chapter.

6.2. Overview of econometric considerations

Before starting the analysis, we want to highlight some of our econometrics considerations with respect to choosing the optimal models.

6.2.1. Heteroscedasticity and autocorrelation

Our estimates are affected by both heteroscedasticity and autocorrelation. This is a common problem with time series. When we test, we identify very high persistency in the sense that in expectation the dependency from one period to the next is 1-to-1 and the error term is the only difference²⁴ in expectation between the variables in two subsequent periods.

Additionally, we have an overlap of 11 months in the observations, since the survey reports yearly expectations every month. In order to overcome these issues, we use HAC standard errors with a bandwidth of 12 in all the models we run.

Furthermore, we use the fixed effect (FE) model in the panel data regression, to try and overcome the autocorrelation given by time-constant elements. By removing the mean levels of variables and error term - as is done via the FE approach - we overcome bias due to country specifics and clean the errors from most serial correlation as would usually occur due to dependency on model variable levels -.

Thus, the FE model assumes the source of bias is due to time independent effects. In our case this is the country characteristics which may bias the model variable estimates and ruin the error term with noise²⁵. It is not possible to control for the fixed part of the error term in the regular way as we cannot observe it and therefore cannot isolate it.

For completion, we should mention that there are alternative panel regression methods with some of the same characteristics as the FE model. The random effect model is deemed irrelevant to our dataset despite the attractive feature that the model presents small standard errors. This is due to the circumstance that the random effect model is a special case of the FE model which assumes no correlation between the individual specific effects (they are assumed to fluctuate at random) and the independent variables in the model. This is very unrealistic in our case as we on the contrary would expect country-specific differences which would affect the EIS estimate. However, to verify that we should indeed use the FE model, we employ a Durbin-Wu-Hausman test to see whether FE test results are consistent when compared to pooled OLS. The FE model passes the test.

6.2.2. Dummies and interaction terms with respect to recessions and the eurozone

We also include control dummies for the 2008 financial crisis and the sovereign debt crisis in Europe which started in late 2011. In this way, we can isolate the concrete effect on consumption growth from each abnormal period.

²⁴ The error term is naturally equal to zero in expectation

²⁵ Large or non-normal error terms due to dependency on model variable levels

In determining when to allocate the recession dummies we use the Euro Area Business Cycle Dating Committee's conclusions (Centre for Economic Policy research, 2015) which results in recession dummies in the following time spans:

- 2008Q1 – 2009Q2
- 2011Q3 – 2013Q1

We also include interaction terms with respect to the crisis, the recession and the eurozone, which allow us to see how the EIS differs when we are in a crisis, in a recession or in eurozone countries respectively²⁶.

6.2.3. *Choice of instruments and controls*

Early studies of the EIS (often) suffer from bias in the estimates due to endogeneity stemming from (a) correlation with the error term due to omitted variable, (b) measurement error and (c) simultaneity bias. Correlation with the error term due to omitted variables should be accounted for in our model when we include controls. The control variables we decide to include come from our dataset and are in expectations. They are:

- % change in wages,
- unemployment rate, expressed as % of labour force,
- government budget balance.

The intuition for why we have chosen these controls is as follows: expectations of unemployment and wage growth affect the consumer's expectation of disposable income and thus his or her consumption plan. In parallel, expected rise/fall in the budget deficit is relevant as control since expectations of failing government financials are likely to make the consumer expect a rise in taxes and thus make him postpone current consumption and save more for the future instead.

We have not included all macro variables which may be correlated with the interest rate as controls. This would simply do harm to the EIS estimate. Therefore we do not include macro variables such as expected rise in GDP or inflation, which have an ambiguous relationship with consumption²⁷. Additionally, we include those three macro variables when running the tests for instrumental variables explained below to test their correlation with consumption growth.

²⁶ See appendix for the code used

²⁷ Furthermore, GDP is often used as a proxy for consumption as mentioned in previous chapters.

Another reason why early studies may suffer from estimation bias is that the measurement error is correlated with the error term²⁸ and this causes attenuation bias. Thus, early studies often report a small estimate for the EIS. When we use expectations, we remove the estimates from most of this noise.

Finally, we try to solve the simultaneity problem and account for any omitted variable that we cannot identify by means of instrumental variables. We identify the following candidate instruments from our dataset:

- Lags of the 3-month interest rate beyond past 12 periods
- 10-year government bond yield²⁹ (10y),
- Lags of the 10-year rate
- Macro variables as listed above (% change in wages, unemployment rate, expressed as % of labour force, government budget balance).

The choice of the lags of the 3-month interest rate (3m) is justified by the literature and used for example by Vissing-Jørgensen (2002). The specific lags we choose are 12, 13 and 14. This is because as already explained we have 11 months of overlapping observations, so we pick the lags outside of the overlap, as also Vissing-Jørgensen (2002) does, as explained in the Literature Review chapter.

The 10-year rate could be a good instrument, but because of its possible correlation with consumption growth, we also include its first, second and third lags.

Finally, we test the three macro variables we introduced above as possible instruments as well. The three macro variables are possible candidates both as instruments and as controls. Depending on the tests, we include them as one or the other. All of these variables are available in our dataset for all time periods and denoted in expectations.

We run a number of tests and models with different combinations of the instruments, whose code and output are reported in the [appendix A.1](#). We first regress 3m on all the instruments and they all prove more or less significant. We proceed running different instrumental-variable-regressions testing for overidentifying restrictions and endogeneity after each of them. This analysis gives us an idea of which instruments are better than others. We observe that the macro variables are all either statistically or economically *insignificant* in predicting the 3m, thus they do not pass the first test of a good instrument. Consequently, we use the `ivreg2` code, which performs a number of tests for instrumental variables, and run it with different combinations of instruments.

From the same regression on explanatory power with respect to the 3m, as first step in choosing the best instrument for the primary regression, we find that 10y has statistical significance albeit small economic significance in predicting 3m. We include 10y as we believe it could be a very good instrument candidate since

²⁸ More specifically with the macro variables reflecting the state of the economy as found in the error term when not controlled for.

²⁹ Transformed into an annual rate.

whereas 3m is driven by changes in macro variables, this is not to the same extent the case when it comes to 10y. As explained in a previous chapter, theoretically, we would expect risk premia to stay constant and the long run rate to be a function of short-term rates, to satisfy the concept of no arbitrage. This implies that the levels of the two variables are closely correlated, - which is also what we find -.

However, we are aware that the variable changes are not linear due to the role of the risk premium in the 10y. Even though risk premia are assumed to stay constant over time, what we observe is that risk premia change, according to risk perception, and in fact this is the primary explanation for variance in the long run yield (Buraschi et al., 2017). The change in risk perception may very well depend on changes in macro variables and thus the changes in the long run rate entails some of the same issues as 3m. Also, we may fear that the change in risk perception has direct impact on the change in consumption, the dependent variable. This is also what we find as 10y does not pass the Sargan test, implying that 10y has independent effect on the change in consumption. This rules out 10y as a preferred instrument. However, the lags of the 10y do pass the test and these we choose to employ.

Finally, we pick the optimal instruments which have passed the tests for instrumental variables: lags 12, 13 and 14 of 3m and lags 1, 2 and 3 of the 10y. These will serve as our choice of instrument throughout our analysis as we progress.

6.3. Model testing overview

The purpose of this section is to provide an overview of the estimation approach before we start analysing findings. The section is split between panel and time series model estimation approach.

6.3.1. Panel data analysis

The first part of our analysis is the estimation of a benchmark EIS for the whole panel of 14 countries across 22 years, as well as an analysis of what occurs when we include recession dummies and a dummy for eurozone countries³⁰. We run panel regressions by means of pooled OLS and fixed effect, adding controls and using instrumental variables. As mentioned before, all our models have HAC standard errors. We run the following models, which include different combinations of interaction terms, dummy variables, control variables and use of instruments:

³⁰ Added as interaction term with 3m

Model #	Model	Fixed effect	Instrument	Interaction terms for crisis	Interaction term for eurozone	Dummies for crisis	Macro control variables
1	Pooled OLS classic model						
2	Pooled OLS interaction crisis			x			
3	Pooled OLS interaction eurozone				x		
4	Pooled OLS interactions			x	x		
5	Pooled OLS dummies					x	
6	Pooled OLS with dummies + interact			x	x	x	
7	Pooled OLS with controls						x
8	Pooled OLS with controls + interact			x	x		x
9	Pooled OLS with controls + dummies					x	x
10	Pooled OLS with controls + inter + dummies			x	x	x	x
11	Pooled OLS IV (all)		x				
12	Pooled OLS IV + inter crisis		x	x			
13	Pooled OLS IV + inter euro		x		x		
14	Pooled OLS IV + interaction		x	x	x		
15	Pooled OLS IV + dummies		x			x	
16	Pooled OLS IV with dummies + interaction		x	x	x	x	
17	Pooled OLS IV with controls		x				x
18	Pooled OLS IV with controls + interaction		x	x	x		x
19	Pooled OLS IV with controls + dummies		x			x	x
20	Pooled OLS IV with controls + dummies+inter		x	x	x	x	x
21	FE classic model	x					
22	FE + inter crisis	x		x			
23	FE + inter euro	x			x		
24	FE + interaction	x		x	x		
25	FE + dummy	x				x	
26	FE with dummies + interaction	x		x	x	x	
27	FE with controls	x					x
28	FE with controls + interaction	x		x	x		x
29	FE with controls + dummy	x				x	x
30	FE with controls + dummy + interaction	x		x	x	x	x
31	FE IV (all)	x	x				
32	FE IV + inter crisis	x	x	x			
33	FE IV + inter euro	x	x		x		
34	FE IV + interaction	x	x	x	x		
35	FE IV + dummies	x	x			x	
36	FE IV + dummies + interaction	x	x	x	x	x	
37	FE IV + controls	x	x				x
38	FE IV + controls + interaction	x	x	x	x		x
39	FE IV + controls + dummy	x	x			x	x
40	FE IV + controls + dummy + interaction	x	x	x	x	x	x

We report the results for all the models below and details of the code in the [appendix A.2](#).

6.3.2. Time series analysis

Subsequently we run a number of time series models for each country, using OLS and 2SLS (i.e. OLS with IV), all of them using HAC standard errors. A time series operation implies that we test for the correlation between vectors of the estimates for each country across the entire period. We thus arrive to a single EIS estimate per country.

The first model we run is the classic OLS with no controls and no instruments. Consequently, we add controls and use instruments in different combinations in the following models:

Model #	Model	Instrument	Interaction terms for crisis	Interaction term for eurozone	Dummies for crisis	Macro control variables
1	OLS classic model					
2	OLS IV (all)	x				
3	OLS with controls					x
4	OLS with dummies		x	x	x	
5	OLS IV with dummies	x	x	x	x	
6	OLS IV with controls & dummies	x	x	x	x	x

6.4. Panel data analysis

In this section, we present and analyse our findings from the panel data models.

6.4.1. Results

The EIS estimates resulting from the analysis are listed in [Table 6.1](#) and [6.2](#), for pooled OLS, and [Table 6.3](#) and [6.4](#), for FE.

Table 6.1: Pooled OLS results from panel data analysis, models 1-10

VARIABLES	(1) Pooled OLS classic model	(2) Pooled OLS interaction crisis	(3) Pooled OLS interaction eurozone	(4) Pooled OLS interactions	(5) Pooled OLS dummies	(6) Pooled OLS with dummies + interact	(7) Pooled OLS with controls	(8) Pooled OLS with controls + interact	(9) Pooled OLS with controls + dummies	(10) Pooled OLS with controls + inter + dummies
E_m3	0.253*** (0.0520)	0.260*** (0.0552)	0.295*** (0.0437)	0.302*** (0.0468)	0.229*** (0.0505)	0.250*** (0.0401)	0.162*** (0.0427)	0.206*** (0.0321)	0.137*** (0.0377)	0.167*** (0.0259)
m3_crisis08		-0.228** (0.0892)		-0.237** (0.0889)		0.184*** (0.0553)		-0.269*** (0.0794)		0.0765 (0.0466)
m3_recess11		0.0583 (0.0650)		0.00875 (0.0617)		0.401*** (0.0935)		0.00287 (0.0452)		0.272*** (0.0574)
m3_euzone			-0.153*** (0.0397)	-0.156*** (0.0398)		-0.153*** (0.0381)		-0.147** (0.0468)		-0.154*** (0.0455)
crisis08					-1.199*** (0.316)	-1.763*** (0.345)			-1.314*** (0.219)	-1.504*** (0.332)
recess11					-0.439*** (0.115)	-1.051*** (0.167)			-0.345*** (0.0755)	-0.788*** (0.125)
E_wages							0.321*** (0.0383)	0.309*** (0.0254)	0.340*** (0.0348)	0.310*** (0.0278)
E_unem							-0.127*** (0.0319)	-0.0590 (0.0401)	-0.138*** (0.0296)	-0.0538 (0.0389)
E_budget_def							-0.000826** (0.000266)	-0.000740** (0.000277)	-0.000893*** (0.000226)	-0.000863*** (0.000250)
Constant	1.075*** (0.205)	1.088*** (0.202)	1.115*** (0.199)	1.138*** (0.193)	1.269*** (0.169)	1.392*** (0.153)	1.317*** (0.245)	0.951*** (0.231)	1.544*** (0.218)	1.112*** (0.239)
Observations	3,422	3,422	3,422	3,422	3,422	3,422	2,140	2,140	2,140	2,140
R-squared	0.220	0.249	0.282	0.311	0.287	0.368	0.432	0.515	0.519	0.562
Number of groups	14	14	14	14	14	14	9	9	9	9

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.2: Pooled OLS results from panel data analysis, models 11-20

VARIABLES	(11) Pooled OLS IV (all)	(12) Pooled OLS IV + inter crisis	(13) Pooled OLS IV + inter euro	(14) Pooled OLS IV + interaction	(15) Pooled OLS IV + dummies	(16) Pooled OLS IV with dummies + interaction	(17) Pooled OLS IV with controls	(18) Pooled OLS IV with controls + interaction	(19) Pooled OLS IV with controls + dummies	(20) Pooled OLS IV with controls + dummies+inter
E_m3	0.240*** (0.0301)	0.246*** (0.0307)	0.292*** (0.0255)	0.298*** (0.0250)	0.216*** (0.0318)	0.249*** (0.0283)	0.127*** (0.0361)	0.162*** (0.0302)	0.104*** (0.0363)	0.124*** (0.0329)
m3_crisis08		-0.231*** (0.0530)		-0.242*** (0.0477)		0.187** (0.0896)		-0.269*** (0.0595)		0.0926 (0.102)
m3_recess11		0.0428 (0.0829)		-0.00557 (0.0788)		0.401*** (0.128)		-0.00965 (0.0601)		0.288*** (0.0851)
m3_euzone			-0.162*** (0.0333)	-0.163*** (0.0330)		-0.164*** (0.0313)		-0.132*** (0.0460)		-0.140*** (0.0434)
crisis08					-1.230*** (0.183)	-1.796*** (0.312)			-1.324*** (0.241)	-1.573*** (0.437)
recess11					-0.492** (0.243)	-1.087*** (0.340)			-0.392** (0.199)	-0.865*** (0.277)
E_wages							0.368*** (0.0548)	0.365*** (0.0510)	0.381*** (0.0560)	0.362*** (0.0527)
E_unem							-0.125*** (0.0231)	-0.0639* (0.0335)	-0.136*** (0.0214)	-0.0582* (0.0315)
E_budget_def							-0.000767** (0.000350)	-0.000671** (0.000342)	-0.000844*** (0.000249)	-0.000810*** (0.000275)
Constant	1.137*** (0.113)	1.157*** (0.114)	1.151*** (0.102)	1.181*** (0.102)	1.339*** (0.123)	1.431*** (0.116)	1.300*** (0.177)	0.977*** (0.195)	1.536*** (0.180)	1.147*** (0.206)
Observations	3,324	3,324	3,324	3,324	3,324	3,324	2,112	2,112	2,112	2,112
R-squared	0.237	0.267	0.309	0.341	0.305	0.395	0.425	0.506	0.514	0.554
Number of groups										

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.3: Fixed effect results from panel data analysis, models 1-10

VARIABLES	(1) FE classic model	(2) FE + inter crisis	(3) FE + inter euro	(4) FE + interaction	(5) FE + dummy	(6) FE with dummies + interaction	(7) FE with controls	(8) FE with controls + interaction	(9) FE with controls + dummy	(10) FE with controls + dummy + interaction
E_m3	0.219*** (0.0641)	0.217*** (0.0679)	0.164** (0.0705)	0.158* (0.0746)	0.175** (0.0603)	0.0985 (0.0601)	0.152** (0.0593)	0.163** (0.0665)	0.120* (0.0548)	0.133** (0.0566)
m3_crisis08		-0.240** (0.0920)		-0.241** (0.0946)		0.229*** (0.0491)		-0.289*** (0.0815)		0.0619 (0.0352)
m3_recess11		-0.0696 (0.0813)		-0.0963 (0.0830)		0.264*** (0.0564)		-0.0633 (0.0669)		0.152*** (0.0449)
m3_euzone			0.120 (0.0830)	0.124 (0.0842)		0.136* (0.0730)		-0.0264 (0.0865)		-0.0256 (0.0793)
crisis08					-1.262*** (0.342)	-1.957*** (0.332)			-1.342*** (0.242)	-1.521*** (0.270)
recess11					-0.592*** (0.165)	-0.975*** (0.191)			-0.437*** (0.125)	-0.637*** (0.122)
E_wages							0.323*** (0.0595)	0.335*** (0.0583)	0.314*** (0.0653)	0.298*** (0.0649)
E_unem							-0.0415 (0.0437)	-0.0804* (0.0415)	-0.0847* (0.0398)	-0.0808* (0.0404)
E_budget_def							-6.14e-05 (0.000372)	-0.000244 (0.000287)	-0.000309 (0.000300)	-0.000376 (0.000257)
Constant	1.192*** (0.274)	1.252*** (0.273)	1.237*** (0.286)	1.307*** (0.283)	1.472*** (0.235)	1.576*** (0.237)	0.803* (0.383)	1.092** (0.340)	1.351*** (0.329)	1.343*** (0.338)
Observations	3,422	3,422	3,422	3,422	3,422	3,422	2,140	2,140	2,140	2,140
Number of groups	14	14	14	14	14	14	9	9	9	9
Number of country_id										

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.4: Fixed effect results from panel data analysis, models 11-20

VARIABLES	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	FE IV (all)	FE IV + inter crisis	FE IV + inter euro	FE IV + interaction	FE IV + dummies	FE IV + dummies + interaction	FE IV + controls	FE IV + controls + interaction	FE IV + controls + dummy	FE IV + controls + dummy + interaction
E_m3	0.205*** (0.0536)	0.194*** (0.0557)	0.121 (0.0795)	0.0981 (0.0909)	0.147*** (0.0564)	0.0445 (0.0948)	0.0965* (0.0560)	0.0662 (0.109)	0.0711 (0.0669)	0.0545 (0.105)
m3_crisis08		-0.248*** (0.0338)		-0.248*** (0.0355)		0.249** (0.116)		-0.290*** (0.0435)		0.0732 (0.126)
m3_recess11		-0.109 (0.103)		-0.149 (0.116)		0.242** (0.109)		-0.115 (0.110)		0.126 (0.0971)
m3_euzone			0.186 (0.148)	0.207 (0.154)		0.206 (0.146)		0.0422 (0.0942)		0.0293 (0.0867)
crisis08					-1.308*** (0.196)	-2.063*** (0.494)			-1.352*** (0.250)	-1.572*** (0.562)
recess11					-0.684** (0.280)	-1.032** (0.413)			-0.499* (0.282)	-0.678* (0.385)
E_wages							0.424*** (0.0911)	0.448*** (0.0944)	0.397*** (0.0848)	0.388*** (0.0824)
E_unem							-0.0211 (0.0204)	-0.0634*** (0.0195)	-0.0680*** (0.0181)	-0.0674*** (0.0202)
E_budget_def							4.22e-05 (0.000279)	-1.66e-05 (0.000394)	-0.000226 (0.000235)	-0.000202 (0.000315)
Constant	1.253*** (0.179)	1.348*** (0.188)	1.316*** (0.211)	1.430*** (0.241)	1.590*** (0.203)	1.696*** (0.269)	0.588*** (0.196)	0.944*** (0.302)	1.188*** (0.237)	1.235*** (0.337)
Observations	3,324	3,324	3,324	3,324	3,324	3,324	2,112	2,112	2,112	2,112
Number of groups										
Number of country_id	14	14	14	14	14	14	9	9	9	9

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

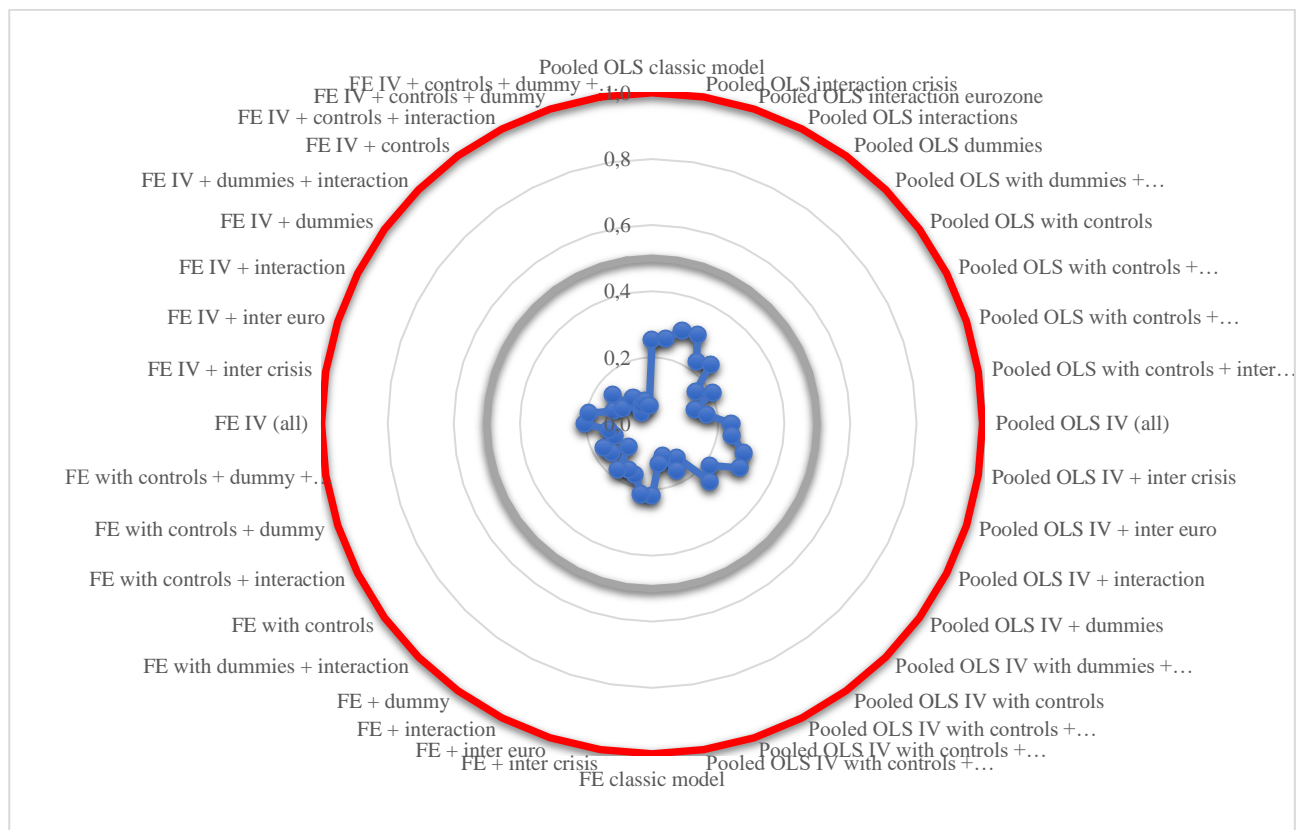
6.4.2. Analysis of results

First of all, when looking at our results as we test different models in each column of the tables, we observe that all EIS estimates are positive and highly significant (except for the last FE models), but they differ in magnitude, with values that range from 0.096³¹ to 0.302³².

A positive EIS value tells us that the substitution effect wins over the income effect, meaning that when there is an increase in the interest rate, individuals will substitute current consumption in order to take advantage of the increased return on investment, and increase future consumption with the means saved during the current period.

Another important thing to mention, before discussing the results separately, is that all the estimates are smaller than 1. It is often discussed in the literature whether the elasticity is above or below 1, so we will keep this 1 as threshold in mind when we discuss the different estimates. Finally, our estimates, although different, do not differ too much when included in a bigger picture, as shown in [Figure 6.1](#).

Figure 6.1: EIS estimates obtained from the different panel data models plotted between 0 and 1



Source: Own analysis.

³¹ The estimate from the FEIV with controls.

³² The estimate from the pooled OLS with interaction terms. Across both tables and excluding insignificant results.

The red line is at 1, which is the standard EIS threshold³³, while the grey line is at 0.5, which is the mean estimate EIS value found by Havranek et al. in their aggregate study of 2,735 EIS estimates³⁴. Still, our estimates are all below. The implication from a low EIS estimate is that the effect from a change in the monetary policy rate on the change in consumption growth has an effect which is less than one-to-one.

The first model we run on the whole panel is the classic model using a pooled OLS regression, which gives an EIS estimate of 0.253, highly significant. We believe this regression suffers from bias as explained above, so we run an instrumental regression. Before we test this, we test the value of the EIS in the 2008 economic crisis and the recession in Europe which started in 2011 by means of interaction terms in column 2. We see that the impact on the EIS is negative and significant for the crisis and not significant and close to zero for the recession. Thus, we find that consumers are less willing to reallocate their consumption during the crisis. This may be explained by capital constraint and general lack of faith in the financial system during this period. Further, we do not find evidence that the recession had a similar impact. Our results are not significant and they are very small. However, the sign is positive which is contradictory to what we would expect. We would expect a negative effect, similar to the crisis, but lower in magnitude.

In column 3 we do the same analysis but for the eurozone. That the eurozone has a negative and significant impact on the EIS is surprising at first glance since we would expect that the eurozone is an area which contains consumers who are both wealthier and more active participants in the asset markets than the average consumer. However, we must pay attention to the external group of countries we are comparing to and since these are countries like Australia and the United States, we feel more comfortable with the regression output. In column 4 we see that these effects persist as we include all three interaction terms at the same time. In column 5 we have pooled OLS with dummies and we see that the effect on consumption from the crisis and the recession are negative and significant in both cases, however larger for the 2008 crisis. Which is consistent with expectations. We observe that the EIS coefficient is slightly reduced when we account for these periods, but remains very close to the initial estimates we get without controls.

If we move on to column 7, the pooled OLS with macro variable controls, we observe that when we control for change in wages, the unemployment rate and budget deficit³⁵, we observe a diminished EIS coefficient, but still very significant. Whereas Hall (1988) prefers the so-called classic model to estimate the EIS, and his approach has been applied by many, we draw on inspiration from more recent academic papers and consider it more accurate to control for other factors which we identify have independent effect on change in intertemporal substitution. From the test results, we observe that expected change in wages has a positive effect on consumption growth which is both statistically highly significant and of a large magnitude. Thus, expected rise in wages makes the general consumer inclined to consume more in the next period. As expected,

³³ Please refer to the Literature Review chapter, where we discuss different EIS estimates and it can be noticed that they are around 1. Whether the EIS is above or below 1 is important since it defines how the consumer reacts to a change in the interest rate: he either changes consumption more, when $EIS > 1$, or less, when $EIS < 1$.

³⁴ In research question 2 we employ some of the country-specific IS estimates his paper gathers

³⁵ Choice of controls are dealt with in the section Choice of instruments and controls

we find a negative effect on consumption growth from a rise in unemployment and the coefficient is both statistically and economically significant.

The effect from the budget deficit is very small in magnitude, however still significant and as expected with a negative sign so that a higher budget deficit has a negative impact on future consumption. This implies that if a budget deficit is high, trust in solvent government management is low and consumers would be expected to be more sceptical towards consuming in the future, maybe also due to expected raise in taxes. By means of including these controls we isolate the change in planned consumption stemming from a change in the interest rate. Therefore, we would also expect a reduction in the magnitude of the EIS estimate, as we observe.

When we include both crisis and recession dummy and our standard controls, we find that the effect from a change in wages and from the budget deficit is persistent and still highly significant, however the effect on consumption from change in unemployment falls away and decreases in significance.

Moving on, we look at column 11 and we find that the IV estimates do not differ much from the OLS estimates. This suggests that the bias of the first regression is not very severe, and it suggests that we have found a very good instrument for the original explanatory variable.

When we look at column 12 we see that when we account for the crisis and the recession impact on the EIS we observe an increase in the EIS estimate, as would be expected. This is also what we observe in column 2. Again, similar to before we observe a drop in the EIS estimate as we include macro variable controls in column 17, as would be expected.

If we look at the next table, where we list tests results from fixed effect model regressions, we observe a similar pattern as described for the OLS and IV regressions above with respect to when we go from the classic FE, to FEIV, and further to include controls and crisis and recession dummies. The main differences though are the fact that the EIS coefficients for the last three models (column 18, 19 and 20) as well as column 16 are smaller in magnitude and not significant.

It is important to identify that the EIS estimates we retrieve are consistently lower than for the OLS tests. This is due to the circumstance that we now clean the regression from country fixed effects across the sample. However, this should be a more accurate measure of the isolated effect of a change in the interest rate by means of employing FE models.

6.4.3. Concluding remarks on panel regression

On the basis of the panel regression tests we arrive at a preferred panel model which is the FEIV model without controls. This model we deem to be the most accurate one to reflect the EIS level across the whole sample since we account for country fixed effects and overcome most endogeneity bias. We choose a model without control variables, which adhere to the classic way of estimating the EIS as seen in the [Theoretical framework](#) chapter. We will further elaborate below on this choice. We thus arrive at an EIS estimate for the entire set of countries of 0.205 for the 1993-2014 period.

6.5. Time series analysis

From the time series analysis, we get an EIS estimate per country for each model we consider. Here we present and analyse these results.

6.5.1. Results

The first model we run is the classic OLS model, whose results are presented in [Table 6.5](#). The 2SLS model's results are reported in [Table 6.6](#).

As in the panel regression, we want to isolate the effect from a change in the interest rate on the change in the planned consumption path. Thus, we run the OLS model with controls and the results are presented in [Table 6.7](#). It is important to notice that we do not have available data on unemployment for the Netherlands, Norway, Spain and Sweden, so for these countries we only have wages and budget deficit as controls. For Switzerland, we only have budget deficit as a control, as we lack data on the other control variables.

[Table 6.8](#) reports the results for the OLS model that includes dummy variables. We add the dummies to control for the 2008 crisis and the 2011 recession, as we did with the panel data, as well as interaction terms between these dummies and 3m. We don't have 2008 data for some of the countries, so in those cases the variable crisis will not have any coefficient.

The results for the 5th model are reported in [Table 6.9](#), while the results for the last model, which is a 2SLS with dummies and controls, are in [Table 6.10](#).

After the complete tables with the model output we report a summary table ([Table 6.11](#)) that collects the different EIS estimates from the models used for each country. The last column reports Havranek et al.'s estimates, to have a benchmark outside our analysis.

Table 6.5: Results from model 1, classic OLS, from time series analysis

VARIABLES	(1) France	(2) Germany	(3) Italy	(4) Netherlands	(5) Spain	(6) Norway	(7) Sweden	(8) Switzerland	(9) UK	(10) Australia	(11) Canada	(12) Japan	(13) New Zealand	(14) USA
E_m3	0.337*** (0.0749)	0.0536 (0.113)	0.141* (0.0798)	0.754*** (0.0880)	0.404** (0.160)	-0.0367 (0.0858)	-0.0796 (0.149)	0.205** (0.0788)	0.354*** (0.0864)	0.200** (0.0832)	0.159** (0.0676)	0.552*** (0.137)	0.115 (0.0854)	0.189*** (0.0693)
Constant	0.675*** (0.215)	0.954*** (0.289)	0.510 (0.393)	-0.870*** (0.270)	0.575 (0.682)	2.982*** (0.459)	2.570*** (0.541)	1.182*** (0.193)	0.512 (0.494)	2.044*** (0.488)	2.055*** (0.262)	0.714*** (0.160)	1.679*** (0.557)	1.990*** (0.319)
Observations	264	264	264	240	240	199	240	199	264	228	264	264	228	264

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.6: Results from model 2, 2SLS with instrumental variables, from time series analysis

VARIABLES	(1) France	(2) Germany	(3) Italy	(4) Netherlands	(5) Spain	(6) Norway	(7) Sweden	(8) Switzerland	(9) UK	(10) Australia	(11) Canada	(12) Japan	(13) NewZealand	(14) USA
E_m3	0.313*** (0.0757)	0.0711 (0.116)	0.0904* (0.0546)	0.871*** (0.0968)	0.445*** (0.162)	-0.0347 (0.0667)	0.113 (0.149)	0.104 (0.0726)	0.318*** (0.0689)	0.338*** (0.0895)	0.0978 (0.0658)	0.842*** (0.228)	0.0218 (0.0651)	0.155*** (0.0545)
Constant	0.749*** (0.236)	0.900*** (0.299)	0.707** (0.325)	-1.145*** (0.352)	0.573 (0.649)	3.017*** (0.349)	2.027*** (0.501)	1.327*** (0.159)	0.671* (0.390)	1.386*** (0.501)	2.275*** (0.270)	0.505*** (0.172)	2.170*** (0.407)	2.100*** (0.262)
Observations	264	264	264	226	226	185	226	185	264	214	264	264	214	264
R-squared	0.464	0.009	0.126	0.606	0.368	0.002	0.101	0.193	0.473	0.234	0.160	0.205	0.013	0.217

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.7: Results from model 3, OLS with controls, from time series analysis

VARIABLES	(1) France	(2) Germany	(3) Italy	(4) Netherlands	(5) Spain	(6) Norway	(7) Sweden	(8) Switzerland	(9) UK	(10) Australia	(11) Canada	(12) Japan	(13) NewZealand	(14) USA
E_m3	0.450*** (0.122)	0.0942 (0.123)	0.267** (0.127)	0.740*** (0.126)	0.650 (0.607)	0.116 (0.163)	0.154 (0.252)	0.0764 (0.166)	0.167 (0.109)	0.214** (0.0875)	0.311*** (0.103)	0.401** (0.179)	0.225*** (0.0719)	-0.0108 (0.0795)
E_wages	0.0988 (0.317)	0.457 (0.325)	-0.00425 (0.286)	-1.426*** (0.294)	-0.608 (0.667)	0.835** (0.381)	-0.399 (0.334)		-0.534* (0.317)	-0.923*** (0.354)	0.209 (0.245)	0.447*** (0.106)	-2.242*** (0.330)	0.220 (0.335)
E_unem	0.182 (0.132)	0.167 (0.139)	-0.0216 (0.0788)						-0.0249 (0.0338)	0.00483 (0.0617)	-0.447 (0.399)	0.0254 (0.179)	-0.447*** (0.108)	-0.250* (0.147)
E_budget_def	0.00470** (0.00199)	0.00918* (0.00499)	0.00961* (0.00526)	0.0733*** (0.0264)	-0.00897 (0.0215)	-0.00266 (0.00186)	-0.00347 (0.00619)	0.0404* (0.0203)	-0.0221*** (0.00697)	0.0188*** (0.00574)	-0.00768 (0.0166)	-0.00655 (0.00979)	0.00651 (0.0244)	-4.79e-05 (0.000840)
Constant	-1.085 (1.186)	-1.204 (1.515)	0.877 (0.712)	3.257*** (0.866)	-0.740 (1.866)	0.406 (1.041)	2.967** (1.112)	1.475*** (0.166)	4.591*** (1.389)	5.422*** (0.992)	4.312 (2.761)	0.252 (0.888)	8.768*** (1.099)	3.450*** (1.072)
Observations	260	260	260	58	58	58	58	58	260	228	125	260	228	259

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.8: Results from model 4, OLS with dummy variables, from time series

VARIABLES	(1) France	(2) Germany	(3) Italy	(4) Netherlands	(5) Spain	(6) Norway	(7) Sweden	(8) Switzerland	(9) UK	(10) Australia	(11) Canada	(12) Japan	(13) NewZealand	(14) USA
E_m3	0.277*** (0.0815)	0.0288 (0.129)	0.0613 (0.0711)	0.726*** (0.0997)	0.263* (0.138)	-0.103 (0.0764)	-0.181 (0.129)	0.172* (0.0896)	0.277*** (0.0819)	0.139** (0.0685)	0.0883 (0.0561)	0.546*** (0.144)	0.0702 (0.0788)	0.105** (0.0521)
m3_crisis08	0.171* (0.103)	0.361*** (0.134)	0.408*** (0.0826)	0.156 (0.114)	0.997*** (0.167)	0.880*** (0.126)	0.909*** (0.134)	0.435*** (0.0887)	0.589*** (0.101)	0.373*** (0.0710)	1.214*** (0.0903)	2.336*** (0.215)	0.202** (0.0986)	0.730*** (0.166)
m3_recess11	0.313*** (0.100)	-0.0834 (0.136)	1.047*** (0.275)	0.0738 (0.178)	1.849*** (0.173)	-0.321 (0.222)	0.235 (0.245)	-0.108 (1.864)	-1.073*** (0.224)	-0.0595 (0.114)	0.271 (0.208)	-0.0596 (0.611)	-0.0821 (0.0993)	1.812** (0.837)
crisis08	-1.277*** (0.286)	-1.743*** (0.351)	-2.473*** (0.351)	-1.168*** (0.348)	-5.359*** (0.625)	-5.201*** (0.606)	-4.115*** (0.475)	-1.234*** (0.210)	-4.045*** (0.466)	-3.107*** (0.392)	-2.936*** (0.235)	-2.540*** (0.230)	-2.913*** (0.603)	-3.211*** (0.378)
recess11	-1.021*** (0.245)	-0.0116 (0.352)	-2.937*** (0.430)	-0.326 (0.356)	-4.204*** (0.638)	0.738 (0.672)	-1.536** (0.688)	-0.0258 (0.235)	0.408 (0.478)	0.125 (0.512)	-0.743** (0.320)		0.199 (0.547)	-0.604** (0.233)
Constant	0.961*** (0.240)	1.080*** (0.349)	1.053*** (0.344)	-0.721** (0.340)	1.431** (0.633)	3.390*** (0.374)	3.125*** (0.474)	1.277*** (0.215)	1.017** (0.447)	2.455*** (0.378)	2.372*** (0.216)	0.764*** (0.176)	2.071*** (0.498)	2.420*** (0.205)
Observations	264	264	264	240	240	199	240	199	264	228	264	264	228	264

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.9: Results from model 5, 2SLS with dummy variables, from time series analysis

VARIABLES	(1) France	(2) Germany	(3) Italy	(4) Netherlands	(5) Spain	(6) Norway	(7) Sweden	(8) Switzerland	(9) UK	(10) Australia	(11) Canada	(12) Japan	(13) NewZealand	(14) USA
E_m3	0.226*** (0.0859)	0.0425 (0.135)	0.0335 (0.0562)	0.871*** (0.127)	0.327** (0.164)	-0.0666 (0.0783)	-0.0437 (0.145)	0.0525 (0.0849)	0.270*** (0.0766)	0.329*** (0.0838)	0.00860 (0.0638)	0.815*** (0.227)	-0.0403 (0.0595)	0.0720 (0.0481)
m3_crisis08	0.222** (0.106)	0.347** (0.141)	0.436*** (0.0707)	0.0105 (0.140)	0.934*** (0.193)	0.843*** (0.121)	0.772*** (0.150)	0.554*** (0.0843)	0.597*** (0.0932)	0.183** (0.0864)	1.294*** (0.0960)	2.066*** (0.275)	0.312*** (0.0729)	0.763*** (0.161)
m3_recess11	0.364*** (0.106)	-0.0971 (0.143)	1.075*** (0.262)	-0.0716 (0.195)	1.785*** (0.195)	-0.357 (0.222)	0.0973 (0.253)	0.0117 (1.879)	-1.066*** (0.224)	-0.249* (0.139)	0.351* (0.212)	0.342 (0.604)	0.0285 (0.0859)	1.845** (0.866)
crisis08	-1.443*** (0.325)	-1.698*** (0.382)	-2.590*** (0.304)	-0.798 (0.506)	-5.260*** (0.676)	-5.104*** (0.573)	-3.727*** (0.479)	-1.426*** (0.173)	-4.079*** (0.424)	-2.161*** (0.479)	-3.246*** (0.284)	-2.339*** (0.229)	-3.527*** (0.465)	-3.330*** (0.370)
recess11	-1.187*** (0.288)	0.0333 (0.382)	-3.054*** (0.377)	0.0438 (0.506)	-4.105*** (0.673)	0.834 (0.661)	-1.148* (0.690)	-0.218 (0.200)	0.374 (0.443)	1.072 (0.666)	-1.053*** (0.359)		-0.415 (0.451)	-0.723*** (0.216)
Constant	1.127*** (0.284)	1.035*** (0.379)	1.170*** (0.296)	-1.090** (0.496)	1.332** (0.669)	3.293*** (0.357)	2.736*** (0.478)	1.470*** (0.178)	1.051** (0.412)	1.508*** (0.466)	2.682*** (0.267)	0.563*** (0.179)	2.685*** (0.390)	2.538*** (0.185)
Observations	264	264	264	226	226	185	226	185	264	214	264	264	214	264
R-squared	0.560	0.070	0.483	0.624	0.619	0.527	0.373	0.381	0.720	0.513	0.429	0.285	0.473	0.615

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.10: Results from model 6, 2SLS with controls and dummy variables

VARIABLES	(1) France	(2) Germany	(3) Italy	(4) Netherlands	(5) Spain	(6) Norway	(7) Sweden	(8) Switzerland	(9) UK	(10) Australia	(11) Canada	(12) Japan	(13) NewZealand	(14) USA
E_m3	0.268 (0.277)	0.299* (0.173)	0.121 (0.140)	0.698*** (0.185)	-0.634 (0.515)	0.188 (0.198)	-0.122 (0.145)	-0.227*** (0.0845)	0.347* (0.200)	0.309*** (0.0763)	0.247*** (0.0576)	0.838*** (0.299)	0.179 (0.110)	-0.0877** (0.0381)
E_wages	0.328 (0.586)	0.226 (0.415)	0.112 (0.312)	-0.950*** (0.353)	1.718* (0.885)	0.925** (0.434)	-0.211 (0.236)		-0.783** (0.364)	-0.705*** (0.220)	0.191 (0.157)	0.501*** (0.115)	-1.843*** (0.404)	0.578*** (0.126)
E_unem	0.0236 (0.0979)	0.0218 (0.159)	-0.0344 (0.0678)						-0.0847** (0.0431)	0.0898* (0.0544)	-0.109 (0.264)	0.161 (0.154)	-0.346*** (0.0936)	-0.371*** (0.0970)
E_budget_def	0.00225 (0.00327)	0.0112* (0.00579)	0.00871* (0.00490)	0.0589*** (0.0163)	0.0547** (0.0217)	-0.00270 (0.00207)	0.00747* (0.00414)	0.0328*** (0.00984)	-0.0158*** (0.00460)	0.0127** (0.00549)	0.000256 (0.00882)	-0.0225 (0.0174)	0.0222 (0.0250)	-0.00108** (0.000424)
m3_crisis08	0.0790 (0.195)	-0.256 (0.258)	0.211 (0.173)						0.348*** (0.0785)	0.156* (0.0826)	0.879*** (0.151)	0.885** (0.380)	0.171** (0.0815)	0.572*** (0.208)
m3_recess11	0.357** (0.169)	-0.0369 (0.253)	0.925** (0.418)	0.0320 (0.242)	2.438*** (0.519)	-0.863*** (0.250)	0.0331 (0.229)	0.581 (1.739)	-0.487** (0.212)	-0.0435 (0.180)	-0.0917 (0.230)	-0.268 (0.618)	-0.185 (0.141)	2.510*** (0.953)
crisis08	-1.154** (0.588)	-0.349 (0.629)	-2.035*** (0.501)						-3.020*** (0.279)	-1.767*** (0.447)	-2.301*** (0.284)	-0.736** (0.353)	-1.552** (0.637)	-3.191*** (0.455)
recess11	-1.004*** (0.321)	-0.0540 (0.329)	-2.839*** (0.536)	-0.420 (0.351)	-4.056*** (0.588)	2.024*** (0.596)	-0.963* (0.535)	-0.591*** (0.0807)	0.0618 (0.334)	0.479 (0.742)	-0.113 (0.307)		1.048 (0.702)	-0.563*** (0.185)
Constant	0.248 (1.005)	0.315 (1.855)	1.442** (0.622)	2.327*** (0.618)	3.469*** (1.323)	-0.0612 (1.041)	3.532*** (0.932)	1.758*** (0.0546)	4.879*** (1.057)	3.674*** (0.699)	2.304 (1.716)	-1.122 (1.109)	7.526*** (1.067)	3.077*** (0.653)
Observations	260	260	260	58	58	58	58	58	260	214	125	260	214	259
R-squared	0.677	0.265	0.616	0.654	0.566	0.553	0.693	0.665	0.834	0.683	0.861	0.512	0.680	0.757

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6.11: Summary table of the EIS estimates from the different models used and Havranek et al.'s average estimates

	OLS_classic	OLS_IV	OLS_contr	OLS_dummy	OLS_IV_dum	OLS_IV_contr_dum	Mean EIS from Havranek et al.
France	0.337***	0.313***	0.450***	0.277***	0.226***	0.268	-0.034
Germany	0.0536	0.0711	0.0942	0.0288	0.0425	0.299*	0.080
Italy	0.141*	0.0904*	0.267**	0.0613	0.0335	0.121	0.290
Netherlands	0.754***	0.871***	0.740***	0.726***	0.871***	0.698***	0.027
Spain	0.404**	0.445***	0.65	0.263*	0.327**	-0.634	0.504
Norway	-0.0367	-0.0347	0.116	-0.103	-0.0666	0.188	-0.386
Sweden	-0.0796	0.113	0.154	-0.181	-0.0437	-0.122	0.065
Switzerland	0.205**	0.104	0.0764	0.172*	0.0525	-0.227***	-0.434
UK	0.354***	0.318***	0.167	0.277***	0.270***	0.347*	0.487
Australia	0.200**	0.338***	0.214**	0.139**	0.329***	0.309***	0.362
Canada	0.159**	0.0978	0.311***	0.0883	0.0086	0.247***	0.389
Japan	0.552***	0.842***	0.401**	0.546***	0.815***	0.838***	0.893
New Zealand	0.115	0.0218	0.225***	0.0702	-0.0403	0.179	2.206
USA	0.189***	0.155***	-0.0108	0.105**	0.072	-0.0877**	0.594

Note: *** p<0.01, ** p<0.05, * p<0.1. Havranek et al.'s EIS values are the average per country of the estimates collected in their meta-analysis, excluding estimates bigger than 10 in absolute value.

6.5.2. Analysis of results

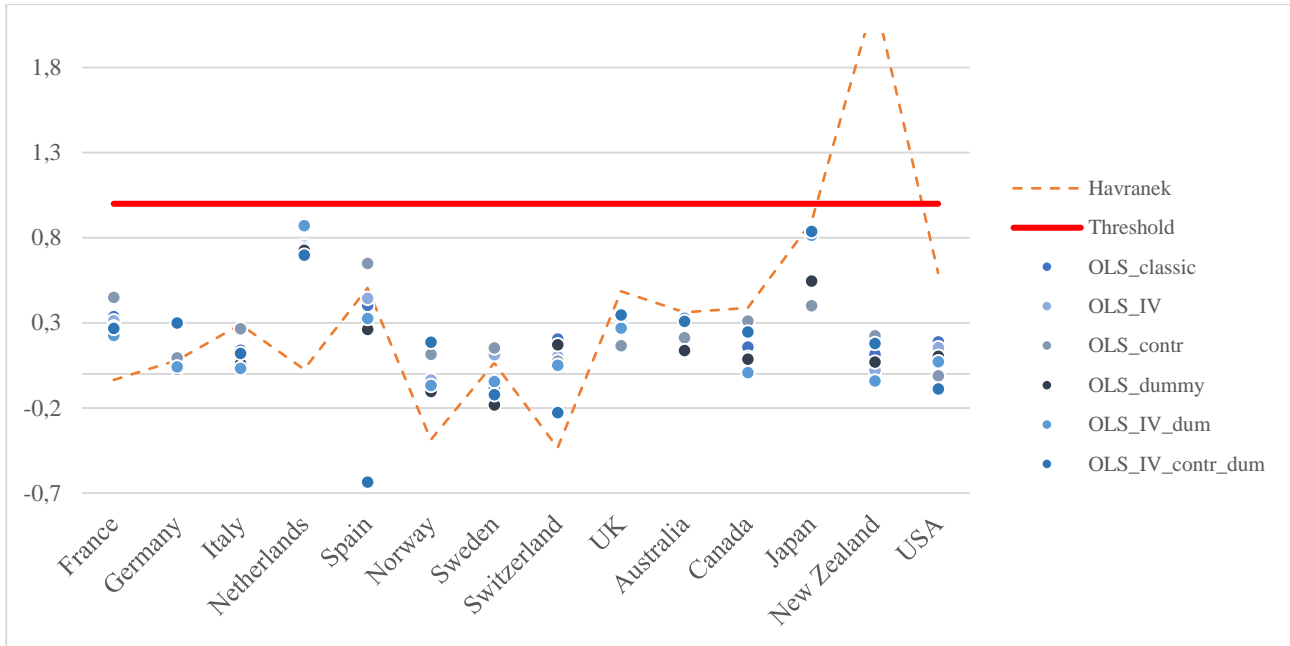
When comparing the EIS estimates across the different models, considering one country at the time, we first notice that the estimates are quite close to each other. This is illustrated in [Figure 6.2](#), where the blue points refer to the EIS estimates from the different econometrics models used, the red line is the 1-threshold and the dashed orange line represents Havranek et al.'s estimates, which again we include as an external benchmark³⁶.

While our country-estimates do not differ too much from each other across models used (please see [Table 6.12](#) for illustration on the following page), some estimates are not significant. This is the case for Germany, Norway and Sweden. These countries' estimates lie close to each other, but are not significant. Other countries, like Italy, Switzerland and New Zealand present only few significant estimates, while the rest of the countries has most of the estimates highly significant.

Some of the countries present a higher variance in their estimates; this is the case for Spain, Norway, Sweden, Switzerland, New Zealand and USA. Instead, some countries have very significant and similar results, such as France, the Netherlands, UK and Australia. This is interesting and allows us to make some initial conclusion on the EIS for these countries.

³⁶ Please find a description of Havranek et al. (2015) estimates in the [Data](#) chapter as we use Havranek et al.'s estimate findings in our further analysis in subsequent chapters.

Figure 6.2: Plot of the time series EIS estimates obtained with different models



Source: own analysis, Havranek et al. (2015).

Note: Havranek et al.'s EIS values are the average per country of the estimates collected in their meta-analysis, excluding estimates bigger than 10 in absolute value.

Some countries present a negative EIS estimate in some runs. This is not to be understood as if a rise in the interest rate may decrease the propensity to save (consume in the future) for the general consumer in that country. The negative estimates for countries such as Norway, Sweden and USA is assumed to be merely very low estimates which turn negative due to estimation error – as may be present in every regression estimate. Thus, we read these negative estimates as simply very low and close to zero EIS estimates for the countries in question. This assumption follows the conclusions made in the paper by Havranek (2014) on bias in EIS estimates. Additionally, all the negative estimates that we get are not significant which supports this way of reading the test estimates.

We discuss the different country estimates – their potential explanation and implications with respect to a monetary policy shock – in subsequent chapters.

6.5.3. Test for EIS heterogeneity

Starting from the results we obtained in the time series regression, we want to verify quantitatively whether these estimates are significantly different from each other.

By means of an Anova test, we confirm that the differences across countries are significant and bigger than the differences within countries across the different models used (see [Appendix A.4](#) for the Anova test result).

Finally, in order to conclude that we do find evidence of EIS heterogeneity between countries we run a Wald test³⁷. The test confirms that the EIS estimates are significantly different from each other, but we also observe that some country estimates are highly similar which suggests that they may be grouped accordingly. We will discuss this further in the chapter concerning [research question 3](#).

6.5.4. Concluding remarks on time series regression

We find evidence of EIS heterogeneity across our sample and across the eurozone countries. This is illustrated in [Table 6.12](#), in which we show how EIS estimates are different from country to country – and in a consistent manner – across various econometric models. The map in [Figure 6.3](#) illustrates the EIS estimates for the different countries.

Table 6.12: Comparison of EIS estimates across countries and time series models used

	OLS_classic	OLS_IV	OLS_contr	OLS_dummy	OLS_IV_dum	OLS_IV_contr_dum
France	0.337	0.313	0.450	0.277	0.226	0.268
Germany	0.054	0.071	0.094	0.029	0.043	0.299
Italy	0.141	0.090	0.267	0.061	0.034	0.121
Netherlands	0.754	0.871	0.740	0.726	0.871	0.698
Spain	0.404	0.445	0.650	0.263	0.327	-0.634
Norway	-0.037	-0.035	0.116	-0.103	-0.067	0.188
Sweden	-0.080	0.113	0.154	-0.181	-0.044	-0.122
Switzerland	0.205	0.104	0.076	0.172	0.053	-0.227
UK	0.354	0.318	0.167	0.277	0.270	0.347
Australia	0.200	0.338	0.214	0.139	0.329	0.309
Canada	0.159	0.098	0.311	0.088	0.009	0.247
Japan	0.552	0.842	0.401	0.546	0.815	0.838
New Zealand	0.115	0.022	0.225	0.070	-0.040	0.179
USA	0.189	0.155	-0.011	0.105	0.072	-0.088

Source: own analysis.

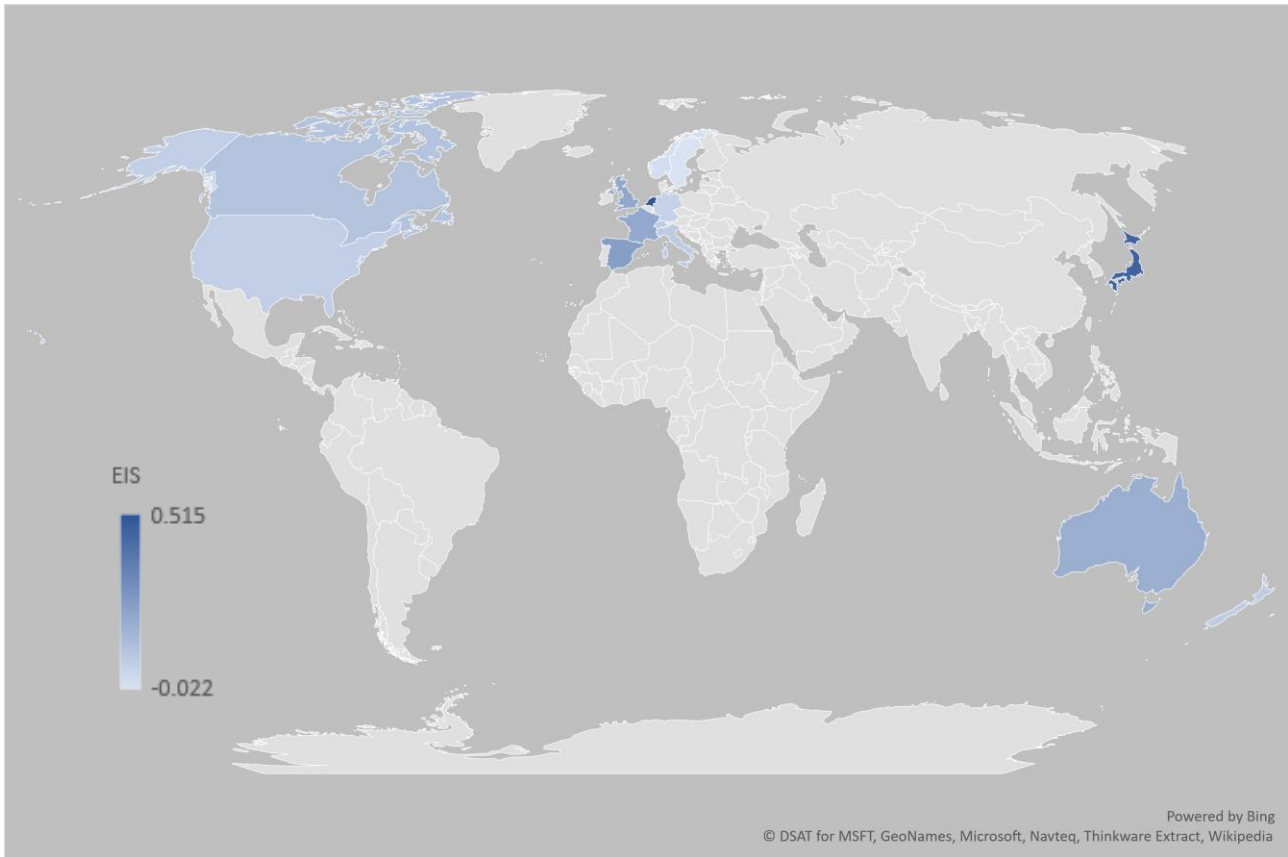
Note: The colours highlight the difference between countries within each model

The fact that the EIS estimates per country are quite consistent across different econometric models indicate that we may rely on a model that does not include control variables³⁸, as suggested by Hall (1988). However, we still prefer a model which uses an instrument to overcome endogeneity issues.

³⁷ The test output is reported in the [Appendix A.5](#).

³⁸ Since whether we add controls or not is not changing our estimates which suggests that the model without controls is not distorted by bias

Figure 6.3: Map with our EIS estimates



Source: own analysis.

Note: The colour of the countries corresponds to the level of EIS in that country found by our analysis. The values of EIS are the average of the results found with the different models we ran. Countries in grey do not have an EIS estimate.

6.6. Discussion of results

The aim of this section is to put our estimates into context and reflect on the validity of our conclusions. To put our estimates into context, Hall (1988), which is one of the most cited empirical studies with respect to the EIS, concludes that the EIS is not likely to be larger than 0.1. A further note is that Hall also does not include controls in his tests. His test method and findings have influenced later studies whereas some have estimated EIS values of 0.2 (Chari et al., 2002; House and Shapiro, 2006; Piazzesi et al., 2007), or a value of as much as 0.5 (Jin, 2012; Trabandt and Uhlig, 2011; Rudebusch and Swanson, 2012). Others again have found reason to conclude an EIS of as much as 2 (Ai, 2010; Barro, 2009; Colacito and Croce, 2011). The first reference points let us know that our estimate may fairly be deemed within the interval which would be expected. However, the fact that some studies find a much higher EIS estimate highlights that EIS estimates may deviate a lot from study to study. In fact, Havranek et al. (2015)'s meta study derives that EIS estimates are highly affected by study design.

Havranek et al. (2015) look across various estimates of the EIS across time and find that obtained estimates are highly influenced by estimation method. This is important when we reflect on how representative our test results as basis for wider assumptions. For instance, Havranek et al. find that studies on longer time series on average report lower EIS estimates, while datasets with high frequency tend to result in higher EIS estimates. Since our dataset has both these traits, we can expect they outweigh each other.

In line with the conclusion that the EIS estimates are highly influenced by estimation method, Vissing-Jørgensen (2002) argues that it is important to take into account consumers' potentially limited asset market participation when estimating the EIS. In fact, she argues that one should aim to exclude non-asset holders from the sample when conducting EIS tests as she argues these consumers create a downward bias to the estimate. We however aim to reflect the elasticity of all citizens across the eurozone, thus even if our dataset allowed it, this exclusion would not be beneficial for what we are trying to estimate. However, it is worth keeping in mind that prior research finds that the EIS measure varies across a country's population depending on whether the consumer is investing in assets dependent on the change in rate of return or not. Thus, implying that the aggregate EIS measures, that we deal with, can reasonably be expected to result in lower EIS estimates than if we were to only consider asset holders in the eurozone.

[Figure 6.4](#) shows how our EIS estimates compare to a broader sample of estimates³⁹ from earlier studies. The dots represent the EIS value as resulting from different studies, while the green diamonds are our EIS estimates resulting from the 2SLS model without controls. The dotted line is the average of all the estimates collected per country. As it is clear from the figure, our results are very close to the average line. This proves that our EIS estimates are within a reasonable range of values. Consequently, we are comfortable in relying on the values we obtained from our research.

6.7. Chapter conclusion

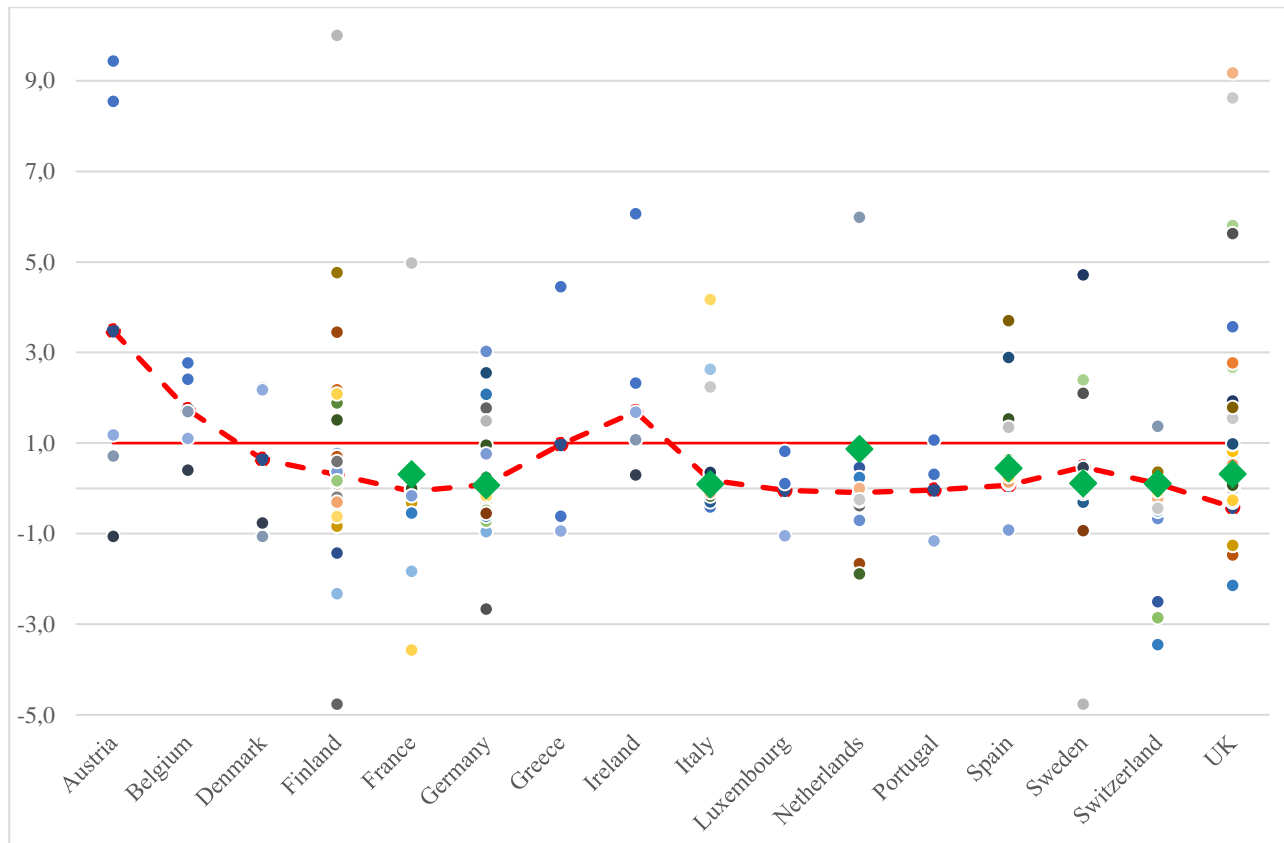
The purpose of this chapter is to detect the presence of EIS heterogeneity among eurozone countries. By means of the panel regression we discuss advantages of different estimation models and assumptions and deem the FEIV results the most accurate as this removes country fixed effects. This results in an EIS benchmark estimate across the sample of 0.205. In the time series regression, we deem the OLS IV (2SLS) regression results most appropriate and conclude that the country-specific estimates are dissimilar and consistently so. We analyse and test for EIS heterogeneity, first by means of plots that illustrate their difference, consequently with an Anova test, that shows that the difference between countries is bigger than the difference

³⁹ This is once again the Havranek et al.'s estimates which we have presented in the Data description chapter and which will be employed in our further analysis.

within countries⁴⁰. Finally, we employ a Wald test to confirm the statistical difference between country-level EIS estimates.

These country-specific estimates resulting from the 2SLS model we will use as primary finding and as basis for our further study.

Figure 6.4: Plot of the EIS estimates from our time series analysis and Havranek et al.'s dataset



Source: Havranek et al. (2015), own analysis.

⁴⁰ The difference within countries being the comparison of EIS values estimated with the various models we use.

7. Empirical Analysis 2: RQ2: If evidence of heterogeneity is found amongst eurozone countries, what country differences can explain these variations?

7.1. Chapter Outline

The objective of this section is, on the back of our findings under [research question 1](#), to explain EIS heterogeneity amongst eurozone countries by means of economic, financial and cultural differences within the common currency area. In order to do so, we employ the preferred⁴¹ EIS estimates for each country as dependent variable and run this vector against multiple vectors of explanatory variables as were first introduced in the [Data](#) chapter.

An important relationship we have identified is the one between EIS and wealth, proxied by GDP per capita. Thus, we focus on this correlation at the beginning of our analysis, and then we turn to include other relevant macroeconomics factors. Since the results of our analysis, as based only on our EIS estimates, are not significant, we rely on additional country EIS estimates from earlier studies, as well as use the literature to discuss the importance of the different macroeconomic factors in explaining EIS heterogeneity.

This chapter is divided into the following sections. 7.2 outlines the methodology used including a list and description of the models we run. 7.3 focuses on the correlation between EIS and GDP, by means of (a) a standalone plot and (b) a regression analysis including the other macroeconomic variables. The findings are discussed at the end of the section. 7.4 expands the discussion to the other relevant macroeconomic factors. 7.5 discusses the overall approach and 7.6 concludes the chapter.

7.2. Methodology

Before starting the analysis, we want to provide an overview of methodology, with special focus on how we extend our dataset, or more specifically add more EIS estimates to enlarge our sample and thereby enable more robust conclusions.

In this chapter, we run a regression of EIS estimates for each country on different macro variables, using a robust OLS model. The EIS estimates we employ are the ones resulting from the 2SLS model as concluded upon in research question 1. Additionally, we add EIS estimates from other studies, as explained below. These constitute the left-hand-side of the regression. The right-hand-side consists macroeconomic

⁴¹ The estimates we selected as preferred in the conclusion of [research question 1](#). This is the OLS IV (2SLS) estimates.

variables, as outlined in the [Data](#) chapter. Since we add EIS estimates from other studies, we also control for the differences in methodology employed, as we include the additional estimates.

We run the regression on the following vectors:

$$EIS = \alpha + \beta \cdot [macro\ variables] + \gamma \cdot [method\ variables] + \varepsilon$$

7.2.1. Dataset extension

Our dataset consists of 14 countries and this results in 14 EIS estimates, which is a small sample for the analysis we want to perform in this section. In order to make our test findings more robust we include EIS measures from the research of Havranek et al. (2015), extending our sample to 1,246 estimates for 28 countries. Havranek et al. (2015) has collected and performed a meta-analysis on a number of studies that estimate the EIS in different countries. By means of including this data, we have different EIS estimates for the same country (coming from different studies and covering different time spans) as well as more countries. We thus find this new, enlarged sample more robust and more valid to make conclusions from. We form four datasets that include different studies:

1. The first one only includes our estimates, as this is the analysis we would have done in any case. Unfortunately, the results are not significant, so this is what encouraged us to add other estimates from different studies.
2. A second dataset consists of Havranek et al.'s model simply adding our estimates, classified accordingly to Havranek et al.'s methods variables.
3. The third dataset includes only euro zone countries, with both our estimates and Havranek et al.'s.
4. Finally, the fourth dataset only contains EIS estimates for the 14 countries that we have data for in our analysis. This means that we continue the analysis on these 14 countries, including more EIS estimates from different studies, classified according to Havranek et al.'s method variables.

7.2.2. Right-hand-side and model classification

In order to include Havranek et al.'s estimates without compromising the quality of the tests we run, we investigate the paper's EIS sampling manner and also how we should control for EIS estimates from different study types when we employ the estimates in connection with our own.

At the beginning of their analysis, Havranek et al. run a BMA (Bayesian model averaging) analysis to find the optimal model to use in terms of which variables to include. They have two types of variables: macro variables, as we have, and method variables, that control for the different models used in the estimation of the EIS in the different papers.

Based on the BMA analysis, they find that “*the very best [model] includes only 9 out of the 30 method variables at our disposal; the variables included are **inverse estimation, top journal, stock return, total consumption, OLS, no. of years, asset holders, exact Euler, and capital return. Monthly data** is not included in the best model, but it belongs to most of the other good models.*” (Havranek et al., 2015, p.105, Journal of International Economics 96 (2015) 100–118). For this reason, we include the same method variables when we run our model. We want to make sure that we control for the different studies used in estimating the elasticities we employ. These variables are presented in the [Data](#) chapter.

Based on the method variables, our study classifies as follows:

Havranek et al.’s variable	Value for our study
Inverse	0 (= the rate is our independent variable)
top journal	0 (= not published in a top journal.. yet)
stock return	0 (= we use 3-month interest rate return on bonds)
total consumption	1
OLS	0
no. of years	$\ln(22)^{42}$
asset holders	0 (= our estimate is related to the whole population)
exact Euler	1
capital return	0
Monthly data	1

We rely on the same methodology variables as Havranek et al., and we always include all of them in the different models we run. Since the EIS estimates in the dataset are estimated from different time spans, we average the macro variables across the years of the study⁴³.

Concerning the choice of macro variables, Havranek et al.’s BMA analysis results in the choice of the following as optimal macro factors to explain the change in EIS: GDP, credit availability, real interest and rule of law. Other macro variables included in their research are stock market participation and trust in institutions. Similarly, Vissing-Jørgensen (2002) finds that the consumer’s asset market participation is a key determinant in EIS differences.

The choice of our own macroeconomic variables take inspiration from these papers among others which we will elaborate on in the discussion of our results, near the end of this chapter⁴⁴.

⁴² This is calculated in STATA.

⁴³ In this regard, Havranek et al. do not specify how they calculate the macro control variables for the different studies, so we need to make an assumption. Since we do not want to complicate this analysis further, we simply take the averages of the macro values across the sample periods.

⁴⁴ Please find additional details on Havranek et al.’s EIS estimates and our method of employing them alongside our own in the Data description chapter.

A final comment is that, running this regression, we implicitly assume a constant EIS measure per country across the sample period. The macro variables are likewise averages. We deem it accurate to employ averages since, as is the case with respect to our EIS estimates, we are concerned about the structural differences between the countries and not the exact levels. Thus, we have chosen to use macro variable averages across the sample period used by the different studies. In other words, the timing of LHS and RHS is matched in order to improve the validity of our analysis.

7.2.3. Models description

In each regression we run, we use the complete set of methodology variables as per Havranek et al.'s optimal model (the ones listed above), even when they are not statistically significant⁴⁵.

In our statistical analysis, we include the macroeconomic factors and run the model with the different dataset. For each dataset, we run the first model with all the macro variables. Because we suspect multicollinearity among the many variables, we run a Variance Inflation Factor (VIF) test for multicollinearity⁴⁶ and observe which independent variables are potentially highly correlated with others. We drop the variable with the highest VIF value, run the model again and test again for multicollinearity. We continue this process until there is no multicollinearity between the RHS variables⁴⁷. At this point, we run the last model, for a given dataset, where we drop the independent variables that prove insignificant.

Below are the models we run:

Dataset	Model #	Model
Only our estimates	1	All variables
	2	Dropped <i>gov_eff</i>
All estimates: our + Havranek's	3	All variables
	4	Dropped <i>corruption</i> because of multicollinearity
Only eurozone	5	All variables
	6	Dropped <i>corruption</i> because of multicollinearity
	7	Dropped <i>stock_part</i> because of multicollinearity
	8	Dropped <i>GDP</i> because of multicollinearity
Only 14 countries for which we have estimates	9	All variables
	10	Dropped <i>gov_eff</i> because of multicollinearity

⁴⁵ They are however not included when we run regressions with our EIS estimates only, as there is no need to control for different methods.

⁴⁶ The Variance Inflation Factor (VIF) test shows how much the variance of the coefficient estimate is inflated by multicollinearity. We consider variables with VIF values above 10 to be highly correlated with other independent variables.

⁴⁷ i.e. when the VIF values are below 10 for all the variables.

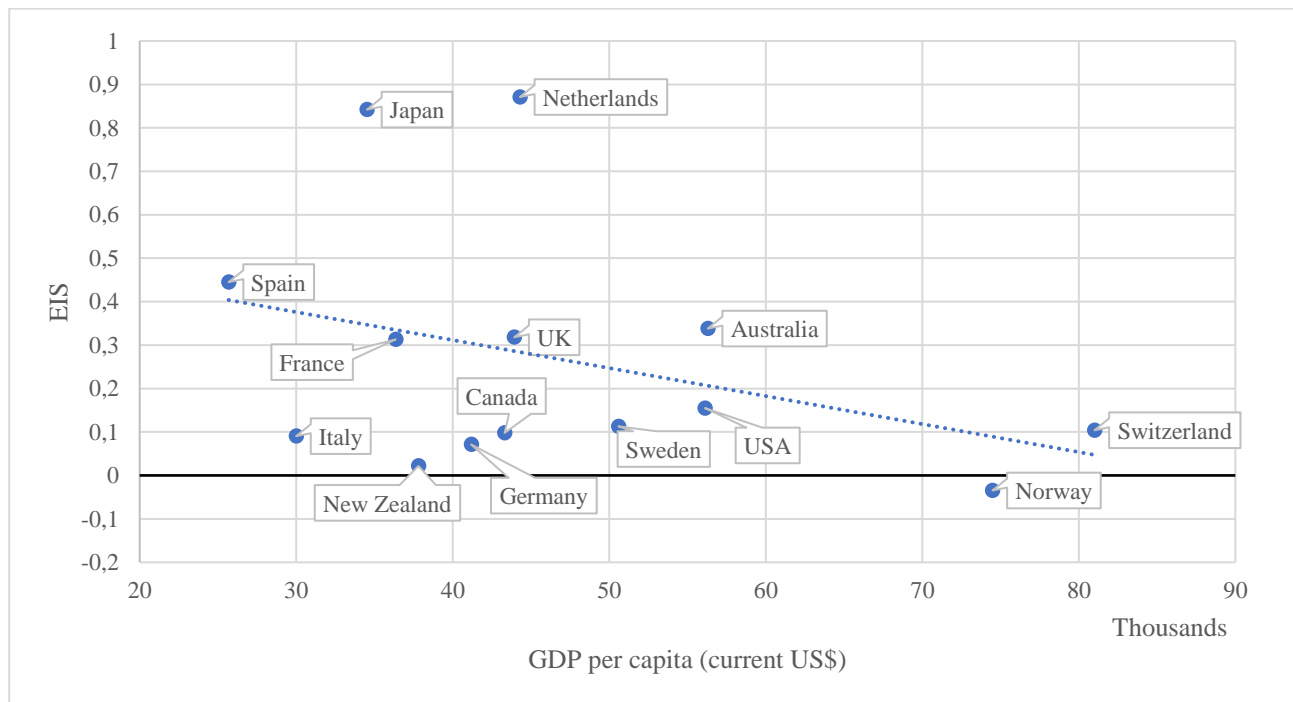
7.3. Analysis of the relationship between EIS and wealth

In this section, we start our analysis focusing on the relationship between EIS and wealth, proxied by GDP per capita. We analyse this correlation graphically, plotting the variables against each other and we then continue verifying our early results with statistical analysis. We conclude discussing the results, in light of the literature's earlier findings.

7.3.1. The EIS and GDP as a standalone plot

In [Figure 7.2](#) we plot our EIS estimates against GDP per capita. Surprisingly we see a negative relationship between the two. Previous studies have often found a positive relationship between wealth and the elasticity of substitution, meaning that wealthier individuals are more willing to exchange consumption between periods of time. In the discussion section, we will reflect on this finding relative to earlier literature.

Figure 7.1: Correlation between EIS and GDP per capita



Source: The World Bank, own analysis

Note: The EIS estimates included in the plot are the ones resulting from our 2SLS model in the time series analysis in research question 1

7.3.2. Statistical analysis including other macroeconomic variables

We then run a regression to test the relationship between EIS and all our selected macro variables. The purpose is to see whether (1) the correlation between EIS and GDP is significant, and (2) if any of the other macroeconomic variables we include are critical in explaining the variation in EIS⁴⁸.

[Table 7.1](#) shows the results from the different models, as presented at the beginning of this section.

The results in the first two columns, i.e. estimated using only our EIS estimates, suggest no correlation between the EIS and the macro variables, since the results are not significant and the coefficients small in magnitude. However, the results start to get significant as we enlarge the sample.

We observe that tax rate⁴⁹ has a negative sign in most of the regressions but is not significant in any of them. The sign makes intuitive sense, since with higher tax rates the consumer is more constrained in his consumption and will be affected less by a change in asset returns, since a portion of the return is paid in taxes. However, even though the sign of the correlation makes sense we are not able to conclude more, since the result is not significant. For this reason, we won't discuss this variable further.

The additional variables will be treated in greater detail in the subsequent sections.

7.3.3. Discussion of wealth

GDP per capita, which is our proxy for wealth, remains significantly negative across the analysis, while the coefficients' magnitude are consistently very small. This result is puzzling, since numerous previous studies concluded that the correlation should be positive; wealthier consumers are considered more elastic in their reallocation of consumption, since wealthier consumers would be assumed to have an income surplus that they may allocate to consumption or investment depending on the returns in the economy. Another way of phrasing this is that wealthier consumers are assumed to have a smaller share of their wealth dedicated to basic consumption needs, i.e. they are not *rule-of-thumb* consumers (Campbell and Mankiw (1989, 1990, 1991)). Wealthier consumers also tend to have a larger portion of their wealth tied into asset markets – as opposed to liquid funds (Mankiw and Zeldes 1991), so they should also be more responsive to changes in the interest rate. Vissing-Jørgensen, among others, finds a positive relationship between wealth and asset holdings and the EIS. Havranek et al. (2015) also suggest this positive relationship, building on literature that explores heterogeneity in the cross-country EIS, such as Atkeson and Ogaki (1996) and studies which explore the relationships with the EIS at the micro level, such as Blundell et al. (1994) and Attanasio and Browning (1995).

⁴⁸ See the [Data](#) chapter for a presentation of the different macroeconomics variables that we include in our model.

⁴⁹ Defined as the tax rate on income, profits and capital gains (% of revenue)

Table 7.1: Results from the regression of EIS on the macro variables, using different datasets

VARIABLES	(1) Our only	(2) Our only	(3) All estimates	(4) All estimates	(5) Euro zone	(6) Euro zone	(7) Euro zone	(8) Euro zone	(9) 14 countries	(10) 14 countries
GDP	-9.57e-06 (6.72e-06)	-8.00e-06 (6.98e-06)	-6.89e-05*** (2.43e-05)	-3.81e-05 (2.27e-05)	-0.000104 (5.81e-05)	-0.000119* (6.13e-05)	-5.99e-05 (4.15e-05)		-0.000128* (6.40e-05)	-9.12e-05 (6.26e-05)
listmktcap	-0 (0)	-0 (0)	1.20e-10*** (0)	0 (0)	-2.50e-10 (2.74e-10)	-4.65e-10 (2.96e-10)	-4.82e-10* (2.25e-10)	-3.41e-10 (1.94e-10)	1.80e-10*** (5.65e-11)	0 (0)
Stock_part	-0.000488 (0.00408)	0.000748 (0.00377)	0.0166** (0.00718)	0.0167 (0.00988)	-0.0531*** (0.0167)	-0.0443** (0.0188)			0.0247** (0.00846)	0.0139 (0.0106)
credit	0.00515 (0.00353)	0.00521 (0.00356)	-0.0113* (0.00636)	-0.0109 (0.00683)	0.00609 (0.0185)	0.0111 (0.0168)	0.00528 (0.0146)	-0.00356 (0.0116)	-0.0146 (0.0194)	0.00323 (0.0176)
tax_rate	-0.000887 (0.00644)	-0.00174 (0.00571)	-0.0299* (0.0175)	-0.0199 (0.0176)	0.0167 (0.0303)	0.000778 (0.0214)	-0.00464 (0.0188)	-8.90e-05 (0.0186)	-0.0475* (0.0242)	-0.0225 (0.0164)
corruption	-0.610 (0.541)	-0.0705 (0.174)	5.099** (1.913)		1.250 (1.376)				8.220*** (2.511)	1.171* (0.556)
gov_eff	0.861 (0.730)		-6.917** (2.867)	-0.0414 (0.502)	-0.834 (1.919)	0.857 (0.623)	0.136 (0.458)	-0.213 (0.373)	-12.32*** (3.878)	
Constant	-0.196 (0.493)	0.146 (0.396)	0.309 (2.660)	-2.488 (2.164)	5.876 (6.899)	4.945 (7.342)	-0.837 (10.47)	-1.710 (10.69)	5.666* (3.185)	-4.974** (2.049)
Observations	14	14	568	568	127	127	127	127	509	509
R-squared	0.340	0.289	0.163	0.146	0.046	0.044	0.036	0.034	0.189	0.161

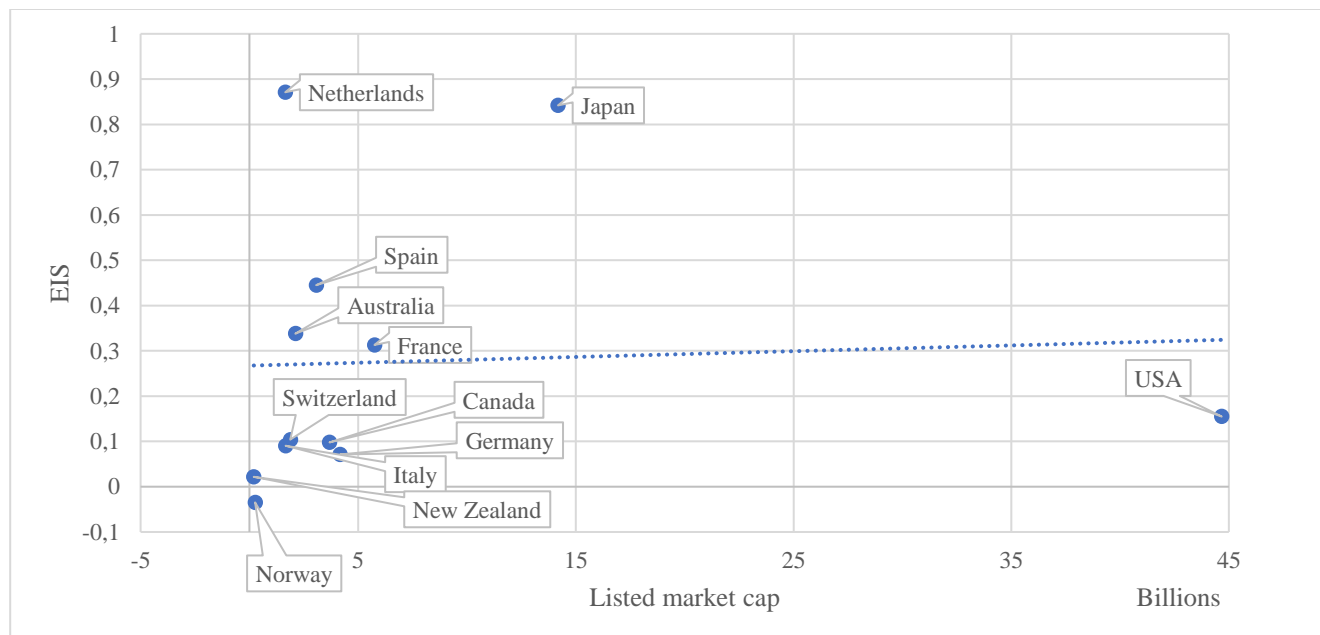
Note: Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

While there is broad consensus of the positive relationship between wealth and EIS, the above-mentioned studies look into micro data, mostly the US, as Vissing-Jørgensen (2002) does. On the contrary, we consider macro data at the country level. Within each country there could be big differences between rich and poor consumers, so we understand our proxy is not perfect. In connection to this, our results could be downward biased due to aggregation across households, as found by Attanasio and Weber (1993) and Beaudry and Wincoop (1996), and time aggregation (Bansal et al. 2010).

The differences in wealth between countries are a somewhat different matter. According to standard macroeconomics literature, countries will reach higher wealth levels if they have a higher propensity to save. Savings translate in investments, which are the fuel of innovation and determine, partly, future wealth⁵⁰. A country like Germany has a high GDP per capita, but at the same time German consumers tend to save a lot and even more when the interest rate is low, as their current savings will return less in the future. We explore the German case further below.

Wealth level could also be proxied by listed market capitalization⁵¹, which we normalize by GDP per capita, to control for the size of the economy. [Figure 7.2](#) shows this relationship, using our EIS estimates only.

Figure 7.2: Correlation between EIS and listed market capitalization



Source: The World Bank, own analysis

Note: The EIS estimates included in the plot are the ones resulting from our 2SLS model in the time series analysis in research question 1

⁵⁰ Based on a basic macroeconomic model, where the consumers' savings are translated into investment for the industry.

⁵¹ Market capitalization of listed domestic companies.

The relationship is weakly positive, suggesting that countries with large stock markets tend to have slightly higher elasticities. As it can be observed from the plot though, the distribution of the observations is very unique: the data points are concentrated around low listed market cap values, where the variance in EIS estimates is quite high. The slope of this relation could be driven by countries like Norway and New Zealand on one hand, with very low listed market cap and small or negative EIS, and from outliers like Japan on the other hand, with bigger market cap and very high EIS.

When looking at the results from the regression, including additional EIS estimates, we observe that listed market capitalization has a very small magnitude, but with a positive sign and significance in some of the runs⁵². This finding puzzles us since we consider stock market size a proxy for wealth as wealthier countries would be expected to have a more developed stock market, and, as argued in detail above, past literature documents a clear positive link between wealth and EIS. We can only add as a final comment that what distinguishes our study approach from the most frequently cited papers is that we rely on macro data as opposed to micro studies and we look at other countries than only the US.

7.3.4. A practical example: the German consumer

Although we are puzzled by the negative correlation between the EIS and wealth, it may be explained in part by the German case. The very low, or even negative, German EIS estimate tells us that the typical German consumer is very conservative and reluctant to reallocate consumption given a change in the interest rate. Firstly, this implies that low interest rates will not make the German consumer spend in excess. Thus, we should not expect price inflation and overheating in Germany from sustained low interest rates. This interpretation is confirmed by Holger Sandte, and he adds that the German consumer might often save more to compensate for the lower return on savings. This may sound counterintuitive⁵³ but it relates to the circumstance that many Germans may have a specific savings target and given lower rates they would need to save a higher fraction than previously. This may explain the very low EIS estimate that we find.

⁵² Specifically, this is the case in column (3) and (9) which list the results from including all EIS estimates (ours and Havranek et al.'s for all OECD countries) and all estimates for the 14 countries (the list of countries which make up our original data sample) respectively.

⁵³ With reference to the [Theoretical framework](#), in the German case the income effect outweighs the substitutions effect.

7.4. Discussion of the other macroeconomic factors

In this section, we will comment our results from the regression, concerning the other macroeconomic variables, and put them into context. We will refer to previous studies and general findings as well as to the intuition – or lack of it – behind our findings.

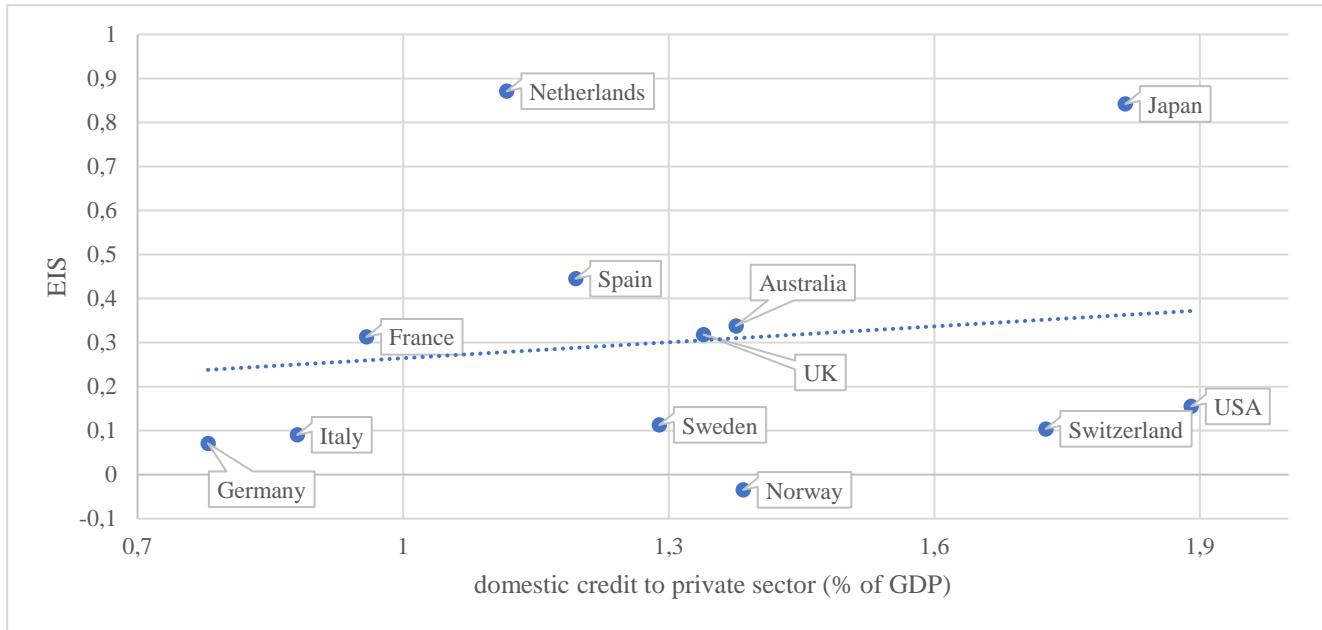
7.4.1. Liquidity constraint

Credit availability is our proxy for liquidity constraint, since an economy where credit is easily available will be less liquidity constrained. In other words, where credit is not easily available to consumers, they might be constrained in their spending and thus not able to reallocate their consumption.

The results we obtain with respect to credit availability are not consistent and not significant. Therefore, we cannot make conclusions on that basis. However, we find it relevant to include this macro variable as earlier literature suggests that access to credit helps explain cross-country variation in the elasticity in the sense that credit provided by domestic financial institutions is positively correlated with EIS. Among others, this is the conclusion made by Havranek et al. (2015) to Vissing-Jørgensen (2002).

The positive link between the EIS and credit availability arguably makes intuitive sense since credit availability serves as proxy for avoidance of liquidity constraints. The suggested negative relationship between EIS and liquidity constraints is supported by the findings of Bayoumi (1993) and Wirjanto (1995), among others. In [Figure 7.3](#) our EIS estimates are plotted against domestic credit to private sector, which is used as proxy for credit availability. As we would expect, there is a positive correlation between the two variables.

Figure 7.3: Correlation between EIS and domestic credit to private sector, as % of GDP



Source: The World Bank, own analysis

Note: The EIS estimates included in the plot are the ones resulting from our 2SLS model in the time series analysis in research question 1

7.4.2. Asset market participation

In our regression, we include stock market participation⁵⁴ as a proxy for asset market participation. The coefficient from the main regression is not consistent across different runs and the variable is dropped in several runs due to multicollinearity or non-significance. We find that the variable becomes significant, yet with negative sign, when used with the eurozone dataset. This suggests that as stock market participation increases in a eurozone country, consumers have lower EIS, which is the opposite of what we would expect. However, we find that the relationship is not consistent enough across different estimation models for us to be able to make robust conclusions. Furthermore, we might be worried that the value of listed domestic companies as fraction of country GDP consists of two variables which may deviate a lot from country to country and the reasons why one sample country has a large listed market relative to size may often not be transferable to another domestic context. This relates to the circumstance that often a majority of stock market participation is driven by big market players and institutions. This does not necessarily reveal much about the behavioural pattern of consumers.

The logic behind a positive correlation between EIS and stock market participation stems from the circumstance that if a consumer has invested wealth, he is more likely to react when a change in the rate of return

⁵⁴ Defined as total value of stocks traded as percentage of GDP.

or the opportunity cost of that investment changes. In other words, the likelihood of a consumer changing consumption streams increases with the extent to which he is affected by the change in asset return. Some studies of the EIS uses stock returns instead of the short-term interest rate. Thereby the link is direct, but in our case the connection between the two would appear in the change in opportunity cost associated with a change in the short-term interest rate. Further, in relation to our findings, we would assume that if consumers in a given country on average tend to invest more in stocks than consumers in a neighbouring country, we suppose these consumers will be more attentive to the planning of their investment and consumption choice so as to obtain the highest return.

In our analysis, we are limited by the circumstance that we deal with macro data. Micro studies are arguably more applicable to make concrete conclusions on the matter of how asset market participation affects the individual consumers' intertemporal choice. Mankiw and Zeldes (1991) first presented, and Attanasio, Banks and Tanner (2002) and Vissing-Jorgensen (2002), among others, have since estimated larger elasticity for asset holders than for non-asset holders.

With reference to such findings we consider additional types of assets and liabilities which may affect consumers' intertemporal consumption choice⁵⁵. These are for instance liabilities such as mortgages and loans.

We have looked at (1) the fraction of citizens in a country which has a house mortgage and (2) the overall lending to income ratio⁵⁶. Concerning the fraction of citizens with a mortgage, on one hand we would expect a negative correlation between the EIS and a country with many homeowners of mortgage loans since a positive change in interest rate would, everything else equal, result in a negative shock to perceived income. However, on the contrary, we may argue that since we consider macro data it is likely that countries with a higher fraction of citizens with house ownership and access to credit in the shape of a mortgage are also wealthier countries and it is still our fundamental argument that wealth and the EIS should be positively associated.

[Figure 7.4](#) and [7.5](#) show the correlation of our EIS estimates with the share of owners with mortgage or loan over the total and the lending to income ratio, respectively.

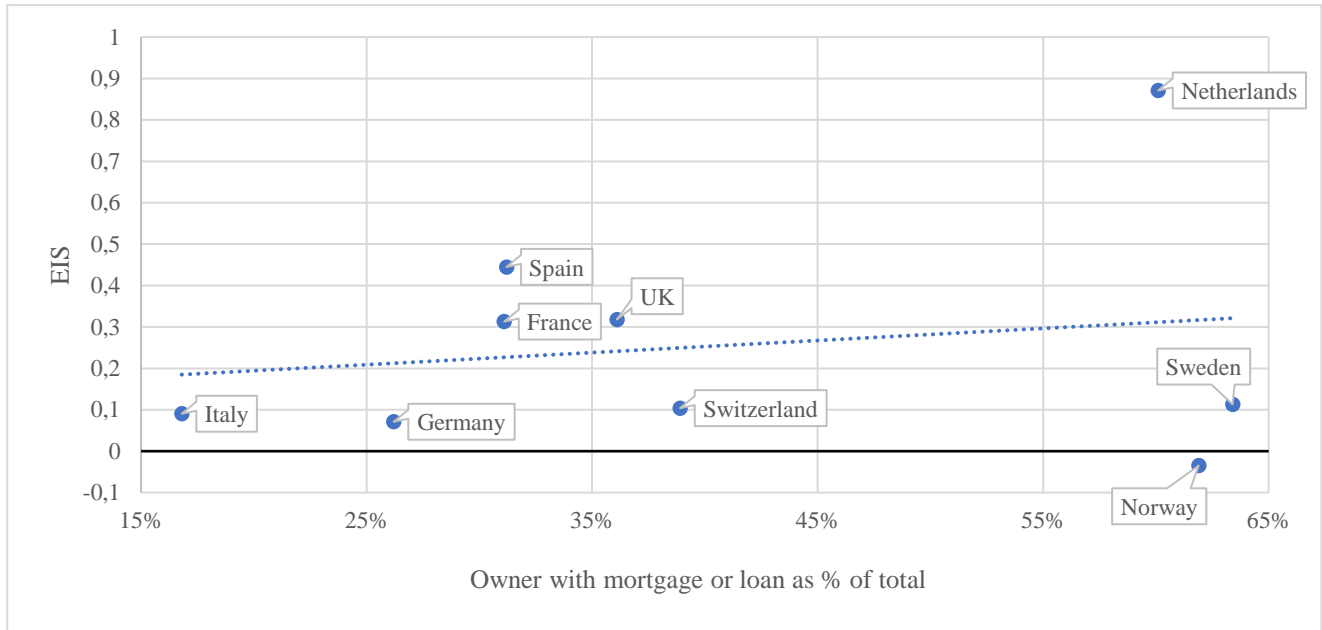
Notice that when it comes to lending relative to income across our country sample, we also find large differences across the board. The average across the eurozone is 94%⁵⁷ with the Netherlands at 219%, Sweden at 152%, Germany at 82% and Italy at 62%. Across the sample, we observe a clear positive trend line.

⁵⁵ In the regressions that we run as part of the analysis in this chapter, we do not include all the different types of variables for asset holders, but instead we discuss them here. This is because we do not want to have too many variables on the right-hand-side. Additionally, we see that these different asset-holding proxies have very similar correlations, so we are confident in only including stock participation in the regression.

⁵⁶ The data is taken from Eurostat, thus we only have figures on European countries for this variable, for 2015.

⁵⁷ Source: Eurostat

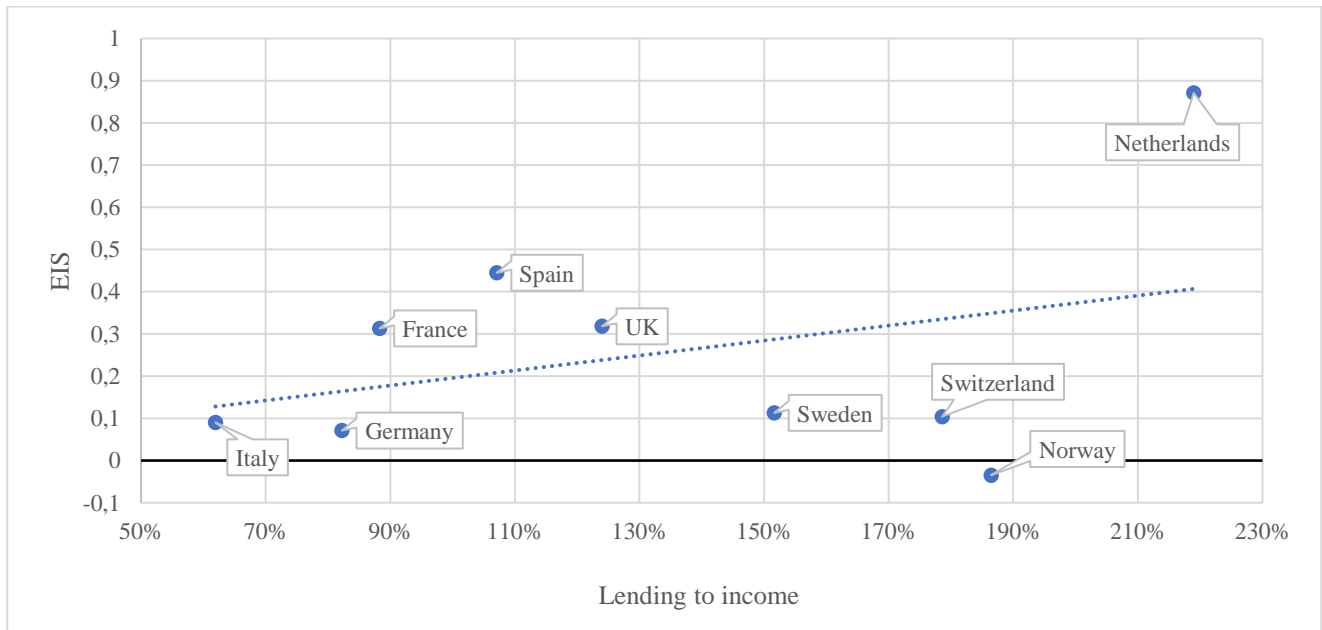
Figure 7.4: Correlation between EIS and % of owner with mortgage or loan



Source: Eurostat, own analysis

Note: The EIS estimates included in the plot are the ones resulting from our 2SLS model in the time series analysis in research question 1

Figure 7.5: Correlation between EIS and lending to income ratio



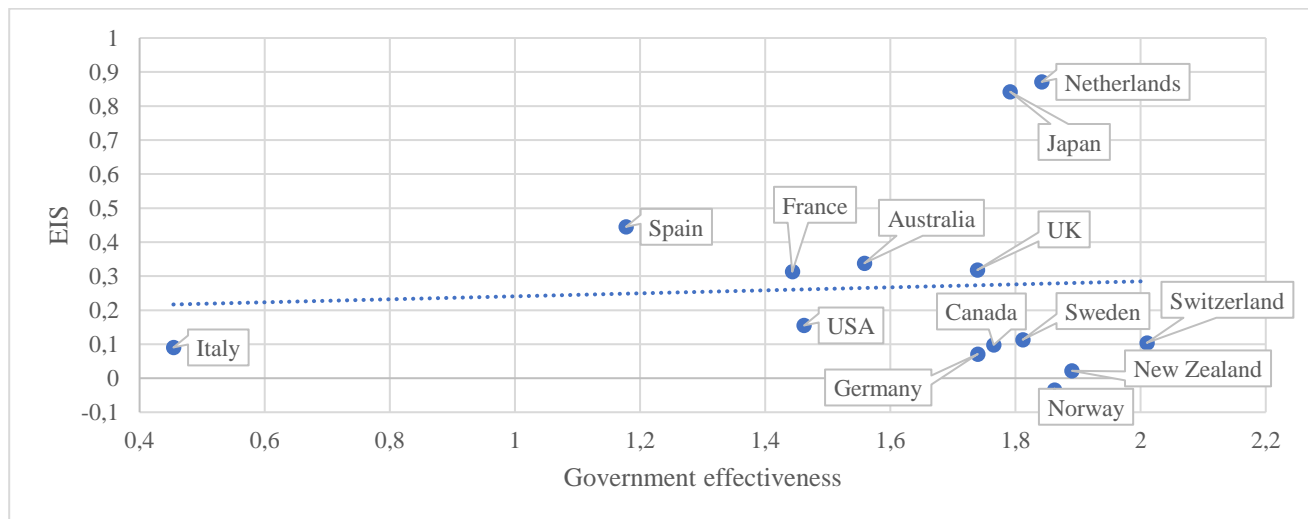
Source: Eurostat, own analysis

Note: The EIS estimates included in the plot are the ones resulting from our 2SLS model in the time series analysis in research question 1

7.4.3. Trust in institutions

Corruption⁵⁸ and government effectiveness⁵⁹ are our proxies for trust in institutions and they represent the cultural differences between the countries we consider. Both variables switch from being significant to insignificant as well as they switch signs across the various models and datasets. Finally, the significant coefficients we observe have the opposite signs respectively than what we would expect. In sum, we avoid conclusions on their impact on the EIS on the basis of our research. In addition to corruption and government effectiveness, we consider two additional cultural variables: control of corruption and level of social support⁶⁰. Therefore, the correlation plots are only to be found in the [appendix B.3](#). However, as an example please see [Figure 7.6](#), where we observe the correlation between the EIS and government effectiveness. We see a slightly positive correlation, however visibly driven by a few outliers such as Japan and the Netherlands. We would anyhow intuitively support the positive association since this variable should be considered a proxy for trust in institutions. Greater trust in institutions would, everything else equal, make the consumer more inclined to allocate more of his wealth in asset markets (as opposed to holding it as cash) which in turn relates to our previous argument as to why asset holders would be more inclined to reallocate their consumptions given changes in rates of return.

Figure 7.6: Correlation between EIS and government effectiveness



Source: The Worldwide Governance Indicators, own analysis

Note: The EIS estimates included in the plot are the ones resulting from our 2SLS model in the time series analysis in research question 1

⁵⁸ Defined as a measure which reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests

⁵⁹ Defined as an indicator that reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.

⁶⁰ Again, we do not include all of these variables in the right-hand-side of our regression, but we instead discuss them here using a graphical analysis

7.5. *Discussion of overall approach*

We recognise our method has weaknesses. First of all, we move away from just looking at our own findings. We do include regressions in which we exclusively use our own EIS estimates, but since the results are not significant, we prefer to expand the dataset to try and find an explanation for EIS heterogeneity. This choice may arguably be at the expense of complete transparency in approach since we compare our EIS estimates with estimates from different studies. We try to control for this by means of including the method variables, as done by Havranek et al. (2015). In this regard, we are aware that we only include part of Havranek et al.'s sample, as explained in the [Data](#) chapter. This restriction of his dataset could have led to a different result in the BMA analysis. Nevertheless, we believe the model used by Havranek et al. should hold with different samples. Finally, we do not want to complicate the analysis further, so we stick to their model in all the regressions we run: this is our best alternative if we want to include the additional estimates.

Another weakness of our approach is the choice of macro variables. We have not found measures of consumer credit availability and trust in institutions for the complete set of countries and time periods to our preference. Instead we have used private sector credit availability and corruption and perception of government effectiveness as alternative proxies.

As a final comment, the aim of this chapter is to make conclusions on the reasons why we observe EIS heterogeneity between countries in current times. Thus, we only consider EIS studies which are less than 40 years old. In other words, a limitation to the scope of our analysis is that we can only infer on current explanations to EIS heterogeneity.

7.6. *Chapter conclusion*

Under [research question 1](#) we identified EIS heterogeneity among eurozone countries. In this section, we connect these heterogeneities with country specific factors which may underpin these dissimilarities. We test a number of explanatory variables against the EIS estimates, as well as plot the EIS estimates against the variables in turn. We find that our own test results are inconclusive, also after including Havranek et al. (2015)'s estimates. We thus focus on the explanatory relations found by earlier studies.

Literature indicates a positive link between wealth levels and EIS, as well as with respect to asset market participation and government effectiveness. Whereas, liquidity constraint is associated with lower EIS estimates, as is higher levels of corruption and low levels of trust in public institutions. The structural differences between countries help explain EIS heterogeneity and their implications will be the topic of the next research question.

8. RQ3: What implications does EIS heterogeneity have for the effectiveness of the eurozone from a monetary policy perspective?

8.1. *Chapter Outline*

The purpose of this chapter is to discuss the effectiveness of the eurozone given that we have found EIS heterogeneity amongst eurozone member countries. Since our findings have implications for common monetary policy effectiveness, this perspective is at the centre of our evaluation of eurozone effectiveness. Thus, the core of the discussion will rely on our findings from previous chapters. However, in order to have a more informed discussion of the implications of our test results we have interviewed economic experts from leading Danish banks.

We want to make the reader aware of the limitations to what we will discuss in this chapter. We only discuss monetary policy's short term effects and do not consider the long run neutrality of money. Furthermore, monetary policy is considered to have short term effects on both investment and consumption. In this chapter we only deal with the effects related to consumption.

In order to provide a starting point for our discussion of eurozone effectiveness, we outline main characteristics from an Optimum Currency Area (OCA) perspective. We then narrow down and discuss effectiveness of the eurozone exclusively by means of an evaluation of the effectiveness of monetary policy based on our results from research question 1 and 2, as well as ECB's alternatives. Specifically, we discuss other steps the ECB has taken to boost the real economy, as well as the realistic monetary policy alternative to being a eurozone member.

The chapter is split in the following manner. In 8.2 we outline optimum currency area theory and discuss the eurozone from this perspective. In 8.3 we then analyse the effectiveness of the eurozone from a monetary policy perspective. We do this primarily by means of (a) analysing the dissimilar economic consequences within member states from a change in the interest rate, supported by (b) an analysis of the sustained low interest rate's limited effect on the real economy. Given that our findings suggest that common monetary policy by means of interest rate setting is to some extent lacking effectiveness, in 8.4 we analyse past steps taken by the ECB and the institutions of the eurozone to provide a better basis for common monetary policy. We finish by (8.5) a discussion on the realistic monetary policy alternative to being part of the eurozone.

8.2. *The eurozone relative to the optimum currency area criteria*

Optimum currency area theory is a recognised and popular method to estimate the effectiveness of a common currency union. Mundell-Flemming (1961) first introduced the theory of optimum currency area which in short describes the benefits from joining a currency area. The benefits should arguably outweigh the costs if the economy in question is small, engages in substantial amounts of cross-border trade with neighbour economies already in the currency union, and finally if the economy would be comparable and react similar to neighbours, given an economic shock.

The purpose of this section is to provide an overview of what it takes to be an optimum currency area and discuss whether the eurozone lives up to these criteria. Overall there are three classical economic criteria and an additional three political criteria before an optimum currency area is achieved based on the works of Mundell (1961), McKinnon (1969), and Kenen (1963). The economic criteria advise that an optimum currency area must have labour mobility, and consist of open and diversified economies. Such properties allow the member states to limit asymmetric economic shocks. Free movement of labour and a high willingness to move around from one region to another within the common currency area allows labourers to move around according to where the demand for labour arises, and similarly to move away when unemployment occurs due to lack of demand.

When speaking to market experts this is also the first key measure to improve upon in order to lessen the diverging effects from an economic shock to the eurozone. Both Holger Sandte, Chief European Analyst at Nordea, and Las Olsen, Chief Economist at Danske Bank, highlight its positive effect on competitiveness as well. Germany is famous for its labour market reforms, but also Denmark is known for its flexicurity model which provides both flexible conditions with respect to hiring and firing, as well as great security for its workers in terms of a supporting welfare state and job market training. However overall Europe has much lower labour market mobility than the US. This is due to the circumstance that Europe in many ways still has many regional differences with respect to culture and language (Baldwin and Wyplosz, 2015).

Open economies are defined as economies which have high net exports as percentage of GDP. Such countries benefit from being part of a common currency area as they may take advantage of an ease of trading terms. Trade is facilitated by means of the elimination of transaction costs related to currency conversion and the transparency in terms of prices of goods and services, everything else equal.

Finally, a diversified economy is less sensitive to shocks, so even though a shock to a currency union may be asymmetric, it would not hit the individual members as harshly if they are better prepared to face it by simply being able to depend on other economic levers within their economy. It is difficult to measure diversification on a single scale, but well-advanced European countries are considered much more diversified than newly-advanced

or less developed countries which have historically depended on a few natural resources or trade partners (Baldwin and Wyplosz, 2015).

In parallel, the following political properties should also be in place, as these would allow the common currency area members to deal with economic shocks in a manner which would minimise dissimilarities. These political properties are fiscal transfers across the union, homogeneous policy measure preferences, and solidarity. Fiscal transfer across the union would allow the transfer of funds and lessening of liquidity constraints from one region to another within the area. In other words, it would allow one region which is doing less well following a shock to quickly recover by means of assistance from other members which are less severely hit.

The criteria related to homogeneous policy preferences refers to the circumstance that a common currency implies a common monetary policy, but not necessarily the same fiscal policy⁶¹. This is the case for the eurozone. We have observed quite different approaches to tackling the eurozone recession from member countries such as Germany and France. Whereas politicians in some eurozone member countries believe strongly in the Keynesian approach in which you apply expansionary fiscal policy and ‘spend your way out of the crisis’, other member countries adhere to more monetaristic principles and do not believe that politicians should interfere with the economic cycle more than absolutely necessary.

Finally, the last political property is solidarity. This property is more fundamental and also difficult to measure. However, the rise in national sentiments and scepticism around Europe in recent decades, and especially post-crisis, suggests that, despite being an implied requirement for effective collaboration, solidarity is also an area where the eurozone may be lacking in terms of OCA theory.

To sum up, we find that the eurozone is well underway with respect to the OCA criteria, however it is still not to be considered an optimum currency area. While this first section here is meant to provide an overview of eurozone effectiveness, the remaining sections will exclusively evaluate the effectiveness of the eurozone by means of an analysis of the effects of common monetary policy and past steps which have been taken by the ECB and the institutions of the eurozone to provide a better basis for common monetary policy.

8.3. *The effectiveness of the policy rate as set by the ECB*

In this section, we analyse the effectiveness of the policy rate set by the ECB primarily by means of (a) analysing the dissimilar economic consequences within member states from a change in the interest rate, given the different elasticities, supported by (b) an analysis of the sustained low interest rate’s effect on the real economy.

⁶¹ This trade-off is called The Impossible Trinity. Please find further details under the Danish case in the [Empirical framework](#) chapter

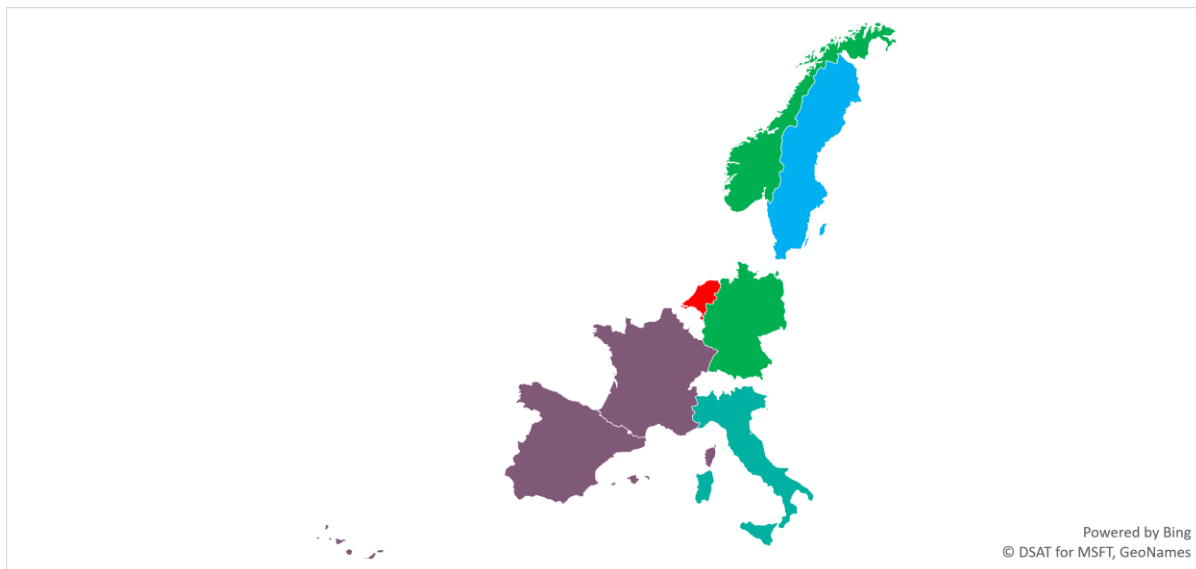
8.3.1. Dissimilar effects from a change in the interest rate

There is little doubt that the eurozone and the common market have brought many economic benefits in terms of increased investments and trade, as well as established financial markets which did not exist before, thus providing credit liquidity and facilitating investment opportunities. These benefits only become more expressed as more countries adopt the same currency and the market expands. However, as a currency area grows larger, it often entails a broader, more dissimilar group of countries which carries some potential costs. If a currency union is formed between dissimilar countries, a common monetary policy is likely to create unintentional consequences since some economies within the union may experience the monetary policy as too expansionary – igniting a bubble sentiment – while others may find the same measures too restrictive with fear of killing tentative sparks of growth. This is what we want to illustrate by means of our EIS estimates from the analyses in previous chapters.

From research question 1 we have found evidence of EIS heterogeneity across the eurozone, and from research question 2 we have seen how these differences may be explained by structural differences between the countries. In this section, we concretise and illustrate what happens to domestic consumption from a change in the monetary policy rate in each of our sample countries.

[Figure 8.1](#) illustrates that our EIS estimates allow us to group the European countries of our sample based on their EIS similarities.

Figure 8.1: Grouping of euro area countries and Scandinavia, based on our EIS estimates



Source: own analysis.

Note: The countries are grouped by means of a Wald test on the EIS values we estimated. Countries with EIS estimates non-significantly different from each other are assigned the same colour.

In order to illustrate the dissimilar effect to a monetary shock which stems from differences in the country-specific EIS estimates across the eurozone, we plot the shock effect to consumption from a 100 basis points increase in the policy rate.

As a starting point, we take inspiration from Smets and Wouters (2007)'s business cycle shock model which Havranek et al. (2015) also depict in their article. Consequently, we build our own model to show the effect of a change in the policy rate on the different eurozone countries we consider. When doing this, we keep Scandinavian countries as part of the analysis, since we think they represent an interesting case⁶².

Smets and Wouters' work depict a complete model which allows to see both the effect on consumption and investment, as well as provide an approximation of a realistic link between the EIS factor and the response to monetary policy⁶³. We limit our analysis to only address the effect on consumption as consistent with the rest of our paper. We take our starting point from a macroeconomic consumption problem based on the utility characteristics outlined in the [Theoretical framework](#) chapter. In particular, we consider the 3-month overnight index swap rate for the euro⁶⁴ and assume it follows an AR(1) process⁶⁵. We then estimate the coefficient of the past rate via an OLS regression. Applying this coefficient and assuming an arbitrary long-run mean, we model the rate path given a shock of 100 basis points in the first period of the series. Starting from the rates calculated this way, we estimate the expected consumption growth as per the Euler equation, where $\Delta c_t = EIS_i \cdot r_t$ and in particular $\Delta c_1 = EIS_i \cdot [r_1 = \mu \cdot (1 - \rho) + \rho \cdot \mu + 0.01]$, where i is the country. [Figure 8.2](#) shows the impulse responses of the different countries expected consumption growth, driven by the different EIS, given the shock to the policy rate⁶⁶. A complete explanation of the methodology can be found in the [Appendix C.1](#) together with a simpler illustration of how future consumption in the different countries diverge given different elasticities of substitution.

What we see from the plot is that when the policy rate increases by 1%, the reaction of the eurozone countries with respect to consumption growth is quite different. An increase in the interest rate would in theory stimulate savings. This is what it does to a great extent in the Netherlands, based on our data. Spain and France also show a large reaction, even though well below the Netherlands. Italy, Germany and Sweden react very similarly and do not change their allocation of consumption too much. Finally, Norway has an opposite reaction, which we can interpret as a close to zero reaction, based on Havranek et al. (2014).

⁶² This is due in particular to the Danish case which we highlighted at the beginning of the paper..

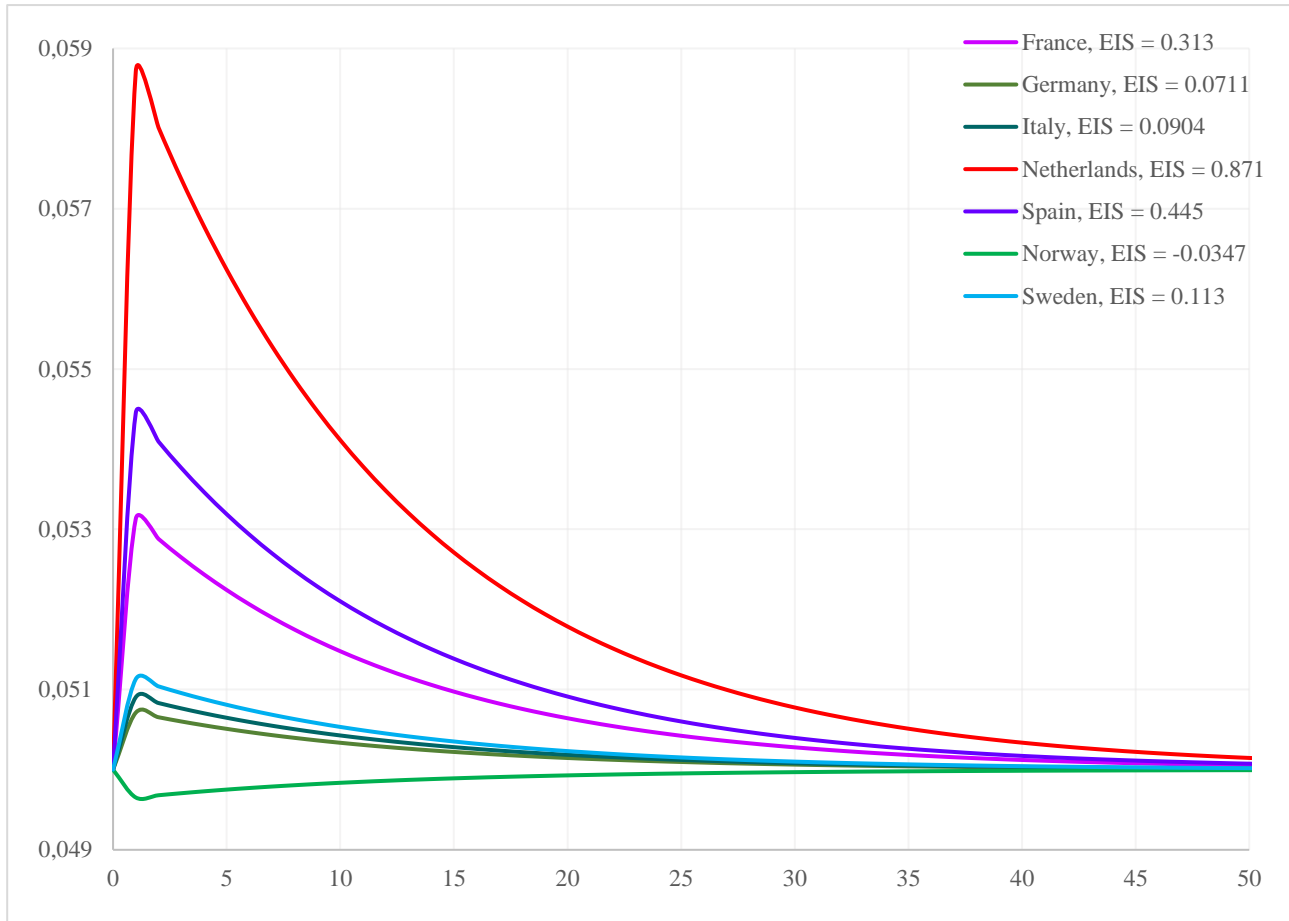
⁶³ This is not easily done as the EIS framework does not include a central bank

⁶⁴ Monthly because our data relies on monthly estimates and the euribor 3m swap rate at this short term, uncovered, rate is considered very close to the risk free interbank market rate (the main refinancing rate) (Pennacchi, 2008)

⁶⁵ This assumption is proved by a partial autocorrelation plot of the series.

⁶⁶ The expected consumption growth is rescaled to highlight the effect of the policy shock.

Figure 8.2: Impulse response of the countries expected consumption growth given a shock to the policy rate of 100 basis points



Source: Bloomberg, own analysis.

The ECB sets its monetary policy rate according to the average eurozone economy. However, if we consider the effect on single eurozone countries, we observe that given the large EIS of the Netherlands, this country will react with an increase in consumption growth higher than all the others, given an increase in the interest rate. France and Spain are next, with a lower EIS than the Netherlands, but still a quite high response reactions. Finally, Germany and Italy, as well as the Scandinavian countries, lie at the bottom. What this means is that when the ECB tries to stimulate the economy lowering the interest rate, this will affect more greatly the Netherlands than Italy. Furthermore, we observe that a shock would have similar effect on the German consumer as on the Italian consumer. This may be a correct conclusion, albeit the two nationalities would be reluctant to reallocate for different reasons. Whereas the Italian may be less sensitive to changes in rates of return it may be because the general Italian is less invested in asset markets and trust less in institutions in general. The German consumer is considered conservative in general.

A popular critique is that on the one hand, ECB's monetary policy guided towards the average economy is not stimulating countries like Spain and Italy enough, while countries like Denmark may be in danger of experiencing an overheating of the economy. When asked about this subject, the market experts we approached all agree that the Danish economy is not in such a situation as the rise in domestic housing prices is explained by fundamentals. This view is confirmed by the National Bank (Danmarks Nationalbank, 2017). If we would be concerned by the effect of low interest rates on the German economy, the very low EIS estimate tells us that the typical German consumer is very conservative and reluctant to reallocate consumption given a change in the interest rate. This also implies that low interest rates will not make the German consumer spend in excess. Thus, we would not expect price inflation and overheating⁶⁷.

Such differences between countries were the topic of research question 2 but in the context of our current topic, the effectiveness of common monetary policy, their differences illustrate that the eurozone has embedded imperfections which may then be overcome by some of the OCA criteria mentioned in the previous section.

8.3.2. The sustained low interest rate's limited effect on the real economy

We currently observe rising inflation in several member state economies and the expectation is a eurozone inflation at 1.7 % for 2017 (Nordea Markets, 2017). However, the current market expectation is that the ECB will proceed with asset purchases beyond the end of 2017, end QE by mid-2018, and then initiate policy rate increases in early 2019, i.e. these would be less negative rates than what we currently observe (Sandte, 2017). The continuation of ultra-low rates may be explained by the circumstance that current signs of inflation are primarily driven by rise in energy prices and the upswing is still considered very vulnerable. Holger Sandte of Nordea Markets puts it in the following manner: "We expect the ECB will not put a foot on the brake, but merely off the accelerator". However, in analysing the effectiveness of the policy rate as set by the ECB we also want to discuss the effect to the real economy from the sustained low interest rate we have observed post-crisis.

One consequence is a rise in demand for AAA-denominated assets. This is partly due to the consequential 'search for yield' where we observe investors looking for low-risk assets which provide returns above the very low bank rates. This demand is emphasised by a structural change towards higher savings rates. Several European economies with substantial welfare states such as Denmark and Sweden have historically not had high savings rates due to the circumstance that citizens would not need to save (a lot) for their retirement as it would be largely financed by the government. However, since the late 80s political efforts have worked to increase the savings rate in such countries to the benefit of the economy as a whole. Furthermore, several European economies currently

⁶⁷ Please see the discussion of results in [research question 2](#) for further comments on the German case

have larger fractions of older people soon to retire, than was the case only twenty years ago. Such citizens also tend to have a higher savings rate than other population segments.

In aggregate such trends turn into a pattern denominated ‘the savings glut’ which describes a situation of excess savings which implies an even further increase in demand for low risk assets, underlined by an unwillingness among private companies and government institutions to invest and put money to use (Gross, 2016). Thus, there are several reasons to believe that interest rates will stay low for a sustained period, even if the ECB does less to keep rates low. The market experts we have consulted all agree that it is highly unlikely that we will observe interest rate levels similar to what we observed ten years back.

While the ECB cannot take on the full responsibility for the low rates we observe, a main concern of such low rates is that there is less room for monetary policy stimulus, should another crisis occur within the next couple of years. This issue has been a hot topic in recent years with reference to the ‘zero lower bound’⁶⁸ (Cœuré, 2015) with which researchers and market observers fear constraint in directing the economy. This is partly due to the circumstance that the commercial banks are reluctant to copy interest rate reductions into negative territory⁶⁹. In addition, such negative – or near zero rates – are expected to have little positive effect on spending. We may in fact worry that such ultra-low rates only encourage further investment in risky assets in search for yield and thus distorts asset prices without boosting the real economy in eurozone member countries such as Spain or Italy, as intended.

Finally, according to Holger Sandte, it is a well-known concern that the ECB may be trapped in the sense that the central bank is forced to keep rates low regardless of policy preference. This is due to the circumstance that sovereign debt levels are still so high that they couldn’t be sustained, if interest rates approached their pre-crisis levels, even by margins.

8.4. *Steps taken to overcome common monetary policy inefficiency*

On the basis of our analysis, we conclude that the effectiveness of the ECB’s policy rate leaves room for further improvement. However, this is not an on-heard-of critique, and the Executive Board of the ECB points out that they have several other means to steer the economy besides interest rate setting (Cœuré, 2015). In this section, we analyse past steps taken by the ECB and related institutions in relation to tackling the most recent crises, including initiative towards fiscal policy alignment within the eurozone. Measures taken so as to provide better conditions for common monetary policy and ultimately improve the efficiency of the eurozone.

⁶⁸ The term describes the situation in which nominal interest rates approach zero

⁶⁹ What we observe is that the commercial banks instead increase other client costs

As described in the [Empirical framework](#), the ECB has attempted to boost the economy by means of quantitative easing programmes under which the bank buys large amounts of member state assets. Such operations should be considered in the light of the mandate provided by the Maastricht Treaty. However, the Maastricht Treaty included a no-bailout clause specifying that the ECB would not have the mandate to take on responsibility of government debt of member states, nor would other member states be allowed to take on responsibility of government debt of their peer member states⁷⁰. For Greece, this meant that default became a necessity⁷¹. To reduce the risk of contagion from Greece to other economies, the EU together with the International Monetary Fund (IMF) set up the European Financial Stability Facility (EFSF) with a lending capacity of 440 billion euros in June 2010 (ESM, 2017a). This temporary crisis resolution mechanism and the European Financial Stabilisation Mechanism (EFSM), were both replaced by the European Stability Fund (ESM) in 2012 with an amendment to the constitution.

The ESM may facilitate loans to member states, as well as perform primary and secondary market purchases, ensure precautionary credit lines and direct recapitalisation of institutions and banks (indirectly). The ESM members, the member countries of the EU, each contribute to the mechanism's authorised capital according to their respective share of the EU total population and GDP.

This is arguably an example of fiscal transfer and 'institutionalised' solidarity which we have argued are some of the building blocks in providing more efficient operating terms for a common currency area in the first section of this chapter. It is also an example of how joint solutions arise in a time of crisis. However such a top-down decision approach which is enabled by an amendment to the EU's original constitution also creates basis for critique and public scepticism.

One may argue that if the intention was to provide credit liquidity and stimulate European markets, the initial effect was limited. Some 22 billion euros of member country securities such as bonds and bills had been acquired by investors between May 2010 and March 2012. However, since then the accumulative effect is now substantial. In the beginning of 2016, the total outstanding loans of the EFSF and ESM combined amounted to 152.3 billion euros (ESM, 2017a).

Member states may apply for a bailout or debt refinancing given that they promise to undergo reforms and fiscal consolidation. The decision of whether and how to assist a member state in such a situation is decided upon by the so-called Troika consisting of the European Commission, the ECB and the IMF. Examples of programmes which have been launched are recapitalisation of Spanish and Cyprian banks.

According to the Delors report, the ECB and ESCB are responsible for monetary policy, and while individual Member States would remain in control of own fiscal policies, they would be required to implement

⁷⁰ Please find a description of ECB's mandate in the Empirical Overview chapter

⁷¹ Whether Greece actually went bankrupt is still subject to conflicting opinions but since Greece could not satisfy its loan obligations most institutions would denote the crisis as a bankruptcy case

binding budgetary rules. By means of these conditional lending facilities, the ECB and related institutions may direct member countries towards more budgetary prudence and stronger control of their national banking sector.

Further, given that the use of QE stands in contrast to the ECB's official mandate, such operations and the power of the Troika have been subject to much debate. While some were initially concerned that the ECB should keep highly risky debt on its balance sheet, more recently the concern has focused on whether the ECB should own large amounts of assets of certain member states and thereby to some extent become powerful or sovereign in itself. Currently there are still court cases in process concerning this matter (Hale, 2017).

Recent years' actions to guide member countries towards more fiscal prudence arguably relate to the eurozone's starting point with respect to member country differences in terms of economics and political preferences. As described in the [Empirical framework](#), member countries needed to fulfil a set of requirements in order to be able to become part of the eurozone in the first place. The most cited requirements are not exceeding 3% budgetary deficit and 60% public debt relative to GDP. These requirements have proven to be subject to discussion⁷² and were ultimately not binding requirements. Furthermore, subsequent to joining, eurozone interest rate convergence implied that countries such as Italy and Greece suddenly were faced with very cheap terms of lending. Thus, while the private sectors of such countries had difficulties competing within the same market as more productive eurozone members, their governments arguably compensated for this by means of expanding the public sector, - with cheap funding -. This resulted in the excessive sovereign debt figures as budgetary requirements were never successfully adhered to (Baldwin and Wyplosz, 2015).

In hindsight, this is an example of why it makes economic sense to have aligned fiscal policy among common currency members. However, the fiscal transfers which are given conditional on budgetary prudence or fiscal reforms, as described above, are examples of steps taken to align fiscal policy and direct member countries away from large budgetary deficits by means of reforms. These steps incrementally move the eurozone towards becoming an optimum currency area.

One considerable concern with regards to these steps taken to improve the conditions for common monetary policy within the eurozone is their sustainability. If the steps towards more fiscal alignment and fiscal transfers are not within the provided mandate and the required solidarity amongst eurozone members to sustain these steps fails, such steps will be short lived.

Such concerns may be counter-argued by referring to the fact that the ESCB, which governs the ECB, operates under the mandate of the European Parliament and in its setup is democratic and consensus-driven (Baldwin and Wyplosz, 2015). Furthermore, asset purchases are most often made in coordination with national central banks in the eurozone countries. This is done under a corporate securities purchasing programme (CSPP)

⁷² Please see [Empirical framework](#) chapter for further details

in line with national priorities (Neslen, 2016). This suggests that in practise actions rely on wider consensus, however public scepticism may still force a political reversal.

8.5. *The realistic alternative to being part of the eurozone from a monetary policy perspective*

We have seen throughout our analysis that the eurozone consists of countries which are dissimilar with respect to their economies, spending preferences and cultural traits. While such structural differences only converge very slowly, they imply that countries will react dissimilarly to ECB policy rate setting with the consequence of decreasing common monetary policy efficiency. OCA theory prescribes that improved efficiency follows from a higher extent of fiscal transfers, fiscal policy alignment and solidarity. In the previous section, we found examples of such steps. The final part of this chapter will reflect on this conclusion. Here we discuss the effectiveness of the eurozone from a monetary policy perspective in light of whether a member state would have room for more independent policy rate setting outside the eurozone.

The classical economic argument as to why a sovereign economy should never join a currency union is that with a floating currency it may direct its own monetary policy. A frequent example of why this is an attractive option to have is that a devaluation of the domestic currency may improve a country's terms of trade overnight. Such exchange rate flexibility insulates the economy from foreign economic shocks and hinders large drops in employment and economic output (Baldwin and Wyplosz, 2015).

Furthermore, monetary policy is a more efficient way to smooth economic cycles – hindering destructive consequences such as rise in unemployment and investment freeze – as it may have immediate effect on the economy. In other words, relative to fiscal policy, monetary policy has less inside and outside gap, denoting the time it takes politicians in parliament to agree and for the new budget to be implemented respectively.

Another benefit from a free-floating currency which should be taken into account is a country's ability to ensure a balance-of-payments equilibrium. Given a free-floating currency, unsustainable current account deficits will automatically be alleviated – and in the long run removed – by adjustments in the economy's currency depending on terms of trade.

As discussed above, a common currency area enables a common market to develop and thereby establish unhindered trade and competition amongst companies in all member countries. The frequently mentioned critique of Germany's large trade surplus is that the country is exporting at the expense of weaker member states. However, Holger Sandte points out that a large part of Germany's trade surplus actually is due to trade with countries outside of the eurozone, like third world countries or China. However, he also makes note that Germany's current account

surplus is almost at 9% of GDP. In parallel we observe Italy whose net growth in GDP per capita has not improved since before 2000, whereas the country's debt levels now make it 'too big to fail' (The Economist, 2017b).

These are valid concerns and arguments for why a sovereign should prefer not to enter a common currency area, however in assessing whether it makes sense for the individual member state to be part of the eurozone we must consider whether it would be a realistic alternative to be able to direct own monetary policy. Las Olsen, Chief Economist at Danske Bank, points out that one could argue that not even the ECB has complete independence with respect to its monetary policy rate. International markets are integrated to such an extent today, that central bank policy is highly influenced by the American Fed and the Japanese Central Bank. However, the level of independence is likely to be as high as realistically attainable since if this example is translated into the reality faced by a member state's national bank, the dependency is arguably much more expressed.

To give a concrete example, we have interviewed Las Olsen of Danske Bank, as well as Holger Sandte and Jan Størup Nielsen of Nordea, and all chief economists brought up the case of Sweden. Sweden is part of the EU but not part of the eurozone. In theory, it would be able to direct its own monetary policy. This is also what we observed post-crisis as Sweden devaluated and was arguably able to recover from the crisis faster for that reason. However, what we observe now is that the Swedish National Bank is forced to direct a policy which is very similar to that of the ECB. This is because, like the majority of central banks, the Swedish National Bank has an inflation target. As inflation is currently very low in Sweden, as is the case for most of the rest of the EU, it conducts expansionary monetary policy – i.e. very low rates – which many economists fear puts a risk under the inflated housing market in Sweden.

This is a concrete example of how European countries which would step out of the eurozone would arguably find it very difficult to conduct independent monetary policy. Whereas a common currency area with a unified central bank should in fact imply a higher degree of monetary policy independence – if we consider eurozone member independence in aggregate terms. This follows from the circumstance that the centralisation of power allows the central bank to become a more important and independent player on the international scene. Furthermore, the quality of the monetary policy should in theory improve as a larger bank is able to draw from a larger pile of specialists as well as when a central bank is distanced from national politics, it will have better conditions to pursue its goal of inflation stabilisation without political interference (Levy-Yeyati et al., 2009)⁷³.

Another reason for why some would prefer a free-floating currency is also that you don't become the target of speculative attacks. According to Las Olsen there are really only two stable alternatives to hinder speculative attacks and uncertainty about long term currency policy, these are either a free float or a currency union. This stems from the circumstance that if a country merely has a currency peg, it is easy to let the peg vary within a

⁷³ This is a contested argument and it is beyond the scope of this paper to judge whether this is the case

range and change that range according to changing political priorities. A commitment to a currency union signals stability and an irreversible peg. Only such a commitment provides investors with long term stability and such a signal is very attractive as it translates into foreign investment and cross border trade without currency risk and price transparency. (Levy-Yeyati et al., 2009). Thus, we conclude that the realistic choice is between a free-float and being member of a currency union and most monetary independence is to be achieved within the eurozone.

8.6. *Chapter conclusion*

We find that EIS heterogeneity has direct implications for the effectiveness of the eurozone. This is illustrated by the circumstance that member country consumers react dissimilarly to a policy rate shock. However, the eurozone's governing institutions have taken important steps to provide better basis for conducting common monetary policy. While in the short term, these have resulted in some degree of public scepticism, such steps arguably institutionalise needed solidarity to improve eurozone effectiveness in the future. On the basis of this discussion, we are of the opinion that a member state is better served by staying within the eurozone as it is unlikely that it would gain more monetary policy independence outside the eurozone.

9. Conclusion

The primary finding of this paper is evidence of EIS heterogeneity within the eurozone. This implies that consumers around Europe differ greatly in willingness to rearrange their intertemporal consumption choice given a change in the short-term interest rate.

Using a panel dataset of subjective expectations on macroeconomic variables, we estimate the EIS for 14 countries through a time series model, including 5 countries belonging to the eurozone and 2 Scandinavian countries. We then compare the estimates and test whether they are significantly different. The result allows us to answer our first research question: the eurozone countries, from our dataset, do have different elasticities of intertemporal substitution.

These country-specific differences in EIS estimates we attempt to explain in the subsequent analysis. Our own test results are inconclusive, also after including additional EIS estimates from Havranek et al (2015)'s meta study. We discuss our findings, reflect on potential explanations of what we observe as well as elaborate on explanatory relationships found by earlier key papers such as Vissing-Jørgensen (2002) and Havranek et al. (2015). We conclude that EIS heterogeneity may be explained by wealth levels, asset market participation, credit availability, as well as cultural traits such as trust in institutions and level of corruption.

The results from research question 1 and 2 suggest that common monetary policy as set by the ECB will have a dissimilar impact around the eurozone. To reflect on the consequences of EIS heterogeneity we discuss implications for the effectiveness of the eurozone from a monetary policy dimension. We evaluate the impact on member state consumption patterns given the EIS values we estimated, as well as review fiscal transfer programmes and initiatives to direct member countries towards more fiscal prudence.

We conclude that eurozone effectiveness is undermined primarily as a consequence of EIS heterogeneity, which results in dissimilar reactions across member countries in short term consumption from a policy rate shock. However, the eurozone's institutions, with the ECB as anchor, have taken steps towards improving the basis for conducting common monetary policy. In addition, we find that member states are highly unlikely to achieve greater monetary policy independence outside the eurozone. Thus, even though EIS heterogeneity implies less effective monetary policy by means of policy rate setting, we conclude that the individual member state has no better, realistic monetary policy alternative.

We have discussed weaknesses of approach as well as our concerns with respect to assumptions and research limitations within each research question. In reflection of these, we want to highlight two potential ways forward

for research on this topic. One way would be the use of micro data at the household level within each country. This would show more insights on the consumption behaviour and country differences.

The second suggestion would be to discuss the eurozone in a broader, political context, as well as considering additional consequences of EIS heterogeneity, for example the impact on investment from a change in the policy rate.

10. References

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10.2. Interviews

Olsen, Las (2017) *Interview with Martina Facino and Anna Ingemann*, May-3 2017, Danske Bank, Copenhagen

Sandte, Holger and Størup Nielsen, Jan, (2017) *Interview with Martina Facino and Anna Ingemann*, May-3 2017, Nordea Markets, Copenhagen

In addition, we have interviewed a representative from the Danish national bank.

Recordings of the interviews can be provided on request.

11. Appendix

A. Empirical Analysis 1

■ A.1. STATA code of IV testing

```

-----
.
. * Set Time Variable
. gen date = ym(year,month)

. format date %tm

. * to use if with date: if date<=>tm(2001m8)
.
. * Set panel structure
. xtset country_id date
      panel variable:  country_id (strongly balanced)
      time variable:   date, 1993m1 to 2014m12
                      delta: 1 month

.
. * ----- *
. ** Instruments considered **
.
. * E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24 E_y10lag1 E_y10lag2 E_y10lag3 E_y10 E_wages E_unem
E_budget_def
.
. * ----- *
. ** part A: individual tests **
.
. * (1)
. * We regress the endogenous variable on all the possible instruments
. reg E_m3 E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24 E_y10lag1 E_y10lag2 E_y10lag3 E_y10 E_wages E_unem
E_budget_def

```

Source	SS	df	MS	Number of obs	=	2,092
Model	9206.56984	11	836.960894	F(11, 2080)	=	1413.14
Residual	1231.92315	2,080	.592270746	Prob > F	=	0.0000
				R-squared	=	0.8820
				Adj R-squared	=	0.8814
Total	10438.493	2,091	4.99210568	Root MSE	=	.76959

E_m3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3lag12	.3249192	.0402358	8.08	0.000	.2460127	.4038258
E_m3lag13	-.014279	.0564926	-0.25	0.800	-.1250669	.0965089
E_m3lag14	-.0652866	.0411425	-1.59	0.113	-.1459714	.0153982
E_m3lag24	-.0203118	.012467	-1.63	0.103	-.0447609	.0041373
E_y10lag1	.1951937	.1504666	1.30	0.195	-.0998871	.4902745
E_y10lag2	.0616597	.1500024	0.41	0.681	-.2325108	.3558301
E_y10lag3	.236884	.0971035	2.44	0.015	.0464538	.4273142
E_y10	.4066538	.0986948	4.12	0.000	.2131029	.6002047
E_wages	.0770075	.0208784	3.69	0.000	.0360628	.1179522
E_unem	-.1503411	.007445	-20.19	0.000	-.1649415	-.1357407
E_budget_def	.0008514	.0000851	10.01	0.000	.0006845	.0010183
_cons	-.7300601	.0640598	-11.40	0.000	-.8556881	-.6044321

```

. * (2)
. * We run different combinations of regressions with the different instruments and run tests for
overidentifying restrictio
> ns and endogeneity just after
. * We need at least 2 instruments
.
. /*
> estat overid performs tests of overidentifying restrictions. If the 2SLS estimator was used, Sargan's
(1958) and Basman's
> (1960)  $\chi^2$ 
> tests are reported, as is Wooldridge's (1995) robust score test; if the LIML estimator was used,
Anderson and Rubin's (195
> 0)  $\chi^2$ 
> test and Basman's F test are reported; and if the GMM estimator was used, Hansen's (1982) J
statistic  $\chi^2$ 
> test is reported. A statistically significant test statistic always indicates that the instruments
may not be valid.
> */
.
. * All
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24 E_y10lag1 E_y10lag2 E_y10lag3
E_y10 E_wages E_unem E
> _budget_def), vce(robust)

```

```

Instrumental variables (2SLS) regression      Number of obs   =      2,092
                                             wald chi2(1)    =      538.39
                                             Prob > chi2      =      0.0000
                                             R-squared        =      0.2602
                                             Root MSE        =      .95818

```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2542789	.0109588	23.20	0.000	.2328001	.2757576
_cons	1.012792	.0400655	25.28	0.000	.9342647	1.091319

```

Instrumented:  E_m3
Instruments:   E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24 E_y10lag1 E_y10lag2
               E_y10lag3 E_y10 E_wages E_unem E_budget_def

```

```

. estat overid

```

Test of overidentifying restrictions:

```
score chi2(10)      =  462.082  (p = 0.0000)
```

```

. * instruments not valid

```

```

. estat endogenous

```

Tests of endogeneity

Ho: variables are exogenous

```
Robust score chi2(1)      =  .001019  (p = 0.9745)
```

```
Robust regression F(1,2089) =  .001018  (p = 0.9746)
```

```

. * test successful

```

```

. * Only macro variables

```

```

. ivregress 2sls E_cons (E_m3 = E_wages E_unem E_budget_def), vce(robust)

```

```

Instrumental variables (2SLS) regression      Number of obs   =      2,140
                                             wald chi2(1)    =      781.86
                                             Prob > chi2      =      0.0000

```

R-squared = 0.2282
Root MSE = .97972

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.3564389	.0127474	27.96	0.000	.3314545	.3814233
_cons	.657819	.0477865	13.77	0.000	.5641593	.7514788

Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def

. estat overid

Test of overidentifying restrictions:

Score chi2(2) = 267.321 (p = 0.0000)

. * instruments not valid
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1) = 132.639 (p = 0.0000)
Robust regression F(1,2137) = 175.459 (p = 0.0000)

. * test failed

. * So we continue without macro variables as instruments

. * Exclude macro variables

. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24 E_y10lag1 E_y10lag2 E_y10lag3 E_y10), vce(robust)

Instrumental variables (2SLS) regression

Number of obs	=	3,254
Wald chi2(1)	=	539.38
Prob > chi2	=	0.0000
R-squared	=	0.2375
Root MSE	=	1.0466

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2399997	.0103339	23.22	0.000	.2197457	.2602538
_cons	1.140017	.037246	30.61	0.000	1.067016	1.213018

Instrumented: E_m3
Instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24 E_y10lag1 E_y10lag2 E_y10lag3 E_y10

. estat overid

Test of overidentifying restrictions:

Score chi2(7) = 58.4925 (p = 0.0000)

. * failed
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1) = 58.5598 (p = 0.0000)
Robust regression F(1,3251) = 68.8683 (p = 0.0000)


```
. * failed
.
. * Exclude 10y rate
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24 E_y10lag1 E_y10lag2 E_y10lag3),
vce(robust)
```

```
Instrumental variables (2SLS) regression      Number of obs   =      3,254
                                             wald chi2(1)    =      538.52
                                             Prob > chi2      =      0.0000
                                             R-squared        =      0.2383
                                             Root MSE        =      1.0461
```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2433452	.0104863	23.21	0.000	.2227925	.2638979
_cons	1.128997	.0379959	29.71	0.000	1.054527	1.203468

```
Instrumented:  E_m3
Instruments:   E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24 E_y10lag1 E_y10lag2
               E_y10lag3
```

```
. * failed
. estat overid
```

Test of overidentifying restrictions:

Score chi2(6) = 57.3865 (p = 0.0000)

```
. * failed
. estat endogenous
```

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1) = 29.5504 (p = 0.0000)
Robust regression F(1,3251) = 21.02 (p = 0.0000)

```
.
. * Only 10y lags
. ivregress 2sls E_cons (E_m3 = E_y10lag1 E_y10lag2 E_y10lag3), vce(robust)
```

```
Instrumental variables (2SLS) regression      Number of obs   =      3,401
                                             wald chi2(1)    =      398.76
                                             Prob > chi2      =      0.0000
                                             R-squared        =      0.2206
                                             Root MSE        =      1.0467
```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2185799	.0109459	19.97	0.000	.1971262	.2400335
_cons	1.196127	.0396859	30.14	0.000	1.118344	1.27391

```
Instrumented:  E_m3
Instruments:   E_y10lag1 E_y10lag2 E_y10lag3
```

```
. estat overid
```

Test of overidentifying restrictions:

Score chi2(2) = .56549 (p = 0.7537)

```
. * successful
```

```
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1)      =   36.496   (p = 0.0000)
Robust regression F(1,3398) =   28.3397  (p = 0.0000)

. * failed
.
. * Only 3m lags
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24), vce(robust)
```

```
Instrumental variables (2SLS) regression      Number of obs   =       3,254
                                              Wald chi2(1)    =       442.78
                                              Prob > chi2     =       0.0000
                                              R-squared      =       0.2420
                                              Root MSE      =       1.0436
```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2646938	.0125791	21.04	0.000	.2400392	.2893485
_cons	1.058676	.0467005	22.67	0.000	.9671446	1.150207

```
Instrumented: E_m3
Instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24
```

```
. estat overid

Test of overidentifying restrictions:

Score chi2(3)      =   52.1809   (p = 0.0000)
```

```
. * failed
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1)      =   1.56662   (p = 0.2107)
Robust regression F(1,3251) =   1.45024   (p = 0.2286)

. * successful
.
. * 3m lags without the 24th lag
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14), vce(robust)
```

```
Instrumental variables (2SLS) regression      Number of obs   =       3,324
                                              Wald chi2(1)    =       441.60
                                              Prob > chi2     =       0.0000
                                              R-squared      =       0.2391
                                              Root MSE      =       1.0385
```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2521278	.011998	21.01	0.000	.2286123	.2756434
_cons	1.095719	.0454502	24.11	0.000	1.006638	1.1848

```
Instrumented: E_m3
Instruments: E_m3lag12 E_m3lag13 E_m3lag14
```

```
. estat overid
```

```

Test of overidentifying restrictions:

Score chi2(2)          =  1.42236  (p = 0.4911)

. * successful
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1)      =  3.50228  (p = 0.0613)
Robust regression F(1,3321) =  3.13777  (p = 0.0766)

. * half-half
.
. * 3m lags
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13), vce(robust)

Instrumental variables (2SLS) regression          Number of obs   =      3,331
                                                  wald chi2(1)    =      444.21
                                                  Prob > chi2     =      0.0000
                                                  R-squared       =      0.2384
                                                  Root MSE       =      1.0381

-----+-----
      E_cons |               Robust
            |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      E_m3 |    .2508784   .0119033    21.08  0.000    .2275484   .2742085
      _cons |    1.098934   .0452233    24.30  0.000    1.010298   1.18757
-----+-----

Instrumented:  E_m3
Instruments:   E_m3lag12 E_m3lag13

. estat overid

Test of overidentifying restrictions:

Score chi2(1)          =  .458043  (p = 0.4985)

. * successful
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1)      =  3.60412  (p = 0.0576)
Robust regression F(1,3328) =  3.22054  (p = 0.0728)

. * half-half
.
. * 3m lags
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag14), vce(robust)

Instrumental variables (2SLS) regression          Number of obs   =      3,324
                                                  wald chi2(1)    =      441.78
                                                  Prob > chi2     =      0.0000
                                                  R-squared       =      0.2391
                                                  Root MSE       =      1.0385

-----+-----
      E_cons |               Robust
            |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      E_m3 |    .2520773   .0119931    21.02  0.000    .2285713   .2755834
      _cons |    1.095888   .0454365    24.12  0.000    1.006834   1.184942
-----+-----

```

Instrumented: E_m3
Instruments: E_m3lag12 E_m3lag14

. estat overid

Test of overidentifying restrictions:

Score chi2(1) = 1.38274 (p = 0.2396)

. * successful
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1) = 3.5189 (p = 0.0607)
Robust regression F(1,3321) = 3.15049 (p = 0.0760)

. * half-half
.
. * 3m lags
. ivregress 2sls E_cons (E_m3 = E_m3lag13 E_m3lag14), vce(robust)

Instrumental variables (2SLS) regression	Number of obs	=	3,324
	wald chi2(1)	=	437.29
	Prob > chi2	=	0.0000
	R-squared	=	0.2395
	Root MSE	=	1.0382

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2545816	.0121742	20.91	0.000	.2307207	.2784426
_cons	1.087523	.0460362	23.62	0.000	.9972935	1.177752

Instrumented: E_m3
Instruments: E_m3lag13 E_m3lag14

. estat overid

Test of overidentifying restrictions:

Score chi2(1) = .93658 (p = 0.3332)

. * successful
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1) = 2.69327 (p = 0.1008)
Robust regression F(1,3321) = 2.46309 (p = 0.1166)

. * half-half, better
.
. * 3m lags and 10y lags combinations
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3),
vce(robust)

Instrumental variables (2SLS) regression	Number of obs	=	3,324
	wald chi2(1)	=	567.03
	Prob > chi2	=	0.0000
	R-squared	=	0.2368
	Root MSE	=	1.0401

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2397951	.0100702	23.81	0.000	.2200578	.2595324
_cons	1.136912	.0373568	30.43	0.000	1.063694	1.21013

Instrumented: E_m3

Instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

. estat overid

Test of overidentifying restrictions:

Score chi2(5) = 3.35653 (p = 0.6452)

. * successful: (p = 0.6452)

. estat endogenous

Tests of endogeneity

Ho: variables are exogenous

Robust score chi2(1) = 29.0314 (p = 0.0000)

Robust regression F(1,3321) = 21.1225 (p = 0.0000)

. * failed

.

. * 3m lags and 10y lags combinations

. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_y10lag1 E_y10lag2 E_y10lag3), vce(robust)

Instrumental variables (2SLS) regression	Number of obs	=	3,331
	wald chi2(1)	=	578.07
	Prob > chi2	=	0.0000
	R-squared	=	0.2361
	Root MSE	=	1.0396

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2393209	.0099539	24.04	0.000	.2198117	.2588301
_cons	1.137598	.0370874	30.67	0.000	1.064908	1.210288

Instrumented: E_m3

Instruments: E_m3lag12 E_m3lag13 E_y10lag1 E_y10lag2 E_y10lag3

. estat overid

Test of overidentifying restrictions:

Score chi2(4) = 2.20193 (p = 0.6987)

. * successful: (p = 0.6987)

. estat endogenous

Tests of endogeneity

Ho: variables are exogenous

Robust score chi2(1) = 28.642 (p = 0.0000)

Robust regression F(1,3328) = 20.7981 (p = 0.0000)

. * failed

.

. * 3m lags and 10y lags combinations

. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_y10lag2 E_y10lag3), vce(robust)

Instrumental variables (2SLS) regression	Number of obs	=	3,331
	wald chi2(1)	=	580.68

```

Prob > chi2      = 0.0000
R-squared        = 0.2368
Root MSE        = 1.0392

```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2423243	.0100561	24.10	0.000	.2226147	.2620339
_cons	1.127551	.0376826	29.92	0.000	1.053694	1.201407

```

Instrumented:  E_m3
Instruments:   E_m3lag12 E_m3lag13 E_y10lag2 E_y10lag3

```

```
. estat overid
```

```
Test of overidentifying restrictions:
```

```
Score chi2(3)      = 1.45431 (p = 0.6929)
```

```
. * successful: (p = 0.6929)
. estat endogenous
```

```
Tests of endogeneity
Ho: variables are exogenous
```

```
Robust score chi2(1)      = 17.9324 (p = 0.0000)
Robust regression F(1,3328) = 12.6835 (p = 0.0004)
```

```
. * failed
```

```
. * 3m lags and 10y lags combinations
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_y10lag3), vce(robust)
```

```

Instrumental variables (2SLS) regression      Number of obs   = 3,331
                                              wald chi2(1)    = 594.66
                                              Prob > chi2      = 0.0000
                                              R-squared       = 0.2374
                                              Root MSE       = 1.0388

```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2451525	.0100531	24.39	0.000	.2254488	.2648562
_cons	1.118089	.0380362	29.40	0.000	1.04354	1.192639

```

Instrumented:  E_m3
Instruments:   E_m3lag12 E_m3lag13 E_y10lag3

```

```
. estat overid
```

```
Test of overidentifying restrictions:
```

```
Score chi2(2)      = .966329 (p = 0.6168)
```

```
. * successful: (p = 0.6168)
. estat endogenous
```

```
Tests of endogeneity
Ho: variables are exogenous
```

```
Robust score chi2(1)      = 11.7327 (p = 0.0006)
Robust regression F(1,3328) = 8.55633 (p = 0.0035)
```

```
. * failed
```

```
. * 3m lags and 10y lags combinations
. ivregress 2sls E_cons (E_m3 = E_m3lag12 E_m3lag13 E_y10lag2), vce(robust)

Instrumental variables (2SLS) regression      Number of obs   =      3,331
                                             wald chi2(1)    =      597.58
                                             Prob > chi2     =      0.0000
                                             R-squared       =      0.2369
                                             Root MSE       =      1.0391
```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2427913	.009932	24.45	0.000	.223325	.2622577
_cons	1.125988	.037351	30.15	0.000	1.052782	1.199195

```
Instrumented:  E_m3
Instruments:   E_m3lag12 E_m3lag13 E_y10lag2
```

```
. estat overid
```

Test of overidentifying restrictions:

Score chi2(2) = 1.31496 (p = 0.5182)

```
. * successful: (p = 0.5182)
```

```
. estat endogenous
```

Tests of endogeneity

H0: variables are exogenous

Robust score chi2(1) = 17.4883 (p = 0.0000)

Robust regression F(1,3328) = 12.4564 (p = 0.0004)

```
. * failed
```

```
. * Adding controls
```

```
. * Exclude macro variables
```

```
. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24
E_y10lag1 E_y10lag2 E_y1
> 0lag3 E_y10), vce(robust)
```

```
Instrumental variables (2SLS) regression      Number of obs   =      2,092
                                             wald chi2(4)    =     1926.90
                                             Prob > chi2     =      0.0000
                                             R-squared       =      0.4218
                                             Root MSE       =      .84711
```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1218713	.0126872	9.61	0.000	.0970048	.1467378
E_wages	.3701578	.0198724	18.63	0.000	.3312087	.409107
E_unem	-.125515	.0072571	-17.30	0.000	-.1397386	-.1112915
E_budget_def	-.0007691	.0001197	-6.42	0.000	-.0010037	-.0005345
_cons	1.310756	.0585098	22.40	0.000	1.196079	1.425433

```
Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_m3lag14
               E_m3lag24 E_y10lag1 E_y10lag2 E_y10lag3 E_y10
```

```
. estat overid
```

Test of overidentifying restrictions:

```

score chi2(7)          = 79.5924 (p = 0.0000)

. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1)      = 14.5173 (p = 0.0001)
Robust regression F(1,2086) = 15.4332 (p = 0.0001)

. * fail
.
. * Exclude 10y rate
. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24
E_y10lag1 E_y10lag2 E_y1
> 0lag3), vce(robust)

Instrumental variables (2SLS) regression      Number of obs   =      2,092
                                              Wald chi2(4)     =    1919.03
                                              Prob > chi2      =      0.0000
                                              R-squared        =      0.4215
                                              Root MSE        =      .84731

-----+-----
      E_cons |          Coef.      Robust          z   P>|z|      [95% Conf. Interval]
-----+-----
      E_m3   |   .1197529   .0127405    9.40   0.000    .0947819   .1447239
    E_wages  |   .3728866   .0198794   18.76   0.000    .3339237   .4118494
    E_unem   |  -.1253851   .0072588  -17.27   0.000   -.1396121  -.1111581
E_budget_def |  -.0007652   .0001198   -6.39   0.000    -.001    -.0005305
      _cons  |   1.310165   .0584684   22.41   0.000    1.195569   1.424761
-----+-----
Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_m3lag14
               E_m3lag24 E_y10lag1 E_y10lag2 E_y10lag3

. estat overid

Test of overidentifying restrictions:

score chi2(6)          = 73.0881 (p = 0.0000)

. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1)      = 16.2689 (p = 0.0001)
Robust regression F(1,2086) = 17.3256 (p = 0.0000)

. * fail
.
. * Only 10y lags
. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_y10lag1 E_y10lag2 E_y10lag3), vce(robust)

Instrumental variables (2SLS) regression      Number of obs   =      2,134
                                              Wald chi2(4)     =    1982.11
                                              Prob > chi2      =      0.0000
                                              R-squared        =      0.4305
                                              Root MSE        =      .84163

-----+-----
      E_cons |          Coef.      Robust          z   P>|z|      [95% Conf. Interval]
-----+-----
      E_m3   |   .1506184   .0133705   11.27   0.000    .1244128   .1768241

```


E_wages		.3373344	.0198366	17.01	0.000	.2984554	.3762134
E_unem		-.1261264	.0071971	-17.52	0.000	-.1402324	-.1120204
E_budget_def		-.0008036	.0001193	-6.74	0.000	-.0010374	-.0005697
_cons		1.309724	.0587046	22.31	0.000	1.194666	1.424783

Instrumented: E_m3

Instruments: E_wages E_unem E_budget_def E_y10lag1 E_y10lag2 E_y10lag3

. estat overid

Test of overidentifying restrictions:

Score chi2(2) = 21.3987 (p = 0.0000)

. * fail

. estat endogenous

Tests of endogeneity

Ho: variables are exogenous

Robust score chi2(1) = 1.79124 (p = 0.1808)

Robust regression F(1,2128) = 1.83075 (p = 0.1762)

. * success

. * Only 3m lags

. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24), vce(robust)

Instrumental variables (2SLS) regression	Number of obs	=	2,092
	wald chi2(4)	=	1838.06
	Prob > chi2	=	0.0000
	R-squared	=	0.4105
	Root MSE	=	.85534

E_cons		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3		.0722634	.0216241	3.34	0.001	.0298809 .1146459
E_wages		.4340592	.0313441	13.85	0.000	.3726259 .4954926
E_unem		-.1224722	.0076713	-15.96	0.000	-.1375077 -.1074367
E_budget_def		-.0006785	.0001281	-5.30	0.000	-.0009296 -.0004274
_cons		1.29692	.0596641	21.74	0.000	1.179981 1.41386

Instrumented: E_m3

Instruments: E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_m3lag14 E_m3lag24

. estat overid

Test of overidentifying restrictions:

Score chi2(3) = 35.734 (p = 0.0000)

. estat endogenous

Tests of endogeneity

Ho: variables are exogenous

Robust score chi2(1) = 11.2059 (p = 0.0008)

Robust regression F(1,2086) = 9.1408 (p = 0.0025)

. * fail

. * 3m lags without the 24th lag

. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14), vce(robust)

```
Instrumental variables (2SLS) regression      Number of obs   =      2,112
                                             wald chi2(4)    =    1863.74
                                             Prob > chi2      =      0.0000
                                             R-squared        =      0.4142
                                             Root MSE        =      .85278
```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_cons						
E_m3	.0781605	.020545	3.80	0.000	.037893	.118428
E_wages	.4301949	.0299321	14.37	0.000	.371529	.4888608
E_unem	-.121759	.0076491	-15.92	0.000	-.136751	-.106767
E_budget_def	-.0006764	.0001274	-5.31	0.000	-.0009262	-.0004267
_cons	1.288071	.05938	21.69	0.000	1.171688	1.404453

```
Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_m3lag14
```

```
. estat overid
```

```
Test of overidentifying restrictions:
```

```
Score chi2(2)          =  1.12359  (p = 0.5702)
```

```
. * success
. estat endogenous
```

```
Tests of endogeneity
Ho: variables are exogenous
```

```
Robust score chi2(1)      = 10.8739  (p = 0.0010)
Robust regression F(1,2106) =  8.90275 (p = 0.0029)
```

```
. * fail
.
. * 3m lags and 10y combinations
. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1
E_y10lag2 E_y10lag3), vc
> e(robust)
```

```
Instrumental variables (2SLS) regression      Number of obs   =      2,112
                                             wald chi2(4)    =    1953.62
                                             Prob > chi2      =      0.0000
                                             R-squared        =      0.4247
                                             Root MSE        =      .84515
```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_cons						
E_m3	.1265735	.01216	10.41	0.000	.1027403	.1504066
E_wages	.3679989	.0191928	19.17	0.000	.3303817	.405616
E_unem	-.1247593	.0072673	-17.17	0.000	-.1390029	-.1105156
E_budget_def	-.0007672	.0001197	-6.41	0.000	-.0010018	-.0005327
_cons	1.299966	.0586026	22.18	0.000	1.185107	1.414825

```
Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_m3lag14
               E_y10lag1 E_y10lag2 E_y10lag3
```

```
. estat overid
```

```
Test of overidentifying restrictions:
```

```
Score chi2(5)          = 35.1925  (p = 0.0000)
```

```
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1)          = 11.5768 (p = 0.0007)
Robust regression F(1,2106)   = 12.1078 (p = 0.0005)

. * fail
.
. * 3m lags and 10y combinations
. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag2
E_y10lag3), vce(robust)
```

```
Instrumental variables (2SLS) regression      Number of obs   =      2,112
                                              wald chi2(4)    =    1940.58
                                              Prob > chi2     =      0.0000
                                              R-squared      =      0.4242
                                              Root MSE      =      .84552
```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1224621	.012233	10.01	0.000	.098486	.1464383
E_wages	.3732807	.0192066	19.43	0.000	.3356364	.410925
E_unem	-.1245045	.0072691	-17.13	0.000	-.1387517	-.1102572
E_budget_def	-.0007595	.0001198	-6.34	0.000	-.0009944	-.0005247
_cons	1.298956	.0585225	22.20	0.000	1.184254	1.413658

```
Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_m3lag14
E_y10lag2 E_y10lag3
```

```
. estat overid

Test of overidentifying restrictions:

Score chi2(4)          = 25.4475 (p = 0.0000)
```

```
. estat endogenous

Tests of endogeneity
Ho: variables are exogenous

Robust score chi2(1)          = 14.6547 (p = 0.0001)
Robust regression F(1,2106)   = 15.3989 (p = 0.0001)

. * fail
.
. * 3m lags and 10y combinations
. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_y10lag2 E_y10lag3),
vce(robust)
```

```
Instrumental variables (2SLS) regression      Number of obs   =      2,114
                                              wald chi2(4)    =    1943.82
                                              Prob > chi2     =      0.0000
                                              R-squared      =      0.4244
                                              Root MSE      =      .84509
```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1228284	.0121267	10.13	0.000	.0990605	.1465964
E_wages	.3728843	.019095	19.53	0.000	.3354588	.4103098

E_unem		-.1245071	.0072703	-17.13	0.000	-.1387567	-.1102576
E_budget_def		-.000076	.0001198	-6.34	0.000	-.0009949	-.0005251
_cons		1.298832	.0585097	22.20	0.000	1.184155	1.413509

Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_y10lag2
E_y10lag3

. estat overid

Test of overidentifying restrictions:

Score chi2(3) = 24.6308 (p = 0.0000)

. estat endogenous

Tests of endogeneity

Ho: variables are exogenous

Robust score chi2(1) = 14.4192 (p = 0.0001)

Robust regression F(1,2108) = 15.1066 (p = 0.0001)

. * fail

. * 3m lags and 10y combinations
. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_y10lag3), vce(robust)

Instrumental variables (2SLS) regression	Number of obs	=	2,114
	wald chi2(4)	=	1922.39
	Prob > chi2	=	0.0000
	R-squared	=	0.4233
	Root MSE	=	.84591

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.115197	.0122415	9.41	0.000	.0912041	.1391899
E_wages	.3826842	.0190862	20.05	0.000	.3452759	.4200926
E_unem	-.124034	.0072706	-17.06	0.000	-.1382841	-.109784
E_budget_def	-.0007456	.0001202	-6.21	0.000	-.0009812	-.0005101
_cons	1.296993	.0583557	22.23	0.000	1.182618	1.411368

Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_y10lag3

. estat overid

Test of overidentifying restrictions:

Score chi2(2) = 4.2531 (p = 0.1192)

. * half-half

. estat endogenous

Tests of endogeneity

Ho: variables are exogenous

Robust score chi2(1) = 21.206 (p = 0.0000)

Robust regression F(1,2108) = 22.5438 (p = 0.0000)

. * fail

. * 3m lags and 10y combinations
. ivregress 2sls E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13), vce(robust)

Instrumental variables (2SLS) regression	Number of obs	=	2,114
--	---------------	---	-------

```

wald chi2(4)      =    1866.27
Prob > chi2       =    0.0000
R-squared         =    0.4145
Root MSE         =    .8523

```

	E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
	E_m3	.0786151	.0204094	3.85	0.000	.0386134	.1186168
	E_wages	.4296609	.0297608	14.44	0.000	.3713308	.487991
	E_unem	-.1217663	.0076455	-15.93	0.000	-.1367512	-.1067813
	E_budget_def	-.0006768	.0001274	-5.31	0.000	-.0009265	-.0004272
	_cons	1.288175	.0593191	21.72	0.000	1.171912	1.404438

```

Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def E_m3lag12 E_m3lag13

```

```
. estat overid
```

```
Test of overidentifying restrictions:
```

```
Score chi2(1)      =    .34927  (p = 0.5545)
```

```
. * success
. estat endogenous
```

```
Tests of endogeneity
```

```
Ho: variables are exogenous
```

```
Robust score chi2(1)      =   10.8629  (p = 0.0010)
```

```
Robust regression F(1,2108) =    8.89102  (p = 0.0029)
```

```
. * fail
```

```
.
```

```
.
```

```
. * ----- *
```

```
.
```

```
. ** part B: ivreg29 **
```

```
.
```

```
. * Use ivreg29 with the instruments that seemed more appropriate, namely: E_m3lag12 E_m3lag13
```

```
E_m3lag14 E_y10lag1 E_y10lag2
```

```
> E_y10lag3
```

```
. * At the bottom there is an explanation of the different output of ivreg29
```

```
.
```

```
. * Run both with and without controls
```

```
.
```

```
. * No controls
```

```
.
```

```
. * All
```

```
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3), bw(auto) robust
```

```
redundant(E_m3lag13 E
```

```
> _m3lag14 E_y10lag1 E_y10lag2 E_y10lag3)
```

```
IV (2SLS) estimation
```

```
-----
```

```
Estimates efficient for homoskedasticity only
```

```
Statistics robust to heteroskedasticity and autocorrelation
```

```
kernel=Bartlett; bandwidth= 44
```

```
Automatic bw selection according to Newey-West (1994)
```

```
time variable (t): date
```

```

Total (centered) SS      =  4711.246464
Number of obs =      3324
F( 1, 3322) =      25.90
Prob > F      =      0.0000
Centered R2     =      0.2368

```

Total (uncentered) SS = 17193.9908 Uncentered R2 = 0.7909
Residual SS = 3595.75521 Root MSE = 1.04

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2397951	.0471083	5.09	0.000	.1474646	.3321256
_cons	1.136912	.1750309	6.50	0.000	.793858	1.479967

Underidentification test (Kleibergen-Paap rk LM statistic): 43.376
Chi-sq(6) P-val = 0.0000

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 37.494
Chi-sq(5) P-val = 0.0000

Instruments tested: E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

Weak identification test (Cragg-Donald Wald F statistic): 2062.465
(Kleibergen-Paap rk Wald F statistic): 229.556

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.311
Chi-sq(5) P-val = 0.6521

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

. * Underidentification test: passed
. * IV redundancy test: passed
. * Weak identification test: passed
. * Overidentification test: passed (p = 0.6521)
.
. * 3m lags
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14), bw(auto) robust redundant(E_m3lag13 E_m3lag14)

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 44
Automatic bw selection according to Newey-West (1994)
time variable (t): date

	Number of obs =	3324
	F(1, 3322) =	28.03
	Prob > F =	0.0000
	Centered R2 =	0.2391
	Uncentered R2 =	0.7915
	Root MSE =	1.038

Total (centered) SS = 4711.246464
Total (uncentered) SS = 17193.9908
Residual SS = 3584.570686

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2521278	.0476055	5.30	0.000	.1588227	.3454329

_cons		1.095719	.1906282	5.75	0.000	.7220946	1.469343
-------	--	----------	----------	------	-------	----------	----------

Underidentification test (Kleibergen-Paap rk LM statistic): 41.987
Chi-sq(3) P-val = 0.0000

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 8.021
Chi-sq(2) P-val = 0.0181

Instruments tested: E_m3lag13 E_m3lag14

Weak identification test (Cragg-Donald Wald F statistic): 1623.899
(Kleibergen-Paap rk Wald F statistic): 138.307

Stock-Yogo weak ID test critical values:	5% maximal IV relative bias	13.91
	10% maximal IV relative bias	9.08
	20% maximal IV relative bias	6.46
	30% maximal IV relative bias	5.39
	10% maximal IV size	22.30
	15% maximal IV size	12.83
	20% maximal IV size	9.54
	25% maximal IV size	7.80

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.383
Chi-sq(2) P-val = 0.3037

Instrumented: E_m3

Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14

. * Underidentification test: passed
. * IV redundancy test: passed (at 1%)
. * Weak identification test: passed
. * Overidentification test: passed (p = 0.3037)
.
. * 3m lags
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13), bw(auto) robust redundant(E_m3lag13)

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 44
Automatic bw selection according to Newey-West (1994)
time variable (t): date

				Number of obs =	3331
				F(1, 3329) =	28.08
				Prob > F =	0.0000
Total (centered) SS	=	4713.270497		Centered R2 =	0.2384
Total (uncentered) SS	=	17226.772		Uncentered R2 =	0.7916
Residual SS	=	3589.820022		Root MSE =	1.038

E_cons		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3		.2508784	.0473317	5.30	0.000	.1581101 .3436468
_cons		1.098934	.1902518	5.78	0.000	.7260472 1.471821

Underidentification test (Kleibergen-Paap rk LM statistic): 41.984
Chi-sq(2) P-val = 0.0000

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 2.993
Chi-sq(1) P-val = 0.0836

Instruments tested: E_m3lag13

```

weak identification test (Cragg-Donald wald F statistic):      2459.768
(Kleibergen-Paap rk wald F statistic):      185.188
Stock-Yogo weak ID test critical values: 10% maximal IV size  19.93
                                           15% maximal IV size  11.59
                                           20% maximal IV size   8.75
                                           25% maximal IV size   7.25

```

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```

-----
Hansen J statistic (overidentification test of all instruments):      0.586
Chi-sq(1) P-val =      0.4439
-----

```

```

Instrumented:      E_m3
Excluded instruments: E_m3lag12 E_m3lag13
-----

```

```

. * Underidentification test: passed
. * IV redundancy test: passed (at 1%)
. * Weak identification test: passed
. * Overidentification test: passed (p = 0.4439)
.
. * 10y lags
. ivreg29 E_cons (E_m3 = E_y10lag1 E_y10lag2 E_y10lag3), bw(auto) robust redundant(E_y10lag2 E_y10lag3)

```

IV (2SLS) estimation

```

-----
Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 44
Automatic bw selection according to Newey-West (1994)
time variable (t): date

```

```

Total (centered) SS      = 4780.449878
Total (uncentered) SS    = 17609.07062
Residual SS              = 3725.961565

Number of obs =      3401
F( 1, 3399) =      20.67
Prob > F      =      0.0000
Centered R2    =      0.2206
Uncentered R2  =      0.7884
Root MSE      =      1.047

```

```

-----
      E_cons |      Coef.      Robust      z      P>|z|      [95% Conf. Interval]
      +-----+-----+-----+-----+-----+
      E_m3 | .2185799   .0480622   4.55   0.000   .1243797   .3127801
      _cons | 1.196127   .1775118   6.74   0.000   .8482105   1.544044
      +-----+-----+-----+-----+

```

```

Underidentification test (Kleibergen-Paap rk LM statistic):      33.853
Chi-sq(3) P-val =      0.0000

```

-redundant- option:

```

IV redundancy test (LM test of redundancy of specified instruments):      4.684
Chi-sq(2) P-val =      0.0961

```

Instruments tested: E_y10lag2 E_y10lag3

```

-----
weak identification test (Cragg-Donald wald F statistic):      3494.363
(Kleibergen-Paap rk wald F statistic):      328.424
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias  13.91
                                           10% maximal IV relative bias   9.08
                                           20% maximal IV relative bias   6.46
                                           30% maximal IV relative bias   5.39
                                           10% maximal IV size          22.30
                                           15% maximal IV size          12.83
                                           20% maximal IV size           9.54
                                           25% maximal IV size           7.80

```

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 0.901
 Chi-sq(2) P-val = 0.6373

 Instrumented: E_m3
 Excluded instruments: E_y10lag1 E_y10lag2 E_y10lag3

. * Underidentification test: passed
 . * IV redundancy test: passed (at 10%)
 . * Weak identification test: passed
 . * Overidentification test: passed (p = 0.6373)
 .
 . * combination
 . ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3), bw(auto) robust
 redundant(E_m3lag14 E_y10lag1 E
 > _y10lag2 E_y10lag3)

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 44
 Automatic bw selection according to Newey-West (1994)
 time variable (t): date

		Number of obs =	3324
		F(1, 3322) =	25.89
		Prob > F =	0.0000
Total (centered) SS	=	4711.246464	Centered R2 = 0.2368
Total (uncentered) SS	=	17193.9908	Uncentered R2 = 0.7909
Residual SS	=	3595.767336	Root MSE = 1.04

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.239784	.0471097	5.09	0.000	.1474507	.3321172
_cons	1.13695	.1750345	6.50	0.000	.7938883	1.480011

 Underidentification test (Kleibergen-Paap rk LM statistic): 42.778
 Chi-sq(5) P-val = 0.0000

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 30.068
 Chi-sq(4) P-val = 0.0000

Instruments tested: E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

 weak identification test (Cragg-Donald wald F statistic): 2475.599
 (Kleibergen-Paap rk wald F statistic): 275.406

Stock-Yogo weak ID test critical values:	5% maximal IV relative bias	18.37
	10% maximal IV relative bias	10.83
	20% maximal IV relative bias	6.77
	30% maximal IV relative bias	5.25
	10% maximal IV size	26.87
	15% maximal IV size	15.09
	20% maximal IV size	10.98
	25% maximal IV size	8.84

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

 Hansen J statistic (overidentification test of all instruments): 1.897
 Chi-sq(4) P-val = 0.7546

Instrumented: E_m3
 Excluded instruments: E_m3lag12 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```

. * Underidentification test: passed
. * IV redundancy test: passed
. * Weak identification test: passed
. * Overidentification test: passed (p = 0.7546)
. * BEST COMBINATION
.
.
. * With controls
.
. * All
. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3), bw(auto)
> robust redundant(E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3)

```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 40
Automatic bw selection according to Newey-West (1994)
time variable (t): date

		Number of obs =	2112
		F(4, 2107) =	26.39
		Prob > F =	0.0000
Total (centered) SS	=	2622.101771	Centered R2 = 0.4247
Total (uncentered) SS	=	10130.71458	Uncentered R2 = 0.8511
Residual SS	=	1508.5595	Root MSE = .8452

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1265735	.052747	2.40	0.016	.0231913	.2299557
E_wages	.3679989	.0743886	4.95	0.000	.2222	.5137978
E_unem	-.1247593	.0332676	-3.75	0.000	-.1899626	-.059556
E_budget_def	-.0007672	.0003907	-1.96	0.050	-.001533	-1.51e-06
_cons	1.299966	.2460608	5.28	0.000	.8176954	1.782236

Underidentification test (Kleibergen-Paap rk LM statistic): 24.068
Chi-sq(6) P-val = 0.0005

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 27.828
Chi-sq(5) P-val = 0.0000

Instruments tested: E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

Weak identification test (Cragg-Donald Wald F statistic): 1174.943
(Kleibergen-Paap rk Wald F statistic): 127.575

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 12.338
Chi-sq(5) P-val = 0.0304

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```

-----
. * Underidentification test: passed
. * IV redundancy test: passed
. * Weak identification test: passed
. * Overidentification test: failed (p = 0.0304)
.
. * 3m lags
. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14), bw(auto) robust
redundant(E_m3lag13 E_m
> 3lag14)

```

IV (2SLS) estimation

```

-----
Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
  kernel=Bartlett; bandwidth= 40
  Automatic bw selection according to Newey-West (1994)
  time variable (t): date

```

		Number of obs =	2112
		F(4, 2107) =	25.85
		Prob > F =	0.0000
		Centered R2 =	0.4142
		Uncentered R2 =	0.8484
		Root MSE =	.8528
Total (centered) SS	=	2622.101771	
Total (uncentered) SS	=	10130.71458	
Residual SS	=	1535.908434	

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	.0781605	.0666427	1.17	0.241	-.0524567 .2087777
E_wages	.4301949	.0919693	4.68	0.000	.2499384 .6104514
E_unem	-.121759	.0346741	-3.51	0.000	-.189719 -.0537991
E_budget_def	-.0006764	.0004065	-1.66	0.096	-.0014732 .0001203
_cons	1.288071	.2483719	5.19	0.000	.8012706 1.77487

```

Underidentification test (Kleibergen-Paap rk LM statistic):      22.821
Chi-sq(3) P-val =      0.0000

```

-redundant- option:

```

IV redundancy test (LM test of redundancy of specified instruments):      3.391
Chi-sq(2) P-val =      0.1835

```

Instruments tested: E_m3lag13 E_m3lag14

```

weak identification test (Cragg-Donald wald F statistic):      586.303
(Kleibergen-Paap rk wald F statistic):      29.381

```

Stock-Yogo weak ID test critical values:	5% maximal IV relative bias	13.91
	10% maximal IV relative bias	9.08
	20% maximal IV relative bias	6.46
	30% maximal IV relative bias	5.39
	10% maximal IV size	22.30
	15% maximal IV size	12.83
	20% maximal IV size	9.54
	25% maximal IV size	7.80

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```

Hansen J statistic (overidentification test of all instruments):      1.923
Chi-sq(2) P-val =      0.3824

```

```

Instrumented:      E_m3
Included instruments: E_wages E_unem E_budget_def
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14

```

```

. * Underidentification test: passed

```

```
. * IV redundancy test: failed
. * Weak identification test: passed (for a small difference)
. * Overidentification test: passed (p = 0.3824)
.
. * 3m lags
. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13), bw(auto) robust
redundant(E_m3lag13)
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 40
Automatic bw selection according to Newey-West (1994)
time variable (t): date

	Number of obs =	2114
	F(4, 2109) =	25.86
	Prob > F =	0.0000
	Centered R2 =	0.4145
	Uncentered R2 =	0.8486
	Root MSE =	.8523
Total (centered) SS	=	2623.031556
Total (uncentered) SS	=	10143.63569
Residual SS	=	1535.65717

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0786151	.0662228	1.19	0.235	-.0511793	.2084095
E_wages	.4296609	.0914897	4.70	0.000	.2503444	.6089774
E_unem	-.1217663	.0346641	-3.51	0.000	-.1897067	-.0538258
E_budget_def	-.0006768	.0004063	-1.67	0.096	-.0014732	.0001196
_cons	1.288175	.2482712	5.19	0.000	.8015725	1.774778

Underidentification test (Kleibergen-Paap rk LM statistic): 22.587
Chi-sq(2) P-val = 0.0000

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 0.349
Chi-sq(1) P-val = 0.5548

Instruments tested: E_m3lag13

Weak identification test (Cragg-Donald Wald F statistic): 887.582
(Kleibergen-Paap rk Wald F statistic): 35.509
Stock-Yogo weak ID test critical values: 10% maximal IV size 19.93
15% maximal IV size 11.59
20% maximal IV size 8.75
25% maximal IV size 7.25

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 0.386
Chi-sq(1) P-val = 0.5346

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def
Excluded instruments: E_m3lag12 E_m3lag13

```
. * Underidentification test: passed
. * IV redundancy test: failed
. * Weak identification test: passed
. * Overidentification test: passed (p = 0.5346)
. * BEST OPTION
.
. * 3m lags
. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag14), bw(auto) robust
redundant(E_m3lag14)
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 40
 Automatic bw selection according to Newey-West (1994)
 time variable (t): date

Total (centered) SS	=	2622.101771	Number of obs =	2112
Total (uncentered) SS	=	10130.71458	F(4, 2107) =	25.84
Residual SS	=	1535.964713	Prob > F =	0.0000
			Centered R2 =	0.4142
			Uncentered R2 =	0.8484
			Root MSE =	.8528

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0780928	.0666665	1.17	0.241	-.0525711	.2087567
E_wages	.4302818	.0919986	4.68	0.000	.2499678	.6105958
E_unem	-.1217548	.034675	-3.51	0.000	-.1897165	-.0537932
E_budget_def	-.0006763	.0004065	-1.66	0.096	-.0014731	.0001204
_cons	1.288054	.2483731	5.19	0.000	.8012516	1.774856

Underidentification test (Kleibergen-Paap rk LM statistic): 21.980
 Chi-sq(2) P-val = 0.0000

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 0.102
 Chi-sq(1) P-val = 0.7500

Instruments tested: E_m3lag14

Weak identification test (Cragg-Donald Wald F statistic): 879.557
 (Kleibergen-Paap rk Wald F statistic): 34.259
 Stock-Yogo weak ID test critical values: 10% maximal IV size 19.93
 15% maximal IV size 11.59
 20% maximal IV size 8.75
 25% maximal IV size 7.25

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 0.597
 Chi-sq(1) P-val = 0.4399

Instrumented: E_m3
 Included instruments: E_wages E_unem E_budget_def
 Excluded instruments: E_m3lag12 E_m3lag14

```

. * Underidentification test: passed
. * IV redundancy test: failed big time
. * Weak identification test: passed
. * Overidentification test: passed (p = 0.4399)
.
. * 10y lags
. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_y10lag1 E_y10lag2 E_y10lag3), bw(auto) robust
redundant(E_y10lag2 E_y
> 10lag3)

```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 40

Automatic bw selection according to Newey-West (1994)
time variable (t): date

		Number of obs =	2134
		F(4, 2129) =	26.98
		Prob > F =	0.0000
Total (centered) SS	=	2654.078979	
Total (uncentered) SS	=	10336.97847	
Residual SS	=	1511.588099	
		Centered R2 =	0.4305
		Uncentered R2 =	0.8538
		Root MSE =	.8416

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1506184	.0545179	2.76	0.006	.0437653	.2574716
E_wages	.3373344	.0759588	4.44	0.000	.1884579	.4862109
E_unem	-.1261264	.0329824	-3.82	0.000	-.1907707	-.0614821
E_budget_def	-.0008036	.0003918	-2.05	0.040	-.0015715	-.0000357
_cons	1.309724	.2476728	5.29	0.000	.8242947	1.795154

Underidentification test (Kleibergen-Paap rk LM statistic): 19.718
Chi-sq(3) P-val = 0.0002

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 5.119
Chi-sq(2) P-val = 0.0774

Instruments tested: E_y10lag2 E_y10lag3

Weak identification test (Cragg-Donald wald F statistic): 1967.306

(Kleibergen-Paap rk wald F statistic): 137.056

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	13.91
10% maximal IV relative bias	9.08
20% maximal IV relative bias	6.46
30% maximal IV relative bias	5.39
10% maximal IV size	22.30
15% maximal IV size	12.83
20% maximal IV size	9.54
25% maximal IV size	7.80

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NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 8.954
Chi-sq(2) P-val = 0.0114

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def
Excluded instruments: E_y10lag1 E_y10lag2 E_y10lag3

```
. * Underidentification test: passed
. * IV redundancy test: passed (at 0.07)
. * Weak identification test: passed
. * Overidentification test: failed (p = 0.0114)
.
. * combination
. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3), bw(auto) robust red
> undant(E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3)
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 40
Automatic bw selection according to Newey-West (1994)
time variable (t): date

Total (centered) SS	=	2622.101771	Number of obs =	2112
Total (uncentered) SS	=	10130.71458	F(4, 2107) =	26.39
Residual SS	=	1508.559522	Prob > F	= 0.0000
			Centered R2	= 0.4247
			Uncentered R2	= 0.8511
			Root MSE	= .8452

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_cons					
E_m3	.1265734	.052747	2.40	0.016	.0231911 .2299556
E_wages	.367999	.0743886	4.95	0.000	.2222 .513798
E_unem	-.1247593	.0332676	-3.75	0.000	-.1899626 -.059556
E_budget_def	-.0007672	.0003907	-1.96	0.050	-.001533 -1.51e-06
_cons	1.299966	.2460608	5.28	0.000	.8176954 1.782236

Underidentification test (Kleibergen-Paap rk LM statistic): 23.283
Chi-sq(5) P-val = 0.0003

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 25.931
Chi-sq(4) P-val = 0.0000

Instruments tested: E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

Weak identification test (Cragg-Donald wald F statistic): 1410.602
(Kleibergen-Paap rk wald F statistic): 153.139

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	18.37
10% maximal IV relative bias	10.83
20% maximal IV relative bias	6.77
30% maximal IV relative bias	5.25
10% maximal IV size	26.87
15% maximal IV size	15.09
20% maximal IV size	10.98
25% maximal IV size	8.84

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 12.149
Chi-sq(4) P-val = 0.0163

Instrumented: E_m3

Included instruments: E_wages E_unem E_budget_def

Excluded instruments: E_m3lag12 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```
. * Underidentification test: passed
. * IV redundancy test: passed
. * Weak identification test: passed
. * Overidentification test: failed (p = 0.0163)
.
. * combination
. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_y10lag1 E_y10lag2
E_y10lag3), bw(auto) robust red
> undant(E_m3lag13 E_y10lag1 E_y10lag2 E_y10lag3)
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 40
Automatic bw selection according to Newey-West (1994)
time variable (t): date

Number of obs =	2114
F(4, 2109) =	26.42
Prob > F	= 0.0000

Total (centered) SS	=	2623.031556	Centered R2	=	0.4249
Total (uncentered) SS	=	10143.63569	Uncentered R2	=	0.8513
Residual SS	=	1508.485271	Root MSE	=	.8447

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.12692	.0523296	2.43	0.015	.0243558	.2294842
E_wages	.3676301	.0739731	4.97	0.000	.2226455	.5126148
E_unem	-.1247608	.03328	-3.75	0.000	-.1899885	-.0595331
E_budget_def	-.0007677	.0003908	-1.96	0.049	-.0015336	-1.81e-06
_cons	1.299818	.2461368	5.28	0.000	.817399	1.782238

Underidentification test (Kleibergen-Paap rk LM statistic): 23.868
Chi-sq(5) P-val = 0.0002

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 26.932
Chi-sq(4) P-val = 0.0000

Instruments tested: E_m3lag13 E_y10lag1 E_y10lag2 E_y10lag3

Weak identification test (Cragg-Donald wald F statistic): 1414.879
(Kleibergen-Paap rk wald F statistic): 154.344

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	18.37
10% maximal IV relative bias	10.83
20% maximal IV relative bias	6.77
30% maximal IV relative bias	5.25
10% maximal IV size	26.87
15% maximal IV size	15.09
20% maximal IV size	10.98
25% maximal IV size	8.84

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 11.971
Chi-sq(4) P-val = 0.0176

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def
Excluded instruments: E_m3lag12 E_m3lag13 E_y10lag1 E_y10lag2 E_y10lag3

```
. * Underidentification test: passed
. * IV redundancy test: passed
. * Weak identification test: passed
. * Overidentification test: failed (p = 0.0176)
.
. * combination
. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1
E_y10lag2), bw(auto) robust red
> undant(E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2)
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 40
Automatic bw selection according to Newey-West (1994)
time variable (t): date

Total (centered) SS	=	2622.101771	Number of obs	=	2112
Total (uncentered) SS	=	10130.71458	F(4, 2107)	=	26.41
Residual SS	=	1508.26043	Prob > F	=	0.0000
			Centered R2	=	0.4248
			Uncentered R2	=	0.8511
			Root MSE	=	.8451

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1275952	.0525965	2.43	0.015	.0245079	.2306824
E_wages	.3666863	.0742084	4.94	0.000	.2212406	.512132
E_unem	-.1248226	.0332695	-3.75	0.000	-.1900296	-.0596156
E_budget_def	-.0007692	.0003906	-1.97	0.049	-.0015348	-3.53e-06
_cons	1.300217	.246162	5.28	0.000	.817748	1.782685

Underidentification test (Kleibergen-Paap rk LM statistic): 23.867
Chi-sq(5) P-val = 0.0002

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 27.337
Chi-sq(4) P-val = 0.0000

Instruments tested: E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2

Weak identification test (Cragg-Donald Wald F statistic): 1408.085
(Kleibergen-Paap rk Wald F statistic): 152.223

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	18.37
10% maximal IV relative bias	10.83
20% maximal IV relative bias	6.77
30% maximal IV relative bias	5.25
10% maximal IV size	26.87
15% maximal IV size	15.09
20% maximal IV size	10.98
25% maximal IV size	8.84

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 11.983
Chi-sq(4) P-val = 0.0175

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2

```
. * Underidentification test: passed
. * IV redundancy test: passed
. * Weak identification test: passed
. * Overidentification test: failed
.
. * ----- *
.
. ** with first lags of 3m **
.
. * w/o controls
. ivreg29 E_cons (E_m3 = E_m3lag1 E_m3lag2 E_m3lag3), bw(auto) robust redundant(E_m3lag2 E_m3lag3)
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 44
Automatic bw selection according to Newey-West (1994)
time variable (t): date

Total (centered) SS	= 4780.449878	Number of obs =	3401
Total (uncentered) SS	= 17609.07062	F(1, 3399) =	31.37
Residual SS	= 3700.432832	Prob > F =	0.0000
		Centered R2 =	0.2259
		Uncentered R2 =	0.7899
		Root MSE =	1.043

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2567703	.0458316	5.60	0.000	.1669421	.3465986
_cons	1.065778	.1805823	5.90	0.000	.7118436	1.419713

Underidentification test (Kleibergen-Paap rk LM statistic): 44.676
Chi-sq(3) P-val = 0.0000

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 29.839
Chi-sq(2) P-val = 0.0000

Instruments tested: E_m3lag2 E_m3lag3

Weak identification test (Cragg-Donald Wald F statistic): 3.9e+04

(Kleibergen-Paap rk Wald F statistic): 3.5e+04

Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 13.91
10% maximal IV relative bias 9.08
20% maximal IV relative bias 6.46
30% maximal IV relative bias 5.39
10% maximal IV size 22.30
15% maximal IV size 12.83
20% maximal IV size 9.54
25% maximal IV size 7.80

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 1.335
Chi-sq(2) P-val = 0.5131

Instrumented: E_m3

Excluded instruments: E_m3lag1 E_m3lag2 E_m3lag3

. * Underidentification test: passed
. * IV redundancy test: passed
. * Weak identification test: passed
. * Overidentification test: passed

. * With controls

. ivreg29 E_cons E_wages E_unem E_budget_def (E_m3 = E_m3lag1 E_m3lag2 E_m3lag3), bw(auto) robust
redundant(E_m3lag2 E_m3lag3
> 3)

IV (2SLS) estimation

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and autocorrelation

kernel=Bartlett; bandwidth= 40

Automatic bw selection according to Newey-West (1994)

time variable (t): date

Total (centered) SS	=	2654.078979	Number of obs =	2134
Total (uncentered) SS	=	10336.97847	F(4, 2129) =	26.82
Residual SS	=	1511.178452	Prob > F	= 0.0000
			Centered R2	= 0.4306
			Uncentered R2	= 0.8538
			Root MSE	= .8415

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1549598	.0497135	3.12	0.002	.0575232	.2523965
E_wages	.3317599	.0684979	4.84	0.000	.1975066	.4660133
E_unem	-.1263995	.0332699	-3.80	0.000	-.1916073	-.0611917

E_budget_def	-.000812	.0003957	-2.05	0.040	-.0015876	-.0000364
_cons	1.310622	.2485165	5.27	0.000	.823539	1.797706

Underidentification test (Kleibergen-Paap rk LM statistic): 26.439
Chi-sq(3) P-val = 0.0000

-redundant- option:

IV redundancy test (LM test of redundancy of specified instruments): 26.151
Chi-sq(2) P-val = 0.0000

Instruments tested: E_m3lag2 E_m3lag3

Weak identification test (Cragg-Donald Wald F statistic): 5.5e+04
(Kleibergen-Paap rk Wald F statistic): 7.1e+04

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	13.91
10% maximal IV relative bias	9.08
20% maximal IV relative bias	6.46
30% maximal IV relative bias	5.39
10% maximal IV size	22.30
15% maximal IV size	12.83
20% maximal IV size	9.54
25% maximal IV size	7.80

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 16.253
Chi-sq(2) P-val = 0.0003

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def
Excluded instruments: E_m3lag1 E_m3lag2 E_m3lag3

. * Underidentification test: passed
. * IV redundancy test: passed
. * Weak identification test: passed
. * Overidentification test: failed

. * ----- *

.
.
.

end of do-file

▪ A.2. STATA code of panel data analysis

```

. * Set Time Variable
. gen date = ym(year,month)

. format date %tm

. * to use if with date: if date<=>tm(2001m8)

. * Set panel structure
. xtset country_id date
      panel variable:  country_id (strongly balanced)
      time variable:  date, 1993m1 to 2014m12
      delta: 1 month

. * ----- *

. * Pooled OLS *

. * 1      Pooled OLS classic model
. xtscs E_cons E_m3, pooled lag(12)

Regression with Driscoll-Kraay standard errors   Number of obs   =       3422
Method: Pooled OLS                               Number of groups  =        14
Group variable (i): country_id                   F( 1, 13)        =       23.62
maximum lag: 12                                 Prob > F          =       0.0003
                                              R-squared         =       0.2205
                                              Root MSE         =       1.0470

```

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2529123	.0520366	4.86	0.000	.1404941	.3653306
_cons	1.074564	.205355	5.23	0.000	.6309214	1.518206

```

. * 2      Pooled OLS interaction crisis
. xtscs E_cons E_m3 m3_crisis08 m3_recess11, pooled lag(12)

Regression with Driscoll-Kraay standard errors   Number of obs   =       3422
Method: Pooled OLS                               Number of groups  =        14
Group variable (i): country_id                   F( 3, 13)        =        7.83
maximum lag: 12                                 Prob > F          =       0.0031
                                              R-squared         =       0.2487
                                              Root MSE         =       1.0281

```

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2599712	.0552225	4.71	0.000	.1406702	.3792721
m3_crisis08	-.228336	.089201	-2.56	0.024	-.4210431	-.0356289
m3_recess11	.0583417	.0650262	0.90	0.386	-.0821389	.1988223
_cons	1.088159	.2018918	5.39	0.000	.651998	1.524319

```

. * 3      Pooled OLS interaction eurozone

```

```
. xtsc E_cons E_m3 m3_euzone, pooled lag(12)
```

```
Regression with Driscoll-Kraay standard errors   Number of obs   =   3422
Method: Pooled OLS                             Number of groups =    14
Group variable (i): country_id                  F( 2,   13)     =   28.23
maximum lag: 12                                Prob > F        =   0.0000
                                                R-squared       =   0.2816
                                                Root MSE       =   1.0052
```

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2949708	.0436973	6.75	0.000	.2005687	.389373
m3_euzone	-.1533759	.0396583	-3.87	0.002	-.2390525	-.0676993
_cons	1.114637	.1987979	5.61	0.000	.6851601	1.544114

```
. * 4 Pooled OLS interactions
```

```
. xtsc E_cons E_m3 m3_crisis08 m3_recess11 m3_euzone, pooled lag(12)
```

```
Regression with Driscoll-Kraay standard errors   Number of obs   =   3422
Method: Pooled OLS                             Number of groups =    14
Group variable (i): country_id                  F( 4,   13)     =   16.23
maximum lag: 12                                Prob > F        =   0.0001
                                                R-squared       =   0.3111
                                                Root MSE       =   0.9847
```

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3017433	.0468135	6.45	0.000	.2006088	.4028778
m3_crisis08	-.2369048	.0889412	-2.66	0.020	-.4290507	-.0447589
m3_recess11	.0087542	.0616831	0.14	0.889	-.1245041	.1420125
m3_euzone	-.1555212	.0398315	-3.90	0.002	-.2415719	-.0694704
_cons	1.138286	.1934012	5.89	0.000	.7204685	1.556104

```
. * 5 Pooled OLS dummies
```

```
. xtsc E_cons E_m3 crisis08 recess11, pooled lag(12)
```

```
Regression with Driscoll-Kraay standard errors   Number of obs   =   3422
Method: Pooled OLS                             Number of groups =    14
Group variable (i): country_id                  F( 3,   13)     =   50.83
maximum lag: 12                                Prob > F        =   0.0000
                                                R-squared       =   0.2871
                                                Root MSE       =   1.0015
```

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2291593	.0505424	4.53	0.001	.119969	.3383495
crisis08	-1.198743	.315652	-3.80	0.002	-1.880667	-.5168183
recess11	-.4387232	.1150355	-3.81	0.002	-.6872423	-.1902041
_cons	1.268728	.168507	7.53	0.000	.9046911	1.632766

```
. * 6 Pooled OLS with dummies + interact
```

```
. xtsc E_cons E_m3 m3_crisis08 m3_recess11 m3_euzone crisis08 recess11, pooled lag(12)
```

```

Regression with Driscoll-Kraay standard errors   Number of obs   =       3422
Method: Pooled OLS                             Number of groups =       14
Group variable (i): country_id                 F(   6,   13)   =    127.89
maximum lag: 12                               Prob > F        =     0.0000
                                              R-squared      =     0.3679
                                              Root MSE      =     0.9435

```

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2498529	.0400917	6.23	0.000	.16324	.3364657
m3_crisis08	.1844693	.0552798	3.34	0.005	.0650446	.303894
m3_recess11	.400545	.0934836	4.28	0.001	.1985859	.6025041
m3_euzone	-.1528142	.0381254	-4.01	0.001	-.2351792	-.0704492
crisis08	-1.763138	.3454213	-5.10	0.000	-2.509375	-1.0169
recess11	-1.051443	.1674301	-6.28	0.000	-1.413154	-.6897324
_cons	1.391679	.15328	9.08	0.000	1.060537	1.72282

```

. * 7      Pooled OLS with controls
. xtsc E_cons E_m3 E_wages E_unem E_budget_def, pooled lag(12)

```

```

Regression with Driscoll-Kraay standard errors   Number of obs   =       2140
Method: Pooled OLS                             Number of groups =        9
Group variable (i): country_id                 F(   4,   8)   =    110.55
maximum lag: 12                               Prob > F        =     0.0000
                                              R-squared      =     0.4316
                                              Root MSE      =     0.8418

```

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1623597	.0427428	3.80	0.005	.0637946	.2609248
E_wages	.3213929	.0382821	8.40	0.000	.2331143	.4096715
E_unem	-.1270796	.0318513	-3.99	0.004	-.2005289	-.0536304
E_budget_def	-.0008256	.0002661	-3.10	0.015	-.0014392	-.000212
_cons	1.316579	.2448782	5.38	0.001	.751889	1.881269

```

. * 8      Pooled OLS with controls + interact
. xtsc E_cons E_m3 E_wages E_unem E_budget_def m3_crisis08 m3_recess11 m3_euzone, pooled lag(12)

```

```

Regression with Driscoll-kraay standard errors   Number of obs   =       2140
Method: Pooled OLS                             Number of groups =        9
Group variable (i): country_id                 F(   7,   8)   =     70.60
maximum lag: 12                               Prob > F        =     0.0000
                                              R-squared      =     0.5151
                                              Root MSE      =     0.7780

```

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2057978	.0321459	6.40	0.000	.1316693	.2799263
E_wages	.3091085	.0254059	12.17	0.000	.2505224	.3676945
E_unem	-.0590294	.0400605	-1.47	0.179	-.1514091	.0333503
E_budget_def	-.0007399	.0002766	-2.67	0.028	-.0013778	-.000102
m3_crisis08	-.2694718	.0793884	-3.39	0.009	-.4525418	-.0864019
m3_recess11	.0028671	.0451588	0.06	0.951	-.1012693	.1070035
m3_euzone	-.1474417	.0468239	-3.15	0.014	-.2554179	-.0394656

```
_cons | .9514322 .2308632 4.12 0.003 .4190606 1.483804
```

```
. * 9 Pooled OLS with controls + dummies
. xtscs E_cons E_m3 E_wages E_unem E_budget_def crisis08 recess11, pooled lag(12)
```

```
Regression with Driscoll-Kraay standard errors   Number of obs   =   2140
Method: Pooled OLS                               Number of groups =    9
Group variable (i): country_id                   F( 6, 8)        =  138.49
maximum lag: 12                                 Prob > F        =  0.0000
                                                R-squared       =  0.5192
                                                Root MSE       =  0.7745
```

	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_cons						
E_m3	.1369637	.0377063	3.63	0.007	.0500127	.2239146
E_wages	.339531	.0347593	9.77	0.000	.259376	.4196861
E_unem	-.1378172	.029623	-4.65	0.002	-.206128	-.0695064
E_budget_def	-.0008932	.0002262	-3.95	0.004	-.0014147	-.0003716
crisis08	-1.314052	.2192855	-5.99	0.000	-1.819726	-.808379
recess11	-.3452239	.0754974	-4.57	0.002	-.5193212	-.1711266
_cons	1.543615	.2183912	7.07	0.000	1.040004	2.047226

```
. * 10 Pooled OLS with controls + inter + dummies
. xtscs E_cons E_m3 E_wages E_unem E_budget_def m3_crisis08 m3_recess11 m3_euzone crisis08 recess11,
pooled lag(12)
```

```
Regression with Driscoll-Kraay standard errors   Number of obs   =   2140
Method: Pooled OLS                               Number of groups =    9
Group variable (i): country_id                   F( 9, 8)        =  121.01
maximum lag: 12                                 Prob > F        =  0.0000
                                                R-squared       =  0.5615
                                                Root MSE       =  0.7402
```

	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_cons						
E_m3	.1674238	.0259431	6.45	0.000	.1075989	.2272487
E_wages	.3101985	.027751	11.18	0.000	.2462046	.3741924
E_unem	-.0537957	.0388535	-1.38	0.204	-.143392	.0358006
E_budget_def	-.0008625	.0002498	-3.45	0.009	-.0014387	-.0002864
m3_crisis08	.0765003	.0466301	1.64	0.140	-.0310289	.1840296
m3_recess11	.2717911	.0574174	4.73	0.001	.1393864	.4041959
m3_euzone	-.1542497	.0454673	-3.39	0.009	-.2590974	-.049402
crisis08	-1.504371	.3322724	-4.53	0.002	-2.270592	-.7381496
recess11	-.7884119	.1250957	-6.30	0.000	-1.076883	-.4999407
_cons	1.111811	.2389759	4.65	0.002	.5607311	1.66289

```
. * 11 Pooled OLS IV (all)
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3), bw(12) robust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation

```
kernel=Bartlett; bandwidth= 12
time variable (t): date
```

		Number of obs =	3324	
		F(1, 3322) =	63.42	
		Prob > F =	0.0000	
Total (centered) SS	=	4711.246464	Centered R2 =	0.2368
Total (uncentered) SS	=	17193.9908	Uncentered R2 =	0.7909
Residual SS	=	3595.75521	Root MSE =	1.04

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2397951	.0301026	7.97	0.000	.180795	.2987952
_cons	1.136912	.1133399	10.03	0.000	.9147703	1.359054

Underidentification test (Kleibergen-Paap rk LM statistic): 114.959
Chi-sq(6) P-val = 0.0000

Weak identification test (Cragg-Donald Wald F statistic): 2062.465
(Kleibergen-Paap rk Wald F statistic): 337.780

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.528
Chi-sq(5) P-val = 0.7723

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```
. * 12 Pooled OLS IV + inter crisis
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) m3_crisis08
m3_recess11, bw(12) robust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	3324	
		F(3, 3320) =	25.06	
		Prob > F =	0.0000	
Total (centered) SS	=	4711.246464	Centered R2 =	0.2674
Total (uncentered) SS	=	17193.9908	Uncentered R2 =	0.7993
Residual SS	=	3451.331695	Root MSE =	1.019

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2459924	.0307009	8.01	0.000	.1858198	.3061649
m3_crisis08	-.2313191	.053026	-4.36	0.000	-.3352481	-.1273901

m3_recess11	.042844	.0829038	0.52	0.605	-.1196445	.2053326
_cons	1.157318	.1136576	10.18	0.000	.9345537	1.380083

Underidentification test (Kleibergen-Paap rk LM statistic): 113.962
Chi-sq(6) P-val = 0.0000

Weak identification test (Cragg-Donald wald F statistic): 2035.421
(Kleibergen-Paap rk wald F statistic): 343.485

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.594
Chi-sq(5) P-val = 0.7622

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```
. * 13 Pooled OLS IV + inter euro
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) m3_euzone, bw(12)
robust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	3324
		F(2, 3321) =	67.38
		Prob > F =	0.0000
Total (centered) SS	=	Centered R2 =	0.3087
Total (uncentered) SS	=	Uncentered R2 =	0.8106
Residual SS	=	Root MSE =	.9898

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	.2923561	.0254943	11.47	0.000	.2423882 .3423241
m3_euzone	-.161587	.0333187	-4.85	0.000	-.2268905 -.0962835
_cons	1.151385	.1018613	11.30	0.000	.9517407 1.35103

Underidentification test (Kleibergen-Paap rk LM statistic): 130.952
Chi-sq(6) P-val = 0.0000

Weak identification test (Cragg-Donald wald F statistic): 1845.597
(Kleibergen-Paap rk wald F statistic): 281.618

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23

20% maximal IV size 11.72
25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.898
Chi-sq(5) P-val = 0.5642

Instrumented: E_m3
Included instruments: m3_euzone
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

```
. * 14 Pooled OLS IV + interaction
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) m3_crisis08
m3_recess11 m3_euzone, bw(
> 12) robust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	3324
		F(4, 3319) =	43.77
		Prob > F =	0.0000
Total (centered) SS	=	Centered R2 =	0.3411
Total (uncentered) SS	=	Uncentered R2 =	0.8195
Residual SS	=	Root MSE =	.9664

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	.2984941	.0250184	11.93	0.000	.249459 .3475292
m3_crisis08	-.241843	.0476724	-5.07	0.000	-.3352792 -.1484067
m3_recess11	-.0055679	.0787534	-0.07	0.944	-.1599217 .148786
m3_euzone	-.1634571	.0330276	-4.95	0.000	-.2281899 -.0987242
_cons	1.181136	.1020256	11.58	0.000	.9811692 1.381102

Underidentification test (Kleibergen-Paap rk LM statistic): 131.858
Chi-sq(6) P-val = 0.0000

Weak identification test (Cragg-Donald Wald F statistic): 1830.357
(Kleibergen-Paap rk Wald F statistic): 282.515

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.472
Chi-sq(5) P-val = 0.7807

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 m3_euzone
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2

E_y10lag3

```
.
. * 15    Pooled OLS IV + dummies
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) crisis08
recess11, bw(12) robust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

Total (centered) SS	=	4711.246464	Number of obs =	3324
Total (uncentered) SS	=	17193.9908	F(3, 3320) =	40.44
Residual SS	=	3276.470857	Prob > F	= 0.0000
			Centered R2	= 0.3045
			Uncentered R2	= 0.8094
			Root MSE	= .9928

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	.2158482	.0318245	6.78	0.000	.1534733 .2782231
crisis08	-1.230451	.1825709	-6.74	0.000	-1.588284 -.8726188
recess11	-.4924524	.2433826	-2.02	0.043	-.9694735 -.0154313
_cons	1.339226	.1231492	10.87	0.000	1.097858 1.580594

Underidentification test (Kleibergen-Paap rk LM statistic): 110.919
 Chi-sq(6) P-val = 0.0000

Weak identification test (Cragg-Donald Wald F statistic): 1860.706
 (Kleibergen-Paap rk Wald F statistic): 279.265

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 5.184
 Chi-sq(5) P-val = 0.3938

Instrumented: E_m3
 Included instruments: crisis08 recess11
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```
.
. * 16    Pooled OLS IV with dummies + interaction
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) m3_crisis08
m3_recess11 m3_euzone cris
> is08 recess11, bw(12) robust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and autocorrelation

kernel=Bartlett; bandwidth= 12

time variable (t): date

		Number of obs =	3324
		F(6, 3317) =	41.65
		Prob > F =	0.0000
Total (centered) SS	=	Centered R2 =	0.3946
Total (uncentered) SS	=	Uncentered R2 =	0.8341
Residual SS	=	Root MSE =	.9263

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2486324	.028293	8.79	0.000	.1931791	.3040857
m3_crisis08	.1872583	.0896018	2.09	0.037	.011642	.3628746
m3_recess11	.4011402	.1279531	3.14	0.002	.1503568	.6519236
m3_euzone	-.1635923	.0312807	-5.23	0.000	-.2249013	-.1022834
crisis08	-1.795531	.3124961	-5.75	0.000	-2.408012	-1.18305
recess11	-1.086627	.3403004	-3.19	0.001	-1.753604	-.4196504
_cons	1.430533	.1155442	12.38	0.000	1.20407	1.656995

Underidentification test (Kleibergen-Paap rk LM statistic): 120.178
Chi-sq(6) P-val = 0.0000

Weak identification test (Cragg-Donald Wald F statistic): 1635.257
(Kleibergen-Paap rk Wald F statistic): 228.669

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 4.846
Chi-sq(5) P-val = 0.4350

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 m3_euzone crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```
. * 17 Pooled OLS IV with controls
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_wages E_unem
E_budget_def, bw(12) ro
> bust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and autocorrelation

kernel=Bartlett; bandwidth= 12

time variable (t): date

		Number of obs =	2112
		F(4, 2107) =	52.56
		Prob > F =	0.0000
Total (centered) SS	=	Centered R2 =	0.4247
Total (uncentered) SS	=	Uncentered R2 =	0.8511

Residual SS = 1508.5595 Root MSE = .8452

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1265735	.0360951	3.51	0.000	.0558284	.1973185
E_wages	.3679989	.0547834	6.72	0.000	.2606254	.4753724
E_unem	-.1247593	.0230737	-5.41	0.000	-.1699828	-.0795357
E_budget_def	-.0007672	.0003504	-2.19	0.029	-.0014539	-.0000806
_cons	1.299966	.1774696	7.33	0.000	.9521316	1.6478

Underidentification test (Kleibergen-Paap rk LM statistic): 51.261
Chi-sq(6) P-val = 0.0000

Weak identification test (Cragg-Donald Wald F statistic): 1174.943
(Kleibergen-Paap rk Wald F statistic): 198.131
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72
25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 10.779
Chi-sq(5) P-val = 0.0559

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```
. * 18 Pooled OLS IV with controls + interaction
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_wages E_unem
E_budget_def m3_crisis0
> 8 m3_recess11 m3_euzone, bw(12) robust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	2622.101771	Number of obs =	2112
Total (uncentered) SS	=	10130.71458	F(7, 2104) =	45.52
Residual SS	=	1294.500288	Prob > F =	0.0000
			Centered R2 =	0.5063
			Uncentered R2 =	0.8722
			Root MSE =	.7829

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1619615	.0301954	5.36	0.000	.1027796	.2211435
E_wages	.3654479	.0509689	7.17	0.000	.2655508	.4653451
E_unem	-.0639063	.0334826	-1.91	0.056	-.1295311	.0017184
E_budget_def	-.0006706	.0003416	-1.96	0.050	-.0013402	-1.05e-06
m3_crisis08	-.2693534	.0595142	-4.53	0.000	-.3859992	-.1527077

m3_recess11		-.00965	.0601485	-0.16	0.873	-.1275389	.1082389
m3_euzone		-.1323355	.0459752	-2.88	0.004	-.2224452	-.0422257
_cons		.9774328	.195452	5.00	0.000	.594354	1.360512

Underidentification test (Kleibergen-Paap rk LM statistic): 58.544
Chi-sq(6) P-val = 0.0000

weak identification test (Cragg-Donald wald F statistic): 1108.133
(Kleibergen-Paap rk wald F statistic): 120.377

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 10.253
Chi-sq(5) P-val = 0.0684

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
m3_euzone
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

```
. * 19 Pooled OLS IV with controls + dummies
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_wages E_unem
E_budget_def crisis08 r
> ecess11, bw(12) robust
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	2112
		F(6, 2105) =	41.74
		Prob > F =	0.0000
Total (centered) SS	=	Centered R2 =	0.5141
Total (uncentered) SS	=	Uncentered R2 =	0.8742
Residual SS	=	Root MSE =	.7767

E_cons		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]

E_m3		.1039716	.0363451	2.86	0.004	.0327365 .1752066
E_wages		.3812761	.0560327	6.80	0.000	.2714541 .4910981
E_unem		-.1358482	.0214073	-6.35	0.000	-.1778057 -.0938906
E_budget_def		-.0008441	.0002489	-3.39	0.001	-.0013319 -.0003562
crisis08		-1.324446	.2408334	-5.50	0.000	-1.796471 -.8524212
recess11		-.39174	.1991987	-1.97	0.049	-.7821622 -.0013177
_cons		1.5365	.1799328	8.54	0.000	1.183838 1.889161

Underidentification test (Kleibergen-Paap rk LM statistic): 50.548
Chi-sq(6) P-val = 0.0000

weak identification test (Cragg-Donald wald F statistic): 1087.353

```

(Kleibergen-Paap rk wald F statistic): 150.664
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
                                         10% maximal IV relative bias 11.12
                                         20% maximal IV relative bias 6.76
                                         30% maximal IV relative bias 5.15
                                         10% maximal IV size 29.18
                                         15% maximal IV size 16.23
                                         20% maximal IV size 11.72
                                         25% maximal IV size 9.38

```

Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```

-----
Hansen J statistic (overidentification test of all instruments): 4.312
Chi-sq(5) P-val = 0.5054
-----

```

```

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
                  E_y10lag3
-----

```

```

. * 20 Pooled OLS IV with controls + dummies+inter
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_wages E_unem
E_budget_def m3_crisis0
> 8 m3_recess11 m3_euzone crisis08 recess11, bw(12) robust

```

IV (2SLS) estimation

```

-----
Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

```

```

Total (centered) SS = 2622.101771
Total (uncentered) SS = 10130.71458
Residual SS = 1168.831962
Number of obs = 2112
F( 9, 2102) = 33.64
Prob > F = 0.0000
Centered R2 = 0.5542
Uncentered R2 = 0.8846
Root MSE = .7439

```

```

-----
      E_cons |      Coef.      Robust      z      P>|z|      [95% Conf. Interval]
-----+-----
      E_m3 | .1243989   .0329078   3.78   0.000   .0599008   .188897
      E_wages | .3619984   .0527041   6.87   0.000   .2587003   .4652965
      E_unem | -.0582289   .0314833  -1.85   0.064  -.119935   .0034772
E_budget_def | -.0008104   .0002749  -2.95   0.003  -.0013492  -.0002715
      m3_crisis08 | .0926059   .1017494   0.91   0.363  -.1068193   .2920311
      m3_recess11 | .2882106   .0850795   3.39   0.001   .1214579   .4549633
      m3_euzone | -.1402099   .0433772  -3.23   0.001  -.2252277  -.0551921
      crisis08 | -1.573332   .4372932  -3.60   0.000  -2.430411  -.7162529
      recess11 | -.8649703   .2773571  -3.12   0.002  -1.40858  -.3213604
      _cons | 1.147105   .2060793   5.57   0.000   .743197   1.551013
-----

```

```

Underidentification test (Kleibergen-Paap rk LM statistic): 57.011
Chi-sq(6) P-val = 0.0000
-----

```

```

weak identification test (Cragg-Donald wald F statistic): 1061.168
(Kleibergen-Paap rk wald F statistic): 104.221
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
                                         10% maximal IV relative bias 11.12
                                         20% maximal IV relative bias 6.76
                                         30% maximal IV relative bias 5.15
                                         10% maximal IV size 29.18

```

15% maximal IV size 16.23
 20% maximal IV size 11.72
 25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 6.947
 Chi-sq(5) P-val = 0.2246

Instrumented: E_m3
 Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
 m3_euzone crisis08 recess11
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
 E_y10lag3

```
. * ----- *
```

```
. * FE *
```

```
. * 21 FE classic model
```

```
. xtsccecons E_m3, fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 3422
 Method: Fixed-effects regression Number of groups = 14
 Group variable (i): country_id F(1, 13) = 11.64
 maximum lag: 12 Prob > F = 0.0046
 within R-squared = 0.1629

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2188245	.0641475	3.41	0.005	.0802422	.3574068
_cons	1.191658	.2744109	4.34	0.001	.5988288	1.784486

```
. * 22 FE + inter crisis
```

```
. xtsccecons E_m3 m3_crisis08 m3_recess11, fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 3422
 Method: Fixed-effects regression Number of groups = 14
 Group variable (i): country_id F(3, 13) = 20.22
 maximum lag: 12 Prob > F = 0.0000
 within R-squared = 0.2068

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.216676	.0678694	3.19	0.007	.0700531	.3632988
m3_crisis08	-.240481	.0919925	-2.61	0.021	-.4392187	-.0417434
m3_recess11	-.0696115	.081303	-0.86	0.407	-.2452559	.1060329
_cons	1.251726	.2728717	4.59	0.001	.6622225	1.84123

```
. * 23 FE + inter euro
```

```
. xtsccecons E_m3 m3_euzone, fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 3422
 Method: Fixed-effects regression Number of groups = 14
 Group variable (i): country_id F(2, 13) = 5.45

maximum lag: 12 Prob > F = 0.0191
within R-squared = 0.1750

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1637184	.0705476	2.32	0.037	.0113096	.3161273
m3_euzone	.1195375	.0829782	1.44	0.173	-.059726	.2988011
_cons	1.237119	.2856086	4.33	0.001	.6200992	1.854139

```
. * 24 FE + interaction
. xtsc E_cons E_m3 m3_crisis08 m3_recess11 m3_euzone, fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 3422
Method: Fixed-effects regression Number of groups = 14
Group variable (i): country_id F(4, 13) = 16.40
maximum lag: 12 Prob > F = 0.0001
within R-squared = 0.2197

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1579587	.0745858	2.12	0.054	-.0031741	.3190915
m3_crisis08	-.2410338	.0946101	-2.55	0.024	-.4454265	-.036641
m3_recess11	-.0962695	.0830346	-1.16	0.267	-.2756548	.0831159
m3_euzone	.1239548	.0842274	1.47	0.165	-.0580074	.305917
_cons	1.306993	.2834903	4.61	0.000	.6945496	1.919437

```
. * 25 FE + dummy
. xtsc E_cons E_m3 crisis08 recess11, fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 3422
Method: Fixed-effects regression Number of groups = 14
Group variable (i): country_id F(3, 13) = 63.14
maximum lag: 12 Prob > F = 0.0000
within R-squared = 0.2750

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1746991	.0602623	2.90	0.012	.0445103	.3048879
crisis08	-1.262094	.3424041	-3.69	0.003	-2.001813	-.522375
recess11	-.5921695	.1654229	-3.58	0.003	-.9495439	-.2347952
_cons	1.471877	.2354611	6.25	0.000	.9631939	1.980559

```
. * 26 FE with dummies + interaction
. xtsc E_cons E_m3 m3_crisis08 m3_recess11 m3_euzone crisis08 recess11 , fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 3422
Method: Fixed-effects regression Number of groups = 14
Group variable (i): country_id F(6, 13) = 59.07
maximum lag: 12 Prob > F = 0.0000
within R-squared = 0.3087

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0985462	.0600687	1.64	0.125	-.0312243	.2283167
m3_crisis08	.2290521	.0490611	4.67	0.000	.123062	.3350421
m3_recess11	.2640296	.0563813	4.68	0.000	.1422252	.385834
m3_euzone	.135958	.0730192	1.86	0.085	-.0217903	.2937063
crisis08	-1.956726	.3315058	-5.90	0.000	-2.672901	-1.240551
recess11	-.9751229	.1912477	-5.10	0.000	-1.388288	-.5619573
_cons	1.57557	.2373241	6.64	0.000	1.062862	2.088277

```
. * 27    FE with controls
. xtscf E_cons E_m3 E_wages E_unem E_budget_def, fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 2140
Method: Fixed-effects regression Number of groups = 9
Group variable (i): country_id F(4, 8) = 18.56
maximum lag: 12 Prob > F = 0.0004
 within R-squared = 0.2916

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1520755	.0592684	2.57	0.033	.0154023	.2887487
E_wages	.3234865	.05951	5.44	0.001	.1862563	.4607168
E_unem	-.0414885	.0437177	-0.95	0.370	-.1423016	.0593247
E_budget_def	-.0000614	.0003716	-0.17	0.873	-.0009182	.0007954
_cons	.8033947	.3834581	2.10	0.069	-.0808612	1.687651

```
. * 28    FE with controls + interaction
. xtscf E_cons E_m3 E_wages E_unem E_budget_def m3_crisis08 m3_recess11 m3_euzone, fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 2140
Method: Fixed-effects regression Number of groups = 9
Group variable (i): country_id F(7, 8) = 27.14
maximum lag: 12 Prob > F = 0.0001
 within R-squared = 0.3771

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1626675	.0665166	2.45	0.040	.00928	.316055
E_wages	.3346921	.058349	5.74	0.000	.2001391	.469245
E_unem	-.0804495	.0414637	-1.94	0.088	-.1760649	.015166
E_budget_def	-.000244	.0002874	-0.85	0.421	-.0009068	.0004187
m3_crisis08	-.2887696	.0814537	-3.55	0.008	-.4766022	-.1009369
m3_recess11	-.0632709	.0669435	-0.95	0.372	-.217643	.0911011
m3_euzone	-.0263991	.0865496	-0.31	0.768	-.225983	.1731847
_cons	1.092217	.3403068	3.21	0.012	.3074681	1.876966

```
. * 29    FE with controls + dummy
. xtscf E_cons E_m3 E_wages E_unem E_budget_def crisis08 recess11 , fe lag(12)
```

Regression with Driscoll-Kraay standard errors Number of obs = 2140
Method: Fixed-effects regression Number of groups = 9
Group variable (i): country_id F(6, 8) = 82.43

		Drisc/Kraay				
E_cons	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.120207	.0547941	2.19	0.060	-.0061484	.2465624
E_wages	.3136166	.0653132	4.80	0.001	.1630041	.4642291
E_unem	-.0846996	.0397851	-2.13	0.066	-.1764442	.0070449
E_budget_def	-.0003085	.0002999	-1.03	0.334	-.0010002	.0003831
crisis08	-1.341851	.2416422	-5.55	0.001	-1.899079	-.784623
recess11	-.4366705	.1250198	-3.49	0.008	-.7249667	-.1483742
_cons	1.351132	.3287342	4.11	0.003	.5930694	2.109194

Regression with Driscoll-Kraay standard errors	Number of obs	=	2140
Method: Fixed-effects regression	Number of groups	=	9
Group variable (i): country_id	F(9, 8)	=	106.45
maximum lag: 12	Prob > F	=	0.0000
	within R-squared	=	0.4458

E_cons	Coef.	Drisc/Kraay Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1333736	.0566049	2.36	0.046	.0028424	.2639047
E_wages	.2984133	.0648904	4.60	0.002	.1487759	.4480508
E_unem	-.0807917	.0404183	-2.00	0.081	-.1739966	.0124132
E_budget_def	-.0003764	.0002574	-1.46	0.182	-.0009699	.0002171
m3_crisis08	.0618777	.0351514	1.76	0.116	-.0191816	.1429371
m3_recess11	.1522009	.0448958	3.39	0.009	.048671	.2557308
m3_euzone	-.0256263	.0792805	-0.32	0.755	-.2084475	.157195
crisis08	-1.520707	.2695508	-5.64	0.000	-2.142293	-.8991223
recess11	-.6366932	.1221478	-5.21	0.001	-.9183665	-.35502
_cons	1.34285	.3382898	3.97	0.004	.5627527	2.122948

```
Fixed-effects (within) IV regression      Number of obs   =      3,324
Group variable: country_id              Number of groups =       14

R-sq:                                    obs per group:
    within = 0.1917                      min =      185
    between = 0.3644                     avg =    237.4
    overall = 0.2410                     max =     264
```

(Std. Err. adjusted for 14 clusters in country_id)

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
--------	-------	------------------	---	------	----------------------

E_m3		.2049492	.0536444	3.82	0.000	.0998082	.3100903
_cons		1.253304	.1791815	6.99	0.000	.9021144	1.604493

sigma_u		.58395978					
sigma_e		.88376281					
rho		.30391723	(fraction of variance due to u_i)				

Instrumented: E_m3
Instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```
. * 32 FE IV + inter crisis
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) m3_crisis08
m3_recess11, fe vce(cluster country_id)
> r country_id)
```

Fixed-effects (within) IV regression	Number of obs	=	3,324
Group variable: country_id	Number of groups	=	14

R-sq:	Obs per group:		
within = 0.2373	min =		185
between = 0.3404	avg =		237.4
overall = 0.2596	max =		264

corr(u_i, xb) = 0.1369	wald chi2(3)	=	136.66
	Prob > chi2	=	0.0000

(Std. Err. adjusted for 14 clusters in country_id)

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
--------	-------	------------------	---	------	----------------------

E_m3	.1944599	.0556986	3.49	0.000	.0852926 .3036272
m3_crisis08	-.2479713	.0338261	-7.33	0.000	-.3142692 -.1816734
m3_recess11	-.109264	.1032655	-1.06	0.290	-.3116606 .0931327
_cons	1.34805	.1882804	7.16	0.000	.9790268 1.717072

sigma_u	.60221857				
sigma_e	.8587027				
rho	.32968621	(fraction of variance due to u_i)			

Instrumented: E_m3
Instruments: m3_crisis08 m3_recess11 E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

```
. * 33 FE IV + inter euro
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) m3_euzone, fe
vce(cluster country_id)
```

Fixed-effects (within) IV regression	Number of obs	=	3,324
Group variable: country_id	Number of groups	=	14

R-sq:	Obs per group:		
within = 0.1930	min =		185
between = 0.0871	avg =		237.4
overall = 0.0291	max =		264

corr(u_i, xb) = -0.3973	wald chi2(2)	=	41.48
	Prob > chi2	=	0.0000

(Std. Err. adjusted for 14 clusters in country_id)

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1205364	.0795193	1.52	0.130	-.0353185	.2763914
m3_euzone	.1864375	.1477928	1.26	0.207	-.1032311	.476106
_cons	1.315996	.211169	6.23	0.000	.9021119	1.729879
sigma_u	.85282964					
sigma_e	.88317711					
rho	.48252415	(fraction of variance due to u_i)				
Instrumented:	E_m3					
Instruments:	m3_euzone E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3					

```
.
. * 34 FE IV + interaction
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) m3_crisis08
m3_recess11 m3_euzone, fe
> vce(cluster country_id)
```

```
Fixed-effects (within) IV regression      Number of obs   =      3,324
Group variable: country_id               Number of groups =       14

R-sq:                                     Obs per group:
    within = 0.2363                        min =          185
    between = 0.2163                       avg =         237.4
    overall = 0.0255                       max =          264
```

```
corr(u_i, xb) = -0.4424                  wald chi2(4)      =      156.14
                                           Prob > chi2       =      0.0000
```

(Std. Err. adjusted for 14 clusters in country_id)

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0981446	.0908566	1.08	0.280	-.0799309	.2762202
m3_crisis08	-.2481242	.0355136	-6.99	0.000	-.3177296	-.1785189
m3_recess11	-.1487025	.1160116	-1.28	0.200	-.376081	.0786759
m3_euzone	.2070729	.1535474	1.35	0.177	-.0938745	.5080204
_cons	1.430235	.2414074	5.92	0.000	.957085	1.903385
sigma_u	.91000404					
sigma_e	.85943023					
rho	.52855858	(fraction of variance due to u_i)				
Instrumented:	E_m3					
Instruments:	m3_crisis08 m3_recess11 m3_euzone E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3					

```
.
. * 35 FE IV + dummies
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) crisis08
recess11, fe vce(cluster coun
> try_id)
```

```
Fixed-effects (within) IV regression      Number of obs   =      3,324
Group variable: country_id               Number of groups =       14

R-sq:                                     Obs per group:
    within = 0.3009                        min =          185
    between = 0.3269                       avg =         237.4
    overall = 0.2848                       max =          264
```

corr(u_i, Xb) = 0.1126	wald chi2(3) = 91.70
	Prob > chi2 = 0.0000

(Std. Err. adjusted for 14 clusters in country_id)

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1467899	.0564365	2.60	0.009	.0361765	.2574034
crisis08	-1.307626	.1959905	-6.67	0.000	-1.691761	-.9234919
recess11	-.6838727	.2803311	-2.44	0.015	-1.233312	-.1344338
_cons	1.590411	.2025074	7.85	0.000	1.193504	1.987318
sigma_u	.61604358					
sigma_e	.8221092					
rho	.35959761	(fraction of variance due to u_i)				

Instrumented: E_m3
Instruments: crisis08 recess11 E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1
E_y10lag2 E_y10lag3

```
. * 36      FE IV + dummies + interaction
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) m3_crisis08
m3_recess11 m3_euzone cris
> is08 recess11, fe vce(cluster country_id)
```

```
Fixed-effects (within) IV regression      Number of obs   =    3,324
Group variable: country_id              Number of groups =     14
```

```
R-sq:          within = 0.3219
              between = 0.2085
              overall = 0.0694

obs per group:  min =      185
                avg =    237.4
                max =      264
```

corr(u_i, Xb) = -0.3762	wald chi2(6) = 107.36
	Prob > chi2 = 0.0000

(Std. Err. adjusted for 14 clusters in country_id)

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0444692	.0948324	0.47	0.639	-.141399	.2303373
m3_crisis08	.2490811	.1156876	2.15	0.031	.0223376	.4758246
m3_recess11	.2416225	.1087666	2.22	0.026	.0284439	.4548011
m3_euzone	.2058507	.1457557	1.41	0.158	-.0798253	.4915266
crisis08	-2.063117	.4940603	-4.18	0.000	-3.031458	-1.094777
recess11	-1.03154	.4127085	-2.50	0.012	-1.840433	-.2226457
_cons	1.695551	.2689714	6.30	0.000	1.168377	2.222725
sigma_u	.90353205					
sigma_e	.81005776					
rho	.55438698	(fraction of variance due to u_i)				

Instrumented: E_m3
Instruments: m3_crisis08 m3_recess11 m3_euzone crisis08 recess11 E_m3lag12
E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

* 37 FE IV + controls

```
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_wages E_unem
E_budget_def, fe vce(c1
> uster country_id)
```

```
Fixed-effects (within) IV regression      Number of obs   =      2,112
Group variable: country_id               Number of groups =         9
```

```
R-sq:                                     Obs per group:
    within = 0.2871                        min =      125
    between = 0.4637                       avg =     234.7
    overall = 0.3612                       max =     260
```

```
corr(u_i, Xb) = -0.0141                  wald chi2(4)      =    71307.73
                                           Prob > chi2       =      0.0000
```

(Std. Err. adjusted for 9 clusters in country_id)

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0965327	.056011	1.72	0.085	-.0132468	.2063122
E_wages	.4243786	.0910752	4.66	0.000	.2458744	.6028827
E_unem	-.021072	.0204452	-1.03	0.303	-.0611438	.0189999
E_budget_def	.0000422	.0002793	0.15	0.880	-.0005052	.0005895
_cons	.5879474	.1956013	3.01	0.003	.2045759	.971319
sigma_u	.54541993					
sigma_e	.73470866					
rho	.35529691	(fraction of variance due to u_i)				

```
Instrumented:      E_m3
Instruments:      E_wages E_unem E_budget_def E_m3lag12 E_m3lag13 E_m3lag14
                  E_y10lag1 E_y10lag2 E_y10lag3
```

```
. * 38      FE IV + controls + interaction
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_wages E_unem
E_budget_def m3_crisis0
> 8 m3_recess11 m3_euzone, fe vce(cluster country_id)
```

```
Fixed-effects (within) IV regression      Number of obs   =      2,112
Group variable: country_id               Number of groups =         9
```

```
R-sq:                                     Obs per group:
    within = 0.3677                        min =      125
    between = 0.4159                       avg =     234.7
    overall = 0.3956                       max =     260
```

```
corr(u_i, Xb) = 0.0174                  wald chi2(7)      =    301381.95
                                           Prob > chi2       =      0.0000
```

(Std. Err. adjusted for 9 clusters in country_id)

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0662272	.1094939	0.60	0.545	-.1483768	.2808313
E_wages	.4475629	.0944406	4.74	0.000	.2624627	.6326631
E_unem	-.0633527	.0195077	-3.25	0.001	-.101587	-.0251184
E_budget_def	-.0000166	.000394	-0.04	0.966	-.0007889	.0007557
m3_crisis08	-.2900662	.043484	-6.67	0.000	-.3752934	-.2048391
m3_recess11	-.115486	.110118	-1.05	0.294	-.3313134	.1003413
m3_euzone	.0422086	.0942302	0.45	0.654	-.1424791	.2268963
_cons	.9438745	.3016277	3.13	0.002	.352695	1.535054

```

-----+-----
sigma_u | .56959043
sigma_e | .69244077
rho | .40357039 (fraction of variance due to u_i)
-----+-----
Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11 m3_euzone
              E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3
-----+-----

. * 39 FE IV + controls + dummy
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_wages E_unem
E_budget_def crisis08 r
> ecess11, fe vce(cluster country_id)

Fixed-effects (within) IV regression      Number of obs   =      2,112
Group variable: country_id                Number of groups =         9

R-sq:                                     Obs per group:
    within = 0.4387                        min =          125
    between = 0.5192                       avg =         234.7
    overall = 0.4844                       max =          260

                                         wald chi2(6)      =    633866.57
corr(u_i, Xb) = 0.0974                    Prob > chi2       =      0.0000

                                         (Std. Err. adjusted for 9 clusters in country_id)
-----+-----
      E_cons |               Coef.   Robust      z    P>|z|    [95% Conf. Interval]
-----+-----
      E_m3   |   .0711222   .0669372    1.06   0.288   - .0600723   .2023166
    E_wages |   .3973116   .0847622    4.69   0.000    .2311807   .5634425
    E_unem   |  -.0679796   .0181312   -3.75   0.000   - .103516   -.0324432
E_budget_def | -.0002262   .0002345   -0.96   0.335   - .0006858   .0002334
  crisis08   | -1.351652   .2503925   -5.40   0.000   -1.842412   -.8608918
  recess11   | -.4992395   .2816867   -1.77   0.076   -1.051335   .0528563
      _cons  |   1.188285   .2374262    5.00   0.000    .7229381   1.653632
-----+-----
sigma_u | .52160139
sigma_e | .65222653
rho | .39007986 (fraction of variance due to u_i)
-----+-----
Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def crisis08 recess11 E_m3lag12
              E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3
-----+-----

. * 40 FE IV + controls + dummy + interaction
. xtivreg E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_wages E_unem
E_budget_def m3_crisis0
> 8 m3_recess11 m3_euzone crisis08 recess11, fe vce(cluster country_id)

Fixed-effects (within) IV regression      Number of obs   =      2,112
Group variable: country_id                Number of groups =         9

R-sq:                                     Obs per group:
    within = 0.4409                        min =          125
    between = 0.4635                       avg =         234.7
    overall = 0.4642                       max =          260

                                         wald chi2(8)      =    1628.88
corr(u_i, Xb) = 0.0960                    Prob > chi2       =      0.0000

```



```

                                (Std. Err. adjusted for 9 clusters in country_id)
-----+-----
      E_cons |               Robust
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      E_m3   |   .0545079   .10482     0.52   0.603    - .1509354   .2599513
      E_wages |   .3878741   .0824177    4.71   0.000    - .2263383   .5494099
      E_unem  |  -.0674207   .020196    -3.34   0.001    - .1070042  -.0278372
E_budget_def |  -.0002017   .0003153    -0.64   0.522    - .0008198   .0004163
m3_crisis08  |   .0731806   .1257274     0.58   0.561    - .1732405   .3196017
m3_recess11  |   .1261022   .0970971     1.30   0.194    - .0642047   .316409
m3_euzone    |   .0292781   .0867142     0.34   0.736    - .1406785   .1992348
crisis08     |  -1.572344   .5623288    -2.80   0.005    -2.674488  -.4701999
recess11     |  -.6775388   .3853542    -1.76   0.079    -1.432819   .0777415
      _cons  |   1.234735   .3367694     3.67   0.000    - .5746787   1.894791
-----+-----
      sigma_u |   .55080351
      sigma_e |   .65145904
      rho     |   .416861   (fraction of variance due to u_i)
-----+-----
Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def m3_crisis08 m3_recess11 m3_euzone
               crisis08 recess11 E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1
               E_y10lag2 E_y10lag3
-----+-----

.
.
.
end of do-file

```

■ A.3. STATA code of time series analysis

```

-----
.
. * Set Time Variable
. gen date = ym(year,month)

. format date %tm

. * to use if with date: if date<=>tm(2001m8)
.
. * Set panel structure
. xtset country_id date
      panel variable:  country_id (strongly balanced)
      time variable:   date, 1993m1 to 2014m12
      delta:           1 month

. *-----*
.
. * Countries:
. * "Australia", "Canada", "France", "Germany", "Italy", "Japan", "Netherlands", "NewZealand",
"Norway", "Spain", "Sweden",
> "Switzerland", "UK", "USA"
. * "Australia Canada France Germany Italy Japan Netherlands NewZealand Norway Spain Sweden Switzerland
UK USA"
. * Ordered countries (Eurozone, EU, others): "France Germany Italy Netherlands Spain Norway Sweden
Switzerland UK Australia
> Canada Japan NewZealand USA"

.
. * all countries
. global c_all "France Germany Italy Netherlands Spain Norway Sweden Switzerland UK Australia Canada
Japan NewZealand USA"

.
. * (a) Eurozone countries with all controls available
. global eu_c_unemp "France Germany Italy"

.
. * (b) countries with no data on unemployment
. global eu_c_nounemp "Netherlands Spain Norway Sweden"

.
. * (c) Switzerland

.
. * (d) other countries with all controls available
. global other_c_unemp "UK Australia Canada Japan NewZealand USA"

.
. *-----*
.
. * (1)
. * OLS classic model

.
. foreach y of global c_all {
2.      newey2 E_cons E_m3 if country=="`y'", lag(12)
3.  }

Regression with Newey-West standard errors      Number of obs   =       264
maximum lag : 12                               F( 1,   262)     =      20.31
                                              Prob > F         =      0.0000
-----

```

| Newey-West

E_cons	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3373339	.0748588	4.51	0.000	.1899324	.4847353
_cons	.6750441	.2147813	3.14	0.002	.2521269	1.097961

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 264
F(1, 262) = 0.23
Prob > F = 0.6347

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0536224	.112732	0.48	0.635	-.1683537	.2755985
_cons	.953575	.2887467	3.30	0.001	.3850155	1.522135

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 264
F(1, 262) = 3.12
Prob > F = 0.0784

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1409404	.079771	1.77	0.078	-.0161335	.2980143
_cons	.5103942	.3931635	1.30	0.195	-.2637682	1.284557

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 240
F(1, 238) = 73.41
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.7538915	.0879882	8.57	0.000	.5805565	.9272266
_cons	-.8704059	.2701924	-3.22	0.001	-1.40268	-.3381318

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 240
F(1, 238) = 6.35
Prob > F = 0.0124

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.4040235	.1603071	2.52	0.012	.0882215	.7198255
_cons	.5752083	.6815753	0.84	0.400	-.7674824	1.917899

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 199
F(1, 197) = 0.18
Prob > F = 0.6692

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
--------	-------	-------------------------	---	------	----------------------	--

E_m3		-.0367207	.0858259	-0.43	0.669	-.2059761	.1325347
_cons		2.981992	.4585991	6.50	0.000	2.077598	3.886385

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 240
F(1, 238) = 0.29
Prob > F = 0.5934

E_cons		Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3		-.0795989	.1488699	-0.53	0.593	-.3728699	.213672
_cons		2.570279	.5407826	4.75	0.000	1.504947	3.635611

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 199
F(1, 197) = 6.76
Prob > F = 0.0100

E_cons		Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3		.2049492	.0788353	2.60	0.010	.0494798	.3604187
_cons		1.182019	.1926573	6.14	0.000	.8020838	1.561954

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 264
F(1, 262) = 16.81
Prob > F = 0.0001

E_cons		Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3		.3543419	.0864225	4.10	0.000	.1841709	.5245129
_cons		.5124108	.4941283	1.04	0.301	-.4605573	1.485379

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 228
F(1, 226) = 5.80
Prob > F = 0.0168

E_cons		Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3		.2003901	.0831852	2.41	0.017	.0364722	.3643079
_cons		2.043912	.4879006	4.19	0.000	1.082495	3.005328

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 264
F(1, 262) = 5.55
Prob > F = 0.0193

E_cons		Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3		.159288	.0676339	2.36	0.019	.0261128	.2924632
_cons		2.055342	.2623957	7.83	0.000	1.538669	2.572015

```

-----
Regression with Newey-West standard errors      Number of obs =      264
maximum lag : 12                               F( 1, 262) =      16.14
                                              Prob > F      =      0.0001

```

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.551717	.1373136	4.02	0.000	.2813383	.8220957
_cons	.7136944	.1596529	4.47	0.000	.3993283	1.028061

```

-----
Regression with Newey-West standard errors      Number of obs =      228
maximum lag : 12                               F( 1, 226) =      1.81
                                              Prob > F      =      0.1804

```

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1147921	.0854382	1.34	0.180	-.0535653	.2831494
_cons	1.679415	.5572192	3.01	0.003	.5814058	2.777425

```

-----
Regression with Newey-West standard errors      Number of obs =      264
maximum lag : 12                               F( 1, 262) =      7.47
                                              Prob > F      =      0.0067

```

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1894422	.0692983	2.73	0.007	.0529898	.3258947
_cons	1.989905	.3192831	6.23	0.000	1.361217	2.618592

```

. *
. *-----*
.
. * (2)
. * OLS IV (all)
.
. foreach y of global c_all {
. 2.      ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) if
country=="`y'", bw(12) r
> obust
. 3.
. }

```

IV (2SLS) estimation

```

-----
Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
  kernel=Bartlett; bandwidth= 12
  time variable (t): date

```

```

                                              Number of obs =      264
                                              F( 1, 262) =      16.96
                                              Prob > F      =      0.0001
Total (centered) SS      =      169.388111    Centered R2      =      0.4638

```

Total (uncentered) SS = 931.1705101 Uncentered R2 = 0.9025
Residual SS = 90.83436455 Root MSE = .5866

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.3128389	.0756771	4.13	0.000	.1645144	.4611634
_cons	.7493744	.2363767	3.17	0.002	.2860846	1.212664

Underidentification test (Kleibergen-Paap rk LM statistic): 10.694
Chi-sq(6) P-val = 0.0983

Weak identification test (Cragg-Donald Wald F statistic): 106.588
(Kleibergen-Paap rk Wald F statistic): 62.998

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 1.044
Chi-sq(5) P-val = 0.9590

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	264
		F(1, 262) =	0.37
		Prob > F =	0.5432
Total (centered) SS	=	184.3454006	
Total (uncentered) SS	=	513.681656	
Residual SS	=	182.7550051	
		Centered R2 =	0.0086
		Uncentered R2 =	0.6442
		Root MSE =	.832

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0710755	.1163121	0.61	0.541	-.1568921	.2990431
_cons	.9004128	.2985154	3.02	0.003	.3153333	1.485492

Underidentification test (Kleibergen-Paap rk LM statistic): 10.829
Chi-sq(6) P-val = 0.0938

Weak identification test (Cragg-Donald Wald F statistic): 102.119
(Kleibergen-Paap rk Wald F statistic): 80.275

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23

20% maximal IV size 11.72
 25% maximal IV size 9.38
 Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.265
 Chi-sq(5) P-val = 0.8114

Instrumented: E_m3
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

		Number of obs =	264
		F(1, 262) =	2.72
		Prob > F =	0.1002
Total (centered) SS	=	Centered R2 =	0.1257
Total (uncentered) SS	=	Uncentered R2 =	0.5710
Residual SS	=	Root MSE =	.9703

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0903696	.0545755	1.66	0.098	-.0165964	.1973355
_cons	.7066102	.3250601	2.17	0.030	.0695042	1.343716

Underidentification test (Kleibergen-Paap rk LM statistic): 8.551
 Chi-sq(6) P-val = 0.2004

Weak identification test (Cragg-Donald Wald F statistic): 148.411
 (Kleibergen-Paap rk Wald F statistic): 99.535

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 4.172
 Chi-sq(5) P-val = 0.5249

Instrumented: E_m3
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

Total (centered) SS	=	480.0088573	Number of obs =	226
Total (uncentered) SS	=	809.1288201	F(1, 224) =	80.18
Residual SS	=	189.2006036	Prob > F	= 0.0000
			Centered R2	= 0.6058
			Uncentered R2	= 0.7662
			Root MSE	= .915

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.870891	.0968268	8.99	0.000	.681114	1.060668
_cons	-1.144863	.3522956	-3.25	0.001	-1.83535	-.4543768

Underidentification test (Kleibergen-Paap rk LM statistic): 10.333
Chi-sq(6) P-val = 0.1113

Weak identification test (Cragg-Donald Wald F statistic): 105.060
(Kleibergen-Paap rk Wald F statistic): 20.543

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.432
Chi-sq(5) P-val = 0.7867

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	752.2609036	Number of obs =	226
Total (uncentered) SS	=	1561.768352	F(1, 224) =	7.52
Residual SS	=	475.0716448	Prob > F	= 0.0066
			Centered R2	= 0.3685
			Uncentered R2	= 0.6958
			Root MSE	= 1.45

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.4453731	.1616647	2.75	0.006	.128516	.7622301
_cons	.5734575	.6489051	0.88	0.377	-.698373	1.845288

Underidentification test (Kleibergen-Paap rk LM statistic): 8.084
Chi-sq(6) P-val = 0.2320

Weak identification test (Cragg-Donald Wald F statistic): 97.065
(Kleibergen-Paap rk Wald F statistic): 29.971

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12

20% maximal	IV relative bias	6.76
30% maximal	IV relative bias	5.15
10% maximal	IV size	29.18
15% maximal	IV size	16.23
20% maximal	IV size	11.72
25% maximal	IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 1.226
Chi-sq(5) P-val = 0.9423

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	185
		F(1, 183) =	0.27
		Prob > F =	0.6052
Total (centered) SS	=	132.2165151	
Total (uncentered) SS	=	1662.668967	
Residual SS	=	131.9098311	
		Centered R2 =	0.0023
		Uncentered R2 =	0.9207
		Root MSE =	.8444

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	-.0347401	.0667318	-0.52	0.603	-.165532 .0960519
_cons	3.017383	.3491502	8.64	0.000	2.333061 3.701705

Underidentification test (Kleibergen-Paap rk LM statistic): 9.411
Chi-sq(6) P-val = 0.1517

Weak identification test (Cragg-Donald wald F statistic): 103.983
(Kleibergen-Paap rk wald F statistic): 27.025

Stock-Yogo weak ID test critical values:

5% maximal	IV relative bias	19.28
10% maximal	IV relative bias	11.12
20% maximal	IV relative bias	6.76
30% maximal	IV relative bias	5.15
10% maximal	IV size	29.18
15% maximal	IV size	16.23
20% maximal	IV size	11.72
25% maximal	IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 4.384
Chi-sq(5) P-val = 0.4955

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and autocorrelation

kernel=Bartlett; bandwidth= 12

time variable (t): date

		Number of obs =	226
		F(1, 224) =	0.58
		Prob > F =	0.4488
Total (centered) SS	=	Centered R2 =	0.1011
Total (uncentered) SS	=	Uncentered R2 =	0.9058
Residual SS	=	Root MSE =	.7802

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1131785	.1485122	0.76	0.446	-.1779001	.4042571
_cons	2.027	.5010379	4.05	0.000	1.044984	3.009017

Underidentification test (Kleibergen-Paap rk LM statistic): 11.131
Chi-sq(6) P-val = 0.0844

Weak identification test (Cragg-Donald wald F statistic): 121.713

(Kleibergen-Paap rk wald F statistic): 20.513

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 7.610
Chi-sq(5) P-val = 0.1791

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and autocorrelation

kernel=Bartlett; bandwidth= 12

time variable (t): date

		Number of obs =	185
		F(1, 183) =	2.02
		Prob > F =	0.1567
Total (centered) SS	=	Centered R2 =	0.1926
Total (uncentered) SS	=	Uncentered R2 =	0.9294
Residual SS	=	Root MSE =	.4103

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1037438	.0725627	1.43	0.153	-.0384764	.245964
_cons	1.327226	.1594371	8.32	0.000	1.014735	1.639717

Underidentification test (Kleibergen-Paap rk LM statistic): 10.099
Chi-sq(6) P-val = 0.1205

```

weak identification test (Cragg-Donald wald F statistic):          95.838
(Kleibergen-Paap rk wald F statistic):                          27.803
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias  19.28
                                           10% maximal IV relative bias  11.12
                                           20% maximal IV relative bias   6.76
                                           30% maximal IV relative bias   5.15
                                           10% maximal IV size          29.18
                                           15% maximal IV size          16.23
                                           20% maximal IV size          11.72
                                           25% maximal IV size           9.38

```

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```

-----
Hansen J statistic (overidentification test of all instruments):    6.327
                                                                    Chi-sq(5) P-val = 0.2757
-----

```

```

Instrumented:      E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
                  E_y10lag3
-----

```

IV (2SLS) estimation

```

-----
Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

```

				Number of obs =	264
				F(1, 262) =	21.18
				Prob > F =	0.0000
Total (centered) SS	=	343.1153246		Centered R2 =	0.4732
Total (uncentered) SS	=	1463.730826		Uncentered R2 =	0.8765
Residual SS	=	180.757162		Root MSE =	.8275

		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_cons						
E_m3		.3181262	.0688696	4.62	0.000	.1831442 .4531081
_cons		.6706117	.389562	1.72	0.085	-.0929159 1.434139

```

-----
Underidentification test (Kleibergen-Paap rk LM statistic):      11.594
                                                                    Chi-sq(6) P-val = 0.0717
-----

```

```

weak identification test (Cragg-Donald wald F statistic):          181.510
(Kleibergen-Paap rk wald F statistic):                          30.835
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias  19.28
                                           10% maximal IV relative bias  11.12
                                           20% maximal IV relative bias   6.76
                                           30% maximal IV relative bias   5.15
                                           10% maximal IV size          29.18
                                           15% maximal IV size          16.23
                                           20% maximal IV size          11.72
                                           25% maximal IV size           9.38

```

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```

-----
Hansen J statistic (overidentification test of all instruments):    2.041
                                                                    Chi-sq(5) P-val = 0.8435
-----

```

```

Instrumented:      E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
                  E_y10lag3
-----

```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	90.4518176	Number of obs =	214
Total (uncentered) SS	=	2156.389959	F(1, 212) =	14.10
Residual SS	=	69.29905305	Prob > F	= 0.0002
			Centered R2	= 0.2339
			Uncentered R2	= 0.9679
			Root MSE	= .5691

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.3377392	.0895257	3.77	0.000	.1622722	.5132063
_cons	1.385741	.5011754	2.76	0.006	.4034556	2.368027

Underidentification test (Kleibergen-Paap rk LM statistic): 9.306
Chi-sq(6) P-val = 0.1571

Weak identification test (Cragg-Donald Wald F statistic): 72.210

(Kleibergen-Paap rk Wald F statistic): 21.829

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.400
Chi-sq(5) P-val = 0.6385

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	105.0325978	Number of obs =	264
Total (uncentered) SS	=	1924.607497	F(1, 262) =	2.20
Residual SS	=	88.25184595	Prob > F	= 0.1396
			Centered R2	= 0.1598
			Uncentered R2	= 0.9541
			Root MSE	= .5782

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0978392	.0657706	1.49	0.137	-.0310689	.2267473
_cons	2.275225	.2697586	8.43	0.000	1.746508	2.803942

```
-----
Underidentification test (Kleibergen-Paap rk LM statistic):      12.119
Chi-sq(6) P-val =      0.0594
-----
```

```
Weak identification test (Cragg-Donald Wald F statistic):      158.034
(Kleibergen-Paap rk Wald F statistic):      74.325
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias  19.28
                                           10% maximal IV relative bias  11.12
                                           20% maximal IV relative bias   6.76
                                           30% maximal IV relative bias   5.15
                                           10% maximal IV size          29.18
                                           15% maximal IV size          16.23
                                           20% maximal IV size          11.72
                                           25% maximal IV size           9.38
```

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```
-----
Hansen J statistic (overidentification test of all instruments):  1.813
Chi-sq(5) P-val =      0.8744
-----
```

```
Instrumented:      E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
                  E_y10lag3
-----
```

IV (2SLS) estimation

```
-----
Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date
```

```

Total (centered) SS      = 173.7148375
Total (uncentered) SS    = 498.4516796
Residual SS              = 138.1493734

Number of obs =      264
F( 1, 262) =      13.50
Prob > F      =      0.0003
Centered R2    =      0.2047
Uncentered R2  =      0.7228
Root MSE      =      .7234
```

```
-----
      E_cons |      Coef.      Robust      z      P>|z|      [95% Conf. Interval]
      +-----+-----+-----+-----+-----+
      E_m3 | .8423218   .2283772   3.69   0.000   .3947106   1.289933
      _cons | .5054325   .1716028   2.95   0.003   .1690972   .8417678
-----
```

```
-----
Underidentification test (Kleibergen-Paap rk LM statistic):      5.708
Chi-sq(6) P-val =      0.4567
-----
```

```
Weak identification test (Cragg-Donald Wald F statistic):      107.194
(Kleibergen-Paap rk Wald F statistic):      24.646
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias  19.28
                                           10% maximal IV relative bias  11.12
                                           20% maximal IV relative bias   6.76
                                           30% maximal IV relative bias   5.15
                                           10% maximal IV size          29.18
                                           15% maximal IV size          16.23
                                           20% maximal IV size          11.72
                                           25% maximal IV size           9.38
```

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```
-----
Hansen J statistic (overidentification test of all instruments):  3.460
Chi-sq(5) P-val =      0.6294
-----
```

```
Instrumented:      E_m3
```

Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	214
		F(1, 212) =	0.11
		Prob > F =	0.7391
		Centered R2 =	0.0134
		Uncentered R2 =	0.9120
		Root MSE =	.7126
Total (centered) SS	=	110.1308895	
Total (uncentered) SS	=	1234.73353	
Residual SS	=	108.6552948	

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0218228	.0651241	0.34	0.738	-.1058181	.1494636
_cons	2.169678	.4074631	5.32	0.000	1.371065	2.968291

Underidentification test (Kleibergen-Paap rk LM statistic): 9.506
Chi-sq(6) P-val = 0.1470

Weak identification test (Cragg-Donald wald F statistic): 67.867
(Kleibergen-Paap rk wald F statistic): 42.342
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72
25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 5.435
Chi-sq(5) P-val = 0.3651

Instrumented: E_m3
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	264
		F(1, 262) =	8.03
		Prob > F =	0.0050
		Centered R2 =	0.2175
		Uncentered R2 =	0.9277
		Root MSE =	.7319
Total (centered) SS	=	180.7201837	
Total (uncentered) SS	=	1956.411115	
Residual SS	=	141.4203592	

	Robust
--	--------

_cons	-1.084568	1.186377	-0.91	0.361	-3.420913	1.251776
-------	-----------	----------	-------	-------	-----------	----------

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 260
F(4, 255) = 4.36
Prob > F = 0.0020

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0942183	.1225789	0.77	0.443	-.1471777	.3356142
E_wages	.4568992	.3251111	1.41	0.161	-.1833456	1.097144
E_unem	.1672567	.1392801	1.20	0.231	-.1070292	.4415425
E_budget_def	.0091797	.0049927	1.84	0.067	-.0006525	.0190119
_cons	-1.204466	1.51537	-0.79	0.427	-4.188701	1.779768

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 260
F(4, 255) = 1.79
Prob > F = 0.1315

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2666466	.1274781	2.09	0.037	.0156026	.5176907
E_wages	-.0042455	.2855463	-0.01	0.988	-.5665749	.5580838
E_unem	-.0216132	.0788367	-0.27	0.784	-.1768672	.1336408
E_budget_def	.0096063	.0052598	1.83	0.069	-.0007518	.0199644
_cons	.8767589	.7117855	1.23	0.219	-.5249679	2.278486

```
. *
.
. * Eu countries without unemployment (b)
. foreach y of global eu_c_nounemp {
2.     newey2 E_cons E_m3 E_wages E_budget_def if country=="`y'", lag(12)
3.
. }
```

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 58
F(3, 54) = 71.74
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.739593	.1260767	5.87	0.000	.4868245	.9923615
E_wages	-1.425989	.2944422	-4.84	0.000	-2.01631	-.8356681
E_budget_def	.073334	.0264117	2.78	0.008	.0203817	.1262863
_cons	3.256895	.8661965	3.76	0.000	1.520275	4.993514

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 58
F(3, 54) = 0.75
Prob > F = 0.5265

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
--------	-------	-------------------------	---	------	----------------------	--

E_m3		.6496614	.6071648	1.07	0.289	-.5676307	1.866953
E_wages		-.6083252	.666743	-0.91	0.366	-1.945064	.7284139
E_budget_def		-.0089703	.0214817	-0.42	0.678	-.0520386	.0340979
_cons		-.7400828	1.865572	-0.40	0.693	-4.48033	3.000165

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 58
F(3, 54) = 5.61
Prob > F = 0.0020

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]
E_m3	.116341	.1625214	0.72	0.477	-.2094947 .4421767
E_wages	.8349749	.3810017	2.19	0.033	.0711124 1.598837
E_budget_def	-.0026577	.0018596	-1.43	0.159	-.0063859 .0010705
_cons	.4057162	1.041448	0.39	0.698	-1.682262 2.493695

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 58
F(3, 54) = 0.70
Prob > F = 0.5538

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]
E_m3	.1536994	.2517078	0.61	0.544	-.3509443 .6583431
E_wages	-.3991306	.334369	-1.19	0.238	-1.0695 .2712389
E_budget_def	-.0034738	.0061921	-0.56	0.577	-.0158883 .0089407
_cons	2.967277	1.112269	2.67	0.010	.7373116 5.197243

```
. *
.
. * Switzerland without unemployment and wages (c)
. newey2 E_cons E_m3 E_budget_def if country=="Switzerland", lag(12)
```

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 58
F(2, 55) = 2.06
Prob > F = 0.1367

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]
E_m3	.0764442	.1658244	0.46	0.647	-.2558754 .4087638
E_budget_def	.0404409	.0202804	1.99	0.051	-.0002019 .0810836
_cons	1.474794	.165567	8.91	0.000	1.14299 1.806597

```
.
.
. * Other countries with all controls (d)
. foreach y of global other_c_unemp {
2.     newey2 E_cons E_m3 E_budget_def E_wages E_unem if country=="`y'", lag(12) force
3.
. }
```

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 260
F(4, 255) = 14.29
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1673507	.109425	1.53	0.127	-.0481412	.3828426
E_budget_def	-.0220831	.0069686	-3.17	0.002	-.0358065	-.0083597
E_wages	-.5337202	.3170308	-1.68	0.094	-1.158052	.0906119
E_unem	-.0248587	.0338377	-0.73	0.463	-.0914956	.0417782
_cons	4.591118	1.389372	3.30	0.001	1.855012	7.327224

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 228
F(4, 223) = 4.18
Prob > F = 0.0028

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2142375	.0875259	2.45	0.015	.0417539	.3867212
E_budget_def	.0188375	.0057377	3.28	0.001	.0075305	.0301445
E_wages	-.9232747	.3536846	-2.61	0.010	-1.620266	-.2262829
E_unem	.0048344	.0617286	0.08	0.938	-.1168117	.1264805
_cons	5.422463	.9923067	5.46	0.000	3.466965	7.377961

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 125
F(4, 120) = 12.83
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3109105	.1028344	3.02	0.003	.1073056	.5145154
E_budget_def	-.0076817	.0166046	-0.46	0.644	-.0405576	.0251942
E_wages	.2089281	.2451439	0.85	0.396	-.2764398	.694296
E_unem	-.4468369	.3994043	-1.12	0.265	-1.23763	.3439557
_cons	4.311597	2.760596	1.56	0.121	-1.154192	9.777385

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 260
F(4, 255) = 22.11
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.4006016	.1791631	2.24	0.026	.0477738	.7534293
E_budget_def	-.0065525	.0097875	-0.67	0.504	-.0258271	.0127222
E_wages	.4471515	.1060548	4.22	0.000	.2382967	.6560063
E_unem	.0254098	.1792641	0.14	0.887	-.3276169	.3784365
_cons	.2524935	.8880005	0.28	0.776	-1.496255	2.001242

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 228
F(4, 223) = 15.12
Prob > F = 0.0000

| Newey-West

E_cons	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2249799	.0719092	3.13	0.002	.0832713	.3666885
E_budget_def	.0065144	.0244323	0.27	0.790	-.0416334	.0546622
E_wages	-2.24233	.3299454	-6.80	0.000	-2.89254	-1.59212
E_unem	-.4467287	.1076098	-4.15	0.000	-.658791	-.2346664
_cons	8.767734	1.099021	7.98	0.000	6.601939	10.93353

Regression with Newey-West standard errors
maximum lag : 12

Number of obs = 259
F(4, 254) = 6.29
Prob > F = 0.0001

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.0107525	.0795129	-0.14	0.893	-.167341	.1458361
E_budget_def	-.0000479	.00084	-0.06	0.955	-.0017021	.0016062
E_wages	.2195404	.3349156	0.66	0.513	-.4400247	.8791056
E_unem	-.2497508	.147402	-1.69	0.091	-.5400366	.040535
_cons	3.449906	1.071562	3.22	0.001	1.339628	5.560184

```
. *
. *-----*
. * (16)
. * OLS with dummies
.
. foreach y of global c_all {
2.     newey E_cons E_m3 m3_crisis08 m3_recess11 crisis08 recess11 if country=="`y'", lag(12)
3.
. }
```

Regression with Newey-West standard errors
maximum lag: 12

Number of obs = 264
F(5, 258) = 58.40
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2773628	.0814891	3.40	0.001	.1168943	.4378313
m3_crisis08	.1710308	.1031439	1.66	0.098	-.0320802	.3741419
m3_recess11	.3128857	.1000448	3.13	0.002	.1158773	.509894
crisis08	-1.277301	.2863297	-4.46	0.000	-1.841142	-.7134598
recess11	-1.021189	.2451389	-4.17	0.000	-1.503917	-.5384615
_cons	.9614735	.2397821	4.01	0.000	.4892941	1.433653

Regression with Newey-West standard errors
maximum lag: 12

Number of obs = 264
F(5, 258) = 530.97
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0287597	.1288952	0.22	0.824	-.2250609	.2825803
m3_crisis08	.3607732	.1341665	2.69	0.008	.0965723	.6249741
m3_recess11	-.0833622	.1361369	-0.61	0.541	-.3514431	.1847187
crisis08	-1.743146	.3510826	-4.97	0.000	-2.434499	-1.051794
recess11	-.0115533	.3522644	-0.03	0.974	-.7052328	.6821262
_cons	1.079576	.3492077	3.09	0.002	.3919158	1.767236

Regression with Newey-West standard errors Number of obs = 264
maximum lag: 12 F(5, 258) = 60.40
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0612726	.0710679	0.86	0.389	-.0786744	.2012196
m3_crisis08	.4084333	.0825922	4.95	0.000	.2457926	.571074
m3_recess11	1.04718	.2747652	3.81	0.000	.5061122	1.588248
crisis08	-2.473207	.3506803	-7.05	0.000	-3.163767	-1.782647
recess11	-2.937292	.4295196	-6.84	0.000	-3.783102	-2.091481
_cons	1.053484	.3435855	3.07	0.002	.3768948	1.730073

Regression with Newey-West standard errors Number of obs = 240
maximum lag: 12 F(5, 234) = 91.31
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.7257261	.0996507	7.28	0.000	.5293989	.9220533
m3_crisis08	.1558977	.1138386	1.37	0.172	-.0683818	.3801772
m3_recess11	.0737762	.1781877	0.41	0.679	-.2772809	.4248333
crisis08	-1.167816	.3481178	-3.35	0.001	-1.853661	-.4819701
recess11	-.3256674	.3564952	-0.91	0.362	-1.028018	.3766829
_cons	-.7206004	.3404185	-2.12	0.035	-1.391277	-.0499237

Regression with Newey-West standard errors Number of obs = 240
maximum lag: 12 F(5, 234) = 174.83
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2633088	.1379716	1.91	0.058	-.0085164	.5351339
m3_crisis08	.9973768	.1669537	5.97	0.000	.6684524	1.326301
m3_recess11	1.848799	.172791	10.70	0.000	1.508375	2.189224
crisis08	-5.359242	.6245978	-8.58	0.000	-6.589796	-4.128689
recess11	-4.204202	.6384276	-6.59	0.000	-5.462003	-2.946402
_cons	1.431061	.6329333	2.26	0.025	.1840854	2.678037

Regression with Newey-West standard errors Number of obs = 199
maximum lag: 12 F(5, 193) = 28.37
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.1034444	.0764243	-1.35	0.177	-.2541785	.0472897
m3_crisis08	.8796965	.1263471	6.96	0.000	.6304981	1.128895
m3_recess11	-.32062	.2222781	-1.44	0.151	-.7590261	.1177862
crisis08	-5.20056	.6056187	-8.59	0.000	-6.395041	-4.006079
recess11	.7375407	.6720735	1.10	0.274	-.5880111	2.063093
_cons	3.390079	.3744652	9.05	0.000	2.651509	4.128649

Regression with Newey-West standard errors Number of obs = 240

maximum lag: 12

F(5, 234) = 215.52
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.181018	.1292702	-1.40	0.163	-.4357002	.0736643
m3_crisis08	.9089142	.1341451	6.78	0.000	.6446278	1.173201
m3_recess11	.2345529	.244852	0.96	0.339	-.2478432	.716949
crisis08	-4.11526	.4749547	-8.66	0.000	-5.050993	-3.179526
recess11	-1.536337	.688082	-2.23	0.027	-2.891964	-.1807097
_cons	3.124568	.4742978	6.59	0.000	2.190128	4.059007

Regression with Newey-West standard errors
maximum lag: 12

Number of obs = 199
F(5, 193) = 341.80
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1720358	.0896138	1.92	0.056	-.0047123	.3487839
m3_crisis08	.4347144	.0886746	4.90	0.000	.2598186	.6096102
m3_recess11	-.1078501	1.864108	-0.06	0.954	-3.784489	3.568788
crisis08	-1.233617	.2104904	-5.86	0.000	-1.648774	-.8184604
recess11	-.0258291	.2350318	-0.11	0.913	-.4893897	.4377316
_cons	1.277068	.2145361	5.95	0.000	.8539317	1.700204

Regression with Newey-West standard errors
maximum lag: 12

Number of obs = 264
F(5, 258) = 1984.90
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2773425	.0819436	3.38	0.001	.1159791	.438706
m3_crisis08	.5894083	.1007125	5.85	0.000	.391085	.7877316
m3_recess11	-1.073327	.2242805	-4.79	0.000	-1.51498	-.6316734
crisis08	-4.044773	.4659538	-8.68	0.000	-4.96233	-3.127216
recess11	.40815	.4776372	0.85	0.394	-.5324139	1.348714
_cons	1.017372	.4474613	2.27	0.024	.1362303	1.898513

Regression with Newey-West standard errors
maximum lag: 12

Number of obs = 228
F(5, 222) = 702.69
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.139455	.0685455	2.03	0.043	.0043718	.2745381
m3_crisis08	.3725817	.0709856	5.25	0.000	.2326899	.5124735
m3_recess11	-.0594654	.1138504	-0.52	0.602	-.2838312	.1649004
crisis08	-3.107483	.3920196	-7.93	0.000	-3.880039	-2.334927
recess11	.1251056	.511675	0.24	0.807	-.8832561	1.133467
_cons	2.454995	.3783589	6.49	0.000	1.70936	3.20063

Regression with Newey-West standard errors
maximum lag: 12

Number of obs = 264
F(5, 258) = 338.91
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0883071	.0561023	1.57	0.117	-.0221697	.1987838
m3_crisis08	1.213826	.090325	13.44	0.000	1.035958	1.391694
m3_recess11	.2708036	.2084656	1.30	0.195	-.1397072	.6813144
crisis08	-2.935609	.2348539	-12.50	0.000	-3.398083	-2.473134
recess11	-.7427187	.3202706	-2.32	0.021	-1.373396	-.1120414
_cons	2.372077	.215553	11.00	0.000	1.94761	2.796544

note: recess11 omitted because of collinearity

Regression with Newey-West standard errors Number of obs = 264
maximum lag: 12 F(4, 259) = 86.68
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.5455005	.144327	3.78	0.000	.2612966	.8297043
m3_crisis08	2.335592	.215159	10.86	0.000	1.911909	2.759276
m3_recess11	-.0595528	.610527	-0.10	0.922	-1.261781	1.142676
crisis08	-2.540256	.2299415	-11.05	0.000	-2.993049	-2.087463
recess11	0 (omitted)					
_cons	.7643946	.1755407	4.35	0.000	.4187259	1.110063

Regression with Newey-West standard errors Number of obs = 228
maximum lag: 12 F(5, 222) = 160.90
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0702253	.0787842	0.89	0.374	-.0850353	.225486
m3_crisis08	.2018304	.0986352	2.05	0.042	.0074493	.3962115
m3_recess11	-.0820909	.0993036	-0.83	0.409	-.2777892	.1136074
crisis08	-2.913001	.6034842	-4.83	0.000	-4.102292	-1.72371
recess11	.1991473	.5473966	0.36	0.716	-.8796113	1.277906
_cons	2.07143	.4984413	4.16	0.000	1.089149	3.053712

Regression with Newey-West standard errors Number of obs = 264
maximum lag: 12 F(5, 258) = 43.46
Prob > F = 0.0000

E_cons	Coef.	Newey-West Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1053219	.0521001	2.02	0.044	.0027264	.2079174
m3_crisis08	.72961	.1663428	4.39	0.000	.4020475	1.057172
m3_recess11	1.811918	.8374791	2.16	0.031	.1627527	3.461083
crisis08	-3.21075	.3782952	-8.49	0.000	-3.95569	-2.465811
recess11	-.6038579	.2329149	-2.59	0.010	-1.062514	-.1452015
_cons	2.419557	.2045595	11.83	0.000	2.016738	2.822376

. *
.
.

.
* (17)
* OLS IV with dummies

```

. foreach y of global c_all {
.   2.       ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3)
m3_crisis08 m3_recess11 cri
> sis08 recess11 if country=="`y'", bw(12) robust
.   3.
. }

```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	169.388111	Number of obs =	264
Total (uncentered) SS	=	931.1705101	F(5, 258) =	56.91
Residual SS	=	74.5060602	Prob > F	= 0.0000
			Centered R2	= 0.5601
			Uncentered R2	= 0.9200
			Root MSE	= .5312

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	.2261287	.0858616	2.63	0.008	.0578431 .3944143
m3_crisis08	.2222649	.1061321	2.09	0.036	.0142498 .4302799
m3_recess11	.3641197	.1055448	3.45	0.001	.1572557 .5709836
crisis08	-1.443109	.3247544	-4.44	0.000	-2.079616 -.8066021
recess11	-1.186998	.2883102	-4.12	0.000	-1.752076 -.6219202
_cons	1.127282	.2843677	3.96	0.000	.5699313 1.684632

Underidentification test (Kleibergen-Paap rk LM statistic): 9.391
Chi-sq(6) P-val = 0.1528

Weak identification test (Cragg-Donald Wald F statistic): 94.957
(Kleibergen-Paap rk Wald F statistic): 42.522

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.059
Chi-sq(5) P-val = 0.8409

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	184.3454006	Number of obs =	264
Total (uncentered) SS	=	513.681656	F(5, 258) =	477.52
Residual SS	=	171.4533054	Prob > F =	0.0000
			Centered R2 =	0.0699
			Uncentered R2 =	0.6662
			Root MSE =	.8059

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.042537	.1351918	0.31	0.753	-.2224341	.3075082
m3_crisis08	.3469958	.1412663	2.46	0.014	.070119	.6238727
m3_recess11	-.0971396	.1426537	-0.68	0.496	-.3767357	.1824566
crisis08	-1.698265	.3815415	-4.45	0.000	-2.446072	-.9504572
recess11	.0333281	.3819322	0.09	0.930	-.7152453	.7819014
_cons	1.034695	.3786817	2.73	0.006	.2924921	1.776897

Underidentification test (Kleibergen-Paap rk LM statistic): 9.023
Chi-sq(6) P-val = 0.1723

Weak identification test (Cragg-Donald Wald F statistic): 80.462
(Kleibergen-Paap rk Wald F statistic): 42.087

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.774
Chi-sq(5) P-val = 0.7348

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	284.2989264	Number of obs =	264
Total (uncentered) SS	=	579.3900718	F(5, 258) =	61.11
Residual SS	=	147.0281001	Prob > F =	0.0000
			Centered R2 =	0.4828
			Uncentered R2 =	0.7462
			Root MSE =	.7463

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0335021	.0562397	0.60	0.551	-.0767257	.1437298
m3_crisis08	.4362038	.0706762	6.17	0.000	.2976811	.5747265
m3_recess11	1.074951	.2624418	4.10	0.000	.5605742	1.589327
crisis08	-2.589959	.3043972	-8.51	0.000	-3.186566	-1.993351
recess11	-3.054044	.3774168	-8.09	0.000	-3.793767	-2.314321

_cons		1.170236	.2961818	3.95	0.000	.5897301	1.750741
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Underidentification test (Kleibergen-Paap rk LM statistic): 8.383
Chi-sq(6) P-val = 0.2114

Weak identification test (Cragg-Donald Wald F statistic): 173.728
(Kleibergen-Paap rk Wald F statistic): 114.471

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.872
Chi-sq(5) P-val = 0.5680

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	226
		F(5, 220) =	107.58
		Prob > F =	0.0000
Total (centered) SS	=	480.0088573	Centered R2 = 0.6241
Total (uncentered) SS	=	809.1288201	Uncentered R2 = 0.7770
Residual SS	=	180.4257749	Root MSE = .8935

E_cons		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3		.8711204	.126747	6.87	0.000	.6227008 1.11954
m3_crisis08		.0105034	.1395627	0.08	0.940	-.2630346 .2840414
m3_recess11		-.0716181	.1954281	-0.37	0.714	-.4546501 .3114139
crisis08		-.7983647	.5057161	-1.58	0.114	-1.78955 .1928206
recess11		.0437835	.5063015	0.09	0.931	-.9485493 1.036116
_cons		-1.090051	.4961403	-2.20	0.028	-2.062468 -.1176342

Underidentification test (Kleibergen-Paap rk LM statistic): 8.277
Chi-sq(6) P-val = 0.2185

Weak identification test (Cragg-Donald Wald F statistic): 84.370
(Kleibergen-Paap rk Wald F statistic): 14.066

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 1.704
Chi-sq(5) P-val = 0.8884

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Number of obs = 226
F(5, 220) = 178.41
Prob > F = 0.0000
Centered R2 = 0.6188
Uncentered R2 = 0.8164
Root MSE = 1.126

Total (centered) SS = 752.2609036
Total (uncentered) SS = 1561.768352
Residual SS = 286.7684002

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	.3271119	.1637424	2.00	0.046	.0061827 .6480411
m3_crisis08	.9335737	.1929947	4.84	0.000	.555311 1.311836
m3_recess11	1.784996	.1945579	9.17	0.000	1.40367 2.166323
crisis08	-5.259821	.6760827	-7.78	0.000	-6.584918 -3.934723
recess11	-4.104781	.6728772	-6.10	0.000	-5.423596 -2.785966
_cons	1.331639	.6689958	1.99	0.047	.0204318 2.642847

Underidentification test (Kleibergen-Paap rk LM statistic): 7.611
Chi-sq(6) P-val = 0.2680

Weak identification test (Cragg-Donald Wald F statistic): 108.651
(Kleibergen-Paap rk Wald F statistic): 20.539

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 5.067
Chi-sq(5) P-val = 0.4077

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation

kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	185
		F(5, 179) =	26.14
		Prob > F =	0.0000
Total (centered) SS	=	132.2165151	
Total (uncentered) SS	=	1662.668967	
Residual SS	=	62.56585134	
		Centered R2 =	0.5268
		Uncentered R2 =	0.9624
		Root MSE =	.5815

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	-.0666249	.0783424	-0.85	0.395	-.2201733	.0869235
m3_crisis08	.842877	.1208673	6.97	0.000	.6059815	1.079772
m3_recess11	-.3574395	.2219569	-1.61	0.107	-.7924671	.0775881
crisis08	-5.103667	.5728308	-8.91	0.000	-6.226395	-3.980939
recess11	.8344337	.6614684	1.26	0.207	-.4620206	2.130888
_cons	3.293186	.356584	9.24	0.000	2.594294	3.992078

Underidentification test (Kleibergen-Paap rk LM statistic): 8.492
Chi-sq(6) P-val = 0.2042

Weak identification test (Cragg-Donald Wald F statistic): 111.249
(Kleibergen-Paap rk Wald F statistic): 28.686

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 4.871
Chi-sq(5) P-val = 0.4318

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	226
		F(5, 220) =	220.93
		Prob > F =	0.0000
Total (centered) SS	=	153.037604	
Total (uncentered) SS	=	1460.773103	
Residual SS	=	95.88575609	
		Centered R2 =	0.3734
		Uncentered R2 =	0.9344
		Root MSE =	.6514

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	-.0437254	.1450775	-0.30	0.763	-.3280721	.2406214
m3_crisis08	.7716216	.1497405	5.15	0.000	.4781356	1.065108

m3_recess11		.0972603	.2533345	0.38	0.701	-.3992661	.5937867
crisis08		-3.726586	.4789728	-7.78	0.000	-4.665355	-2.787816
recess11		-1.147663	.6899912	-1.66	0.096	-2.500021	.2046945
_cons		2.735894	.4783705	5.72	0.000	1.798305	3.673483

Underidentification test (Kleibergen-Paap rk LM statistic): 9.376
Chi-sq(6) P-val = 0.1535

Weak identification test (Cragg-Donald Wald F statistic): 119.929

(Kleibergen-Paap rk Wald F statistic): 23.569

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 6.006
Chi-sq(5) P-val = 0.3056

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only

Statistics robust to heteroskedasticity and autocorrelation

kernel=Bartlett; bandwidth= 12

time variable (t): date

					Number of obs =	185
					F(5, 179) =	260.97
					Prob > F =	0.0000
Total (centered) SS	=	38.57175706			Centered R2 =	0.3812
Total (uncentered) SS	=	441.0847117			Uncentered R2 =	0.9459
Residual SS	=	23.86724912			Root MSE =	.3592

		Robust				
E_cons		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
E_m3		.0525167	.0849165	0.62	0.536	-.1139165 .2189499
m3_crisis08		.5542335	.084264	6.58	0.000	.3890791 .7193879
m3_recess11		.011669	1.878979	0.01	0.995	-3.671062 3.6944
crisis08		-1.426184	.173303	-8.23	0.000	-1.765852 -1.086516
recess11		-.2183957	.1996076	-1.09	0.274	-.6096194 .1728281
_cons		1.469635	.1779757	8.26	0.000	1.120809 1.818461

Underidentification test (Kleibergen-Paap rk LM statistic): 8.547
Chi-sq(6) P-val = 0.2007

Weak identification test (Cragg-Donald Wald F statistic): 80.051

(Kleibergen-Paap rk Wald F statistic): 28.066

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23

20% maximal IV size 11.72
 25% maximal IV size 9.38
 Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 5.034
 Chi-sq(5) P-val = 0.4117

Instrumented: E_m3
 Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

Number of obs = 264
 F(5, 258) = 1702.56
 Prob > F = 0.0000
 Centered R2 = 0.7195
 Uncentered R2 = 0.9343
 Root MSE = .6038
 Total (centered) SS = 343.1153246
 Total (uncentered) SS = 1463.730826
 Residual SS = 96.23321088

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2701729	.0766477	3.52	0.000	.1199462	.4203995
m3_crisis08	.596578	.0931777	6.40	0.000	.413953	.779203
m3_recess11	-1.066157	.224162	-4.76	0.000	-1.505507	-.6268078
crisis08	-4.078844	.4242191	-9.61	0.000	-4.910298	-3.247389
recess11	.3740791	.4430369	0.84	0.398	-.4942572	1.242416
_cons	1.051442	.4124012	2.55	0.011	.2431509	1.859734

Underidentification test (Kleibergen-Paap rk LM statistic): 9.210
 Chi-sq(6) P-val = 0.1621

Weak identification test (Cragg-Donald Wald F statistic): 149.905
 (Kleibergen-Paap rk Wald F statistic): 17.875
 Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
 10% maximal IV relative bias 11.12
 20% maximal IV relative bias 6.76
 30% maximal IV relative bias 5.15
 10% maximal IV size 29.18
 15% maximal IV size 16.23
 20% maximal IV size 11.72
 25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.292
 Chi-sq(5) P-val = 0.8074

Instrumented: E_m3
 Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

		Number of obs =	214
		F(5, 208) =	737.79
		Prob > F =	0.0000
Total (centered) SS	=	Centered R2 =	0.5133
Total (uncentered) SS	=	Uncentered R2 =	0.9796
Residual SS	=	Root MSE =	.4536

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.3291614	.0837728	3.93	0.000	.1649697	.4933531
m3_crisis08	.1828753	.0863556	2.12	0.034	.0136215	.3521291
m3_recess11	-.2491718	.1393037	-1.79	0.074	-.5222021	.0238585
crisis08	-2.16081	.4787596	-4.51	0.000	-3.099162	-1.222459
recess11	1.071778	.6660452	1.61	0.108	-.2336463	2.377203
_cons	1.508322	.4659381	3.24	0.001	.5951004	2.421544

Underidentification test (Kleibergen-Paap rk LM statistic): 9.537
 Chi-sq(6) P-val = 0.1456

Weak identification test (Cragg-Donald wald F statistic): 58.547

(Kleibergen-Paap rk wald F statistic): 18.369
 Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.423
 Chi-sq(5) P-val = 0.6351

Instrumented: E_m3
 Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

		Number of obs =	264
		F(5, 258) =	337.14
		Prob > F =	0.0000
Total (centered) SS	=	Centered R2 =	0.4287
Total (uncentered) SS	=	Uncentered R2 =	0.9688
Residual SS	=	Root MSE =	.4767

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
--------	-------	------------------	---	------	----------------------	--

E_m3	.0086042	.0637613	0.13	0.893	-.1163657	.133574
m3_crisis08	1.293529	.0959573	13.48	0.000	1.105456	1.481602
m3_recess11	.3505065	.2121121	1.65	0.098	-.0652255	.7662385
crisis08	-3.245933	.2839734	-11.43	0.000	-3.802511	-2.689355
recess11	-1.053043	.3587802	-2.94	0.003	-1.75624	-.349847
_cons	2.682401	.2669772	10.05	0.000	2.159136	3.205667

Underidentification test (Kleibergen-Paap rk LM statistic): 9.224
Chi-sq(6) P-val = 0.1614

Weak identification test (Cragg-Donald Wald F statistic): 113.030
(Kleibergen-Paap rk Wald F statistic): 38.625

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 5.075
Chi-sq(5) P-val = 0.4068

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

Warning - collinearities detected
Vars dropped: recess11

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	264
		F(4, 259) =	77.15
		Prob > F =	0.0000
Total (centered) SS	= 173.7148375	Centered R2	= 0.2851
Total (uncentered) SS	= 498.4516796	Uncentered R2	= 0.7508
Residual SS	= 124.1941549	Root MSE	= .6859

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.8149817	.2268938	3.59	0.000	.3702781	1.259685
m3_crisis08	2.066111	.2748627	7.52	0.000	1.52739	2.604832
m3_recess11	.3424154	.6035716	0.57	0.570	-.8405631	1.525394
crisis08	-2.338821	.2288623	-10.22	0.000	-2.787383	-1.890259
_cons	.5629597	.179465	3.14	0.002	.2112147	.9147047

Underidentification test (Kleibergen-Paap rk LM statistic): 5.796
Chi-sq(6) P-val = 0.4464

Weak identification test (Cragg-Donald Wald F statistic): 113.501
(Kleibergen-Paap rk Wald F statistic): 25.499

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12

20% maximal	IV relative bias	6.76
30% maximal	IV relative bias	5.15
10% maximal	IV size	29.18
15% maximal	IV size	16.23
20% maximal	IV size	11.72
25% maximal	IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.163
Chi-sq(5) P-val = 0.6748

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3
Dropped collinear: recess11

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	110.1308895	Number of obs =	214
Total (uncentered) SS	=	1234.73353	F(5, 208) =	139.34
Residual SS	=	58.06432588	Prob > F =	0.0000
			Centered R2 =	0.4728
			Uncentered R2 =	0.9530
			Root MSE =	.5209

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	-.0403428	.059483	-0.68	0.498	-.1569273	.0762417
m3_crisis08	.3123985	.0728956	4.29	0.000	.1695257	.4552714
m3_recess11	.0284773	.0858943	0.33	0.740	-.1398724	.1968269
crisis08	-3.526967	.4649941	-7.58	0.000	-4.438339	-2.615595
recess11	-.4148184	.4506033	-0.92	0.357	-1.297985	.4683479
_cons	2.685396	.3895145	6.89	0.000	1.921962	3.448831

Underidentification test (Kleibergen-Paap rk LM statistic): 8.502
Chi-sq(6) P-val = 0.2036

Weak identification test (Cragg-Donald Wald F statistic): 48.353
(Kleibergen-Paap rk Wald F statistic): 45.440

Stock-Yogo weak ID test critical values:

5% maximal	IV relative bias	19.28
10% maximal	IV relative bias	11.12
20% maximal	IV relative bias	6.76
30% maximal	IV relative bias	5.15
10% maximal	IV size	29.18
15% maximal	IV size	16.23
20% maximal	IV size	11.72
25% maximal	IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 5.823
Chi-sq(5) P-val = 0.3239

Instrumented: E_m3
Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2

E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

		Number of obs =	264
		F(5, 258) =	38.21
		Prob > F =	0.0000
Total (centered) SS	=	180.7201837	Centered R2 = 0.6153
Total (uncentered) SS	=	1956.411115	Uncentered R2 = 0.9645
Residual SS	=	69.5316027	Root MSE = .5132

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.0719851	.0480578	1.50	0.134	-.0222064	.1661765
m3_crisis08	.7629468	.1606225	4.75	0.000	.4481325	1.077761
m3_recess11	1.845254	.8663868	2.13	0.033	.1471675	3.543341
crisis08	-3.329623	.3699768	-9.00	0.000	-4.054764	-2.604481
recess11	-.7227301	.2160347	-3.35	0.001	-1.14615	-.2993098
_cons	2.538429	.1849535	13.72	0.000	2.175927	2.900931

Underidentification test (Kleibergen-Paap rk LM statistic): 12.309
 Chi-sq(6) P-val = 0.0554

Weak identification test (Cragg-Donald Wald F statistic): 221.983
 (Kleibergen-Paap rk Wald F statistic): 65.611
 Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 6.689
 Chi-sq(5) P-val = 0.2448

Instrumented: E_m3
 Included instruments: m3_crisis08 m3_recess11 crisis08 recess11
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
 E_y10lag3

```
. *
. *
. *-----*
.
. * (18)
. * OLS IV with controls & dummies
.
. * All controls, eu countries (a)
. foreach y of global eu_c_unemp {
.   2.      ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3)
E_wages E_unem E_budget_def
> m3_crisis08 m3_recess11 crisis08 recess11 if country=="y", bw(12) robust
.   3.
```

. }

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

Total (centered) SS	=	168.915284	Number of obs =	260
Total (uncentered) SS	=	915.0409342	F(8, 251) =	99.02
Residual SS	=	54.48616347	Prob > F =	0.0000
			Centered R2 =	0.6774
			Uncentered R2 =	0.9405
			Root MSE =	.4578

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2683793	.2770152	0.97	0.333	-.2745604	.8113191
E_wages	.3281404	.586445	0.56	0.576	-.8212705	1.477551
E_unem	.0235654	.0979456	0.24	0.810	-.1684044	.2155352
E_budget_def	.0022468	.0032665	0.69	0.492	-.0041554	.0086489
m3_crisis08	.0790194	.1951939	0.40	0.686	-.3035536	.4615924
m3_recess11	.3572822	.1694314	2.11	0.035	.0252028	.6893617
crisis08	-1.154102	.5883305	-1.96	0.050	-2.307209	-.0009953
recess11	-1.004148	.321312	-3.13	0.002	-1.633908	-.3743885
_cons	.2477888	1.00456	0.25	0.805	-1.721112	2.21669

Underidentification test (Kleibergen-Paap rk LM statistic): 8.192
 Chi-sq(6) P-val = 0.2244

Weak identification test (Cragg-Donald Wald F statistic): 10.645
 (Kleibergen-Paap rk Wald F statistic): 2.682
 Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 1.780
 Chi-sq(5) P-val = 0.8787

Instrumented: E_m3
 Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
 crisis08 recess11
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
 E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

Number of obs =	260
F(8, 251) =	27.85

Total (centered) SS	=	177.846648	Prob > F	=	0.0000
Total (uncentered) SS	=	513.4659311	Centered R2	=	0.2653
Residual SS	=	130.6674764	Uncentered R2	=	0.7455
			Root MSE	=	.7089

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2989149	.1732406	1.73	0.084	-.0406304	.6384602
E_wages	.225703	.4149545	0.54	0.586	-.5875928	1.038999
E_unem	.0217663	.1587169	0.14	0.891	-.289313	.3328457
E_budget_def	.0112156	.0057933	1.94	0.053	-.0001391	.0225702
m3_crisis08	-.2561715	.257618	-0.99	0.320	-.7610936	.2487505
m3_recess11	-.0369003	.2532583	-0.15	0.884	-.5332774	.4594768
crisis08	-.3486716	.628949	-0.55	0.579	-1.581389	.8840459
recess11	-.0540432	.3292965	-0.16	0.870	-.6994525	.5913661
_cons	.3153844	1.854584	0.17	0.865	-3.319533	3.950302

Underidentification test (Kleibergen-Paap rk LM statistic): 11.835
Chi-sq(6) P-val = 0.0657

Weak identification test (Cragg-Donald Wald F statistic): 65.644
(Kleibergen-Paap rk Wald F statistic): 8.542
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72
25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.896
Chi-sq(5) P-val = 0.7160

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	279.9569003	Number of obs	=	260
Total (uncentered) SS	=	579.2906913	F(8, 251)	=	84.94
Residual SS	=	107.6052415	Prob > F	=	0.0000
			Centered R2	=	0.6156
			Uncentered R2	=	0.8142
			Root MSE	=	.6433

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1210129	.1401008	0.86	0.388	-.1535797	.3956054
E_wages	.1117748	.3117714	0.36	0.720	-.4992859	.7228354
E_unem	-.034418	.0677856	-0.51	0.612	-.1672753	.0984392

E_budget_def		.008708	.0048952	1.78	0.075	-.0008864	.0183024
m3_crisis08		.210883	.1734832	1.22	0.224	-.1291378	.5509037
m3_recess11		.9254036	.4177227	2.22	0.027	.1066821	1.744125
crisis08		-2.034716	.500659	-4.06	0.000	-3.01599	-1.053442
recess11		-2.839471	.5364505	-5.29	0.000	-3.890895	-1.788048
_cons		1.442403	.6220934	2.32	0.020	.2231224	2.661684

Underidentification test (Kleibergen-Paap rk LM statistic): 10.113
Chi-sq(6) P-val = 0.1200

Weak identification test (Cragg-Donald Wald F statistic): 104.180
(Kleibergen-Paap rk Wald F statistic): 31.340

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.528
Chi-sq(5) P-val = 0.6192

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

```
. *
.
. * Without unemployment, eu countries (b)
. foreach y of global eu_c_nounemp {
.   2.      ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3)
E_wages E_budget_def m3_cri
> sis08 m3_recess11 crisis08 recess11 if country=="`y'", bw(12) robust
.   3.
. }
Warning - collinearities detected
Vars dropped:      m3_crisis08 crisis08
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	58
		F(5, 52) =	65.22
		Prob > F =	0.0000
Total (centered) SS	=	Centered R2 =	0.6537
Total (uncentered) SS	=	Uncentered R2 =	0.6546
Residual SS	=	Root MSE =	.3917

		Robust				
E_cons		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
E_m3		.6982139	.1846364	3.78	0.000	.3363332 1.060095
E_wages		-.9500377	.3531726	-2.69	0.007	-1.642243 -.2578321
E_budget_def		.0588817	.0163235	3.61	0.000	.0268882 .0908752

m3_recess11		.0319599	.2420922	0.13	0.895	-.4425321	.5064519
recess11		-.4202687	.3506675	-1.20	0.231	-1.107564	.267027
_cons		2.327392	.6181399	3.77	0.000	1.11586	3.538924

Underidentification test (Kleibergen-Paap rk LM statistic): 2.419
Chi-sq(6) P-val = 0.8775

Weak identification test (Cragg-Donald Wald F statistic): 85.401
(Kleibergen-Paap rk Wald F statistic): 167.886
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72
25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 4.721
Chi-sq(5) P-val = 0.4508

Instrumented: E_m3
Included instruments: E_wages E_budget_def m3_recess11 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3
Dropped collinear: m3_crisis08 crisis08

Warning - collinearities detected
Vars dropped: m3_crisis08 crisis08

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

					Number of obs =	58
					F(5, 52) =	60.40
					Prob > F =	0.0000
Total (centered) SS	=	84.14286386			Centered R2 =	0.5659
Total (uncentered) SS	=	84.25564623			Uncentered R2 =	0.5665
Residual SS	=	36.52700473			Root MSE =	.7936

E_cons		Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3		-.6337638	.5145733	-1.23	0.218	-1.642309 .3747813
E_wages		1.717591	.885333	1.94	0.052	-.0176297 3.452812
E_budget_def		.0546911	.0217379	2.52	0.012	.0120857 .0972966
m3_recess11		2.437741	.5189525	4.70	0.000	1.420613 3.454869
recess11		-4.05646	.5882211	-6.90	0.000	-5.209352 -2.903567
_cons		3.468822	1.323448	2.62	0.009	.8749107 6.062733

Underidentification test (Kleibergen-Paap rk LM statistic): 4.228
Chi-sq(6) P-val = 0.6459

Weak identification test (Cragg-Donald Wald F statistic): 12.546
(Kleibergen-Paap rk Wald F statistic): 20.957
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15

10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 4.624
Chi-sq(5) P-val = 0.4635

Instrumented: E_m3
Included instruments: E_wages E_budget_def m3_recess11 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3
Dropped collinear: m3_crisis08 crisis08

Warning - collinearities detected
Vars dropped: m3_crisis08 crisis08

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

		Number of obs =	58
		F(5, 52) =	5.26
		Prob > F =	0.0006
Total (centered) SS	=	Centered R2	= 0.5526
Total (uncentered) SS	=	Uncentered R2	= 0.9890
Residual SS	=	Root MSE	= .3174

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	.1879604	.1977482	0.95	0.342	-.199619 .5755397
E_wages	.9249972	.4342779	2.13	0.033	.0738281 1.776166
E_budget_def	-.0027023	.0020665	-1.31	0.191	-.0067526 .001348
m3_recess11	-.8627048	.2504342	-3.44	0.001	-1.353547 -.3718628
recess11	2.024299	.5956961	3.40	0.001	.8567556 3.191842
_cons	-.0612415	1.041085	-0.06	0.953	-2.101731 1.979248

Underidentification test (Kleibergen-Paap rk LM statistic): 5.201
Chi-sq(6) P-val = 0.5183

Weak identification test (Cragg-Donald Wald F statistic): 20.768
(Kleibergen-Paap rk Wald F statistic): 28.646

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.819
Chi-sq(5) P-val = 0.5757

Instrumented: E_m3
Included instruments: E_wages E_budget_def m3_recess11 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2

```

Dropped collinear:      E_y10lag3
                      m3_crisis08 crisis08

```

```

Warning - collinearities detected
Vars dropped:          m3_crisis08 crisis08

```

```

IV (2SLS) estimation

```

```

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
  kernel=Bartlett; bandwidth=    12
  time variable (t):  date

```

```

Total (centered) SS      =    12.568985
Total (uncentered) SS   =   300.8667326
Residual SS              =    3.859760233

Number of obs =      58
F( 5, 52) =    26.39
Prob > F      =    0.0000
Centered R2    =    0.6929
Uncentered R2  =    0.9872
Root MSE      =    .258

```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3	-.121905	.1452864	-0.84	0.401	-.4066611 .162851
E_wages	-.2113973	.2360885	-0.90	0.371	-.6741222 .2513276
E_budget_def	.0074698	.0041409	1.80	0.071	-.0006461 .0155858
m3_recess11	.0331273	.2292527	0.14	0.885	-.4161998 .4824544
recess11	-.962834	.5351	-1.80	0.072	-2.011611 .0859427
_cons	3.531861	.9322293	3.79	0.000	1.704725 5.358997

```

Underidentification test (Kleibergen-Paap rk LM statistic):    5.252
Chi-sq(6) P-val =    0.5119

```

```

Weak identification test (Cragg-Donald Wald F statistic):    12.479
(Kleibergen-Paap rk Wald F statistic):    11.277
Stock-Yogo weak ID test critical values:
  5% maximal IV relative bias    19.28
  10% maximal IV relative bias   11.12
  20% maximal IV relative bias    6.76
  30% maximal IV relative bias    5.15
  10% maximal IV size            29.18
  15% maximal IV size            16.23
  20% maximal IV size            11.72
  25% maximal IV size             9.38

```

```

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```

```

Hansen J statistic (overidentification test of all instruments):    3.233
Chi-sq(5) P-val =    0.6642

```

```

Instrumented:      E_m3
Included instruments: E_wages E_budget_def m3_recess11 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
                  E_y10lag3
Dropped collinear: m3_crisis08 crisis08

```

```

. *
.
. * without unemployment and wages, Switzerland (c)
. ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3) E_budget_def
m3_crisis08 m3_recess11 c
> risis08 recess11 if country=="Switzerland", bw(12) robust
Warning - collinearities detected
Vars dropped:      m3_crisis08 crisis08

```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	5.091162407	Number of obs =	58
Total (uncentered) SS	=	143.0835609	F(4, 53) =	100.57
Residual SS	=	1.706173766	Prob > F	= 0.0000
			Centered R2	= 0.6649
			Uncentered R2	= 0.9881
			Root MSE	= .1715

	E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
E_m3		-.2267264	.0844675	-2.68	0.007	-.3922796 -.0611732
E_budget_def		.0328461	.0098399	3.34	0.001	.0135603 .0521319
m3_recess11		.5813345	1.739027	0.33	0.738	-2.827095 3.989764
recess11		-.5905087	.0807133	-7.32	0.000	-.7487039 -.4323135
_cons		1.75774	.0545644	32.21	0.000	1.650796 1.864684

Underidentification test (Kleibergen-Paap rk LM statistic): 3.345
Chi-sq(6) P-val = 0.7644

Weak identification test (Cragg-Donald Wald F statistic): 27.985
(Kleibergen-Paap rk Wald F statistic): 31.824
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72
25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 3.936
Chi-sq(5) P-val = 0.5587

Instrumented: E_m3
Included instruments: E_budget_def m3_recess11 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3
Dropped collinear: m3_crisis08 crisis08

```
.
.
. * All controls, other countries (d)
. foreach y of global other_c_unemp {
.   2.   ivreg29 E_cons (E_m3 = E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2 E_y10lag3)
E_wages E_unem E_budget_def
> m3_crisis08 m3_recess11 crisis08 recess11 if country=="`y'", bw(12) robust
.   3.
. }
```

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12

time variable (t): date

Total (centered) SS	=	340.6927052	Number of obs =	260
Total (uncentered) SS	=	1456.354732	F(8, 251) =	1228.24
Residual SS	=	56.50178038	Prob > F	= 0.0000
			Centered R2	= 0.8342
			Uncentered R2	= 0.9612
			Root MSE	= .4662

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.3472368	.1996251	1.74	0.082	-.0440213	.7384948
E_wages	-.7825494	.3639676	-2.15	0.032	-1.495913	-.0691859
E_unem	-.084668	.0431274	-1.96	0.050	-.169196	-.0001399
E_budget_def	-.015794	.0046003	-3.43	0.001	-.0248105	-.0067776
m3_crisis08	.3476005	.0785087	4.43	0.000	.1937262	.5014748
m3_recess11	-.4874468	.2124153	-2.29	0.022	-.903773	-.0711205
crisis08	-3.019676	.2793142	-10.81	0.000	-3.567122	-2.47223
recess11	.0617936	.3339327	0.19	0.853	-.5927024	.7162896
_cons	4.878781	1.056731	4.62	0.000	2.807626	6.949936

Underidentification test (Kleibergen-Paap rk LM statistic): 9.480
Chi-sq(6) P-val = 0.1483

Weak identification test (Cragg-Donald Wald F statistic): 41.146
(Kleibergen-Paap rk Wald F statistic): 12.527

Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 6.443
Chi-sq(5) P-val = 0.2655

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	90.4518176	Number of obs =	214
Total (uncentered) SS	=	2156.389959	F(8, 205) =	151.06
Residual SS	=	28.70043273	Prob > F	= 0.0000
			Centered R2	= 0.6827
			Uncentered R2	= 0.9867
			Root MSE	= .3662

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
--------	-------	------------------	---	------	----------------------	--

E_m3	.3091667	.0763239	4.05	0.000	.1595746	.4587587
E_wages	-.7053075	.2196861	-3.21	0.001	-1.135884	-.2747306
E_unem	.0898419	.0543781	1.65	0.098	-.0167372	.1964211
E_budget_def	.0126709	.005494	2.31	0.021	.001903	.0234389
m3_crisis08	.1563224	.0825823	1.89	0.058	-.0055359	.3181808
m3_recess11	-.0434572	.1801891	-0.24	0.809	-.3966214	.3097069
crisis08	-1.767439	.4469328	-3.95	0.000	-2.643412	-.8914673
recess11	.4787091	.7422318	0.64	0.519	-.9760386	1.933457
_cons	3.67437	.6986579	5.26	0.000	2.305025	5.043714

Underidentification test (Kleibergen-Paap rk LM statistic): 11.165
Chi-sq(6) P-val = 0.0834

Weak identification test (Cragg-Donald Wald F statistic): 96.369
(Kleibergen-Paap rk Wald F statistic): 27.670

Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72
25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.

NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 6.329
Chi-sq(5) P-val = 0.2755

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Total (centered) SS	=	69.34060185	Number of obs	=	125
Total (uncentered) SS	=	867.9173284	F(8, 116)	=	335.09
Residual SS	=	9.638750365	Prob > F	=	0.0000
			Centered R2	=	0.8610
			Uncentered R2	=	0.9889
			Root MSE	=	.2777

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.2467064	.0575907	4.28	0.000	.1338307	.3595821
E_wages	.1907854	.1566342	1.22	0.223	-.116212	.4977828
E_unem	-.1086778	.2640465	-0.41	0.681	-.6261994	.4088438
E_budget_def	.0002562	.0088166	0.03	0.977	-.017024	.0175363
m3_crisis08	.8791672	.1509978	5.82	0.000	.5832169	1.175118
m3_recess11	-.0916635	.2303703	-0.40	0.691	-.5431809	.3598539
crisis08	-2.300563	.2838373	-8.11	0.000	-2.856874	-1.744252
recess11	-.1131125	.3065438	-0.37	0.712	-.7139273	.4877024
_cons	2.304026	1.715707	1.34	0.179	-1.058698	5.666749

Underidentification test (Kleibergen-Paap rk LM statistic): 7.708

```

Chi-sq(6) P-val = 0.2603
-----
weak identification test (Cragg-Donald wald F statistic): 84.267
(Kleibergen-Paap rk wald F statistic): 42.345
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72
25% maximal IV size 9.38

```

Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

```

Hansen J statistic (overidentification test of all instruments): 5.795
Chi-sq(5) P-val = 0.3266
-----

```

```

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3
-----

```

warning - collinearities detected
 Vars dropped: recess11

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

```

Total (centered) SS = 172.1071231
Total (uncentered) SS = 486.3923057
Residual SS = 84.01689773
Number of obs = 260
F( 7, 252) = 101.26
Prob > F = 0.0000
Centered R2 = 0.5118
Uncentered R2 = 0.8273
Root MSE = .5685

```

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.8376348	.2991732	2.80	0.005	.2512662	1.424003
E_wages	.500653	.1147668	4.36	0.000	.2757143	.7255918
E_unem	.1614723	.1544581	1.05	0.296	-.14126	.4642046
E_budget_def	-.0224598	.0174294	-1.29	0.198	-.0566208	.0117012
m3_crisis08	.8846647	.3799938	2.33	0.020	.1398905	1.629439
m3_recess11	-.2683165	.6181134	-0.43	0.664	-1.479797	.9431636
crisis08	-.7355697	.352719	-2.09	0.037	-1.426886	-.0442533
_cons	-1.121951	1.109044	-1.01	0.312	-3.295637	1.051735

```

Underidentification test (Kleibergen-Paap rk LM statistic): 10.358
Chi-sq(6) P-val = 0.1103
-----

```

```

weak identification test (Cragg-Donald wald F statistic): 43.974
(Kleibergen-Paap rk wald F statistic): 9.293
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72

```

25% maximal IV size 9.38
Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 2.250
Chi-sq(5) P-val = 0.8135

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
crisis08
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
E_y10lag3
Dropped collinear: recess11

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
Statistics robust to heteroskedasticity and autocorrelation
kernel=Bartlett; bandwidth= 12
time variable (t): date

Number of obs = 214
F(8, 205) = 199.88
Prob > F = 0.0000
Total (centered) SS = 110.1308895
Total (uncentered) SS = 1234.73353
Residual SS = 35.27478142
Centered R2 = 0.6797
Uncentered R2 = 0.9714
Root MSE = .406

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	.1790396	.1101062	1.63	0.104	-.0367645	.3948438
E_wages	-1.843218	.4035243	-4.57	0.000	-2.634111	-1.052325
E_unem	-.3457027	.0936225	-3.69	0.000	-.5291995	-.162206
E_budget_def	.0221603	.0250228	0.89	0.376	-.0268834	.0712041
m3_crisis08	.1711538	.0815224	2.10	0.036	.0113729	.3309347
m3_recess11	-.1845199	.140691	-1.31	0.190	-.4602692	.0912294
crisis08	-1.552077	.6369066	-2.44	0.015	-2.800391	-.3037629
recess11	1.047884	.7016646	1.49	0.135	-.3273538	2.423121
_cons	7.525598	1.067013	7.05	0.000	5.43429	9.616906

Underidentification test (Kleibergen-Paap rk LM statistic): 12.357
Chi-sq(6) P-val = 0.0545

Weak identification test (Cragg-Donald Wald F statistic): 43.992
(Kleibergen-Paap rk Wald F statistic): 33.927
Stock-Yogo weak ID test critical values: 5% maximal IV relative bias 19.28
10% maximal IV relative bias 11.12
20% maximal IV relative bias 6.76
30% maximal IV relative bias 5.15
10% maximal IV size 29.18
15% maximal IV size 16.23
20% maximal IV size 11.72
25% maximal IV size 9.38

Source: Stock-Yogo (2005). Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 7.640
Chi-sq(5) P-val = 0.1772

Instrumented: E_m3
Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
crisis08 recess11
Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2

E_y10lag3

IV (2SLS) estimation

Estimates efficient for homoskedasticity only
 Statistics robust to heteroskedasticity and autocorrelation
 kernel=Bartlett; bandwidth= 12
 time variable (t): date

Total (centered) SS	=	179.9625694	Number of obs =	259
Total (uncentered) SS	=	1921.129173	F(8, 250) =	39.32
Residual SS	=	43.7176083	Prob > F	= 0.0000
			Centered R2	= 0.7571
			Uncentered R2	= 0.9772
			Root MSE	= .4108

E_cons	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
E_m3	-.0877455	.0380782	-2.30	0.021	-.1623773	-.0131136
E_wages	.5779471	.1259819	4.59	0.000	.3310271	.8248671
E_unem	-.3707463	.0969556	-3.82	0.000	-.5607758	-.1807168
E_budget_def	-.001081	.0004243	-2.55	0.011	-.0019127	-.0002493
m3_crisis08	.5723018	.2077748	2.75	0.006	.1650706	.979533
m3_recess11	2.510123	.9534223	2.63	0.008	.6414491	4.378796
crisis08	-3.191272	.4547391	-7.02	0.000	-4.082545	-2.3
recess11	-.5633063	.1847078	-3.05	0.002	-.9253269	-.2012858
_cons	3.076994	.6526414	4.71	0.000	1.79784	4.356148

Underidentification test (Kleibergen-Paap rk LM statistic): 12.839
 Chi-sq(6) P-val = 0.0457

Weak identification test (Cragg-Donald Wald F statistic): 142.903
 (Kleibergen-Paap rk Wald F statistic): 31.298
 Stock-Yogo weak ID test critical values:

5% maximal IV relative bias	19.28
10% maximal IV relative bias	11.12
20% maximal IV relative bias	6.76
30% maximal IV relative bias	5.15
10% maximal IV size	29.18
15% maximal IV size	16.23
20% maximal IV size	11.72
25% maximal IV size	9.38

Source: Stock-Yogo (2005). Reproduced by permission.
 NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.

Hansen J statistic (overidentification test of all instruments): 9.747
 Chi-sq(5) P-val = 0.0827

Instrumented: E_m3
 Included instruments: E_wages E_unem E_budget_def m3_crisis08 m3_recess11
 crisis08 recess11
 Excluded instruments: E_m3lag12 E_m3lag13 E_m3lag14 E_y10lag1 E_y10lag2
 E_y10lag3

```

. *
. *-----*
.
. * Other models *
.
. * OLS with instruments
.
. * OLS IV lag1

```

```
. foreach y of global c_all {
2.     ivreg E_cons (E_m3=lag1) if country=="`y'", robust
3.
. }
```

```
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =     175.05
                                              Prob > F         =     0.0000
                                              R-squared        =     0.4662
                                              Root MSE        =     .58747
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3352145	.025336	13.23	0.000	.2853265	.3851026
_cons	.6814752	.0730465	9.33	0.000	.5376422	.8253082

```
Instrumented: E_m3
Instruments: lag1
```

```
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =      2.26
                                              Prob > F         =     0.1338
                                              R-squared        =     0.0096
                                              Root MSE        =     .83478
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0578308	.0384528	1.50	0.134	-.017885	.1335466
_cons	.9407563	.1019541	9.23	0.000	.7400026	1.14151

```
Instrumented: E_m3
Instruments: lag1
```

```
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =     28.53
                                              Prob > F         =     0.0000
                                              R-squared        =     0.1440
                                              Root MSE        =     .96376
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1472645	.0275707	5.34	0.000	.0929761	.2015529
_cons	.4858567	.1260165	3.86	0.000	.2377226	.7339907

```
Instrumented: E_m3
Instruments: lag1
```

```
Instrumental variables (2SLS) regression      Number of obs   =      239
                                              F(1, 237)       =     509.64
                                              Prob > F         =     0.0000
                                              R-squared        =     0.5959
                                              Root MSE        =     .91732
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.7674276	.0339941	22.58	0.000	.7004584	.8343969

```

      _cons |  -.9018541   .1092188   -8.26   0.000   -1.117018   -.6866904
-----+-----
Instrumented:  E_m3
Instruments:   lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      239
                                              F(1, 237)       =      62.48
                                              Prob > F         =      0.0000
                                              R-squared       =      0.2847
                                              Root MSE       =      1.5136

```

```

-----+-----
      E_cons |      Coef.   Robust      t   P>|t|   [95% Conf. Interval]
-----+-----
      E_m3   |   .4039478   .0511021   7.90  0.000   .3032754   .5046201
      _cons   |   .584451    .2102406   2.78  0.006   .170272    .99863

```

```

Instrumented:  E_m3
Instruments:   lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      198
                                              F(1, 196)       =      3.21
                                              Prob > F         =      0.0747
                                              R-squared       =      0.0044
                                              Root MSE       =      .85208

```

```

-----+-----
      E_cons |      Coef.   Robust      t   P>|t|   [95% Conf. Interval]
-----+-----
      E_m3   |  -.0562611   .0313982  -1.79  0.075   -.1181828   .0056606
      _cons   |   3.060576   .1650757  18.54  0.000   2.735024   3.386129

```

```

Instrumented:  E_m3
Instruments:   lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      239
                                              F(1, 237)       =      2.71
                                              Prob > F         =      0.1013
                                              R-squared       =      0.0161
                                              Root MSE       =      .93932

```

```

-----+-----
      E_cons |      Coef.   Robust      t   P>|t|   [95% Conf. Interval]
-----+-----
      E_m3   |  -.0809786   .0492214  -1.65  0.101   -.177946    .0159888
      _cons   |   2.584478   .179772   14.38  0.000   2.230323   2.938634

```

```

Instrumented:  E_m3
Instruments:   lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      198
                                              F(1, 196)       =     56.77
                                              Prob > F         =      0.0000
                                              R-squared       =      0.2539
                                              Root MSE       =      .38436

```

```

-----+-----
      E_cons |      Coef.   Robust      t   P>|t|   [95% Conf. Interval]
-----+-----

```

E_m3		.199366	.0264593	7.53	0.000	.1471845	.2515475
_cons		1.191425	.062858	18.95	0.000	1.06746	1.31539

Instrumented: E_m3
Instruments: lag1

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(1, 262)	=	151.18
	Prob > F	=	0.0000
	R-squared	=	0.4782
	Root MSE	=	.82666

E_cons		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3		.3541947	.0288068	12.30	0.000	.2974725 .4109169
_cons		.5130535	.1601406	3.20	0.002	.1977271 .82838

Instrumented: E_m3
Instruments: lag1

Instrumental variables (2SLS) regression	Number of obs	=	227
	F(1, 225)	=	36.54
	Prob > F	=	0.0000
	R-squared	=	0.1779
	Root MSE	=	.57883

E_cons		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3		.1927766	.0318898	6.05	0.000	.1299358 .2556175
_cons		2.088455	.1812978	11.52	0.000	1.731197 2.445714

Instrumented: E_m3
Instruments: lag1

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(1, 262)	=	40.64
	Prob > F	=	0.0000
	R-squared	=	0.1876
	Root MSE	=	.57068

E_cons		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3		.1559476	.0244625	6.37	0.000	.1077796 .2041157
_cons		2.067295	.0996387	20.75	0.000	1.8711 2.263489

Instrumented: E_m3
Instruments: lag1

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(1, 262)	=	118.15
	Prob > F	=	0.0000
	R-squared	=	0.2832
	Root MSE	=	.6894

E_cons		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
--------	--	-------	------------------	---	------	----------------------

E_m3		.5651508	.051994	10.87	0.000	.4627715	.6675301
_cons		.7040671	.0565844	12.44	0.000	.592649	.8154852

Instrumented: E_m3
Instruments: lag1

Instrumental variables (2SLS) regression	Number of obs	=	227
	F(1, 225)	=	8.71
	Prob > F	=	0.0035
	R-squared	=	0.0609
	Root MSE	=	.71093

E_cons		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3		.0954091	.0323249	2.95	0.003	.0317108 .1591074
_cons		1.789348	.2011197	8.90	0.000	1.393029 2.185667

Instrumented: E_m3
Instruments: lag1

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(1, 262)	=	65.17
	Prob > F	=	0.0000
	R-squared	=	0.2244
	Root MSE	=	.73143

E_cons		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3		.1799354	.0222883	8.07	0.000	.1360484 .2238224
_cons		2.020194	.1016715	19.87	0.000	1.819997 2.220391

Instrumented: E_m3
Instruments: lag1

```
. *
.
. * OLS IV lag2
. foreach y of global c_all {
2.     ivreg E_cons (E_m3=lag2) if country=="`y'", robust
3.
. }
```

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(1, 262)	=	150.33
	Prob > F	=	0.0000
	R-squared	=	0.4660
	Root MSE	=	.58755

E_cons		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3		.3311062	.0270053	12.26	0.000	.2779311 .3842813
_cons		.6939421	.0776587	8.94	0.000	.5410275 .8468568

Instrumented: E_m3
Instruments: lag2

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(1, 262)	=	2.39
	Prob > F	=	0.1235
	R-squared	=	0.0092
	Root MSE	=	.83493

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0645788	.0417882	1.55	0.123	-.0177048	.1468623
_cons	.9202019	.1124951	8.18	0.000	.6986923	1.141711

Instrumented: E_m3
Instruments: lag2

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(1, 262)	=	28.62
	Prob > F	=	0.0000
	R-squared	=	0.1433
	Root MSE	=	.96418

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1529715	.028592	5.35	0.000	.0966722	.2092708
_cons	.4637133	.1302941	3.56	0.000	.2071565	.7202702

Instrumented: E_m3
Instruments: lag2

Instrumental variables (2SLS) regression	Number of obs	=	238
	F(1, 236)	=	536.99
	Prob > F	=	0.0000
	R-squared	=	0.6011
	Root MSE	=	.91277

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.7809255	.0336998	23.17	0.000	.7145346	.8473164
_cons	-.9327411	.1119389	-8.33	0.000	-1.153268	-.7122139

Instrumented: E_m3
Instruments: lag2

Instrumental variables (2SLS) regression	Number of obs	=	238
	F(1, 236)	=	61.49
	Prob > F	=	0.0000
	R-squared	=	0.2896
	Root MSE	=	1.5112

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.4029422	.0513869	7.84	0.000	.3017067	.5041778
_cons	.5962261	.2106145	2.83	0.005	.1813015	1.011151

Instrumented: E_m3
Instruments: lag2

Instrumental variables (2SLS) regression	Number of obs	=	197
	F(1, 195)	=	7.02
	Prob > F	=	0.0087
	R-squared	=	.
	Root MSE	=	.85622

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.082292	.0310556	-2.65	0.009	-.14354	-.0210439
_cons	3.165148	.157077	20.15	0.000	2.85536	3.474936

Instrumented: E_m3
Instruments: lag2

Instrumental variables (2SLS) regression	Number of obs	=	238
	F(1, 236)	=	3.16
	Prob > F	=	0.0768
	R-squared	=	0.0055
	Root MSE	=	.93108

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.085776	.0482635	-1.78	0.077	-.1808584	.0093064
_cons	2.611016	.1765859	14.79	0.000	2.26313	2.958902

Instrumented: E_m3
Instruments: lag2

Instrumental variables (2SLS) regression	Number of obs	=	197
	F(1, 195)	=	49.21
	Prob > F	=	0.0000
	R-squared	=	0.2528
	Root MSE	=	.38563

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1883202	.026846	7.01	0.000	.1353745	.2412659
_cons	1.208174	.0625438	19.32	0.000	1.084825	1.331523

Instrumented: E_m3
Instruments: lag2

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(1, 262)	=	147.67
	Prob > F	=	0.0000
	R-squared	=	0.4782
	Root MSE	=	.82668

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3522027	.0289836	12.15	0.000	.2951324	.4092731
_cons	.5217552	.1602141	3.26	0.001	.2062841	.8372262

Instrumented: E_m3
Instruments: lag2

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      226
                                              F(1, 224)       =      31.26
                                              Prob > F        =      0.0000
                                              R-squared      =      0.1840
                                              Root MSE      =      .57733

```

```

-----
      E_cons |      Coef.      Robust      t      P>|t|      [95% Conf. Interval]
-----+-----
      E_m3   |   .1813372   .032435   5.59   0.000   .1174204   .245254
      _cons  |   2.152545   .1841398  11.69   0.000   1.789677   2.515413

```

```

-----
Instrumented:  E_m3
Instruments:   lag2

```

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =      36.52
                                              Prob > F        =      0.0000
                                              R-squared      =      0.1871
                                              Root MSE      =      .57087

```

```

-----
      E_cons |      Coef.      Robust      t      P>|t|      [95% Conf. Interval]
-----+-----
      E_m3   |   .150067   .0248314   6.04   0.000   .1011724   .1989616
      _cons  |   2.088337   .1001221  20.86   0.000   1.891191   2.285484

```

```

-----
Instrumented:  E_m3
Instruments:   lag2

```

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =     107.54
                                              Prob > F        =      0.0000
                                              R-squared      =      0.2830
                                              Root MSE      =      .68951

```

```

-----
      E_cons |      Coef.      Robust      t      P>|t|      [95% Conf. Interval]
-----+-----
      E_m3   |   .5723258   .05519   10.37   0.000   .4636534   .6809982
      _cons  |   .6989251   .0586565  11.92   0.000   .583427   .8144233

```

```

-----
Instrumented:  E_m3
Instruments:   lag2

```

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      226
                                              F(1, 224)       =       4.91
                                              Prob > F        =      0.0278
                                              R-squared      =      0.0525
                                              Root MSE      =      .71416

```

```

-----
      E_cons |      Coef.      Robust      t      P>|t|      [95% Conf. Interval]
-----+-----
      E_m3   |   .0716041   .032324   2.22   0.028   .0079061   .1353021
      _cons  |   1.924406   .1978135   9.73   0.000   1.534592   2.314219

```

```

-----
Instrumented:  E_m3

```

Instruments: lag2

```
-----
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =      61.84
                                              Prob > F        =      0.0000
                                              R-squared       =      0.2222
                                              Root MSE       =      .73246
-----
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1685233	.0214308	7.86	0.000	.1263248	.2107218
_cons	2.056553	.0982064	20.94	0.000	1.863179	2.249927

Instrumented: E_m3
Instruments: lag2

```
-----
. *
.
. * OLS all IV
. foreach y of global c_all {
2.     ivreg E_cons (E_m3=lag1 lag2) if country=="`y'", robust
3.
. }
```

```
-----
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =     174.15
                                              Prob > F        =      0.0000
                                              R-squared       =      0.4662
                                              Root MSE       =      .58746
-----
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3356766	.0254365	13.20	0.000	.2855906	.3857626
_cons	.6800732	.0734484	9.26	0.000	.535449	.8246975

Instrumented: E_m3
Instruments: lag1 lag2

```
-----
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =       2.22
                                              Prob > F        =      0.1372
                                              R-squared       =      0.0096
                                              Root MSE       =      .83478
-----
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.057401	.0385059	1.49	0.137	-.0184195	.1332214
_cons	.9420655	.1022146	9.22	0.000	.7407989	1.143332

Instrumented: E_m3
Instruments: lag1 lag2

```
-----
Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(1, 262)       =      28.61
                                              Prob > F        =      0.0000
                                              R-squared       =      0.1440
                                              Root MSE       =      .96376
-----
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1473309	.027545	5.35	0.000	.0930932	.2015686
_cons	.4855989	.1259417	3.86	0.000	.2376122	.7335856

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs	=	238
F(1, 236)	=	544.85
Prob > F	=	0.0000
R-squared	=	0.6012
Root MSE	=	.91273

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.7774745	.0333079	23.34	0.000	.7118556	.8430933
_cons	-.9230506	.1078607	-8.56	0.000	-1.135543	-.7105578

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs	=	238
F(1, 236)	=	61.50
Prob > F	=	0.0000
R-squared	=	0.2904
Root MSE	=	1.5103

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.4192402	.0534592	7.84	0.000	.313922	.5245584
_cons	.542273	.2139591	2.53	0.012	.1207591	.9637868

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs	=	197
F(1, 195)	=	2.70
Prob > F	=	0.1018
R-squared	=	0.0054
Root MSE	=	.8531

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.05235	.0318399	-1.64	0.102	-.1151447	.0104447
_cons	3.041609	.1677371	18.13	0.000	2.710797	3.372421

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs	=	238
F(1, 236)	=	1.43
Prob > F	=	0.2334
R-squared	=	0.0099

Root MSE = .92902

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.0610567	.0511046	-1.19	0.233	-.1617361	.0396228
_cons	2.521488	.184236	13.69	0.000	2.15853	2.884445

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs	=	197
F(1, 195)	=	58.51
Prob > F	=	0.0000
R-squared	=	0.2547
Root MSE	=	.38515

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2030264	.0265416	7.65	0.000	.150681	.2553718
_cons	1.186834	.0631245	18.80	0.000	1.062339	1.311328

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs	=	264
F(1, 262)	=	150.67
Prob > F	=	0.0000
R-squared	=	0.4782
Root MSE	=	.82666

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3542902	.0288631	12.27	0.000	.297457	.4111234
_cons	.5126364	.1603591	3.20	0.002	.1968798	.8283931

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs	=	226
F(1, 224)	=	41.96
Prob > F	=	0.0000
R-squared	=	0.1885
Root MSE	=	.57572

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2077066	.032065	6.48	0.000	.1445189	.2708942
_cons	2.01482	.1820853	11.07	0.000	1.656	2.373639

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs	=	264
F(1, 262)	=	41.17
Prob > F	=	0.0000

R-squared = 0.1877
Root MSE = .57066

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1570676	.0244798	6.42	0.000	.1088654	.2052697
_cons	2.063287	.0998224	20.67	0.000	1.866731	2.259844

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs = 264
F(1, 262) = 117.50
Prob > F = 0.0000
R-squared = 0.2832
Root MSE = .6894

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.5646704	.0520927	10.84	0.000	.4620968	.6672441
_cons	.7044114	.0565955	12.45	0.000	.5929714	.8158514

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs = 226
F(1, 224) = 8.79
Prob > F = 0.0034
R-squared = 0.0591
Root MSE = .71165

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.097274	.0328121	2.96	0.003	.0326141	.161934
_cons	1.776421	.2039806	8.71	0.000	1.374455	2.178387

Instrumented: E_m3
Instruments: lag1 lag2

Instrumental variables (2SLS) regression

Number of obs = 264
F(1, 262) = 65.42
Prob > F = 0.0000
R-squared = 0.2246
Root MSE = .73133

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1819653	.0224977	8.09	0.000	.1376659	.2262646
_cons	2.013727	.1024077	19.66	0.000	1.81208	2.215374

Instrumented: E_m3
Instruments: lag1 lag2

. *


```

. * OLS IV with dummies
.
. * OLS IV lag1 with dummies
. foreach y of global c_all {
2.     ivreg E_cons (E_m3=lag1) crisis08 recess11 m3_crisis08 m3_recess11 if country=="`y'",
robust
3.
. }

```

```

Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(5, 258)       =     210.58
                                              Prob > F         =      0.0000
                                              R-squared        =      0.5688
                                              Root MSE        =      .53209

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2784692	.0285371	9.76	0.000	.2222738	.3346645
crisis08	-1.27372	.1870969	-6.81	0.000	-1.642152	-.9052886
recess11	-1.017609	.1091387	-9.32	0.000	-1.232525	-.8026929
m3_crisis08	.1699244	.0682844	2.49	0.013	.0354586	.3043902
m3_recess11	.3117793	.0865005	3.60	0.000	.1414425	.4821161
_cons	.9578929	.087382	10.96	0.000	.7858201	1.129966

```

Instrumented:  E_m3
Instruments:   crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(5, 258)       =     130.02
                                              Prob > F         =      0.0000
                                              R-squared        =      0.0702
                                              Root MSE        =      .81509

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0385026	.0456636	0.84	0.400	-.0514183	.1284236
crisis08	-1.711407	.1550755	-11.04	0.000	-2.016782	-1.406033
recess11	.0201855	.1380157	0.15	0.884	-.2515951	.2919661
m3_crisis08	.3510303	.0629997	5.57	0.000	.2269711	.4750894
m3_recess11	-.0931052	.0638044	-1.46	0.146	-.218749	.0325386
_cons	1.047837	.131336	7.98	0.000	.7892101	1.306464

```

Instrumented:  E_m3
Instruments:   crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      264
                                              F(5, 258)       =     235.06
                                              Prob > F         =      0.0000
                                              R-squared        =      0.4873
                                              Root MSE        =      .7516

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0691827	.0262233	2.64	0.009	.0175438	.1208217
crisis08	-2.439951	.1721561	-14.17	0.000	-2.778961	-2.100941
recess11	-2.904036	.1684975	-17.23	0.000	-3.235842	-2.572231
m3_crisis08	.4005231	.0580025	6.91	0.000	.2863046	.5147417
m3_recess11	1.03927	.1946504	5.34	0.000	.6559642	1.422576

```

      _cons | 1.020228 .1230569 8.29 0.000 .7779045 1.262552
-----+-----
Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      239
                                              F(5, 233)       =     208.33
                                              Prob > F         =      0.0000
                                              R-squared        =     0.6137
                                              Root MSE        =     .90453

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.7470442	.040817	18.30	0.000	.6666266	.8274618
crisis08	-1.111384	.2585811	-4.30	0.000	-1.620839	-.6019279
recess11	-.2692355	.1757908	-1.53	0.127	-.6155781	.0771072
m3_crisis08	.1345796	.0886181	1.52	0.130	-.0400156	.3091749
m3_recess11	.0524581	.1379397	0.38	0.704	-.2193103	.3242265
_cons	-.7770323	.1431384	-5.43	0.000	-1.059043	-.4950214

```

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      239
                                              F(5, 233)       =     430.06
                                              Prob > F         =      0.0000
                                              R-squared        =     0.5655
                                              Root MSE        =     1.1897

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2680493	.0468139	5.73	0.000	.1758166	.360282
crisis08	-5.350042	.3138015	-17.05	0.000	-5.968292	-4.731791
recess11	-4.195001	.2405002	-17.44	0.000	-4.668834	-3.721168
m3_crisis08	.9926363	.134861	7.36	0.000	.7269333	1.258339
m3_recess11	1.844059	.1451344	12.71	0.000	1.558115	2.130002
_cons	1.42186	.2145622	6.63	0.000	.9991302	1.84459

```

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      198
                                              F(5, 192)       =      24.16
                                              Prob > F         =      0.0000
                                              R-squared        =     0.4813
                                              Root MSE        =     .62137

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.1115048	.0287767	-3.87	0.000	-.1682639	-.0547458
crisis08	-5.233269	.5527692	-9.47	0.000	-6.323549	-4.14299
recess11	.7048311	.4490102	1.57	0.118	-.1807951	1.590457
m3_crisis08	.887757	.1105468	8.03	0.000	.6697149	1.105799
m3_recess11	-.3125595	.1854173	-1.69	0.093	-.678276	.0531569
_cons	3.422789	.1439965	23.77	0.000	3.138771	3.706807

```

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      239
                                             F(5, 233)       =     186.63
                                             Prob > F         =      0.0000
                                             R-squared       =     0.3396
                                             Root MSE       =     .77613

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.1748176	.0455694	-3.84	0.000	-.2645983	-.0850368
crisis08	-4.100309	.2040675	-20.09	0.000	-4.502362	-3.698256
recess11	-1.521386	.3544987	-4.29	0.000	-2.219819	-.8229539
m3_crisis08	.9027139	.0656222	13.76	0.000	.7734252	1.032003
m3_recess11	.2283525	.1695439	1.35	0.179	-.1056825	.5623876
_cons	3.109617	.173832	17.89	0.000	2.767134	3.452101

```

-----
Instrumented:  E_m3
Instruments:   crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      198
                                             F(5, 192)       =     243.68
                                             Prob > F         =      0.0000
                                             R-squared       =     0.4468
                                             Root MSE       =     .33439

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.173297	.0315634	5.49	0.000	.1110414	.2355526
crisis08	-1.233272	.0886235	-13.92	0.000	-1.408072	-1.058471
recess11	-.0254835	.103163	-0.25	0.805	-.2289618	.1779948
m3_crisis08	.4334532	.0406133	10.67	0.000	.3533476	.5135587
m3_recess11	-.1091113	1.201644	-0.09	0.928	-2.47923	2.261007
_cons	1.276722	.0753146	16.95	0.000	1.128172	1.425273

```

-----
Instrumented:  E_m3
Instruments:   crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      264
                                             F(5, 258)       =     928.16
                                             Prob > F         =      0.0000
                                             R-squared       =     0.7195
                                             Root MSE       =     .61075

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2849262	.0303576	9.39	0.000	.2251459	.3447065
crisis08	-4.008734	.1937981	-20.69	0.000	-4.390362	-3.627107
recess11	.4441884	.2155104	2.06	0.040	.019805	.8685718
m3_crisis08	.5818246	.059031	9.86	0.000	.4655807	.6980685
m3_recess11	-1.080911	.2098427	-5.15	0.000	-1.494133	-.6676881
_cons	.9813332	.167449	5.86	0.000	.6515924	1.311074

```

-----
Instrumented:  E_m3
Instruments:   crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      227
                                             F(5, 221)       =     669.30

```

Prob > F = 0.0000
R-squared = 0.4675
Root MSE = .47004

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1465321	.0308092	4.76	0.000	.0858147	.2072496
crisis08	-3.074492	.1855127	-16.57	0.000	-3.440092	-2.708892
recess11	.1580963	.3508903	0.45	0.653	-.5334228	.8496155
m3_crisis08	.3655046	.0340032	10.75	0.000	.2984926	.4325166
m3_recess11	-.0665425	.0821995	-0.81	0.419	-.2285378	.0954527
_cons	2.422004	.173896	13.93	0.000	2.079298	2.764711

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

Instrumental variables (2SLS) regression Number of obs = 264
F(5, 258) = 127.49
Prob > F = 0.0000
R-squared = 0.4638
Root MSE = .4672

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0863141	.0230584	3.74	0.000	.0409075	.1317206
crisis08	-2.943368	.1893603	-15.54	0.000	-3.316257	-2.57048
recess11	-.7504785	.24773	-3.03	0.003	-1.238309	-.2626482
m3_crisis08	1.215819	.0925536	13.14	0.000	1.033563	1.398076
m3_recess11	.2727966	.2029325	1.34	0.180	-.1268183	.6724116
_cons	2.379837	.0955942	24.90	0.000	2.191593	2.568081

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

Instrumental variables (2SLS) regression Number of obs = 264
F(4, 259) = 96.01
Prob > F = 0.0000
R-squared = 0.3507
Root MSE = .65994

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.5618452	.0543536	10.34	0.000	.4548141	.6688764
crisis08	-2.528038	.183623	-13.77	0.000	-2.889622	-2.166454
recess11	-.0105517	.0985362	-0.11	0.915	-.2045857	.1834823
m3_crisis08	2.319247	.2138177	10.85	0.000	1.898205	2.74029
m3_recess11	0 (omitted)					
_cons	.752177	.0618949	12.15	0.000	.6302957	.8740582

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

Instrumental variables (2SLS) regression Number of obs = 227
F(5, 221) = 141.93
Prob > F = 0.0000
R-squared = 0.4789
Root MSE = .53436

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0657743	.0344216	1.91	0.057	-.0020623	.1336108
crisis08	-2.937685	.2799042	-10.50	0.000	-3.489307	-2.386062
recess11	.1744639	.4521542	0.39	0.700	-.7166218	1.06555
m3_crisis08	.2062815	.0456968	4.51	0.000	.1162242	.2963387
m3_recess11	-.0776398	.1229686	-0.63	0.528	-.3199809	.1647013
_cons	2.096114	.2180718	9.61	0.000	1.666348	2.52588

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

Instrumental variables (2SLS) regression Number of obs = 264
F(5, 258) = 109.35
Prob > F = 0.0000
R-squared = 0.6202
Root MSE = .51577

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0975093	.0197988	4.93	0.000	.0585214	.1364972
crisis08	-3.238608	.2898898	-11.17	0.000	-3.80946	-2.667757
recess11	-.6317159	.2575489	-2.45	0.015	-1.138882	-.1245502
m3_crisis08	.7374226	.1513465	4.87	0.000	.4393908	1.035454
m3_recess11	1.81973	2.136803	0.85	0.395	-2.388066	6.027526
_cons	2.447415	.0839956	29.14	0.000	2.282011	2.612819

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag1

```
. *
.
. * OLS IV lag2 with dummies
. foreach y of global c_all {
2.     ivreg E_cons (E_m3=lag2) crisis08 recess11 m3_crisis08 m3_recess11 if country=="`y'",
robust
3.
. }
```

Instrumental variables (2SLS) regression Number of obs = 264
F(5, 258) = 210.04
Prob > F = 0.0000
R-squared = 0.5688
Root MSE = .53209

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2779929	.0309646	8.98	0.000	.2170172	.3389685
crisis08	-1.275262	.1908367	-6.68	0.000	-1.651057	-.8994657
recess11	-1.01915	.1151002	-8.85	0.000	-1.245806	-.7924949
m3_crisis08	.1704007	.0692392	2.46	0.015	.0340548	.3067467
m3_recess11	.3122556	.0873837	3.57	0.000	.1401795	.4843317
_cons	.9594344	.0946554	10.14	0.000	.7730389	1.14583

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression Number of obs = 264

F(5, 258) = 129.73
 Prob > F = 0.0000
 R-squared = 0.0688
 Root MSE = .8157

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0538208	.050596	1.06	0.288	-.0458129	.1534546
crisis08	-1.661506	.16967	-9.79	0.000	-1.995621	-1.327392
recess11	.0700864	.1541743	0.45	0.650	-.2335138	.3736866
m3_crisis08	.3357121	.0665877	5.04	0.000	.2045875	.4668366
m3_recess11	-.1084234	.0674209	-1.61	0.109	-.2411886	.0243419
_cons	.9979364	.1482261	6.73	0.000	.7060493	1.289823

Instrumented: E_m3
 Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression Number of obs = 264
 F(5, 258) = 235.37
 Prob > F = 0.0000
 R-squared = 0.4862
 Root MSE = .75248

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0770917	.0275903	2.79	0.006	.0227609	.1314226
crisis08	-2.4067	.1765051	-13.64	0.000	-2.754275	-2.059126
recess11	-2.870786	.1725857	-16.63	0.000	-3.210642	-2.53093
m3_crisis08	.3926141	.0586618	6.69	0.000	.2770972	.5081311
m3_recess11	1.031361	.1947558	5.30	0.000	.6478476	1.414875
_cons	.9869775	.1288008	7.66	0.000	.7333428	1.240612

Instrumented: E_m3
 Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression Number of obs = 238
 F(5, 232) = 223.34
 Prob > F = 0.0000
 R-squared = 0.6187
 Root MSE = .90009

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.7697872	.0408753	18.83	0.000	.6892529	.8503214
crisis08	-1.051425	.2597544	-4.05	0.000	-1.563204	-.5396462
recess11	-.2092769	.1789313	-1.17	0.243	-.5618148	.143261
m3_crisis08	.1118367	.0882853	1.27	0.207	-.0621068	.2857801
m3_recess11	.0297152	.1377874	0.22	0.829	-.2417594	.3011897
_cons	-.8369909	.1472136	-5.69	0.000	-1.127037	-.5469444

Instrumented: E_m3
 Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression Number of obs = 238
 F(5, 232) = 428.70
 Prob > F = 0.0000
 R-squared = 0.5685
 Root MSE = 1.1879

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2747704	.0479955	5.72	0.000	.1802075	.3693332
crisis08	-5.333446	.3153375	-16.91	0.000	-5.954737	-4.712154
recess11	-4.178405	.242641	-17.22	0.000	-4.656467	-3.700344
m3_crisis08	.9859152	.1351646	7.29	0.000	.7196083	1.252222
m3_recess11	1.837338	.1454737	12.63	0.000	1.550719	2.123956
_cons	1.405264	.2169971	6.48	0.000	.9777274	1.832801

Instrumented: E_m3

Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	197
	F(5, 191)	=	24.46
	Prob > F	=	0.0000
	R-squared	=	0.4812
	Root MSE	=	.62253

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.1222951	.0297051	-4.12	0.000	-.1808873	-.0637029
crisis08	-5.276869	.5538282	-9.53	0.000	-6.369274	-4.184464
recess11	.6612311	.4500801	1.47	0.143	-.2265348	1.548997
m3_crisis08	.8985472	.1106739	8.12	0.000	.6802471	1.116847
m3_recess11	-.3017693	.1855441	-1.63	0.106	-.667748	.0642095
_cons	3.466389	.1475376	23.49	0.000	3.175376	3.757401

Instrumented: E_m3

Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	238
	F(5, 232)	=	187.80
	Prob > F	=	0.0000
	R-squared	=	0.3354
	Root MSE	=	.76764

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.1699644	.0458824	-3.70	0.000	-.2603639	-.079565
crisis08	-4.090907	.2051996	-19.94	0.000	-4.4952	-3.686614
recess11	-1.511984	.3551222	-4.26	0.000	-2.211661	-.8123075
m3_crisis08	.8978607	.0659013	13.62	0.000	.7680192	1.027702
m3_recess11	.2234994	.1696674	1.32	0.189	-.1107865	.5577852
_cons	3.100215	.1749873	17.72	0.000	2.755448	3.444982

Instrumented: E_m3

Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	197
	F(5, 191)	=	240.22
	Prob > F	=	0.0000
	R-squared	=	0.4475
	Root MSE	=	.33507

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
--------	-------	------------------	---	------	----------------------	--

E_m3	.1693944	.0317925	5.33	0.000	.1066849	.2321038
crisis08	-1.240535	.0888911	-13.96	0.000	-1.41587	-1.065201
recess11	-.0327472	.1034319	-0.32	0.752	-.2367627	.1712683
m3_crisis08	.4373558	.0408327	10.71	0.000	.3568148	.5178968
m3_recess11	-.1052087	1.202009	-0.09	0.930	-2.476125	2.265708
_cons	1.283986	.0754912	17.01	0.000	1.135083	1.43289

Instrumented: E_m3

Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(5, 258)	=	945.97
	Prob > F	=	0.0000
	R-squared	=	0.7190
	Root MSE	=	.61127

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2923421	.031694	9.22	0.000	.2299302	.3547539
crisis08	-3.973494	.200284	-19.84	0.000	-4.367893	-3.579094
recess11	.4794292	.2214557	2.16	0.031	.0433382	.9155201
m3_crisis08	.5744087	.0596911	9.62	0.000	.456865	.6919525
m3_recess11	-1.088326	.2100681	-5.18	0.000	-1.501993	-.6746601
_cons	.9460924	.1749359	5.41	0.000	.6016085	1.290576

Instrumented: E_m3

Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	226
	F(5, 220)	=	680.80
	Prob > F	=	0.0000
	R-squared	=	0.4764
	Root MSE	=	.46663

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.15231	.0332828	4.58	0.000	.0867162	.2179039
crisis08	-3.048386	.1999815	-15.24	0.000	-3.442511	-2.654261
recess11	.1842024	.3591508	0.51	0.609	-.523614	.8920189
m3_crisis08	.3597267	.0362589	9.92	0.000	.2882674	.431186
m3_recess11	-.0723204	.0832146	-0.87	0.386	-.2363202	.0916794
_cons	2.395898	.1891592	12.67	0.000	2.023102	2.768694

Instrumented: E_m3

Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(5, 258)	=	126.63
	Prob > F	=	0.0000
	R-squared	=	0.4637
	Root MSE	=	.46725

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0834057	.0246793	3.38	0.001	.0348072	.1320042
crisis08	-2.954692	.1920082	-15.39	0.000	-3.332795	-2.576589
recess11	-.7618021	.2499304	-3.05	0.003	-1.253965	-.2696387

m3_crisis08		1.218728	.0929259	13.12	0.000	1.035738	1.401718
m3_recess11		.275705	.2031124	1.36	0.176	-.1242643	.6756742
_cons		2.39116	.1012394	23.62	0.000	2.1918	2.590521

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(4, 259)	=	94.00
	Prob > F	=	0.0000
	R-squared	=	0.3503
	Root MSE	=	.66014

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3	.5722375	.0579356	9.88	0.000	.4581526 .6863224
crisis08	-2.52027	.1843514	-13.67	0.000	-2.883288 -2.157252
recess11	-.0059013	.0991925	-0.06	0.953	-.2012277 .1894252
m3_crisis08	2.308855	.2146958	10.75	0.000	1.886084 2.731627
m3_recess11	0 (omitted)				
_cons	.7444089	.0643197	11.57	0.000	.6177527 .871065

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	226
	F(5, 220)	=	141.38
	Prob > F	=	0.0000
	R-squared	=	0.4778
	Root MSE	=	.53495

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3	.0559203	.0358663	1.56	0.120	-.0147651 .1266057
crisis08	-2.994948	.2873826	-10.42	0.000	-3.561323 -2.428572
recess11	.1172008	.4562973	0.26	0.798	-.7820725 1.016474
m3_crisis08	.2161354	.0468294	4.62	0.000	.1238438 .308427
m3_recess11	-.0677858	.1233414	-0.55	0.583	-.3108678 .1752961
_cons	2.153377	.2269634	9.49	0.000	1.706076 2.600678

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	264
	F(5, 258)	=	108.07
	Prob > F	=	0.0000
	R-squared	=	0.6194
	Root MSE	=	.51633

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3	.0899205	.0200643	4.48	0.000	.0504099 .1294311
crisis08	-3.265668	.2905487	-11.24	0.000	-3.837817 -2.69352
recess11	-.658776	.2578525	-2.55	0.011	-1.16654 -.1510125
m3_crisis08	.7450114	.1514686	4.92	0.000	.4467391 1.043284
m3_recess11	1.827319	2.136813	0.86	0.393	-2.380497 6.035135
_cons	2.474475	.084851	29.16	0.000	2.307387 2.641564

Instrumented: E_m3
Instruments: crisis08 recess11 m3_crisis08 m3_recess11 lag2

```

. *
.
. * OLS IV, with controls and dummies
.
. * OLS IV lag1 with controls & dummies
.
. * All controls, eu countries (a)
. foreach y of global eu_c_unemp {
2.       ivreg E_cons (E_m3=lag1) E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 if country=="`y'"
> ", robust
3.
. }

```

Instrumental variables (2SLS) regression

Number of obs	=	260
F(8, 251)	=	271.62
Prob > F	=	0.0000
R-squared	=	0.6823
Root MSE	=	.4624

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3298578	.0433491	7.61	0.000	.2444834	.4152322
E_wages	.1938885	.1178213	1.65	0.101	-.0381558	.4259329
E_unem	.0370697	.0376091	0.99	0.325	-.0369999	.1111393
E_budget_def	.0028088	.0006602	4.25	0.000	.0015086	.004109
crisis08	-1.043987	.1994753	-5.23	0.000	-1.436845	-.6511278
recess11	-.9631771	.1061789	-9.07	0.000	-1.172292	-.7540619
m3_crisis08	.0454009	.0687264	0.66	0.509	-.089953	.1807547
m3_recess11	.3404963	.0926553	3.67	0.000	.1580154	.5229771
_cons	.3451385	.3473577	0.99	0.321	-.3389688	1.029246

Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag1

Instrumental variables (2SLS) regression

Number of obs	=	260
F(8, 251)	=	42.54
Prob > F	=	0.0000
R-squared	=	0.3220
Root MSE	=	.69309

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.084832	.0467376	1.82	0.071	-.0072158	.1768798
E_wages	.4721274	.1239337	3.81	0.000	.2280449	.7162099
E_unem	.1393259	.0464671	3.00	0.003	.0478107	.230841
E_budget_def	.0098734	.0016683	5.92	0.000	.0065878	.013159
crisis08	-1.008588	.2007697	-5.02	0.000	-1.403996	-.6131797
recess11	-.4324919	.1107232	-3.91	0.000	-.6505568	-.2144269
m3_crisis08	.0005632	.0788668	0.01	0.994	-.1547617	.1558882
m3_recess11	.2162304	.0873451	2.48	0.014	.0442077	.388253
_cons	-.8263757	.5429073	-1.52	0.129	-1.89561	.2428587

Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag1

```

-----
Instrumental variables (2SLS) regression      Number of obs   =      260
                                              F(8, 251)       =     174.72
                                              Prob > F         =      0.0000
                                              R-squared        =     0.6316
                                              Root MSE        =     .64106

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2171939	.0834549	2.60	0.010	.0528327	.381555
E_wages	-.1246967	.0905207	-1.38	0.170	-.3029736	.0535801
E_unem	-.042484	.023937	-1.77	0.077	-.0896269	.004659
E_budget_def	.009608	.0058512	1.64	0.102	-.0019157	.0211317
crisis08	-1.779455	.4339337	-4.10	0.000	-2.63407	-.9248397
recess11	-2.783867	.2049005	-13.59	0.000	-3.187411	-2.380324
m3_crisis08	.1375877	.1464189	0.94	0.348	-.1507786	.4259539
m3_recess11	.8633151	.2442738	3.53	0.000	.3822275	1.344403
_cons	1.820266	.2029173	8.97	0.000	1.420629	2.219904

```

-----
Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
               m3_recess11 lag1

```

```

. *
.
. * Without unemployment, eu countries (b)
. foreach y of global eu_c_nounemp {
.   2.      ivreg E_cons (E_m3=lag1) E_wages E_budget_def crisis08 recess11 m3_crisis08 m3_recess11 if
country=="`y'", robu
> st
.   3.
. }

```

```

Instrumental variables (2SLS) regression      Number of obs   =      58
                                              F(5, 52)        =     32.48
                                              Prob > F         =      0.0000
                                              R-squared        =     0.6542
                                              Root MSE        =     .41337

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.761666	.1153628	6.60	0.000	.5301736	.9931584
E_wages	-.9478446	.3328901	-2.85	0.006	-1.615838	-.2798517
E_budget_def	.0628047	.0145778	4.31	0.000	.0335522	.0920572
crisis08	0	(omitted)				
recess11	-.3671108	.1901093	-1.93	0.059	-.748593	.0143714
m3_crisis08	0	(omitted)				
m3_recess11	-.0329827	.16868	-0.20	0.846	-.3714638	.3054984
_cons	2.352724	.7293102	3.23	0.002	.8892559	3.816192

```

-----
Instrumented:  E_m3
Instruments:   E_wages E_budget_def crisis08 recess11 m3_crisis08
               m3_recess11 lag1

```

```

Instrumental variables (2SLS) regression      Number of obs   =      58
                                              F(5, 52)        =     90.37
                                              Prob > F         =      0.0000
                                              R-squared        =     0.6201
                                              Root MSE        =     .78403

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0282326	.1769041	0.16	0.874	-.3267515	.3832168
E_wages	.9830331	.3228738	3.04	0.004	.3351396	1.630927
E_budget_def	.0466713	.0115899	4.03	0.000	.0234144	.0699282
crisis08	0	(omitted)				
recess11	-3.509075	.3640824	-9.64	0.000	-4.23966	-2.778491
m3_crisis08	0	(omitted)				
m3_recess11	1.878503	.2208426	8.51	0.000	1.43535	2.321656
_cons	2.883292	.7643746	3.77	0.000	1.349463	4.417122

Instrumented: E_m3
Instruments: E_wages E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag1

Instrumental variables (2SLS) regression Number of obs = 58
F(5, 52) = 14.00
Prob > F = 0.0000
R-squared = 0.5313
Root MSE = .3431

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.396061	.2453715	1.61	0.113	-.0963129	.8884348
E_wages	.5657212	.4831345	1.17	0.247	-.4037592	1.535202
E_budget_def	-.0002535	.0033399	-0.08	0.940	-.0069555	.0064484
crisis08	0	(omitted)				
recess11	2.181237	.4492556	4.86	0.000	1.27974	3.082734
m3_crisis08	0	(omitted)				
m3_recess11	-.9080146	.1865449	-4.87	0.000	-1.282344	-.5336849
_cons	-.0310787	.8085452	-0.04	0.969	-1.653543	1.591386

Instrumented: E_m3
Instruments: E_wages E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag1

Instrumental variables (2SLS) regression Number of obs = 58
F(5, 52) = 19.29
Prob > F = 0.0000
R-squared = 0.6953
Root MSE = .2714

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.0588876	.0846411	-0.70	0.490	-.2287324	.1109571
E_wages	-.1443152	.1565207	-0.92	0.361	-.458397	.1697667
E_budget_def	.0055916	.0028451	1.97	0.055	-.0001174	.0113007
crisis08	0	(omitted)				
recess11	-.8891466	.3473148	-2.56	0.013	-1.586085	-.1922085
m3_crisis08	0	(omitted)				
m3_recess11	.002508	.1869272	0.01	0.989	-.3725889	.3776049
_cons	3.175576	.6021393	5.27	0.000	1.967295	4.383857

Instrumented: E_m3
Instruments: E_wages E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag1

. *

```

. * Without unemployment and wages, Switzerland (c)
. ivreg E_cons (E_m3=lag1) E_budget_def crisis08 recess11 m3_crisis08 m3_recess11 if
country=="Switzerland", robust

```

```

Instrumental variables (2SLS) regression      Number of obs      =          58
                                              F(4, 53)           =         41.56
                                              Prob > F           =         0.0000
                                              R-squared          =         0.6653
                                              Root MSE          =         .17931

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.2216912	.0637564	-3.48	0.001	-.3495704	-.0938121
E_budget_def	.0332484	.009366	3.55	0.001	.0144625	.0520342
crisis08	0	(omitted)				
recess11	-.5890265	.0749484	-7.86	0.000	-.739354	-.4386991
m3_crisis08	0	(omitted)				
m3_recess11	.5798563	1.129231	0.51	0.610	-1.685095	2.844808
_cons	1.755229	.0421775	41.62	0.000	1.670632	1.839826

```

Instrumented: E_m3
Instruments: E_budget_def crisis08 recess11 m3_crisis08 m3_recess11 lag1

```

```

.
.
. * All controls, other countries (d)
. foreach y of global other_c_unemp {
2.     ivreg E_cons (E_m3=lag1) E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 if country=="`y'"
> ", robust
3.
. }

```

```

Instrumental variables (2SLS) regression      Number of obs      =         260
                                              F(8, 251)          =        312.69
                                              Prob > F           =         0.0000
                                              R-squared          =         0.8398
                                              Root MSE          =         .46628

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0884993	.0705221	1.25	0.211	-.0503911	.2273897
E_wages	-.2461417	.1488818	-1.65	0.100	-.5393586	.0470751
E_unem	-.019521	.0179188	-1.09	0.277	-.0548115	.0157694
E_budget_def	-.0162514	.0019215	-8.46	0.000	-.0200356	-.0124671
crisis08	-3.144434	.2167901	-14.50	0.000	-3.571394	-2.717475
recess11	-.0365084	.1555541	-0.23	0.815	-.3428659	.2698492
m3_crisis08	.3996989	.0599484	6.67	0.000	.2816329	.5177648
m3_recess11	-.554219	.1650695	-3.36	0.001	-.8793168	-.2291213
_cons	3.676866	.4560238	8.06	0.000	2.778745	4.574986

```

Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag1

```

```

Instrumental variables (2SLS) regression      Number of obs      =         227
                                              F(8, 218)          =         88.43
                                              Prob > F           =         0.0000
                                              R-squared          =         0.6416
                                              Root MSE          =         .38829

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1172277	.0345685	3.39	0.001	.0490964	.1853589
E_wages	-.5230643	.1241231	-4.21	0.000	-.7676992	-.2784294
E_unem	-.0029397	.0230802	-0.13	0.899	-.0484287	.0425493
E_budget_def	.0174618	.0021012	8.31	0.000	.0133206	.021603
crisis08	-2.230942	.2707172	-8.24	0.000	-2.7645	-1.697383
recess11	-.3728637	.5109061	-0.73	0.466	-1.379811	.634084
m3_crisis08	.2239429	.047704	4.69	0.000	.1299227	.317963
m3_recess11	.1113083	.1337031	0.83	0.406	-.1522079	.3748245
_cons	4.565176	.3866935	11.81	0.000	3.803039	5.327312

Instrumented: E_m3

Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag1

Instrumental variables (2SLS) regression	Number of obs	=	125
	F(8, 116)	=	159.67
	Prob > F	=	0.0000
	R-squared	=	0.8619
	Root MSE	=	.28729

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2858622	.0278343	10.27	0.000	.2307329	.3409915
E_wages	.1323197	.0875812	1.51	0.134	-.0411459	.3057853
E_unem	-.0998334	.1460672	-0.68	0.496	-.3891379	.189471
E_budget_def	-.0009442	.0044858	-0.21	0.834	-.0098288	.0079404
crisis08	-2.296569	.245401	-9.36	0.000	-2.782617	-1.810522
recess11	-.1408559	.2559106	-0.55	0.583	-.6477191	.3660072
m3_crisis08	.8904267	.1201374	7.41	0.000	.6524795	1.128374
m3_recess11	-.0475162	.2144006	-0.22	0.825	-.4721636	.3771312
_cons	2.293609	1.011455	2.27	0.025	.2902949	4.296923

Instrumented: E_m3

Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag1

Instrumental variables (2SLS) regression	Number of obs	=	260
	F(7, 252)	=	181.74
	Prob > F	=	0.0000
	R-squared	=	0.5629
	Root MSE	=	.54638

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.3391711	.0788223	4.30	0.000	.1839368	.4944054
E_wages	.3990315	.059215	6.74	0.000	.2824121	.5156508
E_unem	.0036225	.0886537	0.04	0.967	-.1709742	.1782191
E_budget_def	-.0018053	.0053759	-0.34	0.737	-.0123927	.0087822
crisis08	-.783338	.2047311	-3.83	0.000	-1.18654	-.3801361
recess11	.0211775	.1074742	0.20	0.844	-.1904846	.2328396
m3_crisis08	.675026	.2212916	3.05	0.003	.2392094	1.110843
m3_recess11	0 (omitted)					
_cons	.57258	.4333519	1.32	0.188	-.2808729	1.426033

Instrumented: E_m3

Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08

m3_recess11 lag1

```
Instrumental variables (2SLS) regression      Number of obs      =      227
                                             F(8, 218)          =      114.05
                                             Prob > F            =      0.0000
                                             R-squared           =      0.6771
                                             Root MSE            =      .42354
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1721296	.0408219	4.22	0.000	.0916735	.2525858
E_wages	-1.783918	.1934925	-9.22	0.000	-2.165273	-1.402562
E_unem	-.3153635	.0537475	-5.87	0.000	-.4212947	-.2094322
E_budget_def	.0277929	.010062	2.76	0.006	.0079616	.0476241
crisis08	-1.610775	.3448519	-4.67	0.000	-2.290445	-.9311042
recess11	1.002442	.5471828	1.83	0.068	-.0760034	2.080888
m3_crisis08	.1755262	.0481105	3.65	0.000	.0807049	.2703475
m3_recess11	-.1707974	.1520414	-1.12	0.263	-.4704568	.1288619
_cons	7.270583	.5780876	12.58	0.000	6.131227	8.409939

```
Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
              m3_recess11 lag1
```

```
Instrumental variables (2SLS) regression      Number of obs      =      259
                                             F(8, 250)          =      109.59
                                             Prob > F            =      0.0000
                                             R-squared           =      0.7575
                                             Root MSE            =      .41783
```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.0831439	.0190114	-4.37	0.000	-.1205868	-.0457009
E_wages	.5717724	.0614824	9.30	0.000	.450683	.6928618
E_unem	-.37014	.047497	-7.79	0.000	-.4636852	-.2765948
E_budget_def	-.0010869	.0002039	-5.33	0.000	-.0014885	-.0006852
crisis08	-3.191353	.3540669	-9.01	0.000	-3.888687	-2.494019
recess11	-.5597501	.256915	-2.18	0.030	-1.065744	-.0537564
m3_crisis08	.5743634	.1634396	3.51	0.001	.2524693	.8962574
m3_recess11	2.50565	2.160614	1.16	0.247	-1.749675	6.760975
_cons	3.075154	.3219231	9.55	0.000	2.441127	3.709181

```
Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
              m3_recess11 lag1
```

```
. *
. *
. * 30 OLS IV lag2 with controls & dummies
.
. * All controls, eu countries (a)
. foreach y of global eu_c_unemp {
.   2.      ivreg E_cons (E_m3=lag2) E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 if country=="`y'"
> ", robust
.   3.
. }
```

```
Instrumental variables (2SLS) regression      Number of obs      =      260
                                             F(8, 251)          =      278.18
```

Prob > F = 0.0000
R-squared = 0.6776
Root MSE = .46581

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2697113	.049895	5.41	0.000	.171445	.3679776
E_wages	.3252318	.1290151	2.52	0.012	.0711417	.579322
E_unem	.0238579	.0372352	0.64	0.522	-.0494752	.0971911
E_budget_def	.0022589	.0006486	3.48	0.001	.0009815	.0035364
crisis08	-1.151716	.2141209	-5.38	0.000	-1.573419	-.7300136
recess11	-1.003261	.1083694	-9.26	0.000	-1.21669	-.7898315
m3_crisis08	.078291	.0710408	1.10	0.271	-.061621	.2182031
m3_recess11	.3569186	.0905349	3.94	0.000	.1786137	.5352234
_cons	.2498979	.3463796	0.72	0.471	-.4322828	.9320787

Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag2

Instrumental variables (2SLS) regression Number of obs = 260
F(8, 251) = 42.82
Prob > F = 0.0000
R-squared = 0.3216
Root MSE = .69331

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0759807	.0483875	1.57	0.118	-.0193166	.1712781
E_wages	.4823158	.1237331	3.90	0.000	.2386284	.7260033
E_unem	.1441864	.0472694	3.05	0.003	.0510912	.2372816
E_budget_def	.0098179	.0016537	5.94	0.000	.006561	.0130748
crisis08	-1.035872	.2032054	-5.10	0.000	-1.436077	-.635667
recess11	-.4481389	.1141119	-3.93	0.000	-.6728778	-.2234
m3_crisis08	.011178	.0795184	0.14	0.888	-.1454303	.1677862
m3_recess11	.2266961	.0893377	2.54	0.012	.050749	.4026432
_cons	-.8735819	.5455289	-1.60	0.111	-1.947979	.2008155

Instrumented: E_m3
Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag2

Instrumental variables (2SLS) regression Number of obs = 260
F(8, 251) = 176.00
Prob > F = 0.0000
R-squared = 0.6308
Root MSE = .6417

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2037206	.0831604	2.45	0.015	.0399394	.3675017
E_wages	-.0915711	.0978524	-0.94	0.350	-.2842876	.1011453
E_unem	-.0413541	.0240308	-1.72	0.087	-.0886817	.0059736
E_budget_def	.009482	.0057559	1.65	0.101	-.001854	.0208179
crisis08	-1.815213	.4278582	-4.24	0.000	-2.657862	-.9725629
recess11	-2.791656	.2056078	-13.58	0.000	-3.196593	-2.38672
m3_crisis08	.1478551	.1444288	1.02	0.307	-.1365917	.4323019
m3_recess11	.8720126	.2440445	3.57	0.000	.3913767	1.352649
_cons	1.767334	.2081746	8.49	0.000	1.357343	2.177326


```

-----
Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
               m3_recess11 lag2
-----

```

```

. *
.
. * Without unemployment, eu countries (b)
. foreach y of global eu_c_nounemp {
.   2.       ivreg E_cons (E_m3=lag2) E_wages E_budget_def crisis08 recess11 m3_crisis08 m3_recess11 if
country=="`y'", robu
> st
.   3.
. }

```

```

Instrumental variables (2SLS) regression      Number of obs   =          58
                                              F(5, 52)        =         30.46
                                              Prob > F         =         0.0000
                                              R-squared        =         0.6516
                                              Root MSE        =         .41494

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.8041631	.1243643	6.47	0.000	.5546079	1.053718
E_wages	-.9463758	.3280049	-2.89	0.006	-1.604566	-.2881858
E_budget_def	.0654322	.01514	4.32	0.000	.0350515	.0958129
crisis08	0	(omitted)				
recess11	-.3315082	.1890096	-1.75	0.085	-.7107838	.0477673
m3_crisis08	0	(omitted)				
m3_recess11	-.0764781	.1707957	-0.45	0.656	-.4192047	.2662486
_cons	2.36969	.7165943	3.31	0.002	.9317387	3.807642

```

-----
Instrumented:  E_m3
Instruments:   E_wages E_budget_def crisis08 recess11 m3_crisis08
               m3_recess11 lag2
-----

```

```

Instrumental variables (2SLS) regression      Number of obs   =          58
                                              F(5, 52)        =         91.50
                                              Prob > F         =         0.0000
                                              R-squared        =         0.6197
                                              Root MSE        =         .78449

```

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.0731668	.1892259	0.39	0.701	-.3065428	.4528763
E_wages	.9331737	.329211	2.83	0.007	.2725635	1.593784
E_budget_def	.0461269	.0117111	3.94	0.000	.022627	.0696269
crisis08	0	(omitted)				
recess11	-3.471921	.3725339	-9.32	0.000	-4.219465	-2.724377
m3_crisis08	0	(omitted)				
m3_recess11	1.840544	.2274818	8.09	0.000	1.384068	2.297019
_cons	2.843549	.7768062	3.66	0.001	1.284773	4.402324

```

-----
Instrumented:  E_m3
Instruments:   E_wages E_budget_def crisis08 recess11 m3_crisis08
               m3_recess11 lag2
-----

```

```

Instrumental variables (2SLS) regression      Number of obs   =          58
                                              F(5, 52)        =         14.26
                                              Prob > F         =         0.0000

```

R-squared = 0.5393
Root MSE = .34015

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.347263	.2834228	1.23	0.226	-.2214665	.9159925
E_wages	.6499686	.5529569	1.18	0.245	-.4596205	1.759558
E_budget_def	-.0008277	.0035905	-0.23	0.819	-.0080326	.0063771
crisis08	0	(omitted)				
recess11	2.144436	.4743026	4.52	0.000	1.192678	3.096194
m3_crisis08	0	(omitted)				
m3_recess11	-.8973898	.1924924	-4.66	0.000	-1.283654	-.5111255
_cons	-.0381517	.8007752	-0.05	0.962	-1.645025	1.568721

Instrumented: E_m3
Instruments: E_wages E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag2

Instrumental variables (2SLS) regression

Number of obs = 58
F(5, 52) = 19.47
Prob > F = 0.0000
R-squared = 0.6939
Root MSE = .27203

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.1090627	.0957495	-1.14	0.260	-.3011981	.0830727
E_wages	-.1977266	.1561247	-1.27	0.211	-.5110138	.1155606
E_budget_def	.0070871	.0032697	2.17	0.035	.0005259	.0136483
crisis08	0	(omitted)				
recess11	-.9478173	.3457784	-2.74	0.008	-1.641672	-.2539623
m3_crisis08	0	(omitted)				
m3_recess11	.0268874	.1862885	0.14	0.886	-.3469279	.4007027
_cons	3.459254	.6318354	5.47	0.000	2.191383	4.727124

Instrumented: E_m3
Instruments: E_wages E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag2

. *

. *

. * Without unemployment and wages, Switzerland (c)

. ivreg E_cons (E_m3=lag2) E_budget_def crisis08 recess11 m3_crisis08 m3_recess11 if country=="Switzerland", robust

Instrumental variables (2SLS) regression

Number of obs = 58
F(4, 53) = 43.40
Prob > F = 0.0000
R-squared = 0.6636
Root MSE = .17977

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	-.2391232	.0773882	-3.09	0.003	-.3943442	-.0839021
E_budget_def	.0318556	.0101784	3.13	0.003	.0114403	.052271
crisis08	0	(omitted)				
recess11	-.5941578	.0766632	-7.75	0.000	-.7479247	-.4403909
m3_crisis08	0	(omitted)				
m3_recess11	.584974	1.135766	0.52	0.609	-1.693085	2.863033

_cons		1.763922	.0467542	37.73	0.000	1.670145	1.857699
-------	--	----------	----------	-------	-------	----------	----------

Instrumented: E_m3

Instruments: E_budget_def crisis08 recess11 m3_crisis08 m3_recess11 lag2

```
.
.
. * All controls, other countries (d)
. foreach y of global other_c_unemp {
2.     ivreg E_cons (E_m3=lag2) E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 if country=="`y'"
> ", robust
3.
. }
```

Instrumental variables (2SLS) regression	Number of obs	=	260
	F(8, 251)	=	278.33
	Prob > F	=	0.0000
	R-squared	=	0.8356
	Root MSE	=	.47238

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3	.006454	.0771016	0.08	0.933	-.1453947 .1583026
E_wages	-.0760475	.1683648	-0.45	0.652	-.4076353 .2555404
E_unem	.001137	.0197248	0.06	0.954	-.0377102 .0399842
E_budget_def	-.0163964	.0018987	-8.64	0.000	-.0201357 -.0126571
crisis08	-3.183995	.2403655	-13.25	0.000	-3.657385 -2.710604
recess11	-.0676798	.155346	-0.44	0.663	-.3736275 .2382679
m3_crisis08	.4162192	.0638305	6.52	0.000	.2905075 .5419309
m3_recess11	-.5753924	.165792	-3.47	0.001	-.9019132 -.2488717
_cons	3.29574	.503394	6.55	0.000	2.304325 4.287154

Instrumented: E_m3

Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	226
	F(8, 217)	=	87.46
	Prob > F	=	0.0000
	R-squared	=	0.6423
	Root MSE	=	.38834

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
E_m3	.0986851	.0379358	2.60	0.010	.0239154 .1734548
E_wages	-.4628844	.1279238	-3.62	0.000	-.7150167 -.2107521
E_unem	.0021106	.0230206	0.09	0.927	-.0432619 .0474832
E_budget_def	.0174	.0021031	8.27	0.000	.0132549 .021545
crisis08	-2.324423	.285108	-8.15	0.000	-2.886358 -1.762488
recess11	-.4275275	.5182856	-0.82	0.410	-1.449046 .5939909
m3_crisis08	.2387422	.0498624	4.79	0.000	.1404656 .3370189
m3_recess11	.119048	.1348589	0.88	0.378	-.146753 .3848491
_cons	4.413591	.3865112	11.42	0.000	3.651794 5.175387

Instrumented: E_m3

Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
m3_recess11 lag2

Instrumental variables (2SLS) regression	Number of obs	=	125
--	---------------	---	-----

F(8, 116) = 152.62
 Prob > F = 0.0000
 R-squared = 0.8615
 Root MSE = .28769

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.302693	.0294662	10.27	0.000	.2443315	.3610544
E_wages	.1071888	.0910338	1.18	0.241	-.0731151	.2874926
E_unem	-.0960318	.1450474	-0.66	0.509	-.3833163	.1912528
E_budget_def	-.0014602	.0045034	-0.32	0.746	-.0103798	.0074594
crisis08	-2.294853	.2460664	-9.33	0.000	-2.782218	-1.807487
recess11	-.1527812	.2594712	-0.59	0.557	-.6666967	.3611343
m3_crisis08	.8952665	.1203763	7.44	0.000	.656846	1.133687
m3_recess11	-.0285399	.2180785	-0.13	0.896	-.4604719	.4033921
_cons	2.289131	1.009547	2.27	0.025	.2895956	4.288667

Instrumented: E_m3
 Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
 m3_recess11 lag2

Instrumental variables (2SLS) regression Number of obs = 260
 F(7, 252) = 170.86
 Prob > F = 0.0000
 R-squared = 0.5612
 Root MSE = .54742

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.2862661	.0853221	3.36	0.001	.118231	.4543013
E_wages	.3882458	.0597239	6.50	0.000	.2706242	.5058674
E_unem	-.0131311	.0903851	-0.15	0.885	-.1911375	.1648753
E_budget_def	.0003869	.0055409	0.07	0.944	-.0105254	.0112992
crisis08	-.788408	.2071229	-3.81	0.000	-1.196321	-.3804954
recess11	.0319686	.1085639	0.29	0.769	-.1818396	.2457768
m3_crisis08	.6527758	.2242945	2.91	0.004	.2110451	1.094506
m3_recess11	0 (omitted)					
_cons	.7524309	.4477771	1.68	0.094	-.1294314	1.634293

Instrumented: E_m3
 Instruments: E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
 m3_recess11 lag2

Instrumental variables (2SLS) regression Number of obs = 226
 F(8, 217) = 115.73
 Prob > F = 0.0000
 R-squared = 0.6756
 Root MSE = .42459

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
E_m3	.1589952	.0454508	3.50	0.001	.0694135	.2485768
E_wages	-1.748263	.2029808	-8.61	0.000	-2.148329	-1.348196
E_unem	-.3039073	.0568217	-5.35	0.000	-.4159003	-.1919143
E_budget_def	.0307641	.0101605	3.03	0.003	.0107382	.0507901
crisis08	-1.678392	.360945	-4.65	0.000	-2.389798	-.9669846
recess11	.9402341	.5592972	1.68	0.094	-.1621163	2.042584
m3_crisis08	.1841663	.0497161	3.70	0.000	.086178	.2821546
m3_recess11	-.1563798	.1536809	-1.02	0.310	-.459278	.1465185

```

      _cons |   7.200325   .5897758   12.21   0.000   6.037902   8.362747
-----+-----
Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
               m3_recess11 lag2
-----+-----

```

```

Instrumental variables (2SLS) regression      Number of obs   =      259
                                              F(8, 250)       =     110.41
                                              Prob > F        =      0.0000
                                              R-squared       =      0.7548
                                              Root MSE       =      .42009

```

```

-----+-----
      E_cons |      Coef.      Robust      t      P>|t|      [95% Conf. Interval]
-----+-----
      E_m3   |  -.1055212   .0184595   -5.72   0.000   -.1418771   -.0691653
      E_wages |  .6017997   .0616418    9.76   0.000   .4803962   .7232032
      E_unem  |  -.3730884   .0477791   -7.81   0.000   -.4671893   -.2789875
E_budget_def |  -.0010584   .0002054   -5.15   0.000   -.0014629   -.0006539
      crisis08 | -3.190961   .3587287   -8.90   0.000   -3.897476   -2.484445
      recess11 | -.5770438   .2616984   -2.20   0.028   -1.092458   -.0616292
      m3_crisis08 | .5643378   .1647283    3.43   0.001   .2399057   .88877
      m3_recess11 | 2.5274   2.208114    1.14   0.253   -1.821476   6.876277
      _cons   |   3.0841   .3221531    9.57   0.000    2.44962    3.71858
-----+-----

```

```

Instrumented:  E_m3
Instruments:   E_wages E_unem E_budget_def crisis08 recess11 m3_crisis08
               m3_recess11 lag2
-----+-----

```

```

. *
.
end of do-file

```

▪ A.4. Anova test result

Table A. 1: Anova test result

ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	4.319749949	13	0.332288458	12.73400322	0.00000000	1.862661458
Within Groups	1.826620555	70		0.026094579		
Total	6.146370504	83				

Source: own analysis

▪ A.5. Wald test and country grouping

Base country: 1 = Australia

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
country_id#c.E_m3						
2	-.0411021	.0399703	-1.03	0.304	-.1194704	.0372662
3	.1369438	.040136	3.41	0.001	.0582506	.2156369
4	-.1467677	.0478207	-3.07	0.002	-.2405279	-.0530074
5	-.0594497	.0415	-1.43	0.152	-.1408172	.0219179
6	.3513269	.058716	5.98	0.000	.2362047	.4664492
7	.5535015	.0468082	11.82	0.000	.4617264	.6452766
8	-.085598	.0453238	-1.89	0.059	-.1744627	.0032667
9	-.2371108	.0456072	-5.20	0.000	-.326531	-.1476905
10	.2036335	.059985	3.39	0.001	.0860231	.3212438
11	-.279989	.0590876	-4.74	0.000	-.3958399	-.1641381
12	.0045592	.0411533	0.11	0.912	-.0761286	.0852469
13	.1539518	.0427411	3.60	0.000	.0701509	.2377527
14	-.0109478	.0393231	-0.28	0.781	-.0880471	.0661514

Based on these first results, we group the following countries together:

1, 2, 5, 12, 14.

Base country: 2 = Canada

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
country_id#c.E_m3						
1	.0411021	.0399703	1.03	0.304	-.0372662	.1194704
3	.1780459	.0342228	5.20	0.000	.1109464	.2451453
4	-.1056656	.0429781	-2.46	0.014	-.1899312	-.0213999
5	-.0183476	.0358128	-0.51	0.608	-.0885644	.0518692
6	.392429	.0548441	7.16	0.000	.2848983	.4999598
7	.5946036	.0418487	14.21	0.000	.5125524	.6766547
8	-.0444959	.0401815	-1.11	0.268	-.1232782	.0342864
9	-.1960087	.0405008	-4.84	0.000	-.2754172	-.1166002
10	.2447355	.0562005	4.35	0.000	.1345452	.3549259
11	-.2388869	.0552418	-4.32	0.000	-.3471974	-.1305764
12	.0456613	.0354104	1.29	0.197	-.0237667	.1150892
13	.1950539	.0372439	5.24	0.000	.1220312	.2680766
14	.0301543	.0332657	0.91	0.365	-.0350686	.0953771

We group country 2, 1, 5, 8, 12, 14

Base country: 3 = France

| Robust

E_cons	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
country_id#c.E_m3						
1	-.1369438	.040136	-3.41	0.001	-.2156369	-.0582506
2	-.1780459	.0342228	-5.20	0.000	-.2451453	-.1109464
4	-.2837115	.0431323	-6.58	0.000	-.3682793	-.1991436
5	-.1963934	.0359976	-5.46	0.000	-.2669726	-.1258143
6	.2143832	.0549649	3.90	0.000	.1066154	.3221509
7	.4165577	.0420069	9.92	0.000	.3341962	.4989191
8	-.2225418	.0403463	-5.52	0.000	-.3016472	-.1434363
9	-.3740546	.0406643	-9.20	0.000	-.4537836	-.2943255
10	.0666897	.0563185	1.18	0.236	-.0437319	.1771112
11	-.4169328	.0553617	-7.53	0.000	-.5254785	-.308387
12	-.1323846	.0355973	-3.72	0.000	-.202179	-.0625902
13	.017008	.0374216	0.45	0.650	-.0563632	.0903792
14	-.1478916	.0334646	-4.42	0.000	-.2135044	-.0822788

Group: 3, 10, 13

Base country: 4 = Germany

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
country_id#c.E_m3						
1	.1467677	.0478207	3.07	0.002	.0530074	.2405279
2	.1056656	.0429781	2.46	0.014	.0213999	.1899312
3	.2837115	.0431323	6.58	0.000	.1991436	.3682793
5	.087318	.0444043	1.97	0.049	.0002561	.1743799
6	.4980946	.0608035	8.19	0.000	.3788795	.6173097
7	.7002691	.0494014	14.18	0.000	.6034096	.7971287
8	.0611697	.0479973	1.27	0.203	-.0329368	.1552762
9	-.0903431	.048265	-1.87	0.061	-.1849745	.0042882
10	.3504011	.0620298	5.65	0.000	.2287817	.4720206
11	-.1332213	.0611624	-2.18	0.029	-.2531402	-.0133024
12	.1513268	.0440805	3.43	0.001	.0648999	.2377538
13	.3007195	.0455664	6.60	0.000	.2113791	.3900598
14	.1358198	.0423769	3.21	0.001	.0527331	.2189066

Group: 4, 8, 9, (less 2, 5, 11)

Base country: 5 = Italy

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
country_id#c.E_m3						
1	.0594497	.0415	1.43	0.152	-.0219179	.1408172
2	.0183476	.0358128	0.51	0.608	-.0518692	.0885644
3	.1963934	.0359976	5.46	0.000	.1258143	.2669726
4	-.087318	.0444043	-1.97	0.049	-.1743799	-.0002561
6	.4107766	.0559687	7.34	0.000	.3010408	.5205124

7		.6129511	.0433121	14.15	0.000	.5280308	.6978715
8		-.0261483	.0417034	-0.63	0.531	-.1079146	.055618
9		-.1776611	.0420112	-4.23	0.000	-.2600309	-.0952913
10		.2630831	.0572986	4.59	0.000	.1507399	.3754263
11		-.2205393	.0563585	-3.91	0.000	-.3310393	-.1100394
12		.0640088	.0371285	1.72	0.085	-.0087876	.1368052
13		.2134015	.038881	5.49	0.000	.137169	.289634
14		.0485018	.0350889	1.38	0.167	-.0202957	.1172994

Group: 5, 1, 2, 8, 14 (less 4, 12)

Base country: 6 = Japan

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
country_id#c.E_m3						
1	-.3513269	.058716	-5.98	0.000	-.4664492	-.2362047
2	-.392429	.0548441	-7.16	0.000	-.4999598	-.2848983
3	-.2143832	.0549649	-3.90	0.000	-.3221509	-.1066154
4	-.4980946	.0608035	-8.19	0.000	-.6173097	-.3788795
5	-.4107766	.0559687	-7.34	0.000	-.5205124	-.3010408
7	.2021745	.0600104	3.37	0.001	.0845143	.3198348
8	-.4369249	.0588599	-7.42	0.000	-.5523294	-.3215204
9	-.5884377	.0590784	-9.96	0.000	-.7042706	-.4726049
10	-.1476935	.0707703	-2.09	0.037	-.2864503	-.0089367
11	-.6313159	.0700114	-9.02	0.000	-.7685847	-.4940472
12	-.3467678	.0557121	-6.22	0.000	-.4560005	-.2375351
13	-.1973751	.0568951	-3.47	0.001	-.3089272	-.0858231
14	-.3622748	.0543742	-6.66	0.000	-.4688842	-.2556654

Group: 6 (less 10)

Base country: 7 = Netherlands

E_cons		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----							
country_id#c.E_m3							
1		-.5535015	.0468082	-11.82	0.000	-.6452766	-.4617264
2		-.5946036	.0418487	-14.21	0.000	-.6766547	-.5125524
3		-.4165577	.0420069	-9.92	0.000	-.4989191	-.3341962
4		-.7002691	.0494014	-14.18	0.000	-.7971287	-.6034096
5		-.6129511	.0433121	-14.15	0.000	-.6978715	-.5280308
6		-.2021745	.0600104	-3.37	0.001	-.3198348	-.0845143
8		-.6390995	.0469886	-13.60	0.000	-.7312283	-.5469706
9		-.7906123	.047262	-16.73	0.000	-.8832772	-.6979474
10		-.349868	.0612526	-5.71	0.000	-.4699638	-.2297723
11		-.8334905	.0603741	-13.81	0.000	-.9518638	-.7151172
12		-.5489423	.04298	-12.77	0.000	-.6332116	-.464673
13		-.3995497	.0445027	-8.98	0.000	-.4868044	-.3122949

14 | -.5644493 .0412309 -13.69 0.000 -.6452893 -.4836094
Group: 7

Base country: 10 = Spain

E_cons	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
country_id#c.E_m3						
1	-.2036335	.059985	-3.39	0.001	-.3212438	-.0860231
2	-.2447355	.0562005	-4.35	0.000	-.3549259	-.1345452
3	-.0666897	.0563185	-1.18	0.236	-.1771112	.0437319
4	-.3504011	.0620298	-5.65	0.000	-.4720206	-.2287817
5	-.2630831	.0572986	-4.59	0.000	-.3754263	-.1507399
6	.1476935	.0707703	2.09	0.037	.0089367	.2864503
7	.349868	.0612526	5.71	0.000	.2297723	.4699638
8	-.2892314	.0601259	-4.81	0.000	-.407118	-.1713449
9	-.4407442	.0603398	-7.30	0.000	-.5590502	-.3224383
11	-.4836224	.071079	-6.80	0.000	-.6229844	-.3442605
12	-.1990743	.057048	-3.49	0.000	-.3109261	-.0872225
13	-.0496817	.0582037	-0.85	0.393	-.1637996	.0644363
14	-.2145813	.0557421	-3.85	0.000	-.3238727	-.1052899

Group: 10, 3, 13 (less 6)

B. Empirical Analysis 2

▪ B.1. STATA code of Empirical Analysis 2

```

.
.
. * Generate log of number of years of each study, as Havranek did
. gen lnyears = ln(years)

.
. gen lngdp = ln(GDP)

.
. * -----*
.
. * Method variables included in optimal model of Havranek:
. * inverse topirstock totalc ols lnyears stockhold exact ircap monthly
.
. * -----*
. * -----*
. * (B)
. * -----*

.
. * Only our estimates
.
. * 1 All variables
. reg eis GDP listmktcap Stock_part credit tax_rate corruption gov_eff if our_study == 1, vce(cluster idcountry)

```

```

Linear regression              Number of obs   =          14
                             F(6, 13)         =           .
                             Prob > F          =           .
                             R-squared         =        0.3399
                             Root MSE      =        .33973

```

(Std. Err. adjusted for 14 clusters in idcountry)

eis	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
GDP	-9.57e-06	6.72e-06	-1.42	0.178	-.0000241	4.94e-06
listmktcap	-1.33e-11	1.35e-11	-0.99	0.342	-4.26e-11	1.59e-11
Stock_part	-.0004877	.0040785	-0.12	0.907	-.0092987	.0083233
credit	.0051456	.0035295	1.46	0.169	-.0024794	.0127706
tax_rate	-.0008871	.0064448	-0.14	0.893	-.0148103	.0130361
corruption	-.6101439	.5412636	-1.13	0.280	-1.779473	.5591851
gov_eff	.86115	.7302133	1.18	0.259	-.7163799	2.43868
_cons	-.1958405	.4934877	-0.40	0.698	-1.261956	.8702749

```

. * test for multicollinearity
. vif

```

Variable	VIF	1/VIF
gov_eff	25.47	0.039262
corruption	24.08	0.041527
Stock_part	3.67	0.272670
listmktcap	3.05	0.327879
credit	1.96	0.511167
GDP	1.76	0.567857
tax_rate	1.68	0.594265

```
-----+-----
Mean VIF |      8.81
```

```
. * drop gov eff
.
. * 2      Drop variables with multicollinearity
. reg eis GDP listmktcap Stock_part credit tax_rate corruption if our_study == 1, vce(cluster
idcountry)
```

```
Linear regression              Number of obs    =      14
                              F(5, 13)         =      .
                              Prob > F          =      .
                              R-squared          =     0.2892
                              Root MSE       =     .32639
```

(Std. Err. adjusted for 14 clusters in idcountry)

eis	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
GDP	-8.00e-06	6.98e-06	-1.15	0.273	-.0000231	7.08e-06
listmktcap	-1.28e-11	1.43e-11	-0.89	0.389	-4.37e-11	1.82e-11
Stock_part	.0007481	.0037742	0.20	0.846	-.0074055	.0089017
credit	.0052064	.0035591	1.46	0.167	-.0024826	.0128954
tax_rate	-.0017404	.0057058	-0.31	0.765	-.014067	.0105861
corruption	-.0705152	.1735547	-0.41	0.691	-.4454573	.304427
_cons	.1460164	.3961349	0.37	0.718	-.709781	1.001814

```
. vif
```

Variable	VIF	1/VIF
listmktcap	3.04	0.328574
Stock_part	2.98	0.335180
credit	1.96	0.511442
GDP	1.69	0.591174
tax_rate	1.64	0.610277
corruption	1.34	0.745901
Mean VIF	2.11	

```
. * test ok
.
. * All variables are insignificant, so we stop here
.
. * -----*
.
. * All estimates: our + Havranek's
.
. * 3      All variables
. reg eis GDP listmktcap Stock_part credit tax_rate corruption gov_eff inverse top irstock totalc ols
lneyars stockhold exac
> t ircap monthly, vce(cluster idcountry)
```

```
Linear regression              Number of obs    =     568
                              F(16, 23)         =      .
                              Prob > F          =      .
                              R-squared          =     0.1628
                              Root MSE       =     3.6358
```

(Std. Err. adjusted for 24 clusters in idcountry)

eis	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
GDP	-.0000689	.0000243	-2.83	0.009	-.0001192	-.0000186

listmktcap	1.20e-10	3.95e-11	3.03	0.006	3.81e-11	2.02e-10
stock_part	.0165861	.0071793	2.31	0.030	.0017346	.0314376
credit	-.0112971	.0063557	-1.78	0.089	-.0244448	.0018505
tax_rate	-.0299434	.0174661	-1.71	0.100	-.0660748	.006188
corruption	5.098553	1.912738	2.67	0.014	1.141754	9.055352
gov_eff	-6.917246	2.866982	-2.41	0.024	-12.84805	-.9864431
inverse	1.584362	.6911957	2.29	0.031	.1545144	3.014209
top	2.635631	.8527755	3.09	0.005	.87153	4.399731
irstock	-1.012362	.2909726	-3.48	0.002	-1.614284	-.4104392
totalc	.4460328	.7522572	0.59	0.559	-1.11013	2.002195
ols	1.835929	.6901112	2.66	0.014	.4083254	3.263533
lnyears	1.33706	.4171137	3.21	0.004	.4741941	2.199925
stockhold	1.004082	.2381416	4.22	0.000	.5114485	1.496715
exact	2.312396	1.028772	2.25	0.034	.1842188	4.440574
ircap	-.7914203	.3925452	-2.02	0.056	-1.603462	.0206213
monthly	2.227781	.3946022	5.65	0.000	1.411485	3.044078
_cons	.3088675	2.660217	0.12	0.909	-5.19421	5.811945

```

. * test multicollinearity
. vif

```

Variable	VIF	1/VIF
corruption	15.37	0.065053
gov_eff	13.58	0.073624
tax_rate	6.68	0.149746
listmktcap	6.64	0.150653
credit	5.47	0.182757
stock_part	3.96	0.252365
top	3.49	0.286415
GDP	3.18	0.314186
exact	2.92	0.342956
totalc	1.81	0.552108
ols	1.80	0.555008
monthly	1.80	0.555762
ircap	1.61	0.622340
inverse	1.55	0.645156
stockhold	1.52	0.656005
lnyears	1.47	0.680211
irstock	1.32	0.755089
Mean VIF	4.36	

```

. * drop corruption
.
. * 4 All variables, dropped corruption
. reg eis GDP listmktcap Stock_part credit tax_rate gov_eff inverse top irstock totalc ols lnyears
stockhold exact ircap mon
> thly, vce(cluster idcountry)

```

```

Linear regression              Number of obs   =          568
                               F(15, 23)         =           .
                               Prob > F           =           .
                               R-squared          =         0.1459
                               Root MSE       =         3.6688

```

(Std. Err. adjusted for 24 clusters in idcountry)

	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
eis						
GDP	-.0000381	.0000227	-1.68	0.107	-.000085	8.83e-06
listmktcap	2.94e-11	3.37e-11	0.87	0.392	-4.02e-11	9.90e-11
Stock_part	.0167163	.0098839	1.69	0.104	-.0037301	.0371627
credit	-.0108974	.0068263	-1.60	0.124	-.0250187	.0032239
tax_rate	-.0198579	.0176287	-1.13	0.272	-.0563257	.01661

gov_eff	-.0414199	.5017086	-0.08	0.935	-1.079283	.9964435
inverse	1.678746	.7861046	2.14	0.044	.0525649	3.304927
top	2.442203	.954284	2.56	0.018	.468116	4.41629
irstock	-1.114831	.3432067	-3.25	0.004	-1.824808	-.404854
totalc	.5570541	.9682563	0.58	0.571	-1.445937	2.560045
ols	1.931194	.6326278	3.05	0.006	.6225041	3.239885
lnyears	1.136799	.5077427	2.24	0.035	.0864534	2.187145
stockhold	.9729296	.29125	3.34	0.003	.3704331	1.575426
exact	2.239002	1.221079	1.83	0.080	-.2869927	4.764997
ircap	-.8783002	.4720645	-1.86	0.076	-1.85484	.0982395
monthly	2.232737	.4439412	5.03	0.000	1.314374	3.151099
_cons	-2.487518	2.163981	-1.15	0.262	-6.964055	1.989019

```
. * test multicollinearity
. vif
```

Variable	VIF	1/VIF
tax_rate	6.60	0.151602
credit	5.47	0.182778
listmktcap	4.46	0.224229
Stock_part	3.96	0.252369
top	3.46	0.288871
GDP	3.07	0.325453
exact	2.91	0.343377
gov_eff	2.55	0.392232
totalc	1.81	0.553789
monthly	1.80	0.555764
ols	1.80	0.556640
ircap	1.60	0.624676
inverse	1.54	0.648349
stockhold	1.52	0.656226
lnyears	1.45	0.689773
irstock	1.32	0.758719
Mean VIF	2.83	

```
. * test ok
.
. * All variables are insignificant, so we stop here
.
. * -----*
.
. * Only euro zone
.
. * 5 All variables
. reg eis GDP listmktcap Stock_part credit tax_rate corruption gov_eff inverse top irstock totalc ols
lnyears stockhold exac
> t ircap monthly if eurozone == 1, vce(cluster idcountry)
note: top omitted because of collinearity
note: stockhold omitted because of collinearity
```

Linear regression	Number of obs	=	127
	F(10, 11)	=	.
	Prob > F	=	.
	R-squared	=	0.0460
	Root MSE	=	2.6478

(Std. Err. adjusted for 12 clusters in idcountry)

	eis	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
GDP		-.0001035	.0000581	-1.78	0.102	-.0002314 .0000243
listmktcap		-2.50e-10	2.74e-10	-0.91	0.382	-8.53e-10 3.54e-10
Stock_part		-.0531442	.0166978	-3.18	0.009	-.0898958 -.0163927

credit		.0060875	.018479	0.33	0.748	-.0345846	.0467596
tax_rate		.0167158	.0303432	0.55	0.593	-.0500691	.0835008
corruption		1.249722	1.376188	0.91	0.383	-1.779248	4.278692
gov_eff		-.8335223	1.919288	-0.43	0.672	-5.057846	3.390801
inverse		.1513753	.0937671	1.61	0.135	-.0550047	.3577552
top		0	(omitted)				
irstock		-.2019886	.1838287	-1.10	0.295	-.6065929	.2026156
totalc		5.058399	1.095646	4.62	0.001	2.646898	7.469899
ols		.8067046	.4265809	1.89	0.085	-.1321937	1.745603
lnyears		-1.536258	2.31081	-0.66	0.520	-6.622317	3.5498
stockhold		0	(omitted)				
exact		-3.752319	2.418756	-1.55	0.149	-9.075965	1.571327
ircap		3.073059	1.32118	2.33	0.040	.1651611	5.980957
monthly		-.0898449	1.786403	-0.05	0.961	-4.021692	3.842002
_cons		5.876224	6.89873	0.85	0.412	-9.307778	21.06023

```
. * test multicollinearity
. vif
```

Variable	VIF	1/VIF
ircap	32.18	0.031077
corruption	31.07	0.032188
gov_eff	28.49	0.035101
monthly	19.95	0.050127
stock_part	19.71	0.050730
GDP	17.66	0.056613
totalc	12.74	0.078478
exact	8.19	0.122108
listmktcap	6.70	0.149246
credit	4.26	0.234828
lnyears	4.08	0.244959
tax_rate	2.76	0.361895
ols	2.51	0.397921
inverse	2.36	0.424304
irstock	1.54	0.650513
Mean VIF	12.95	

```
. * drop corruption
```

```
. * 6 All variables, dropped corruption
```

```
. reg eis GDP listmktcap Stock_part credit tax_rate gov_eff inverse top irstock totalc ols lnyears
stockhold exact ircap mon
> thly if eurozone == 1, vce(cluster idcountry)
note: top omitted because of collinearity
note: stockhold omitted because of collinearity
```

Linear regression	Number of obs	=	127
	F(10, 11)	=	.
	Prob > F	=	.
	R-squared	=	0.0441
	Root MSE	=	2.6385

(Std. Err. adjusted for 12 clusters in idcountry)

eis	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
GDP	-.0001189	.0000613	-1.94	0.078	-.0002538 .000016
listmktcap	-4.65e-10	2.96e-10	-1.57	0.144	-1.12e-09 1.86e-10
Stock_part	-.0442676	.0188462	-2.35	0.039	-.0857478 -.0027874
credit	.0111118	.0168425	0.66	0.523	-.0259522 .0481881
tax_rate	.0007779	.0214479	0.04	0.972	-.0464287 .0479845
gov_eff	.8572117	.6228836	1.38	0.196	-.5137459 2.228169
inverse	.1435348	.1052003	1.36	0.200	-.0880094 .3750791

top	0	(omitted)				
irstock	-.2098291	.1805752	-1.16	0.270	-.6072723	.1876142
totalc	4.670013	1.064	4.39	0.001	2.328166	7.011861
ols	.7428107	.4606261	1.61	0.135	-.2710206	1.756642
lyears	-1.338378	2.492085	-0.54	0.602	-6.823419	4.146663
stockhold	0	(omitted)				
exact	-3.679613	2.628018	-1.40	0.189	-9.463841	2.104614
ircap	2.964983	1.436269	2.06	0.063	-.1962246	6.12619
monthly	.4850626	1.83292	0.26	0.796	-3.549166	4.519291
_cons	4.945198	7.342244	0.67	0.515	-11.21497	21.10537

```
. * test multicollinearity
. vif
```

Variable	VIF	1/VIF
ircap	31.97	0.031274
monthly	18.54	0.053933
Stock_part	16.80	0.059530
GDP	16.63	0.060137
totalc	12.01	0.083234
exact	8.18	0.122208
listmktcap	4.19	0.238450
gov_eff	4.19	0.238935
lyears	4.03	0.247839
credit	3.95	0.253173
ols	2.46	0.406191
inverse	2.36	0.424530
tax_rate	1.90	0.527693
irstock	1.54	0.650860
Mean VIF	9.20	

```
. * drop Stock_part
```

```
. * 7 All variables, dropped corruption Stock_part
. reg eis GDP listmktcap credit tax_rate gov_eff inverse top irstock totalc ols lyears stockhold exact
ircap monthly if eur
> ozone == 1, vce(cluster idcountry)
note: top omitted because of collinearity
note: stockhold omitted because of collinearity
```

Linear regression	Number of obs	=	127
	F(10, 11)	=	.
	Prob > F	=	.
	R-squared	=	0.0359
	Root MSE	=	2.6381

(Std. Err. adjusted for 12 clusters in idcountry)

eis	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
GDP	-.0000599	.0000415	-1.44	0.177	-.0001511 .0000314
listmktcap	-4.82e-10	2.25e-10	-2.15	0.055	-9.77e-10 1.24e-11
credit	.0052821	.0145501	0.36	0.723	-.0267425 .0373066
tax_rate	-.004635	.0187961	-0.25	0.810	-.0460049 .0367349
gov_eff	.1357119	.4584703	0.30	0.773	-.8733744 1.144798
inverse	.1732149	.1083072	1.60	0.138	-.0651677 .4115975
top	0	(omitted)			
irstock	-.180149	.1798876	-1.00	0.338	-.576079 .215781
totalc	3.644353	1.243693	2.93	0.014	.907002 6.381704
ols	.5130577	.3741147	1.37	0.198	-.3103633 1.336479
lyears	.6291346	3.418588	0.18	0.857	-6.895127 8.153396
stockhold	0	(omitted)			
exact	.1874668	2.422419	0.08	0.940	-5.144241 5.519175

ircap		.6680003	.7139843	0.94	0.370	-.9034684	2.239469
monthly		-1.648041	1.155577	-1.43	0.182	-4.191448	.8953662
_cons		-.8368666	10.4742	-0.08	0.938	-23.89043	22.2167

```
. * test multicollinearity
. vif
```

Variable		VIF	1/VIF
monthly		14.05	0.071175
GDP		13.08	0.076437
totalc		10.84	0.092273
ircap		10.69	0.093503
listmktcap		4.19	0.238658
credit		3.85	0.259497
exact		3.79	0.263910
gov_eff		3.16	0.316525
lyears		2.95	0.339220
inverse		2.35	0.425282
ols		2.31	0.433173
tax_rate		1.87	0.534237
irstock		1.53	0.652013
Mean VIF		5.74	

```
. * drop GDP
```

```
. * 8 All variables, dropped corruption Stock_part GDP
. reg eis listmktcap credit tax_rate gov_eff inverse top irstock totalc ols lyears stockhold exact
ircap monthly if eurozon
> e == 1, vce(cluster idcountry)
note: top omitted because of collinearity
note: stockhold omitted because of collinearity
```

Linear regression		Number of obs	=	127
		F(9, 11)	=	.
		Prob > F	=	.
		R-squared	=	0.0336
		Root MSE	=	2.6296

(Std. Err. adjusted for 12 clusters in idcountry)

eis		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
listmktcap		-3.41e-10	1.94e-10	-1.75	0.107	-7.69e-10 8.70e-11
credit		-.0035645	.0116259	-0.31	0.765	-.029153 .0220241
tax_rate		-.000089	.0186392	-0.00	0.996	-.0411137 .0409356
gov_eff		-.2129756	.3733576	-0.57	0.580	-1.03473 .6087789
inverse		.1761309	.1098858	1.60	0.137	-.0657261 .417988
top		0	(omitted)			
irstock		-.177233	.1771844	-1.00	0.339	-.5672133 .2127473
totalc		3.626585	1.267012	2.86	0.015	.8379103 6.41526
ols		.3759678	.3794158	0.99	0.343	-.4591208 1.211056
lyears		.9263827	3.496703	0.26	0.796	-6.769809 8.622574
stockhold		0	(omitted)			
exact		1.173345	2.255385	0.52	0.613	-3.790725 6.137415
ircap		-.0053369	.6044515	-0.01	0.993	-1.335726 1.325052
monthly		-2.761508	.9537306	-2.90	0.015	-4.860655 -.6623613
_cons		-1.709969	10.69396	-0.16	0.876	-25.24723 21.82729

```
. * test multicollinearity
. vif
```

Variable		VIF	1/VIF
----------	--	-----	-------

totalc	10.84	0.092284
monthly	9.66	0.103555
ircap	4.13	0.242062
listmktcap	3.29	0.303910
credit	3.06	0.326837
lyears	2.86	0.349786
exact	2.76	0.361770
inverse	2.35	0.425309
gov_eff	2.30	0.434927
ols	2.11	0.473356
tax_rate	1.81	0.551554
irstock	1.53	0.652053
Mean VIF	3.89	

. * test ok
. * no variable significant

. * -----*

. * Only 14 countries for which we have estimates

. * 9 All variables

. reg eis GDP listmktcap Stock_part credit tax_rate corruption gov_eff inverse top irstock totalc ols
lyears stockhold exac
> t ircap monthly if countries14 == 1, vce(cluster idcountry)

Linear regression	Number of obs	=	509
	F(12, 13)	=	.
	Prob > F	=	.
	R-squared	=	0.1888
	Root MSE	=	3.6275

(Std. Err. adjusted for 14 clusters in idcountry)

eis	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
GDP	-.0001285	.000064	-2.01	0.066	-.0002668	9.84e-06
listmktcap	1.80e-10	5.65e-11	3.18	0.007	5.79e-11	3.02e-10
stock_part	.0246946	.0084587	2.92	0.012	.0064207	.0429686
credit	-.0145621	.0194045	-0.75	0.466	-.056483	.0273588
tax_rate	-.047526	.0242165	-1.96	0.071	-.0998426	.0047906
corruption	8.219692	2.510718	3.27	0.006	2.795615	13.64377
gov_eff	-12.31874	3.878119	-3.18	0.007	-20.69691	-3.940573
inverse	1.4708	.8256088	1.78	0.098	-.3128194	3.254419
top	2.828928	.7776429	3.64	0.003	1.148932	4.508923
irstock	-.9752728	.2522037	-3.87	0.002	-1.520126	-.4304198
totalc	.3203623	.6998313	0.46	0.655	-1.191531	1.832256
ols	1.786304	1.048656	1.70	0.112	-.4791795	4.051788
lyears	1.352178	.3782731	3.57	0.003	.5349686	2.169387
stockhold	1.018605	.2267119	4.49	0.001	.5288236	1.508386
exact	2.485748	.9327209	2.67	0.019	.4707272	4.500769
ircap	-.7245924	.2927766	-2.47	0.028	-1.357098	-.092087
monthly	2.34929	.6154592	3.82	0.002	1.019672	3.678909
_cons	5.665696	3.185178	1.78	0.099	-1.215462	12.54685

. * test multicollinearity
. vif

Variable	VIF	1/VIF
gov_eff	16.19	0.061767
corruption	15.06	0.066397
credit	7.30	0.136993

listmktcap	6.73	0.148595
tax_rate	6.41	0.155906
stock_part	5.05	0.198054
GDP	4.41	0.226758
top	3.38	0.295430
exact	2.90	0.344902
monthly	2.01	0.497333
ols	1.92	0.521213
totalc	1.86	0.536815
ircap	1.53	0.654243
inverse	1.51	0.661908
stockhold	1.50	0.665245
lyears	1.47	0.679003
irstock	1.29	0.772231

Mean VIF	4.74	

. * drop gov_eff

. * 10 All variables, dropped gov_eff

. reg eis GDP listmktcap stock_part credit tax_rate corruption inverse top irstock totalc ols lyears stockhold exact ircap

> monthly if countries14 == 1, vce(cluster idcountry)

Linear regression	Number of obs	=	509
	F(12, 13)	=	.
	Prob > F	=	.
	R-squared	=	0.1610
	Root MSE	=	3.6855

(Std. Err. adjusted for 14 clusters in idcountry)

eis	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
GDP	-.0000912	.0000626	-1.46	0.168	-.0002264	.0000439
listmktcap	4.32e-11	3.55e-11	1.22	0.246	-3.35e-11	1.20e-10
stock_part	.0138838	.010579	1.31	0.212	-.0089707	.0367383
credit	.0032333	.0176298	0.18	0.857	-.0348536	.0413203
tax_rate	-.0225021	.0164368	-1.37	0.194	-.0580117	.0130074
corruption	1.171121	.5563633	2.10	0.055	-.0308285	2.373071
inverse	1.518469	.9988819	1.52	0.152	-.6394844	3.676422
top	2.571558	.9383128	2.74	0.017	.5444565	4.598659
irstock	-1.135124	.3231969	-3.51	0.004	-1.833349	-.4368998
totalc	.6757057	.9867552	0.68	0.506	-1.456049	2.807461
ols	2.129574	.7655254	2.78	0.016	.4757564	3.783391
lyears	1.170323	.4332771	2.70	0.018	.2342851	2.106362
stockhold	.9763447	.2848774	3.43	0.005	.3609045	1.591785
exact	2.325687	1.182207	1.97	0.071	-.2283156	4.87969
ircap	-.913554	.3683602	-2.48	0.028	-1.709348	-.1177602
monthly	2.572343	.6518338	3.95	0.002	1.164142	3.980545
_cons	-4.973806	2.04858	-2.43	0.030	-9.399493	-.5481185

. * test multicollinearity

. vif

Variable	VIF	1/VIF

credit	6.71	0.149082
tax_rate	6.15	0.162484
stock_part	4.80	0.208457
GDP	4.33	0.231020
listmktcap	4.13	0.241961
top	3.35	0.298334
exact	2.89	0.346194
corruption	2.72	0.368280

monthly		2.00	0.499617
ols		1.88	0.531727
totalc		1.83	0.547263
ircap		1.51	0.660692
inverse		1.51	0.662373
stockhold		1.50	0.665513
lnyears		1.46	0.684053
irstock		1.29	0.778155

-----+-----

Mean VIF | 3.00

. * tet ok => drop insignificant

. * All insignificant, so we stop here

end of do-file

▪ B.2. Alternative results tables of Empirical Analysis 2

Table A. 2: Results of Empirical Analysis 2, using all the EIS estimates, models 1-5

VARIABLES	(1) Our only	(2) Our only	(3) All estimates	(4) All estimates	(5) All estimates
GDP	-9.57e-06 (6.72e-06)	-8.70e-06 (7.06e-06)	-0.000143*** (3.66e-05)	-0.000152*** (3.16e-05)	-0.000153*** (4.59e-05)
listmktcap	-0 (0)	-0 (0)	7.66e-11* (0)	1.04e-10*** (0)	0 (0)
Stock_part	-0.000488 (0.00408)	0.000828 (0.00384)	-0.0114 (0.0172)	-0.0115 (0.0169)	
credit	0.00515 (0.00353)	0.00515 (0.00375)	0.0452*** (0.0129)	0.0451*** (0.0127)	0.0267** (0.0111)
tax_rate	-0.000887 (0.00644)	-0.00199 (0.00570)	-0.0319 (0.0309)	-0.0349 (0.0276)	
corruption	-0.610 (0.541)		-1.553 (2.212)		
gov_eff	0.861 (0.730)	-0.0583 (0.241)	1.782 (2.674)	-0.314 (0.960)	
Constant	-0.196 (0.493)	0.151 (0.374)	-1.521 (3.316)	-0.660 (4.277)	-0.478 (2.563)
Observations	14	14	573	573	927
R-squared	0.340	0.279	0.026	0.026	0.022

Table A. 3: Results of Empirical Analysis 2, using all the EIS estimates, models 6-12

VARIABLES	(6) Euro zone	(7) Euro zone	(8) Euro zone	(9) Euro zone	(10) 14 countries	(11) 14 countries	(12) 14 countries
GDP	-0.000330 (0.000211)	-0.000396* (0.000219)	-0.000143 (0.000120)		-0.000188** (7.50e-05)	-0.000191** (7.67e-05)	-9.32e-05** (3.76e-05)
listmktcap	3.39e-10 (1.05e-09)	-5.75e-10 (8.47e-10)	-6.48e-10 (4.70e-10)	-3.10e-10 (3.36e-10)	7.69e-11 (0)	8.51e-11** (0)	5.50e-11* (0)
Stock_part	-0.227*** (0.0716)	-0.190** (0.0714)			-0.000295 (0.0185)	0.000342 (0.0155)	
credit	0.0877 (0.0694)	0.109 (0.0680)	0.0842 (0.0550)	0.0631 (0.0416)	0.0438* (0.0221)	0.0428** (0.0167)	0.0191 (0.0122)
tax_rate	0.0659 (0.0991)	-0.00164 (0.0612)	-0.0249 (0.0490)	-0.0140 (0.0480)	-0.0324 (0.0384)	-0.0339 (0.0355)	
corruption	5.296 (4.535)				-1.295 (3.341)	-0.875 (1.004)	
gov_eff	-4.533 (6.509)	2.633 (2.313)	-0.461 (1.264)	-1.293 (1.222)	0.736 (4.730)		
Constant	-66.08* (30.72)	-70.07* (32.78)	-95.08* (47.98)	-97.18* (48.61)	1.743 (2.105)	2.382 (4.278)	-0.156 (2.355)
Observations	128	128	128	128	513	513	839
R-squared	0.039	0.038	0.035	0.035	0.026	0.026	0.022

Table A. 4: Results of Empirical Analysis 2, using only EIS estimates smaller than 10 in absolute value, models 1-4

VARIABLES	(1) Our only	(2) Our only	(3) All estimates	(4) All estimates
GDP	-9.57e-06 (6.72e-06)	-8.00e-06 (6.98e-06)	-1.90e-05 (1.26e-05)	-1.15e-05 (1.24e-05)
listmktcap	-0 (0)	-0 (0)	0** (0)	0 (0)
Stock_part	-0.000488 (0.00408)	0.000748 (0.00377)	0.00264 (0.00441)	0.00254 (0.00504)
credit	0.00515 (0.00353)	0.00521 (0.00356)	-0.00458 (0.00395)	-0.00441 (0.00438)
tax_rate	-0.000887 (0.00644)	-0.00174 (0.00571)	0.00475 (0.0133)	0.00734 (0.0152)
corruption	-0.610 (0.541)	-0.0705 (0.174)	1.205 (0.754)	
gov_eff	0.861 (0.730)		-2.392** (1.146)	-0.774* (0.401)
Constant	-0.196 (0.493)	0.146 (0.396)	2.200* (1.094)	1.574 (1.120)
Observations	14	14	550	550
R-squared	0.340	0.289	0.203	0.196

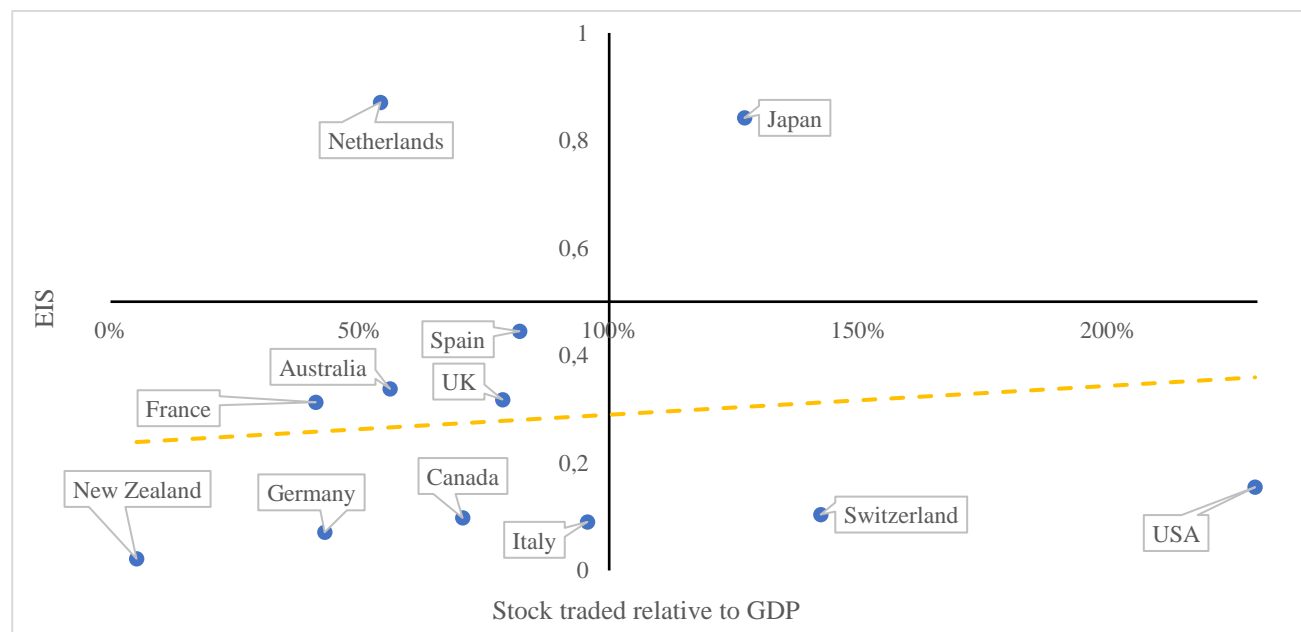
Table A. 5: Results of Empirical Analysis 2, using only EIS estimates smaller than 10 in absolute value, models 5-11

VARIABLES	(5) Euro zone	(6) Euro zone	(7) Euro zone	(8) Euro zone	(9) 14 countries	(10) 14 countries	(11) 14 countries
GDP	-9.27e-05 (5.22e-05)	-0.000106* (5.51e-05)	-5.57e-05 (3.86e-05)		-5.90e-05** (1.96e-05)	-4.64e-05*** (1.42e-05)	-3.59e-05*** (7.63e-06)
listmktcap	-2.78e-10 (2.48e-10)	-4.60e-10 (2.77e-10)	-4.74e-10* (2.20e-10)	-3.42e-10 (1.92e-10)	7.08e-11** (0)	0 (0)	0*** (0)
Stock_part	-0.0448** (0.0150)	-0.0373* (0.0171)			0.00492 (0.00436)	0.00121 (0.00554)	
credit	0.00218 (0.0165)	0.00640 (0.0149)	0.00136 (0.0130)	-0.00689 (0.0107)	0.000346 (0.00478)	0.00624 (0.00553)	0.00622* (0.00313)
tax_rate	0.0144 (0.0275)	0.000894 (0.0200)	-0.00363 (0.0177)	0.000606 (0.0177)	-0.00443 (0.0153)	0.00403 (0.0158)	
corruption	1.056 (1.234)				2.265** (0.992)	-0.0483 (0.298)	
gov_eff	-0.656 (1.714)	0.772 (0.550)	0.165 (0.425)	-0.159 (0.343)	-4.005** (1.529)		
Constant	9.321 (6.079)	8.562 (6.473)	3.843 (9.081)	3.050 (9.297)	3.565** (1.383)	0.195 (0.933)	0.666 (1.067)
Observations	124	124	124	124	494	494	818
R-squared	0.114	0.111	0.096	0.090	0.259	0.232	0.226

▪ B.3. Plots of macroeconomic variables

In this section we collect plots and figures related to the discussion of [research question 2](#). [Figure A.1](#) is a plot of our EIS estimates against stock market participation.

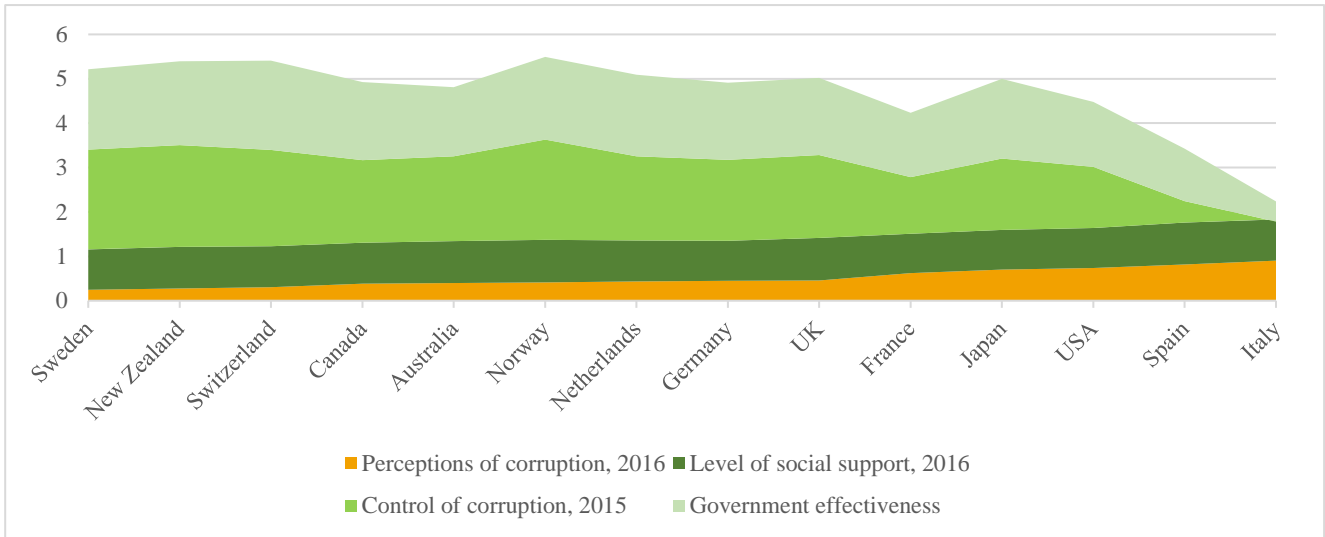
Figure A. 1: Correlation of our EIS estimates and stock traded as % of GDP



In addition to corruption and government effectiveness, which we include in the main regression in research question 2, we consider two additional cultural variables: control of corruption and level of social support⁷⁴. [Figure A.2](#) collects these four indicators for the 14 countries of our analysis, which are sorted by increasing perception of corruption.

⁷⁴ Again, we do not include all of these variables in the right-hand-side of our regression, but we instead discuss them here using a graphical analysis

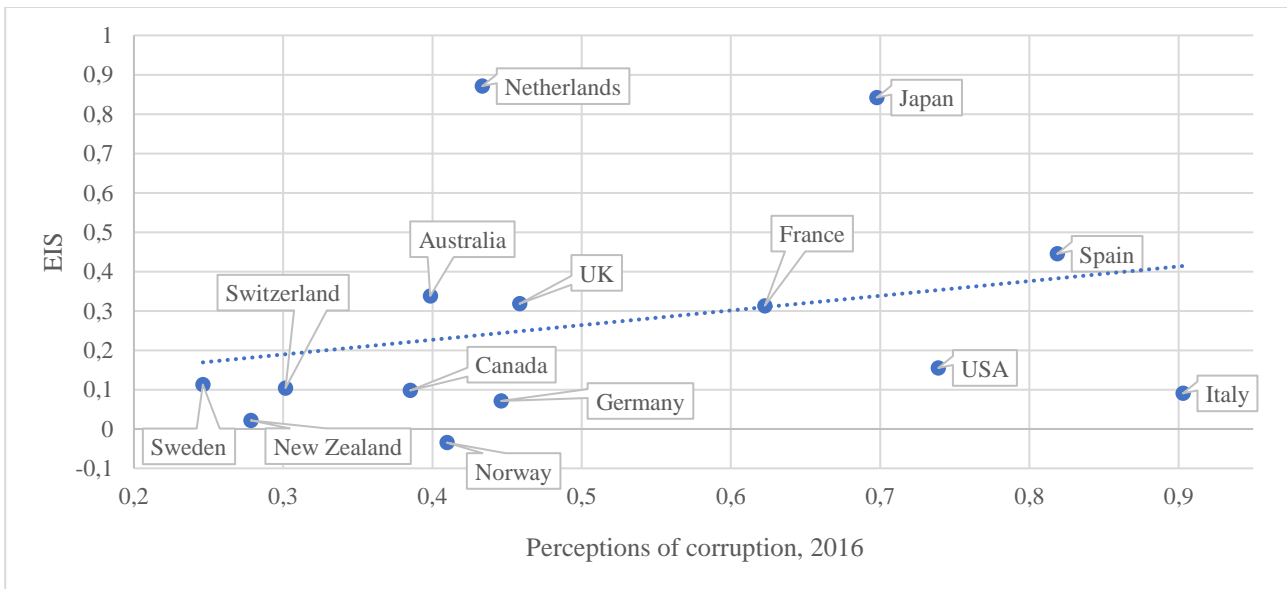
Figure A. 2: Representation of the four cultural variables, per country



Source: The Worldwide Governance Indicators, World Happiness Report 2017, own analysis.

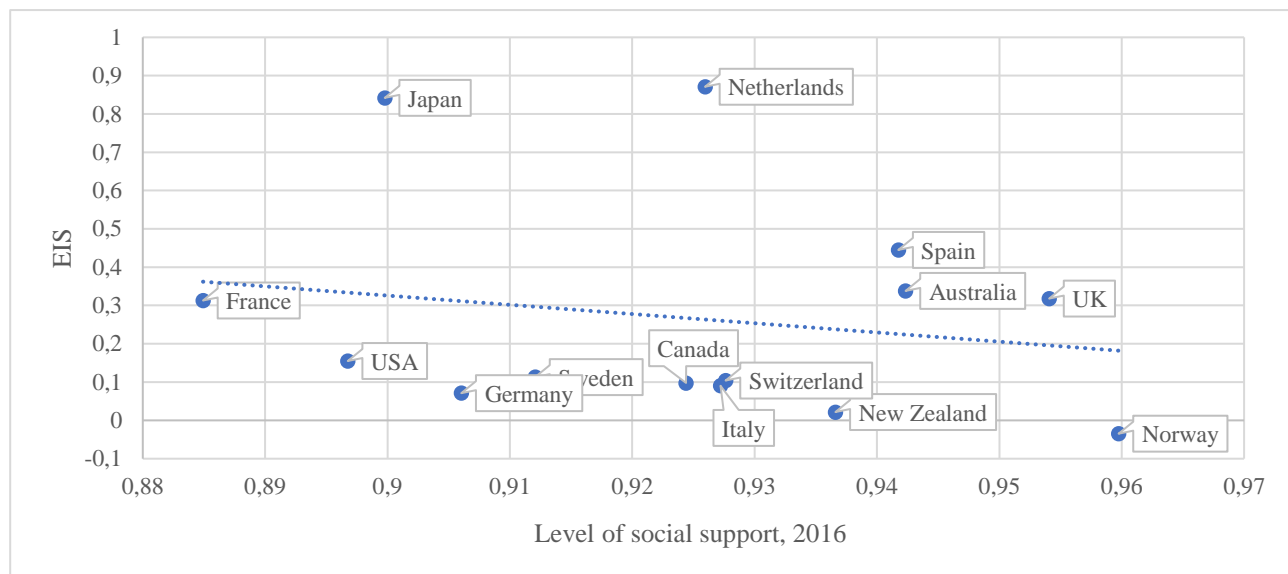
Below we report the different plots that show the correlation between our EIS estimates and these cultural indicators.

Figure A. 3: Correlation between EIS and perception of corruption indicator



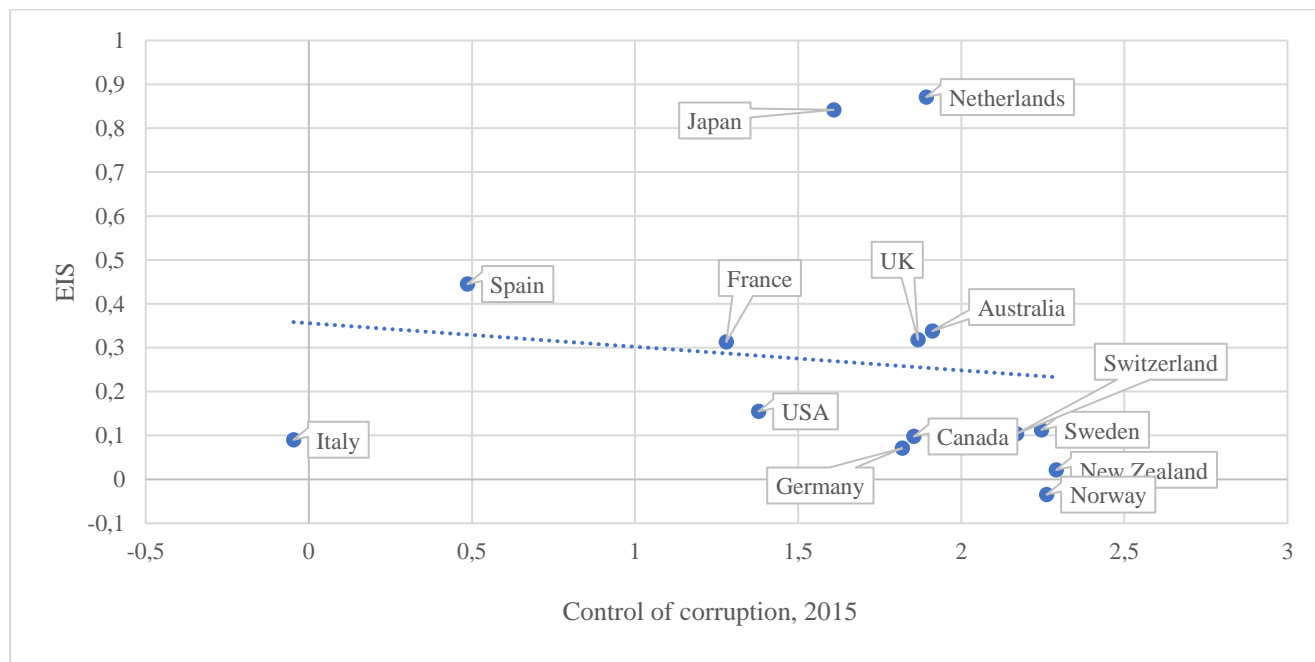
Source: World Happiness Report 2017

Figure A. 4: Correlation between EIS and level of social support



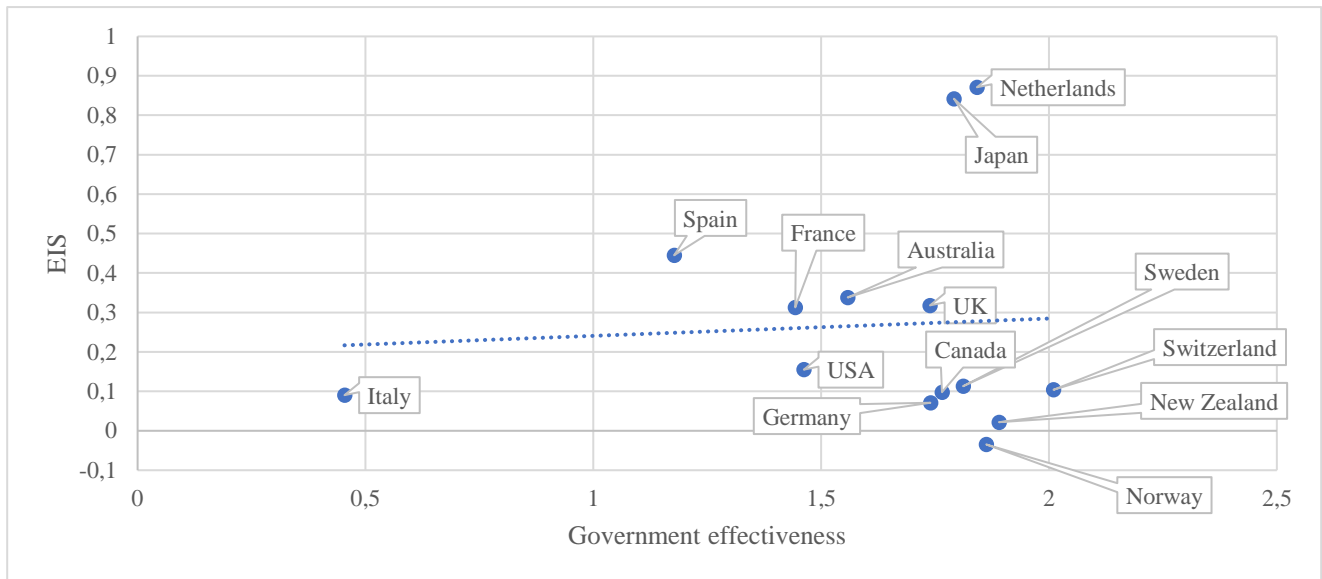
Source: World Happiness Report 2017

Figure A. 5: Correlation between EIS and control of corruption



Source: The Worldwide Governance Indicators

Figure A. 6: Correlation between EIS and government effectiveness



Source: The Worldwide Governance Indicators

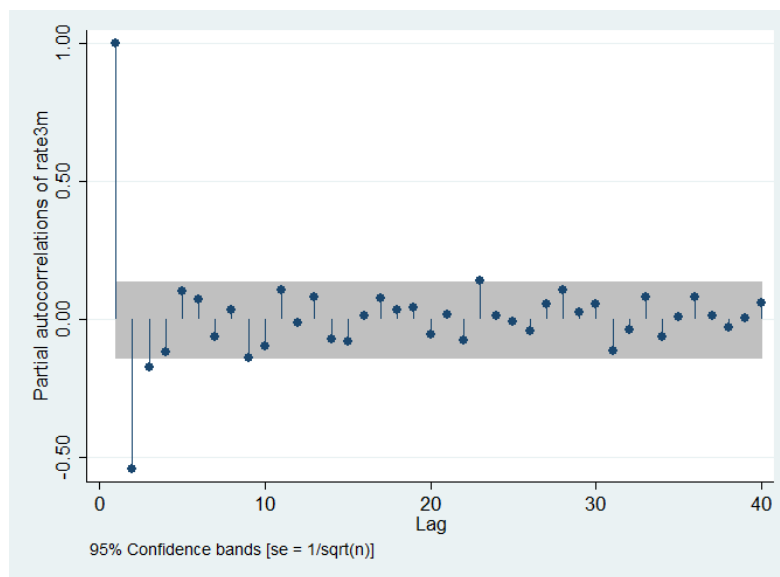
C. Discussion research question 3

▪ C.1 Methodology of the change in consumption plot

We consider the 3-month OIS swap rate. We take the rate at the first day of the month, so that we have monthly data. The OIS is a swap derived from the overnight rate, which is generally fixed by the local central bank.

We assume an AR(1) process, which is partly confirmed by the partial autocorrelation plot below. We keep it as an AR(1) to avoid overcomplication of the analysis.

Figure A. 7: Partial autocorrelation plot for the 3-month OIS swap rate



We regress $r_t = c + \rho \cdot r_{t-1} + \varepsilon$, to find the value of ρ .

VARIABLES	(1) rate3m
r_lag1	0.998*** (0.00675)
Constant	-0.0145 (0.0168)
Observations	200
R-squared	0.991

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

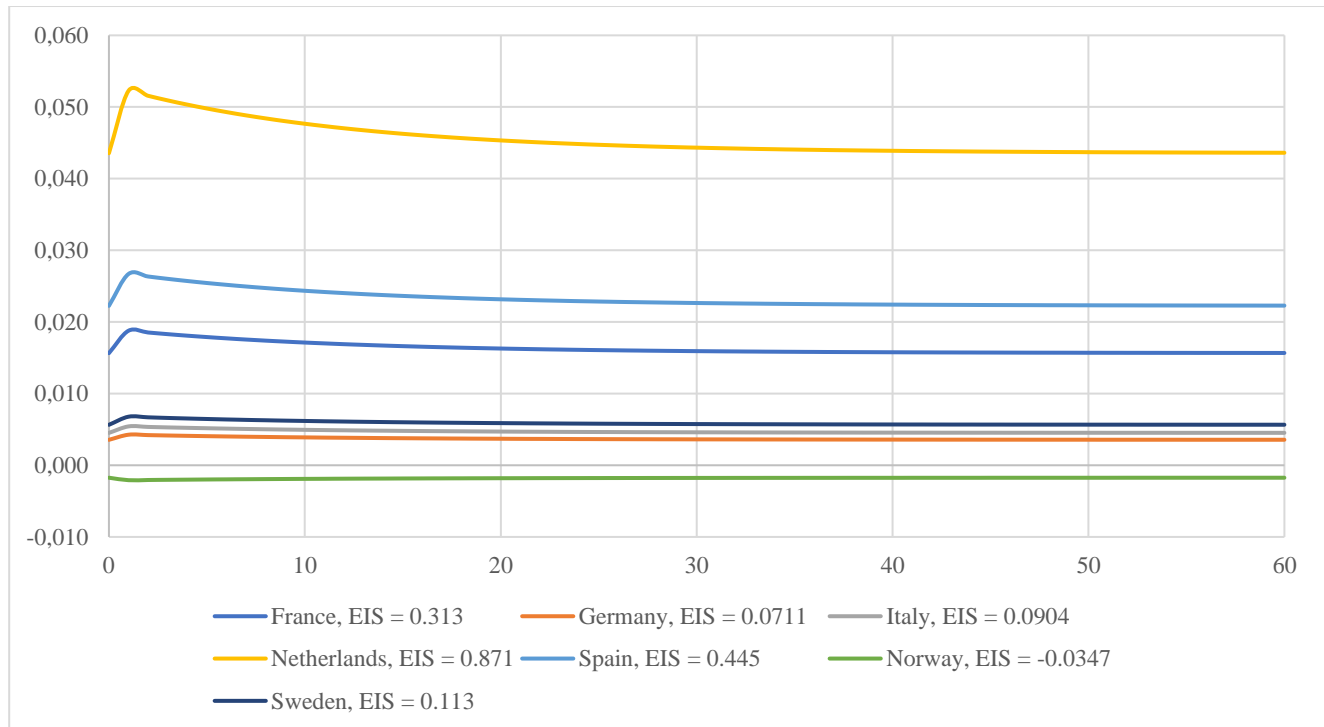
$\rho = 0.998$. We also use $\rho = 0.92$, with which it is easier to see the path of r overtime.

From here we move to Excel. The long run mean is $\mu = c/(1 - \rho)$, so $c = \mu \cdot (1 - \rho)$. Rewriting the expression, we obtain: $r_t = \mu \cdot (1 - \rho) + \rho \cdot r_{t-1} + \varepsilon$. We set $r_0 = \mu = 0.05$, which is an arbitrary value, since we don't know the real mean of the series. Calculating mu from the expression above gives a negative value, because rates have been going down over time. Even though they are bounded by zero, this is something the estimation doesn't know, so it reports a negative mean. Additionally, our goal is to highlight the different responses given different EIS.

Then, we shock ε_1 by 100 basis points. So that $r_1 = \mu \cdot (1 - \rho) + \rho \cdot r_0 + 0.01$ if we shock the rate at time 1. Consequently $r_2 = \mu \cdot (1 - \rho) + \rho \cdot (\mu \cdot (1 - \rho) + \rho \cdot r_0 + 0.01)$ and $r_3 = \mu \cdot (1 - \rho) + \rho \cdot (\mu \cdot (1 - \rho) + \rho \cdot (\mu \cdot (1 - \rho) + \rho \cdot r_0 + 0.01))$, and so on. Eventually the rate will converge to $r_{t+n} = \mu$. The implied consumption growth series will be $\Delta c_t = EIS_i \cdot r_t$, for each country i for each point in time t .

[Figure A.8](#) shows the change in consumption growth given the shock in the rate. In research question 3 is reported the same effect rescaled.

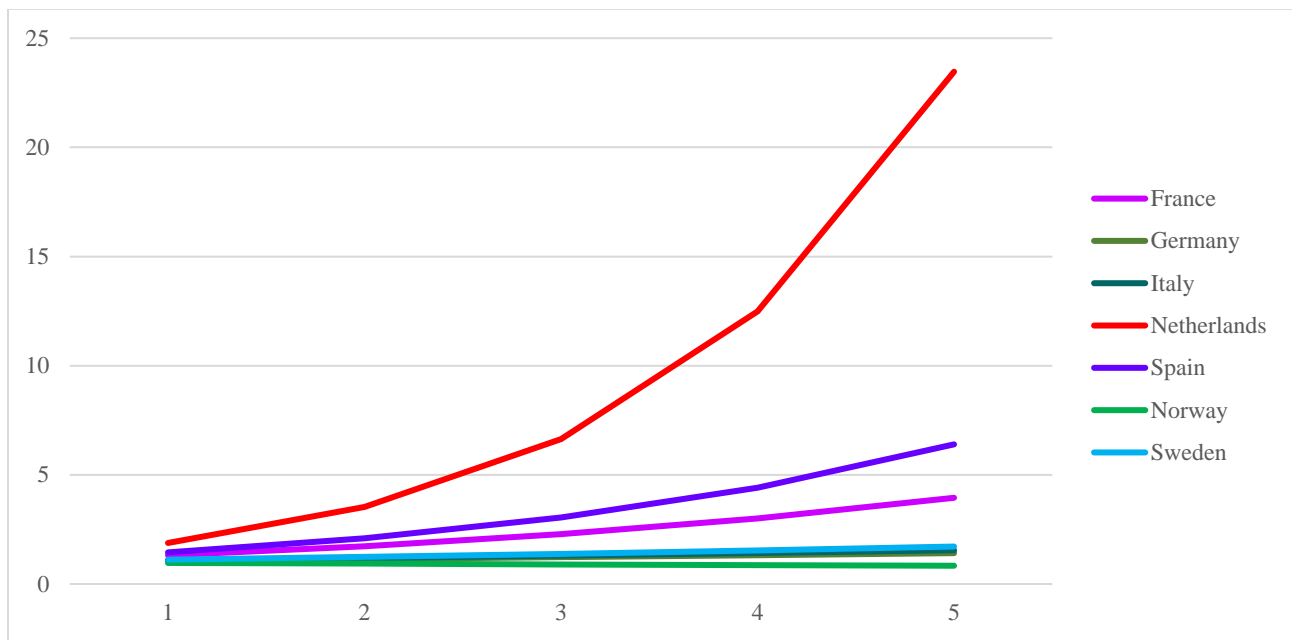
Figure A. 8: Expected consumption growth for the different countries, given a shock to the interest rate at time 1



Source: own analysis.

[Figure A.9](#) is a simpler representation which shows how future consumption in the different countries diverge given different elasticities of substitution.

Figure A. 9: Expected future consumption of the different countries, given different EIS



Source: own analysis.