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Essays in Applied Financial Economics

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Sincerely,
Oguzhan Cepni

August, 2023

Summary

This thesis examines the various factors that influence inflation rates and housing markets across different regions. It does so by focusing on three different aspects: the impact of global factors on inflation rates in European emerging market economies, the role of housing sentiment in predicting house-price growth at the state-level in the US, and the influence of housing media attention on future house prices in the US. The thesis consists of three independent chapters that explore these topics, each offering unique insights into the determinants of inflation and housing market dynamics.

Chapter I

The first chapter of the thesis, *How Local is the Local Inflation Factor? Evidence from Emerging European Countries*, with Michael P. Clements, delves into the ongoing debate regarding the role of global and domestic factors in determining inflation rates. While most of the literature has focused on developed countries like the U.S. and OECD members, we investigate the implications of the globalization of inflation for emerging European economies. The choice to focus on these less developed countries stems from their typically more variable inflation rates, which makes accurate modeling and forecasting crucial for monetary authorities and private-sector agents. Additionally, recent research has suggested that global factors may have a stronger influence on trend inflation in emerging economies compared to developed ones, especially in light of central banks often 'looking through' transitory foreign shocks affecting only the inflation gap.

In examining the impact of global factors on domestic inflation in emerging European economies, several issues are addressed. Firstly, the definition of an appropriate 'global' inflation factor is investigated. Emerging European countries may be influenced by factors derived from all countries, only emerging countries, or solely developed countries. The choice of factor construction method is also examined. Secondly, this chapter considers the role of forecasting models in assessing the importance of global developments. The impact of model selection on the perceived significance of global factors is evaluated, as well as the inclusion of a factor encompassing a broad range of domestic variables. The chapter also explores potential non-linearities in the relationship between domestic variables and inflation, as

evidence from the U.S. has suggested that the traditional Phillips Curve may not fully capture the relationship. The distinction between core and headline inflation is examined, focusing on the influence of global determinants of commodity prices on domestic inflation. Finally, we investigate whether incorporating network effects and exploring country-level characteristics can provide further insight into the relationship between global factors and domestic inflation in emerging markets.

Chapter II

The second chapter of the thesis, *Geography of Housing Sentiment over Business Cycles*, co-authored with Natalia Khorunzhina, explores the relationship between housing sentiment and future house prices and examines how the impact of sentiment on house prices changes over business cycles. Specifically, we construct state-level housing-sentiment indices using data from the Survey of Consumers of the University of Michigan and employ partial least squares method to link regional variations in sentiment composition to state-level house-price growth. Our analysis reveals that state-level housing sentiment is more powerful in explaining future state-level house-price growth than traditional macroeconomic predictors.

Furthermore, we demonstrate that housing sentiment has a greater impact on house prices during housing busts and recessions, consistent with psychological literature showing that people's reactions to news are more pronounced during times of anxiety and fear. The chapter also investigates the relationship between sentiment and house prices in states with different housing-supply elasticity, housing speculation, and economic-policy uncertainty, revealing significant heterogeneity across states. Overall, we contribute to the literature on the role of sentiment in shaping housing prices and highlight the importance of considering regional variations in sentiment and economic conditions in predictive analyses of housing markets.

Chapter III

The last chapter of the thesis, *Fifty Shades of the US States: News Media Coverage and Predictability of House Prices*, examines the relationship between news media coverage and house-price growth in the US. I construct housing-media-attention indices for each of the 50 US states using the Bloomberg Terminal News Trends function, which analyzes news stories and social media posts from over 150,000 sources. Using the partial least squares method, I combine state-level variation in news counts with the target variable of state-level house-price growth rates to create the housing-media-attention indices. I find that the indices accurately capture the heterogeneity in local house-price dynamics and have higher explanatory power compared to other housing market fundamentals. The results show that media coverage accounts for a significant portion of future house-price fluctuations, with an adjusted R^2 of 0.29. The relationship between media coverage and future housing prices is stronger in non-recourse states, states with highly regulated housing markets, and socially connected states. Additionally, greater exposure to high-SES friends amplifies the predictive power of housing media attention for future house-price growth.

This chapter contributes to the literature by constructing new measures of US state-level housing-attention indices, addressing the gap in empirical studies examining the relationship between news media coverage and housing returns. As a robustness check, I also construct a housing-media-attention index for 34 cities in the US as in previous studies and find that the newly constructed media-attention index continues to play a significant role in determining housing prices at both the state and city levels. The study diverges from previous studies by using comprehensive news coverage and constructing housing-media-attention indices at the state level.

Resumé

Denne afhandling undersøger de forskellige faktorer, der påvirker inflation og boligmarkeder i forskellige regioner. Dette gøres ved at fokusere på tre forskellige aspekter: indvirkningen af globale faktorer på inflationen i europæiske vækstmarkeder, boligsentimentets rolle i at forudsige husprisvækst på delstatsniveau i USA og indflydelsen fra boligmedieopmærksomhed på fremtidige huspriser i USA. Afhandlingen består af tre uafhængige kapitler, der udforsker disse emner, og som hver især giver unik indsigt i bestemmelserne af inflation og boligmarkedets dynamik.

Kapitel I

Det første kapitel i afhandlingen, *Hvor lokal er den lokale inflationsfaktor? Evidens fra vækstende europæiske lande*, med Michael P. Clements, dykker ned i den igangværende debat om globale og indenlandske faktorers rolle i fastsættelsen af inflationsrater. Mens det meste af litteraturen har fokuseret på ilande som USA og OECD-medlemmer, undersøger vi globaliseringens effekter på inflation i de vækstende europæiske økonomier. Valget om at fokusere på disse mindre udviklede lande stammer fra deres typisk mere variable inflationsrater, hvilket gør præcis modellering og prognosticering afgørende for monetære myndigheder og private sektoraktører. Desuden har nyere forskning antydet, at globale faktorer muligvis har en stærkere indflydelse på trendinflationen i de vækstende økonomier sammenlignet med ilande, især i lyset af centralbanker ofte 'ser igennem' forbigående udenlandske chok, der kun påvirker inflationsgabet.

Ved at undersøge indvirkningen af globale faktorer på indenlandsk inflation i de vækstende europæiske økonomier, adresseres flere problemstillinger. For det første undersøges definitionen af en passende 'global' inflationsfaktor. Vækstende europæiske lande kan være påvirket af faktorer afledt af alle lande, kun vækstende lande eller udelukkende udviklede lande. Valget af faktorkonstruktionsmetode undersøges også. For det andet overvejer dette kapitel prognosticerede modellers rolle i vurderingen af den globale udviklings betydning. Modelvalgets indvirkning på den opfattede betydning af globale faktorer evalueres, samt inklusionen af en faktor, der omfatter en bred vifte af indenlandske variable. Kapitlet udforsker også mulige ikke-lineariteter i forholdet mellem indenlandske variable og inflation,

da evidens fra USA har antydet, at den traditionelle Phillips kurve muligvis ikke fuldt ud fanger forholdet. Forskellen mellem kerneinflation og hovedinflation undersøges, med fokus på indvirkningen af globale bestemmelser for råvarepriser på indenlandsk inflation. Endelig undersøger vi, om inkludering af netværkseffekter og udforskning af landekarakteristika kan give yderligere indsigt i forholdet mellem globale faktorer og indenlandsk inflation på vækstende markeder.

Kapitel II

Det andet kapitel i afhandlingen, *Geografi af boligsentiment over konjunkturcykler*, medforfattet med Natalia Khorunzhina, undersøger forholdet mellem boligsentiment og fremtidige huspriser og undersøger, hvordan indvirkningen af sentimenter på huspriser ændrer sig over konjunkturcykler. Specifikt konstruerer vi boligsentimentsindekser på delstatsniveau ved hjælp af data fra Survey of Consumers of the University of Michigan og anvender partial least squares til at forbinde regionale variationer i sentimentsammensætning med husprisvækst på delstatsniveau. Vores analyse afslører, at boligsentiment på delstatsniveau er mere kraftfuldt i forklaringen af fremtidig delstatsniveau husprisvækst end traditionelle makroøkonomiske prædiktorer.

Desuden viser vi, at boligstemningen har en større indvirkning på huspriser under boligkrak og recessioner, hvilket er i overensstemmelse med psykologisk litteratur, der viser, at folks reaktioner på nyheder er mere udpræget i tider med angst og frygt. Kapitlet undersøger også forholdet mellem sentimenter og huspriser i stater med forskellig boligforsyningselasticitet, boligspekulation og økonomisk-politisk usikkerhed, hvilket afslører betydelig heterogenitet på tværs af stater. Samlet bidrager vi dermed til litteraturen om sentimenters rolle i formning af huspriser og fremhæver vigtigheden af at overveje regionale variationer i sentimenter og økonomiske forhold i forudsigende analyser af boligmarkeder.

Kapitel III

Det sidste kapitel i afhandlingen, *Fifty Shades of the US States: Mediedækning og husprisers forudsigelighed* , udforsker forholdet mellem nyhedsmediedækning og husprisvækst i USA. Jeg konstruerer boligmedieopmærksomhedsindekser for hver af de 50 stater ved hjælp af Bloomberg Terminal News Trends funktionen, som analyserer nyhedshistorier og sociale medieopslag fra over 150.000 kilder. Ved hjælp af partial least squares metoden kombinerer jeg delstatsniveau variation i nyhedsantal med målvariablen delstatsniveau husprisvækstrater for at skabe boligmedieopmærksomhedsindekserne. Jeg finder, at indekserne præcist indfanger heterogenitet i lokale husprisdynamikker og har en højere forklarende kraft sammenlignet med andre boligmarkedsgrundlag. Resultaterne viser, at mediedækning tegner sig for en betydelig del af fremtidige husprisfluktuationer, med en justeret R^2 på 0,29.

Forholdet mellem mediedækning og fremtidige boligpriser er stærkere i stater der tillader lån uden personlig hæftelse, stater med stærkt regulerede boligmarkeder og socialt forbundne stater. Derudover forstærker større eksponering for venner med høj socioøkonomisk status den forudsigende kraft af boligmedieopmærksomhed for fremtidig husprisvækst.

Dette kapitel bidrager til litteraturen ved at konstruere nye målinger af boligopmærksomhedsindekser på delstatsniveau i USA, hvilket adresserer mangler i empiriske studier, der undersøger forholdet mellem nyhedsmediernes dækning og boligafkast. Som en robusthedstest konstruerer jeg også et boligmedieopmærksomhedsindeks for 34 byer i USA som i tidligere studier og finder, at det nyligt konstruerede medieopmærksomhedsindeks fortsat spiller en væsentlig rolle i bestemmelsen af huspriser på både delstats- og byniveau. Studiet afviger fra tidligere studier ved at bruge omfattende nyhedsdækning og konstruere boligmedieopmærksomhedsindekser på delstatsniveau.

Contents

Introduction

The importance of considering a global inflation factor for forecasting local inflation rates is paramount. In an era of heightened global interconnectedness and international trade, the global inflation factor captures the spillover effects from dominant economies influencing the prices of goods and services in smaller economies Ciccarelli and Mojon, 2010. This global perspective is essential for central banks and policymakers to comprehend the external pressures driving inflation, beyond traditional domestic factors.

Furthermore, the global inflation factor becomes indispensable for countries deeply integrated into global value chains. Such countries, reliant on imported goods either for consumption or as production inputs, find their domestic price levels directly impacted by global inflation. The literature on international interconnectedness emphasizes the increasing role of global slack in determining national inflation rates due to this integration Auer et al., 2017. Especially for countries dependent on specific commodities, global price fluctuations can significantly sway local inflation.

The first chapter of this thesis delves into the profound influence of the global inflation factor on local inflation rates. It reveals that global inflation factors account for a significant variance in national inflation rates for European emerging market economies. This chapter ties the global inflation narrative to the real-world implications, emphasizing the need for central banks and policymakers to factor in global inflation when devising strategies, especially for economies deeply embedded in global value chains.

Transitioning from the macroeconomic landscape of global inflation, the second chapter shifts focus to the microeconomic realm, exploring the relationship between housing sentiment and future house prices. Housing sentiment, driven by collective beliefs and opinions, has emerged as a robust predictor of future national house prices (Bork et al., 2020; Case et al., 2012). With the growing disparity in regional house prices, understanding the nuances of how housing sentiment influences local prices becomes imperative. This chapter seeks to discern whether sentiment-driven price changes manifest more prominently in specific regions or during distinct business-cycle phases.

The policy implications of housing sentiment cannot be understated. Grasping the nexus between housing sentiment and future house prices equips policymakers to devise effective interventions during business cycles (Jordà et al., 2016). Positive housing sentiment, indicative of rising house prices, might necessitate measures to curb market overheating. Conversely, during downturns marked by negative sentiment, targeted stimulus packages can rejuvenate the housing market. Given that housing policies predominantly operate at the state level, gauging sentiment at this granularity facilitates a direct correlation between policy impacts and sentiment shifts.

Building on the insights from the second chapter, the final chapter of the thesis ventures into the realm of media's influence on the housing market. It investigates how housing media attention, a reflection of collective focus on housing topics, can predict future house prices. In today's information age, news media platforms play a pivotal role in shaping perceptions and influencing financial markets, including housing (Shiller, 2002). While several studies have probed the media's impact on financial markets (Tetlock, 2010; Gurun and Butler, 2012; Barber and Odean, 2008; Fang and Peress, 2009; Solomon et al., 2014; Kaniel and Parham, 2017; Tetlock, 2007; Garcıa, 2013; Calomiris and Mamaysky, 2019; Jeon et al., 2022), its effects on real asset markets, especially housing, remain under-explored. This chapter, therefore, bridges this gap, examining the interplay between housing media attention and future house prices, factoring in diverse state characteristics. In doing so, it offers a comprehensive understanding of media's role in the housing market, benefiting both investors and policymakers.

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Chapter 1

How Local is the Local Inflation Factor? Evidence from Emerging European Countries

Oguzhan Cepni & Michael P. Clements

Abstract

We consider whether inflation is a 'global phenomenon' for European emerging market economies, as has been claimed for advanced or high-income countries. We find that a global inflation factor accounts for more than a half of the variance in the national inflation rates, and show that forecasting models of national headline inflation rates that include global inflation factors generally produce more accurate path forecasts than Phillips Curve-type models, and models with local inflation factors. Our results are qualitatively unaffected by allowing for sparsity and non-linearity in the factor forecasting models. We also provide some insight as to why global factors are an important determinant of domestic inflation, by considering the country-level characteristics which tend to increase the importance of global factors over domestic influences.

1.1 Introduction

Over the last decade or so there has been much debate in the literature about the relative importance of global factors and domestic factors (including a country's monetary policy) as determinants of countries' inflation rates. Much of the research has focused on the U.S. and the developed countries of the OECD, with fewer studies of developing and emerging economies. Even for developed countries, the importance of the 'globalisation of inflation', and it's implications for the conduct of domestic monetary policy, has been contested. In this paper, we address the relevance of the globalisation of inflation phenomenon for emerging market economies, analysing a number of emerging European economies.

There are a number of reasons for focusing on less developed countries. Firstly, less advanced countries typically experience more variable inflation rates, putting a premium on the accurate modelling and forecasting of inflation in those countries, both for the conduct of policy by the monetary authorities, as well as for the savings and investment decisions of private-sector agents. Secondly, recent research by Kamber and Wong, 2020 suggests that global factors play a more important role in determining trend inflation (as opposed to cyclical inflation) in emerging economies than in developed economies. They suggest (referring to Draghi, 2015) that although global factors affect the inflation gap in both emerging and developed countries, central banks will 'look through' foreign shocks that only have transitory effects (that is, only affect the inflation gap). Hence for the conduct of monetary policy, determining the effects of foreign shocks on developing countries may be a more pressing concern than for developed economies, especially if these shocks do have a greater effect on trend inflation in developing economies.

As for developed economies, there does not appear to be a clear consensus on the importance of global factors for domestic inflation rates for emerging market economies. (We review a number of the studies in section 1.2.) There are a number of issues that might affect the findings, and we seek to provide a detailed examination of some of these. Firstly, in the context of the emerging European economies, what is an appropriate 'global' inflation factor? A factor could be extracted from all the countries taken together (i.e., emerging and developed), or from the subset of emerging countries, or from the developed countries. The shared geographic location of the emerging European countries, and their close ties in terms of cultural, political and industrial development might suggest an emerging-country factor, but equally we might expect the EU member countries to be affected by European-wide, or even global, inflation. We regard this as an empirical question, and we allow the data to choose between these possibilities based on which generates the best forecasts. Related to the choice of factor, how to calculate the factor(s) turns out to matter. We estimate factors using partial least squares, rather than the oft-used principal component analysis. As we explain, this makes it more likely that the factors will be able to predict national inflation rates.

The second main consideration is the choice of forecasting model in which to determine any potential benefits from including factors. The forecasting models in which 'global' effects are included can affect the importance we attribute to global developments, as can the benchmark models we use as comparators,[1]and the failure to model domestic influences might misleadingly point to an important role for external factors in forecasting domestic inflation. We attempt to guard against finding a role for 'global inflation', because of the omission of relevant domestic sources, by including a factor calculated from a large set of domestic variables, which includes the traditional Phillips curve determinants. We use a factor to capture a wide range of possible domestic influences.

As part of the choice of forecasting model, it may be important to allow for non-linearities. At least for the U.S. evidence has accumulated against the traditional Phillips Curve, with the 'missing disinflation' in the U.S. following the 2008 Financial Crisis (see, e.g., Stock, 2011 and Coibion and Gorodnichenko, 2015), and the recent low rates of inflation despite low rates of unemployment (see, e.g., Ball and Mazumder, 2020). McLeay and Tenreyro, 2019 argue that the actions of the monetary authorities will diminish the observed responsiveness of prices to slack, leading to a flattening of the Phillips Curve. Atkeson and Ohanian, 2001 had earlier found that a simple average of the four quarterly inflation rates up to the forecast origin was more accurate than forecasts obtained from Phillips Curve specifications. That said, our "Phillips Curve" model is broader than a simple relationship between inflation and unemployment rate or the output gap, and captures a broad range of domestic influences. We allow the domestic variables to have a non-linear or time-varying influence on inflation, consistent with the view that the Phillips Curve might exhibit important non-linearities (see, e.g., Hooper et al., 2019). We consider whether our findings change when we allow for non-linearities.

The literature also suggests an important distinction between core and headline inflation, where the former excludes food and energy prices. Global determinants of commodity prices will likely influence domestic energy and food prices, and hence headline inflation. But the 'globalisation of inflation' phenomenon as sometimes understood goes beyond this direct effect, to refer to an effect on core inflation. While food and energy prices will affect the headline figure, they may not be closely related to the domestic level of activity, so that

[1]A case in point is the study by Gillitzer and McCarthy, 2019, which shows that a head-to-head comparison of the forecast performance of the global inflation model of Ciccarelli and Mojon, 2010 with the 'no change' benchmark of Atkeson and Ohanian, 2001 (discussed further below in the main text) does not favour the former. The benchmark model of Atkeson and Ohanian, 2001 happens to closely correspond to the model of Stock and Watson, 2007 for U.S. inflation for a particular epoch. However, adding the global factor to the model of Atkeson and Ohanian, 2001 was found to improve accuracy at longer horizons. This can be understood in terms of the concept of forecast encompassing: a model can be less accurate than another but still carry useful incremental information for forecasting (see, e.g., Chong and Hendry, 1986 and Ericsson and Marquez, 1993).

Phillips Curve specifications may not work well for the headline rate.[2] We unpack these issues as follows. Our primary focus is on headline inflation rates, and we check whether a global factor has predictive power once we have separately controlled for commodity (food and energy) prices. We then consider whether our findings change when headline inflation is replaced with core inflation.

Looking ahead: in our baseline linear models (described in section 1.4) we find that global factors play an important role in determining European emerging market national headline inflation rates, in addition to the explanatory power provided by local, domestic factors: 'inflation is a global phenomenon' for the European emerging market countries' just as it has found to be for advanced economies: see section 1.5. This finding is tempered somewhat when we forecast core inflation instead. For forecasting headline national inflation rates, global inflation is found to have predictive power beyond the information carried by the factor regarding commodity prices.

Our baseline findings are shown to be robust to other modelling approaches. They carry over to factor-selection methods that enforce sparsity, as well as a machine-learning method that allows for a non-linear relationship between national inflation rates and the sets of factors. These results serve as a robustness check, as well as extending the analysis to over a range of models that are becoming increasingly popular in the literature. The additional methods are described in section 1.6.1, and the results in section 1.6.2. We consider a number of methods of evaluating forecast performance, including looking at path forecasts, and the horizon of predictability, but the bottom-line is essentially unchanged.

Finally, we undertake two additional sets of analyses, with the aim of furthering our understanding of why inflation appears to be a global phenomenon for emerging market (EM) economies. In section 1.7, we consider whether we can explain national inflation rates better (in terms of generating more accurate forecasts) if we make an allowance for the different degrees of 'connectedness' between countries when we calculate the global inflation factor. For shorter and medium horizon forecasts allowing for network effects yields improvements for some countries. However, for some EM countries at all horizons, and for most counties at longer horizons, allowing for network effects is not beneficial. Section 1.8 casts light on the country-level characteristics that make a country's inflation rate more responsive to global inflation, as opposed to domestic factors. That is, we explore the potential propagation channels of global factors on domestic inflation rates for emerging markets.

[2]See e.g., Ball and Mazumder, 2020, who argue that large relative price changes may also occur in industries other than food and energy, suggesting measuring inflation using the weighted median of price changes across industries (proposed as a measure of core inflation by Bryan and Cecchetti, 1993).

1.2 Literature Review

Before presenting our approach and results, we briefly review some of the literature on the relative importance of global factors and domestic factors (including a country's monetary policy), as determinants of countries' inflation rates, for both developed and developing countries. Ciccarelli and Mojon, 2010 argue that the international character of economic fluctuations is not new (see, e.g., Kose et al., 2003), but suggest the recognition that inflation might also be a global phenomenon has come more slowly, with Ciccarelli and Mojon, 2010 being an important contribution, along with Neely and Rapach, 2011a and Mumtaz and Surico, 2012, *inter alia*.[3] Ciccarelli and Mojon, 2010 show that a common factor accounts for nearly 70% of the variance of inflation of 22 OECD countries, capturing trend components and cyclical variation. However, the importance of the 'globalisation of inflation' for the effectiveness of domestic monetary policy has been disputed[4] as has the appropriate way of modelling and forecasting inflation.

One reason for suspecting global factors might have been more important is the literature on international interconnectedness, as measured by global value chains - see e.g., Auer et al., 2017. Greater international interconnectedness might result in an increase in the importance of 'global slack' (relative to domestic conditions) in determining national inflation rates. Kabukçuoğlu and Martınez-Garcıa, 2018 find that modelling cross-country inflation spillovers also improves upon traditional 'closed' Phillips Curve forecasting models. Yet the importance of global factors (with the exception of commodity prices) in determining advanced economies' national inflation rates is contested by Mikolajun and Lodge, 2016. They show that in Phillips Curve models for the period of relative stability from the mid 1990s onwards, global factors other than commodity prices tend to be of little importance, especially once forward-looking expectations are included to capture long-term trends. Altansukh et al., 2017, p.2 suggest 'the observed convergence in aggregate and core inflation may be the product of many economies sharing a similar inflation target concurrently, rather than due to a global transmission factor'.

The evidence for emerging or low income countries in favour of globalisation of inflation is also equivocal. Duncan and Martınez-Garcıa, 2019 consider a range of models for 14 emerging market economies, including open-economy Phillips Curve models, and generally find they are outperformed by the Atkeson and Ohanian, 2001 benchmark. Parker, 2018 comes to a similar conclusion for middle and low income countries. His findings match those of Ciccarelli and Mojon, 2010 in that global inflation matters for high-income countries, but

[3] That said, it has long been recognised that the Phillips curve (Phillips, 1958) relationship between the real-side of the economy (the unemployment rate, or an activity variable or measure of slack more generally) and price or wage inflation, ought to be supplemented with a role for international developments, such as oil prices or import prices (see, e.g., Franz and Gordon, 1993 and Roberts, 1995).

[4] See, e.g., Carney, 2015, Draghi, 2015 and Jordan, 2015.

accounts for only 10% or so of the variation in national inflation rates for low income countries (and only 15-20% for middle income countries). Parker, 2018, p.175 argues that in high income countries it is 'the lower average inflation, lower inflation volatility, higher GDP per capita, deeper financial development and more transparent monetary policy that explain a greater role for global inflation factors'. Jašová et al., 2019 find a diminished role for global inflation in determining emerging markets national inflation rates following the global financial crisis, in contrast to their evidence for developed countries. Finally, both Hałka and Szafranek, 2016 and Lovin, 2020 offer a more positive assessment of the effects of global factors on emerging market economies. Hałka and Szafranek, 2016 find central and eastern European countries' inflation rates are affected by inflation in the euro area, and Lovin, 2020 finds a role for euro area inflation and output gap for European emerging countries' inflation rates, although core CPI was less affected than food and energy.

1.3 Data

We collect a large set of macro-economic indicators on the central and eastern European countries: Bulgaria, Czech Republic, Greece, Hungary, Poland, and Romania (hereinafter referred to as EM European). We select the EM European countries which have made the largest strides in terms of globalization in recent years.[5] The data-set includes both 'hard indicators' and country level survey data. In the hard indicators, we have supply-side variables, such as construction, industrial production indices, and demand-side variables, such as energy usage. Among the survey variables, we have consumer confidence indices, European Commission economic sentiment index and Market PMI survey, etc. To capture the potential vulnerability of EM European countries to external factors, we also consider the current account balance, and export and import value indices. The macroeconomic indicators are downloaded from Bloomberg.

In addition to the macroeconomic indicators, we employ a large dataset of disaggregated harmonized indices of consumer prices (HICP), up to product-level, for our sample of countries. This is a higher level of disaggregation than sector-specific price data, and includes product series such as 'meat', 'milk', 'package holidays', and 'dental services', etc. The number of HICP components ranges from 79 and 89 indices across countries, since not all items are available for all countries.[6] The disaggregated price data are obtained from the Euro-stat database.

To construct a proxy for global inflation, we collect a large panel of headline consumer price indices for a set of 98 countries, including the 27 advanced countries, and 71 emerging markets. Hence, our dataset covers inflation rates for countries in different regions such

[5] See Gygli et al. (2019).
[6] We only utilized the indices that have available data for our whole sample period.

as the Middle East, Asia, Africa, and Europe. The selection of countries is based on data availability: earlier-period high-quality data are not available for some countries we would otherwise have included. The country-level headline consumer price indices are taken from the IMF database.

Our complete monthly dataset covers the period January 2002 to January 2020: the starting date being determined by data availability. All series are adjusted for seasonality (where relevant), and made stationary as appropriate by either differencing, year-over-year differencing, or log-differencing. Table 1.1 summarizes the number of variables in each data group across countries.

Table 1.1: Number of variables in each data group across countries

	Bulgaria	Czech R.	Greece	Hungary	Poland	Romania
Macroeconomic variables	84	70	68	65	74	82
Disaggregated price variables	79	89	81	80	89	80
Emerging markets headline CPI	71	71	71	71	71	71
Developed markets headline CPI	27	27	27	27	27	27

1.4 Methodology

1.4.1 Constructing the Local and Global Factors Using Partial Least Squares (PLS)

In much of the existing literature, a proxy for global inflation is constructed as a common factor of a group of country inflation rates, often either as a static factor resulting from the application of principal component analysis (PCA) or from dynamic factor models estimated using Bayesian methods (Ciccarelli and Mojon, 2010; Mumtaz et al., 2011; Parker, 2018). Unlike those studies, we use partial least squares (PLS) to extract common factors, and calculate factors from our three separate datasets. The first is a country-specific macroeconomic indicators dataset, the second a country-specific dataset of disaggregated CPI indices, and finally we calculate a number of factors from a dataset of national inflation rates, as described below. PLS reduces the large number of variables in each of these datasets to a small number of factors, which have maximum explanatory power for a given target variable. As indicated by (Fuentes et al., 2015; Groen and Kapetanios, 2016), PLS estimates the latent factors by maximizing the co-variance between the target forecast variable and predictor variables. The explicit consideration of the target forecast variable counters the main criticism of PCA: it ensures that the resulting factors are related to the target variable.

In this paper, the PLS method is utilized by following the two-step approach proposed by Friedman et al., 2001. For each dataset X, the algorithm standardizes each predictor variables x_j $(j = 1, \ldots, n)$ to have zero mean and unit variance.[7] Then, univariate regression coefficients $\widehat{\gamma_{1j}} = \langle x_j, y \rangle$ are stored for each j, where y alternatively represents the headline inflation rates of our EM European countries. Using these coefficients, the first PLS direction $z_1 = \sum_j \widehat{\gamma_{1j}} x_j$ is determined as the weighted sum of the original set of predictor variables, where the weights are given by the vector of univariate regression coefficients. Accordingly, the estimation of the PLS direction incorporates the degree of association between target variable y and the predictor variables. Subsequently, the target variable y is regressed on z_1, resulting in a coefficient θ_1, and then all inputs are orthogonalized with respect to z_1. This process is repeated until PLS constructs a sequence of $k < n$ orthogonal directions, $\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_k$. Hence, PLS attempts to capture the directions that have high variance and high correlation with the target variable concurrently. In particular, the p^{th} PLS direction $\widehat{\gamma_p}$ solves the following optimization problem:

$$\begin{aligned} &\max_{\alpha} && Corr^2(y, X_\alpha) Var(X_\alpha), \\ &\text{subject to} && \|\alpha\| = 1, \quad \alpha' M \widehat{\gamma_k} = 0, \quad k = 1, ..., p-1 \end{aligned} \tag{1.1}$$

where M denotes the sample covariance matrix of the x_j. The conditions $\alpha' M \widehat{\gamma_k} = 0$ ensures that $\mathbf{z}_k = \mathbf{X}\alpha$ is uncorrelated with all the previous linear combinations $\mathbf{z}_k = \mathbf{X}\widehat{\gamma_k}$.

In our forecasting exercise, we first make use of a factors that summarize the information contained in a broad set of macroeconomic indicators for each of the EM European countries in our sample. We label these PLS-factors as 'Local macro factors' (LocalMACRO) since they are based on only local or 'own-country' variables. Similarly, using the highly-disaggregated CPI data for a given country, we extract PLS-factors for each country, which will be highly correlated with that country's headline inflation rate. We name these 'Local (domestic) inflation factors' (LocalCPI).

Three competing measures of 'global inflation' are considered. We partition our dataset of headline inflation rates, covering countries across the globe, into three sets: 'Global' (includes all countries), 'Emerging' (includes only EM countries) and 'Developed' (includes only DM countries). Each subset is used to generate a PLS factor that may prove instrumental in capturing global inflation dynamics. These new PLS-factors are called the 'Global inflation factor' (GlobalCPI) - constructed using inflation rates of all countries, the 'EM inflation factor' (EMCPI) - constructed using only inflation rates of emerging countries, and the 'DM inflation factor' (DMCPI) - constructed using only inflation rates of developed countries.

[7] For each country, the dataset X alternatively represent the aggregated harmonized indices of consumer prices, the set of macro-economic indicators, headline inflation rates for 98 countries, headline inflation rates of 27 advanced countries and headline inflation rates of 71 emerging markets.

1.4.2 Forecasting Experiment: Factor-Augmented Predictive Regressions

To evaluate the predictive ability of global and local factors for the year-over-year inflation rates of emerging European countries, we specify factor-augmented predictive regressions, where factors are extracted using both PCA and PLS approaches. We utilize both a recursive and 84-months fixed length rolling window forecasting scheme to generate forecasts from the different specifications. We design a set of models which allows us to isolate any accuracy gains from the incorporation of either country-specific or global inflation factors, conditional on the model already including Phillips Curve-type variables (proxied by the LocalMACRO factor). That is, we are not so much interested in whether a model with a global factor (say) is better or worse than a Phillips curve model, as whether the global factor has any additional incremental predictive ability when added to a Phillips curve model. Note that the method of construction of the factors does not impose orthogonality between the factors in different groups (e.g., between the factors in the LocalMACRO and LocalCPI groups). Hence any potential improvement from adding a LocalCPI factor, say, may be tempered to the extent that the LocalCPI factor is correlated with the included LocalMACRO factors. Or, for example, the LocalCPI factor may partly reflect global developments. Nevertheless our suite of models facilitates encompassing-type comparisons (see footnote 3) and will allow us to discern improvements from adding factors conditional on the factors already included, even though some care is required over the interpretation. Hence the forecasting exercise consists of the following models:[8]

- **Specification 1**: Local macro factor model *(+LocalMacro)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \varepsilon_{t+h}$
- **Specification 2**: Local inflation factor model *(+LocalCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \varepsilon_{t+h}$
- **Specification 3**: EM inflation factor model *(+emCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{EMCPI} + \varepsilon_{t+h}$
- **Specification 4**: DM inflation factor model *(+dmCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{DMCPI} + \varepsilon_{t+h}$
- **Specification 5**: Augmented inflation factor model *(+em_dmCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{EMCPI} + \delta' F_t^{DMCPI} + \varepsilon_{t+h}$
- **Specification 6**: Global inflation factor model *(+GlobalCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{GlobalCPI} + \varepsilon_{t+h}$

[8] Lag length is selected via the Schwarz information criterion (SIC) for benchmark AR model.

where y_t, alternatively, is year-over-year inflation rates of European emerging countries, and L^p is shorthand for a pth order lag polynomial, and F_t^j for $j =$ [LocalMACRO, LocalCPI, EMCPI, DMCPI, GlobalCPI] represents the estimated country-specific common factors described in Section 2.2.3.[9] The lag length p of the AR component of each specification type is selected based on SIC criteria. While the specification types 1-2 enable us to assess the importance of local inflation and macro factors in addition to lags of the inflation rate and constant, specification types 3-6 are extensions that include global inflation factors. All models are re-estimated at each step using the information available up to time t. We use exactly 50% of the sample period to assess out-of-sample forecasts, giving us 103-h observations where forecast horizons are evaluated for h = 1, 2 3, 4, 5, 6, 9, 12 step-ahead forecasts. Furthermore, we compare forecast accuracy using the mean squared forecast error (MSFE).

In addition to these models, we also examine the usefulness of various time-varying parameter and shrinkage models in Section 1.6. These models are designed to be flexible enough to capture some forms of structural change and parameter non-constancies (Korobilis, 2019). The use of a rolling-window forecasting scheme will allow some model adaptation, but we also investigate the potential for time-varying parameter models to improve on the linear factor models.

1.4.3 Forecast Evaluation

Our baseline forecasting results consist of the standard approach of comparing models' forecasts for a particular horizon, and testing the null of equal predictive ability, for that specific horizon, popularised by Diebold and Mariano, 1995 test (DM). Various extensions have been proposed, such as the Giacomini and White, 2006 tests of conditional predictive ability, which remain applicable when the forecasts come from nested models (as do the tests of Clark and West, 2007).

However, we also consider the evaluation of forecast performance based on the forecast path. A forecast user (e.g., a central banker) may be more interested in the forecast path than performance at given horizons in isolation. Hence, we compare the different specifications (and thus the incremental usefulness of 'global inflation') in terms of their ability to produce accurate forecast paths (Jordà and Marcellino, 2010). This preempts the practical difficulties which arise when one model fares better at some horizons, and a rival model is better at other horizons - that is, we obtain incoherent inferences. It also allows us to sidestep issues to do with multiple testing, arising from comparing forecast accuracy at many horizons, and the appropriate way of dealing with this (see, e.g., (Hansen, 2005; Patton and Timmermann, 2012; Quaedvlieg, 2021) on this and related issues).

[9] For each country, all the common factors are re-estimated at each forecast origin using the information available up to time t to prevent the look-ahead bias.

Hence, we utilize the multi-horizon superior predictive ability (SPA) test of Quaedvlieg, 2021, as well as reporting results for the DM and related tests. In particular, we denote the variable of interest at time t as y_t over the time period $t = 1, \ldots, T$. Since our aim is to compare the forecast path of 1 to H-step ahead forecasts, we define $\hat{\boldsymbol{y}}_{i,t} = \left[\hat{\boldsymbol{y}}_{i,t}^1, \ldots, \hat{\boldsymbol{y}}_{i,t}^H\right]'$ where $\hat{\boldsymbol{y}}_{i,t}^h$ represents the point forecasts of a model i at horizon $h = 1, \ldots, H$. We also describe a loss function $\boldsymbol{L}_{i,t} = L\left(\boldsymbol{y}_t, \hat{\boldsymbol{y}}_{i,t}\right) = (y_t - \hat{\boldsymbol{y}}_{i,t})^2$ which maps prediction errors into an H-dimensional vector where $L_{i,t}^h = L\left(\boldsymbol{y}_t, \hat{\boldsymbol{y}}_{i,t}^h\right)$ represents a typical element. Based on squared error loss, models' loss differentials are given by:

$$\boldsymbol{d}_{ij,t} \equiv \boldsymbol{L}_{i,t} - \boldsymbol{L}_{j,t}, \tag{1.2}$$

where $\boldsymbol{d}_{ij,t}$ is an H-dimensional vector with elements $d_{ij,t}^h$. Following Quaedvlieg, 2021, we use expected loss differentials $E\left(\boldsymbol{d}_{ij,t}\right) = \boldsymbol{\mu}_{ij,t}$ in our hypothesis, where $\boldsymbol{\mu}_{ij} \equiv \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^T \boldsymbol{\mu}_{ij,t}$.[10] We test the following hypothesis of equal predictive performance at a single horizon h, corresponding to a standard DM test:

$$H^{\mathrm{DM}} : \mu_{ij}^h = 0 \tag{1.3}$$

$$t_{\mathrm{DM},ij}^h = \frac{\sqrt{T}\bar{d}_{ij}^h}{\hat{\omega}_{ij}^h} \tag{1.4}$$

where $\bar{d}_{ij}^h = \frac{1}{T}\sum d_{ij,t}^h$, and $\omega_{ij}^h = \boldsymbol{\Omega}_{ij,hh}^{1/2}$ denotes the square root of the diagonal element in the h^{th} horizon. We test the null hypothesis using a standard t-test with HAC-type standard errors.

Utilizing the DM test may lead to situations where model i yields better forecasts than those of the model j at some specific horizons, while the model j generates significantly better forecasts for other specific horizons. In this case, the DM test may not present a clear picture of which model we should choose. To address this issue, Quaedvlieg, 2021 proposes two types of SPA test: uniform superior predictive ability (uSPA) and average superior predictive ability (aSPA). While the uSPA requires superior forecasts at each individual horizon, the aSPA compares the weighted average loss across horizons by considering the relative importance of superior forecast performance at one horizon against inferior prediction ability at another. The loss difference can be defined as $\mu_{ij}^{(\text{Uniform })} = \min_h \mu_{ij}^h$ for the uSPA and $\mu_{ij}^{(\mathrm{Avg})} = w'\mu_{ij} = \sum_{h=1}^H w_h \mu_{ij}^h$ with weights $\boldsymbol{w} = [w_1, \ldots, w_H]'$ for the aSPA.

To test the uniform superior predictive ability, we test the following null hypothesis:

$$H_{0,\mathrm{uSPA}} : \mu_{ij}^{(\mathrm{Unif})} \leq 0 \tag{1.5}$$

$$t_{\mathrm{uSPA},ij} = \min_h \frac{\sqrt{T}\bar{d}_{ij}^h}{\hat{\omega}_{ij}^h} \tag{1.6}$$

[10] See, Quaedvlieg, 2021 for assumptions regarding the properties of $\boldsymbol{d}_{ij,t}$.

against the one-sided alternative that $\mu_{ij}^{(\text{Uniform})} > 0$ using the t_{uSPA} test statistic which is the minimum of DM test statistics defined in equation (1.4). Similarly, the associated null for the aSPA test can be written as:

$$H_{0,\text{ASPA}} : \mu_{ij}^{(\text{Avg})} \leq 0 \tag{1.7}$$

$$t_{\text{aSPA},ij} = \frac{\sqrt{T}\bar{d}_{ij}}{\hat{\zeta}_{ij}} \tag{1.8}$$

with the alternative $\mu_{ij}^{(\text{Avg})} > 0$, where $\bar{d}_{ij} = \boldsymbol{w}'\overline{\boldsymbol{d}}_{ij}$ and $\zeta_{ij} \equiv \sqrt{\boldsymbol{w}'\boldsymbol{\Omega}_{ij}\boldsymbol{w}}$. Since these 't-statistics' do not follow a Student t distribution in either case, inference is based on the moving block bootstrap techniques of Kunsch, 1989, as suggested by Quaedvlieg, 2021.

1.5 Results

1.5.1 Do Global Inflation Factors Drive Local Inflation Rates ?

Figure 1.1 shows the percentage of the variance in the inflation rates of EM European countries explained by global and local inflation factors, where the factors are obtained using the PLS and PCA methods. As can be seen in Figure 1.1, there is a notable rise in the variance explained by the first common factor, especially for the Czech Republic and Poland, when the factors are extracted utilizing the PLS approach. This finding shows the importance of considering the degree of association between the inflation rate (our target variable) and the predictor variables to construct the common factors. Hence, the PLS-approach results in a better proxy for capturing the local and global price dynamics, although previous studies used PCA (Ciccarelli and Mojon, 2010; Mumtaz et al., 2011; Parker, 2018) Figure 1.1 shows that although the local CPI factor estimated based on disaggregated CPI data explains more than 75% of the variance in inflation rates, the global CPI factor accounts for more than 50% of the variance of national inflation rates, indicating a clear role for global factors in driving headline inflation in EM European countries, in addition to local price dynamics. In particular, the importance of global factors in driving national inflation rates is more pronounced for Bulgaria since the shares of inflation explained by Global CPI and EM CPI factors are slightly higher than the local CPI factor.

In terms of how 'global' is global, we note the higher level of the variance explained by the (PLS-based) EM CPI factor compared to the DM CPI factor, that we observe in all countries.[11] Some of the recent literature would appear to suggest that our European Union

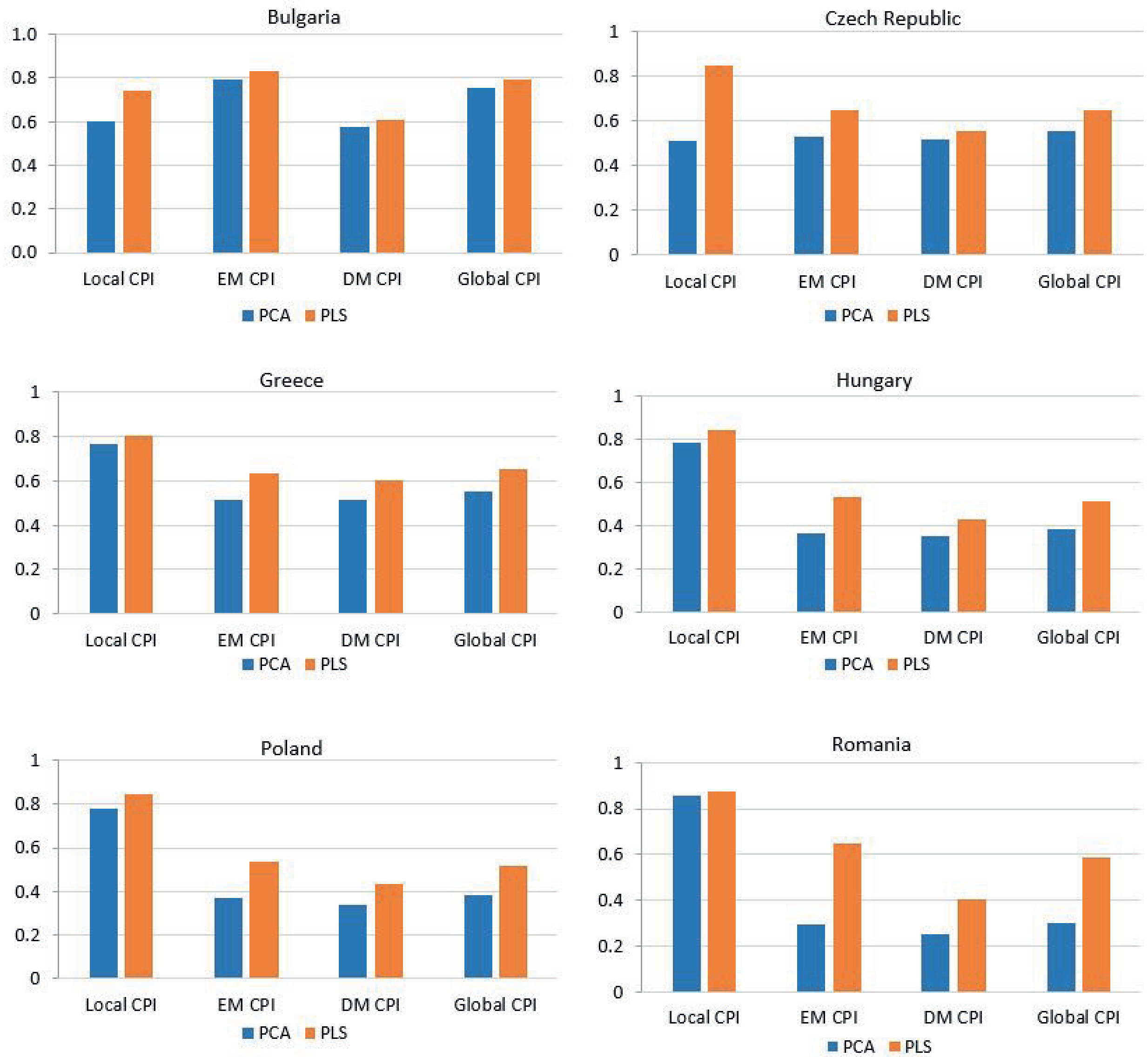
[11] Unsurprisingly, while the first factors of EMCPI and DMCPI are tend to be highly correlated for each country, the correlation coefficients start to decline in the higher number of factors. For instance, the fourth factor of EMCPI and the fourth factor of DMCPI is even negatively correlated for Greece (-0.25) and Romania (-0.03).

member countries might be more affected by DM developments. In particular, recent empirical studies provide evidence that global investors tend to see emerging markets as a single asset class, resulting in correlated investment patterns in emerging markets (Miyajima and Shim, 2014). This results in an increase in the convergence of emerging market economies' response to global and domestic monetary policy shocks, making them more connected. Furthermore, although our sample countries are members of the EU, they do not use the euro as their currency (except for Greece), which may play an essential role in the exchange rate pass-through into inflation during large capital outflows from emerging markets. Hence, decomposing the global price dynamics into emerging and developed market components expands on the existing literature by exploring the different facets of inflation dynamics, which yields interesting nuances.

Figure 1.2 plots the PLS-based local and global inflation factors along with the actual inflation rates. An examination of these plots indicates that estimated factors tend to capture turning points relatively well. Both global and local factors stay high around the years 2007-2008 for almost all countries. However, since the onset of the global financial crisis in 2008-09, and again after the European sovereign debt crisis in 2011-12, there is a persistent decline in the global and local factors along with the inflation rates. It appears that low consumer price inflation has been a common feature of all EM European countries between 2014 and 2018. The national inflation rates move in tandem with the global factors reflecting the difficulty faced by the ECB in defusing global propagation channels that pose downside risks to the Euro area inflation outlook. Furthermore, the world economy has become increasingly integrated in recent years, which leads to an increase in the prevalence of global price shocks in domestic inflation dynamics after 2018. As shown in Figure 1.2, the inflation rates have become more interconnected to both global and local CPI factors after 2018, and they have started to move in a highly synchronized manner, especially in Bulgaria, Czech Republic, Greece, and Romania. [12]

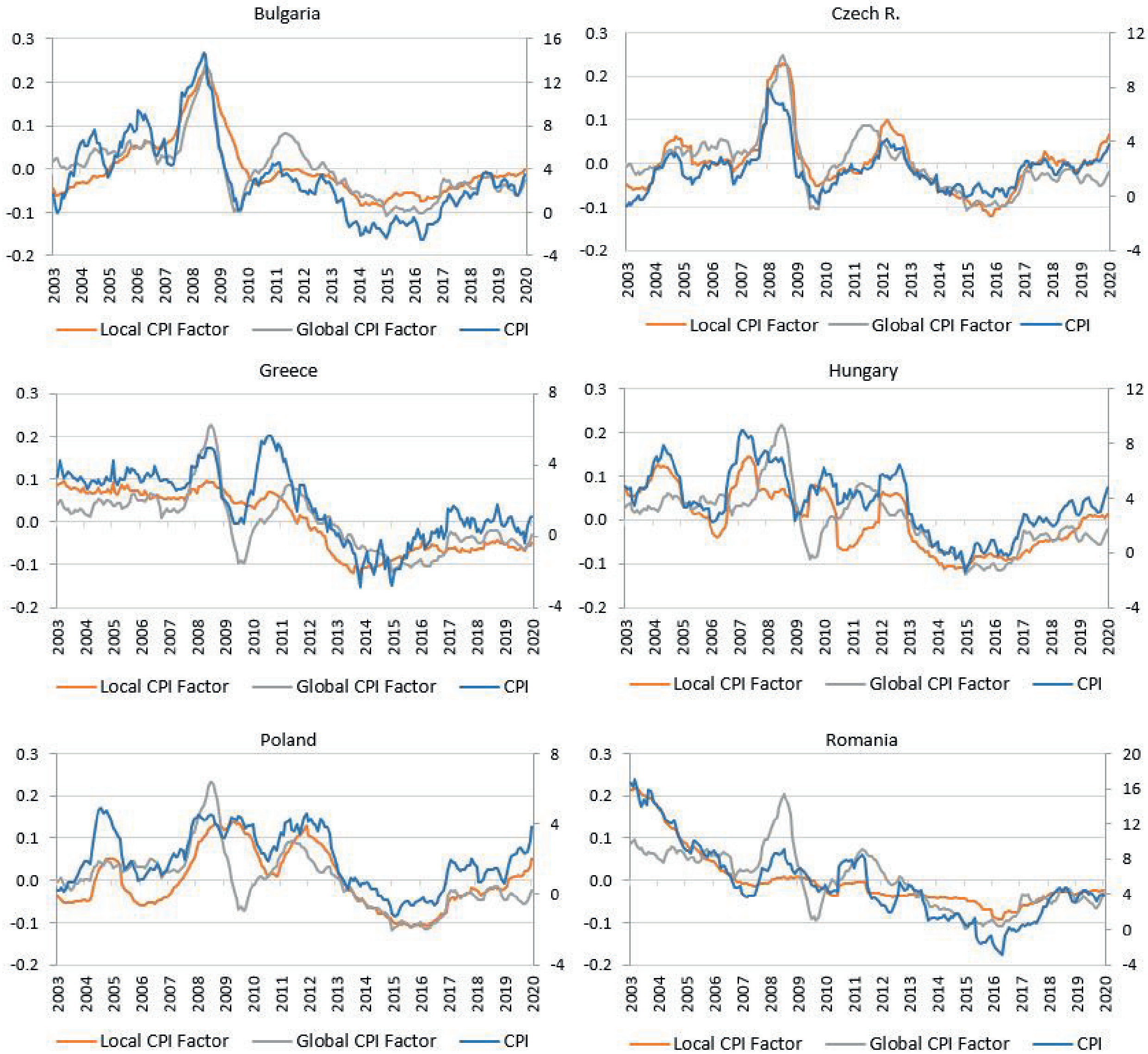
[12] Figures A1 - A2 of the appendix provide the plots of local and global CPI factors over the sample period, where factors are obtained from using the PLS and PCA factor extraction methods. Although they show similar behavior most of the time, the factors estimated using the PLS approach capture inflation turning points relatively well.

Figure 1.1: Share of inflation variance explained by the first common factor of each dataset: PCA vs PLS



Notes: This figure shows the percentage of variance explained in headline inflation rates of EM European countries by the first common factor of each data groups where factors are obtained from using the PLS and PCA factor extraction methods.

Figure 1.2: Co-movement of actual inflation rates with local and global CPI factor estimated using the PLS approach.



Notes: This figure plots the actual inflation rates along with local and global inflation factors where the factors are calculated as the first common component of the PLS approach utilizing the disaggregated CPI and all country-level headline inflation rate data.

1.5.2 Predictability of Inflation Rates: The Role of Global Inflation Factors

Table 1.2 reports the recursive forecasting exercise results where model parameters are updated recursively on a monthly basis. While the entries in the row for the benchmark AR model denote the actual MSFEs, all other entries are the MSFEs relative to those of the AR model. As discussed in Section 1.4.2, there are six different specifications. Specifications 3-6 include the global factors in addition to local factors allowing us to quantify the importance of global factors for forecasting national inflation rates for the EM European countries. These factors are estimated using both PCA and PLS approach, where we set the number of factors to four for each dataset.[13] For the PLS approach, the first four factors of each dataset explain more than 82% variation in inflation rates for each country. The shares of variance explained by each individual factor are given in the Tables A1-A2 of the supplementary appendix. The entries in Table 1.2 lower than unity indicate a better forecast performance than the AR benchmark. We produce a sequence of eight h-step ahead forecasts for each month, i.e., h = 1, 2, 3, 4, 5, 6, 9, 12. To make comparison and interpretation easier, the entries corresponding to the smallest MSFEs are highlighted in bold.

A closer examination of the results in Table 1.2 reveals a number of interesting findings. First, point forecasts from models that include both global and local CPI factors are generally superior to other models that only include local macro and local inflation factors. In particular, the specification types that include global factors perform better, especially for long-term forecast horizons (h= 9, 12), indicating the importance of spillover effects from global price dynamics for forecasting long-term inflation rates in EM European countries. For example, in Table 1.2 we see that the inclusion of global CPI factors (Specification-6) results in the lowest MSFE for 7 out of the 8 forecast horizons for Hungary and Poland. The forecast gains are also increasing in the horizon, and over a 70% reduction in MSFE relative to the benchmark is achieved for h=12, for both countries. Specification-6 (+GlobalCPI) achieves reductions on MSFE of 10% relative to adding local inflation factors (Specification-2), and of nearly 45% relative to the Phillips Curve (Specification-1 with macro factors), for Hungary at h=12. For Poland, the equivalent reductions in MSFE are even larger.

The picture is equally clear for Bulgaria, where the global CPI factor yields substantial predictive gains, and the "Local macro" (Specification-1) and "Local inflation" (Specification-2) forecasting models are the MSFE-best models in only 1 of the 8 cases.

Second, recall that we have eight forecast horizons and six countries, implying that there is a total of 48 comparisons. Of the various specification types, Specification-6, which augments global CPI factors, performs well in that it attains the top rank in 26 of the 48 cases. As a result, our inflation forecasting model exploiting the international information consistently outperforms the AR model. It is also worth remarking that Specification types 3-6 (which include at least one international factor, namely; EMCPI, DMCPI, or Global CPI factors) are best in three quarters (40 out of 48). Hence, Specification types 1-2 are not particularly useful for predicting headline inflation rates. For our sample of European EM countries, some measure of 'global inflation' tends to work well.[14]

[13] We also experimented with selecting the number of factors based on the criterion of Bai and Ng, 2002, but found too many factors were chosen in terms of forecast performance.

[14] As a robustness check, we examine the models performances during the euro area sovereign debt crisis

Furthermore, we check whether the global inflation factor might simply be reflecting common shocks such as those related to commodity prices. The results in Tables A4-A5 of the supplementary appendix indicate that Specification - 6 (+GlobalCPI) remains superior to the other models when these are augmented with commodity prices, for both recursive and rolling window forecasting schemes. Put differently, the explanatory power of global inflation does not disappear when we control for commodity prices: the global inflation factor does not simply proxy for commodity prices.[15]

Third, the plethora of rejections of the DM test in Table 1.2 (note that entries that are marked with either *, **, or ***, imply the rejection of the null hypothesis of equal predictive accuracy) confirms that the improvements in forecast accuracy are also statistically significant, compared to the AR model. Although the DM is commonly used as a test of equal predictive ability, and is reported here for that reason, because our comparisons involve nested models we also use the Giacomini and White, 2006 test of conditional predictive ability. This is applicable for both nested and non-nested models. The findings are reported in Tables A6-A9 of the supplementary appendix, and are shown to give similar conclusions to the DM test.[16] For a detailed discussion of distribution of the test statistics and power of the DM test both in cases of parameter estimation uncertainty and nested models, refer to (McCracken, 2000; Clements and Hendry, 2005; Corradi and Swanson, 2007; Clements and Harvey, 2010; Clark and McCracken, 2012). Table A14 of the supplementary appendix shows the results for the same forecasting exercise as in Table 1.2, except that we now use an 84-month rolling window scheme instead of an expanding window.[17] The use of rolling windows leads to a deterioration in overall forecast accuracy relative to the expanding window scheme, with slightly fewer rejections of the null of equal accuracy with the benchmark.[18]

(May 2010 - May 2012). Table A3 of the appendix shows that global factors play a significant role in driving local inflation rates since Specification types 3-6 attain the top rank in 33 out of 48 cases.

[15]When we undertake pairwise comparisons of Specification - 6 with a model which replaces global inflation factors with the commodity price index, we find Specification - 6 is superior (smaller MSFEs) in 38 cases out of 48. The picture is largely unchanged for the rolling window scheme (see Table A5). As a proxy for commodity prices, we use the Commodity Research Bureau BLS All Commodities Price Index, which measures the price movements of 22 commodities.

[16]Harvey et al., 1997 suggest that the DM test can be over-sized for empirical forecast errors for which the assumption of normality may not hold. Tables A10-A13 of the appendix presents the equality of mean squared forecast error test of Harvey et al., 1997. Again, the findings are similar to those for the DM test.

[17]As a robustness check, we repeat the same forecasting exercise using 60-month and 72-month rolling schemes. Similar results still continue to hold with slightly higher MSFEs.

[18]Tables A15 - A16 summarize the results for the same forecasting exercise, but when factors are extracted using the PCA method. Several interesting conclusions can be drawn - in terms of forecast accuracy and significance - from a comparison of the results with Table 1.2. Immediately apparent is a notable deterioration in forecast performance of the competing models compared to the AR model. In particular, none of the competing models improve on the simple AR model (virtually all the entries exceed one) in Romania (in the recursive window) and in Bulgaria (in the rolling window). This is in sharp contrast to the results obtained when the factors are extracted by PLS. The DM test further shows that incorporating PCA-based factors worsens forecast accuracy. A consideration of the specific target when constructing factors is demonstrably better in our sample. PCA ignores the target variable when the factors are constructed, and

Table 1.2: Point forecast performance: Recursive forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
Specification -1	1.141	1.048	0.963	0.826**	0.721***	0.633***	0.560***	0.497***
Specification -2	1.115	0.868***	0.737***	0.620***	0.578***	0.529***	**0.490*****	0.328***
Specification -3	1.009	0.866**	0.729***	0.589***	0.523***	0.506***	0.542**	**0.315*****
Specification -4	1.091	0.875***	0.754***	0.630***	0.594***	0.587***	0.562***	0.451***
Specification -5	1.054	0.944	0.836*	0.631***	0.549***	0.556***	0.624**	0.373***
Specification -6	**0.955**	**0.811*****	**0.690*****	**0.547*****	**0.495*****	**0.503*****	0.503***	0.347***
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
Specification -1	1.051	1.014	0.973	0.900	0.867	0.804*	0.780*	0.705*
Specification -2	1.035	0.939	0.874*	**0.796****	**0.693*****	**0.601*****	**0.487*****	**0.379*****
Specification -3	1.132	1.058	1.032	0.971	0.871*	0.744**	0.498***	0.430**
Specification -4	1.035	**0.938**	**0.825*****	0.814**	0.869	0.796	0.513***	0.446***
Specification -5	1.128	1.106	1.008	0.921	0.859*	0.736**	0.570***	0.505**
Specification -6	1.113	1.046	1.005	0.980	0.899	0.723***	0.530***	0.404***
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
Specification -1	0.991	0.958	0.943	0.920	0.815	0.692*	0.423**	0.386**
Specification -2	0.908**	**0.807****	**0.759*****	0.721**	0.641**	0.556**	0.270**	0.187**
Specification -3	0.936*	0.869*	0.795***	0.721***	0.591***	**0.482****	0.275**	**0.155****
Specification -4	**0.894*****	0.817**	0.760***	**0.662*****	**0.575*****	0.490**	0.271**	0.188**
Specification -5	0.934**	0.912	0.826**	0.731***	0.645***	0.527**	0.265**	0.174**
Specification -6	0.912**	0.837**	0.789***	0.698***	0.574***	0.485**	**0.238****	0.174**
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
Specification -1	1.005	0.990	0.906	0.790	0.736*	0.670*	0.536*	0.481**
Specification -2	1.015	0.933	0.807*	0.740*	0.680*	0.643*	0.402**	0.297**
Specification -3	**0.935**	0.881*	0.814**	0.738**	0.700**	0.633**	0.334**	0.285**
Specification -4	1.025	0.938	0.805*	0.748*	0.715*	0.683*	0.441**	0.328**
Specification -5	1.006	1.007	0.864*	0.754**	0.680**	0.611***	0.395**	0.340**
Specification -6	0.981	**0.870**	**0.776****	**0.705****	**0.638****	**0.573****	**0.332****	**0.266****
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
Specification -1	0.917**	0.894**	0.886**	0.853***	0.786***	0.728***	0.552***	0.525***
Specification -2	0.924	0.866**	0.802***	0.732***	0.659***	0.585***	0.367***	0.314***
Specification -3	0.892*	0.813***	0.751***	0.726***	0.656***	0.504***	0.312***	0.327***
Specification -4	**0.882***	0.854**	0.815**	0.790**	0.732***	0.648**	0.426***	0.366***
Specification -5	0.892*	0.867**	0.819***	0.822**	0.728***	0.534***	0.484***	0.358***
Specification -6	0.887*	**0.798*****	**0.730*****	**0.695*****	**0.614*****	**0.445*****	**0.295*****	**0.268*****
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
Specification -1	1.079	1.127	1.103	1.083	1.025	0.987	0.880	0.833*
Specification -2	1.098	1.085	1.045	1.010	0.995	0.958	0.866	0.846
Specification -3	1.072	1.022	**0.928**	0.852*	0.784***	0.727***	0.550***	0.591***
Specification -4	1.141	1.208	1.116	1.051	0.978	0.904	0.719***	0.763**
Specification -5	1.119	1.111	0.986	0.904	0.800**	0.726***	0.624***	0.619***
Specification -6	1.146	1.094	0.953	**0.833****	**0.741*****	**0.710*****	**0.483*****	**0.538*****

Notes: The entries are MSFEs, with the Specification types that yields the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

The pairwise comparison of competing models using uSPA and aSPA tests is reported in Table 1.3. As stated by Quaedvlieg, 2021, while this framework accommodates tests of nested models if we use rolling windows of data to estimate the models, it does not allow such comparisons using expanding windows. Hence, we report pairwise compari-

this is shown to be costly for predicting European EM inflation rates.

son results only for the rolling window scheme because of this limitation of the superior predictive ability tests. In particular, we perform the following pairwise tests of models: i) Specification-2 against Specification-1, ii) Specification-3 against Specification-2, iii) Specification-4 against Specification-2, iv) Specification-5 against Specification-4, v) Specification-6 against Specification-5 and vi) Specification-6 against Specification-2. In addition to comparing the accuracy of the complete path, we also investigate a range of additional hypotheses which might be of interest, namely different horizon ranges, i.e., short-, mid and long-term forecasts. In these cases, the uSPA and aSPA tests are applied to subsets of horizons. Hence, we also implement the tests for a subset of horizons by grouping h= 1, 2, 3 for a short horizon, h= 4, 5, 6 for a medium horizon, and h= 9, 12 for a long horizon. This allows us to reap some of the benefits of path evaluation, while tailoring the paths such that we can determine whether the contribution of the added factors depends on the horizon.

An inspection of Table 1.3 leads to several clear-cut conclusions.[19] Firstly, we find strong evidence in favor of Specification-3 (+emCPI) being superior to Specification-2 (+LocalCPI) across the aSPA and uSPA tests for all horizons together, in Bulgaria and Romania, implying that the EMCPI factor contains useful information not already included in the information set comprising Specification-2 (which has only local factors). This finding is in line with a speech made by ECB Governor Mario Draghi in October 2015, in which the inflation outlook was described as “less sanguine” for the Euro Area due to the external weakness in demand, and also highlighted the risks to emerging market economies emanating from weakness in China.[20] Secondly, the aSPA test, combining all horizons, is positive and statistically significant, suggesting that Specification-4 outperforms the Specification-2 in Hungary and Poland. Finally, although there are limited episodes favouring adding global factors for medium and long horizons, the picture is much clearer for short horizons. For all countries (with the exception of Hungary), models with global factors dominate those with only local factors for the shorter horizons.[21] The reason may be that the variance of the loss

[19] Multi-horizon comparison test results for PCA approach are presented in Table A17 of the appendix.

[20] For access to full details of the press conference: `https://www.ecb.europa.eu/press/pressconf/2015/html/is151022.en.html`

[21] Furthermore, the results of the forecast efficiency test of Mincer and Zarnowitz, 1969 are reported in Tables A18-A19 of the supplementary appendix for both recursive and rolling forecasting schemes, for factors extracted using the PLS approach. In the recursive scheme, forecast efficiency varies across the countries. Efficient forecasts are found in Bulgaria, Czech Republic, Hungary, and Poland for horizons $h = 1, 2, 3, 4, 5$ where the null generally cannot be rejected. There is evidence that adding global factors (that is, using Specification-6) reduces forecast inefficiency. That is, generating forecasts from a model which accords a role to global inflation breaks the correlation between these forecasts and their corresponding errors. In Tables A20-A21 of the appendix, we also report the efficiency tests results for competing models where factors are based on the PCA approach. Unlike the PLS-based forecasting models, using PCA-based common factors in forecasting models yields inefficient forecasts for almost all horizons across the countries irrespective of the forecasting scheme. This provides further support for PLS over PCA for calculating factors for the purpose of forecasting a specific variable.

Table 1.3: Multi-horizon forecast comparison: Rolling forecasting - Factors are extracted using the PLS approach -

	short horizon		medium horizon		long horizon		all horizon	
BULGARIA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA
Spec.2 against Spec.1	-1.08	-0.69	0.69**	1.38**	1.74***	2.33***	-1.08	1.60**
Spec.3 against Spec.2	0.55*	1.41**	0.35	0.81*	0.22	0.24	0.22*	0.77*
Spec.4 against Spec.2	-1.08	-0.80	-3.55	-3.11	-2.05	-1.52	-3.55	-2.87
Spec.5 against Spec.4	-0.10	0.80	1.33***	1.73**	0.14	0.28	-0.10	0.96*
Spec.6 against Spec.5	0.73**	0.93**	0.16	0.73*	-0.10	0.69*	-0.10	0.88*
Spec.6 against Spec.2	0.34	1.13**	-0.15	0.13	-0.42	0.06	-0.42	0.36
CZECH REPUBLIC								
Spec.2 against Spec.1	-1.51	-1.20	-0.52	0.20	0.18	0.80*	-1.51	0.10
Spec.3 against Spec.2	1.84***	2.54***	-0.70	0.27	-1.38	-1.30	-1.38	0.49
Spec.4 against Spec.2	0.68**	1.02*	-2.39	-1.67	-1.63	-1.29	-2.39	-1.08
Spec.5 against Spec.4	-0.38	0.49	0.50*	1.40**	-1.31	-1.56	-1.31	0.57
Spec.6 against Spec.5	-0.04	0.26	-3.02	-1.70	1.65***	2.61***	-3.02	0.57
Spec.6 against Spec.2	1.05***	1.65**	-2.70	-1.41	-0.64	-0.03	-2.70	-0.41
GREECE								
Spec.2 against Spec.1	-1.38	-0.98	0.24	0.59	1.73***	1.94**	-1.38	1.12**
Spec.3 against Spec.2	0.60**	1.02*	-2.21	-1.50	-3.88	-3.07	-3.88	-1.99
Spec.4 against Spec.2	-2.03	-1.82	-3.01	-2.15	-2.28	-2.95	-3.01	-2.74
Spec.5 against Spec.4	0.55*	0.76*	-1.17	-0.36	-2.49	-2.63	-2.49	-0.52
Spec.6 against Spec.5	1.44***	2.01**	0.06	0.64	1.24***	2.45***	0.06*	1.97***
Spec.6 against Spec.2	0.09	1.63**	-2.08	-1.56	-1.23	-1.24	-2.08	-1.13
HUNGARY								
Spec.2 against Spec.1	-0.90	0.24	-0.80	-0.81	1.05**	1.21**	-0.90	0.43
Spec.3 against Spec.2	-1.44	-1.04	-0.58	-0.14	-0.76	-0.62	-1.44	-0.78
Spec.4 against Spec.2	-0.09	1.05*	0.49*	1.01*	1.16***	2.28***	-0.09	1.64**
Spec.5 against Spec.4	-2.34	-1.87	-0.32	-0.21	-3.37	-3.33	-3.37	-1.87
Spec.6 against Spec.5	0.14	1.67**	-0.74	-0.55	0.59**	1.96**	-0.74	0.64
Spec.6 against Spec.2	-1.60	-0.55	-0.08	0.26	0.44*	0.59	-1.60	0.27
POLAND								
Spec.2 against Spec.1	-0.68	0.81*	2.57***	3.05***	2.26***	2.54***	-0.68	2.90***
Spec.3 against Spec.2	1.39***	1.69**	-0.86	-0.49	-0.96	-0.18	-0.96	0.05
Spec.4 against Spec.2	0.43**	0.73*	-0.29	0.34	0.63*	1.30**	-0.29	1.67**
Spec.5 against Spec.4	-1.26	-0.03	-2.19	-1.68	-1.20	-1.00	-2.19	-1.52
Spec.6 against Spec.5	0.81***	1.40**	0.31**	1.96**	-0.93	-1.09	-0.93	0.37
Spec.6 against Spec.2	1.37***	1.73**	-0.63	-0.22	-1.10	-0.55	-1.10	-0.02
ROMANIA								
Spec.2 against Spec.1	-1.94	-1.60	-1.90	-1.52	-1.51	-0.90	-1.94	-1.46
Spec.3 against Spec.2	2.54***	3.04***	2.76***	3.13***	0.51**	1.55**	0.51***	3.07***
Spec.4 against Spec.2	1.27***	1.56**	1.36***	1.51**	-2.84	-1.71	-2.84	0.66
Spec.5 against Spec.4	2.38***	2.85***	2.08***	2.82***	-0.28	1.87**	-0.28	2.97***
Spec.6 against Spec.5	-1.73	-0.89	-0.29	-0.19	0.56**	2.71***	-1.73	0.19
Spec.6 against Spec.2	1.79***	3.09***	3.36***	3.84***	-0.26	1.00*	-0.26	3.41***

Notes:This table provides the results of uniform superior predictive ability (uSPA) and average superior predictive ability (aSPA) tests for all horizons across the countries. The moving block bootstrap techniques of Kunsch, 1989 is used for critical values. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% denotes the significance levels. Specification types explanations: Spec.1: +LocalMACRO; Spec.2: +LocalCPI; Spec.3: +emCPI; Spec.4: +dmCPI; Spec.5: +em_dmCPI; Spec.6: +GlobalCPI.

differential increases in forecast horizon h, limiting the ability of the tests to differentiate between competing models, as pointed out by Quaedvlieg, 2021.

1.5.3 Do Global Inflation Dynamics Matter for Predicting Core Inflation Rates?

The global economy may influence domestic price developments in many ways. The routes may be direct, via imports of final consumer goods, or indirectly via commodities and/or intermediate goods imports, as well as by influencing the prices set by domestic producers who are also exporters. However, core inflation is defined as the change in the euro area HICP special aggregate 'all items excluding energy, food, alcohol, and tobacco'. By excluding energy and food from the consumption basket, we are able to control for some of the channels through which global inflation might operate. A direct comparison of the influence of global CPI factors on core and headline inflation should be informative. If the main effects of global inflation on national inflation are confined to the effects of short-run seasonal/cyclical movements in food and energy, we would not expect global factors to contribute to meaningful reductions in forecast errors for core inflation.

Table 1.4 presents the results of the same forecasting exercise for core inflation rates. Specification-6 (which includes global CPI factors) still performs well, and attains the top rank in 16 of the 48 cases. But this marks a deterioration in performance relative to targeting headline inflation,when Specification - 6 was best in 26 of the 48 cases. On the other hand, if we focus on the set of Specifications (types 3-6) which include at least one global factor, these models are best on MSFE in 35 out of 48 cases (compared to 40 out of 48 for headline inflation). We conclude that although global factors still play an important role in determining European emerging market core inflation rates, local factors now play a more prominent role in driving price changes (relative to headline inflation rates).[22]

Drilling down a little deeper, comparing Specifications - 3 and - 4 in Table 1.4 shows that the EMCPI factor produces smaller forecast errors relative to the DMCPI factor, especially for longer forecast horizons. An interesting conjecture for this difference is the following. A deprecation (appreciation) of EM currencies versus the Euro might precipitate a fall (rise) in import prices and ultimately act as a drag (push) on domestic consumer prices. On the contrary, the currency union of Euro area members creates an extra layer of protection against external shocks in the trading of goods and services within the European union, limiting the informativeness of the DMCPI factor. This stands in contrast to European emerging economies, which gravitate around the Euro bloc and usually exhibit higher exchange-rate pass-through.

1.6 Robustness Checks

In this section, we report on a number of additional analyses. These serve as robustness checks, and also extend our analysis. Section 1.6.1 extends the range of models to include various time-varying parameter and shrinkage models. These models are designed to be

[22]In Table A22 of the supplementary appendix, we report the results for rolling forecasting scheme. Point forecasts from models that only have local factors are generally superior to other models that include global inflation factors. In particular, the specification types 1-2 useful for predicting core inflation rates in 23 out of 48 cases (7 out of 48 cases for headline inflation) under a rolling forecasting scheme.

Table 1.4: Core Inflation: Recursive forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.311	0.498	0.639	0.770	0.874	1.016	1.490	2.110
Specification -1	1.042	0.976	0.916	0.861**	0.814***	0.735***	0.527***	0.377***
Specification -2	1.013	**0.888***	0.820**	0.731***	0.697***	0.640***	0.476***	0.341***
Specification -3	1.052	0.906	**0.786*****	**0.694*****	0.660***	0.600***	0.403***	0.369***
Specification -4	1.045	0.944	0.882	0.807***	0.791***	0.694***	0.504***	0.404***
Specification -5	1.091	0.962	0.862***	0.771***	0.749***	0.662***	0.488***	0.532***
Specification -6	1.060	0.982	0.873	0.734**	**0.647*****	**0.578*****	**0.403*****	**0.322*****
CZECH REPUBLIC								
AR	0.219	0.330	0.404	0.468	0.517	0.562	0.644	0.729
Specification -1	1.349	1.377	1.169	1.010	0.887	0.799**	0.735**	0.686**
Specification -2	1.088	1.075	1.027	0.942	0.834**	**0.708*****	**0.534*****	0.427***
Specification -3	1.186	1.205	1.123	1.118	1.049	0.928	0.647***	0.438***
Specification -4	1.171	1.127	**0.951**	**0.828****	**0.759*****	0.784***	0.673**	0.502***
Specification -5	1.237	1.279	1.174	1.216	1.158	0.979	0.746**	0.638***
Specification -6	1.189	1.254	1.153	1.126	0.980	0.888	0.653***	**0.385*****
GREECE								
AR	0.596	0.726	0.821	0.850	0.977	1.066	1.680	2.187
Specification -1	0.855**	0.764**	0.699**	0.710**	0.652***	0.547***	0.355***	0.255***
Specification -2	**0.730*****	**0.595*****	**0.521*****	0.559***	**0.533*****	**0.484*****	0.324***	0.223***
Specification -3	0.761***	0.648**	0.558***	0.580***	0.594***	0.510***	0.340***	0.210***
Specification -4	0.732**	0.619**	0.555***	**0.553*****	0.567***	0.512***	0.325***	0.225***
Specification -5	0.780***	0.670**	0.579***	0.602***	0.677***	0.568***	0.327***	0.222***
Specification -6	0.761***	0.631**	0.550***	0.582***	0.659***	0.514***	**0.308*****	**0.209*****
HUNGARY								
AR	0.275	0.414	0.505	0.618	0.722	0.819	1.205	1.569
Specification -1	1.084	1.137	1.064	0.970	0.915	0.918	0.637***	0.545***
Specification -2	1.190	1.088	0.898	0.761*	0.774*	0.750*	0.453***	0.407***
Specification -3	1.091	0.999	0.886	0.835	0.793	0.712**	0.451***	**0.336*****
Specification -4	1.170	1.027	0.840	**0.729****	0.814	0.744*	0.531***	0.500***
Specification -5	1.071	**0.971**	**0.837***	0.775**	0.807	0.739**	0.491***	0.470***
Specification -6	1.113	0.977	0.842	0.767*	**0.722****	**0.681****	**0.448*****	0.371***
POLAND								
AR	0.242	0.355	0.445	0.533	0.625	0.696	0.903	1.083
Specification -1	1.022	0.929	0.859***	0.805***	0.739***	0.681***	0.561***	0.499***
Specification -2	0.989	0.865**	0.737***	**0.623*****	**0.559*****	**0.536*****	**0.361*****	**0.379*****
Specification -3	0.993	0.885	0.741***	0.655***	0.585***	0.539***	0.488***	0.422***
Specification -4	**0.966**	**0.855****	0.744***	0.691***	0.666***	0.655***	0.384***	0.454***
Specification -5	1.000	0.922	0.784***	0.722***	0.670***	0.624***	0.481***	0.426***
Specification -6	1.000	0.868*	**0.717*****	0.629***	0.577***	0.552***	0.454***	0.390***
ROMANIA								
AR	0.297	0.405	0.515	0.619	0.716	0.801	1.032	1.282
Specification -1	1.106	1.330	1.386	1.410	1.366	1.285	1.039	0.825*
Specification -2	1.166	1.157	1.072	0.986	0.910	0.796*	0.667***	0.588***
Specification -3	1.179	1.195	1.049	0.843*	0.798*	0.773*	0.646***	0.451***
Specification -4	1.271	1.293	1.117	0.978	0.869	0.717**	0.697***	0.644***
Specification -5	1.208	1.226	**0.966**	0.831*	0.782**	0.756**	0.639***	0.440***
Specification -6	1.227	1.230	1.053	**0.830****	**0.775****	**0.716****	**0.605*****	**0.423*****

Notes: See the notes to Table 1.2.

flexible enough to capture some forms of structural change and parameter non-constancies (Korobilis, 2019). We investigate the potential for time-varying parameter models to improve on the linear factor models, because although more complicated models offer greater flexibility and adaptability, this may not result in improved forecast performance out-of-sample. The results for these models are discussed in section 1.6.2. Of interest is whether the key finding for linear models - that global factors are an important determinant of emerging market inflation rates - remains the case when we extend the set of models.

Lastly in section 1.6.3 we consider an alternative way of evaluating forecast performance.

Namely, we calculate how far ahead the models (based on the different sets of information) are able to outperform the simple benchmark model. This supplements the forecast comparisons reported in section 1.5.

1.6.1 Additional Models: Time-Varying Parameters and Shrinkage

Variational Bayes Dynamic Variable Selection (VBDVS) Algorithm

Koop and Korobilis, 2020 introduce the dynamic extension of variational Bayes (VB) to tackle high-dimensional problems where the number of predictors may exceed the number of time-series observations. The main advantage of the VBDVS algorithm is that it is computationally less demanding than Markov chain Monte Carlo (MCMC) algorithm, while achieving estimation accuracy equivalent to that of MCMC.

The VBVDS model of Koop and Korobilis, 2020 has the following form:

$$\begin{aligned} y_t &= x_t \beta_t + \varepsilon_t \\ \beta_t &= \beta_{t-1} + \eta_t \end{aligned} \tag{1.9}$$

where y_t is the dependent variable, $\beta_t = (\beta_{1,t}, \ldots, \beta_{p,t})'$ is a $p \times 1$ vector of time-varying parameters, x_t is a $1 \times p$ vector of predictor variables and lagged dependent variables. Moreover, $\varepsilon_t \sim N(0, \sigma_t^2)$ with σ_t^2 time-varying variance parameter, $\eta_t \sim N(0, W_t)$ with $W_t = \operatorname{diag}(w_{1,t}, \ldots, w_{p,t})$ is a $p \times p$ diagonal matrix. This approach is implemented with a dynamic variable selection (DVS) prior of the form:

$$\begin{aligned} \beta_{j,t} \mid \gamma_{j,t}, \tau_{j,t}^2 &\sim (1 - \gamma_{j,t}) N\left(0, c \times \tau_{j,t}^2\right) + \gamma_{j,t} N\left(0, \tau_{j,t}^2\right) \\ \gamma_{j,t} \mid \pi_t &\sim \text{Bernoulli}(\pi_{0,t}) \\ \frac{1}{\tau_{j,t}^2} &\sim \text{Gamma}(g_0, h_0) \\ \pi_{0,t} &\sim \text{Beta}(1,1) \end{aligned} \tag{1.10}$$

where (j, t) subscripts represent the j^{th} element of a time varying parameter at time t. Furthermore, g_0, h_0 and c denote the prior hyper-parameters where $c \to 0$ resulting in shrinkage of first component prior of $\beta_{j,t}$ to posterior towards zero. Given these prior settings, the posterior distributions are obtained by maximizing the log-marginal likelihood:

$$q^{\star}(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}) = \underset{q(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t})}{\arg\max} \int q(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}) \log\left(\frac{q(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t})}{p(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t})}\right) \tag{1.11}$$

where subscripts $(1:t)$ indicate observations of a state variable from period 1 up to period t.[23]

[23]See Koop and Korobilis, 2020 for more technical details.

Gaussian Process Regression (GPR)

Gaussian process regression is a machine learning method based on non-parametric kernel-based probabilistic models. The GPR can be used to determine whether inflation can be represented by a time-varying parameter model or whether a more complex type of non-linear model is required. Given that a linear regression model is of the form:

$$y = x^T\beta + \varepsilon, \qquad y = f(\mathbf{x}) + \varepsilon \tag{1.12}$$

where $\varepsilon \sim N(0, \sigma^2)$, then the GPR model predicts the value of a dependent variable $y_i \in \mathbb{R}$ given the new input vector $x_i \in \mathbb{R}^d$ and the training data $\{(\mathbf{x}_i, y_i) \mid i = 1, \ldots n\}$. In particular, the GPR estimates the response of y defining latent variables, $f(x_i), i = 1, 2, \ldots, n$, from a Gaussian process (GP), and explicit basis functions ϕ. In other words, contrary to standard Bayesian approach based on the probability distribution of parameters of a specific function, GP is a distribution over functions $\mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$ with a fully specified mean function $m(x) = E(f(x))$ and co-variance function $k(x, x') = E(f(x) - m(x))(f(x') - m(x'))$. As suggested by Rasmussen and Williams, 2006, we utilize the commonly used covariance function which is called squared exponential kernel:

$$k(x, x') = \sigma_f^2 \exp\left(-\frac{1}{2\ell^2}\|x - x'\|^2\right) \tag{1.13}$$

where $\|x - x'\|$ denotes the Euclidean distance between points x and x'; ℓ is correlation length; σ_f^2 is signal variance. These hyper-parameters can be estimated from the data while training the GPR model.

In particular, the GPR changes the simple linear regression model into a new space:

$$\phi(x)^T\beta + f(x) \tag{1.14}$$

where $f(x) \sim GP(0, k(x, x'))$, indicating that $f(x)$ are from zero mean GP with $k(x, x')$. Then, $\phi(x)$ are a set of basis functions that map the input vector $x_i \in \mathbb{R}^d$ into a new feature vector $\phi(x)$ in $\mathbb{R}^p$. Intuitively, the GPR projects the inputs into high dimensional space using the set of basis functions and then estimate the linear model in this high dimensional space rather than directly on the inputs themselves. Thus, this model represent a GPR model and the response y can be defined as:

$$P(y_i \mid f(x_i), x_i) \sim N\left(y_i \mid \phi(x_i)^T\beta + f(x_i), \sigma^2\right) \tag{1.15}$$

Furthermore, the joint distribution of latent variables $f(x_1), f(x_2), \ldots, f(x_n)$ is denoted as follows:

$$P(f \mid X) \sim N(f \mid 0, K(X, X)) \tag{1.16}$$

To estimate the GPR model, we use the Matlab toolbox GPML developed by Rasmussen and Nickisch, 2010.

Least Absolute Shrinkage Operator (LASSO)

We also employ the LASSO approach introduced by Tibshirani, 1996. Unlike the ridge estimator, LASSO imposes an ℓ_1-norm penalty on the regression coefficients for possible shrinkage. The LASSO estimator is denoted below:

$$\hat{\beta}^{lasso} = \min_{\beta} \quad \|Y - X\beta\|_2 + \lambda \sum_{j=1}^{N} |\beta_j|, \tag{1.17}$$

where λ is a tuning parameter that adjusts the strength of the ℓ_1-norm penalty. Given that objective function in the LASSO is not differentiable, we implement the efficient iterative algorithm (shooting algorithm) proposed by Fu, 1998 for numerical optimization.

Elastic Net (ENET)

Tibshirani, 1996 finds that the LASSO's predictive accuracy is often worse than the forecast performance of the ridge regression in the presence of highly correlated variables. Zou and Hastie, 2005 overcome this problem by incorporating a hybrid version of the estimators LASSO and Ridge, known as the elastic net estimator (ENET). The ENET estimator is represented as follows:

$$\hat{\beta}^{EN} = \min_{\beta} \quad \|Y - X\beta\|_2 + \lambda_1 \sum_{j=1}^{N} |\beta_j| + \lambda_2 \sum_{j=1}^{N} {\beta_j}^2, \tag{1.18}$$

where λ_1 and λ_2 are tuning parameters controlling the two penalty functions. Similar to the LASSO, the ENET also results in possible shrinkage of coefficients to zero.

1.6.2 Do These Models Improve on the Linear Models?

Do the time-varying parameter and data shrinkage (TVP) models yield improvements in forecast performance? We estimate the Specification - 6 using four different TVP models to impose sparsity on the local and global factors in the forecasting models. Table 1.5 presents the comparison of the out-of-sample results of the different TVP models for the recursive window procedure. While the VBVDS algorithm, LASSO, and ENET are sparsity-inducing shrinkage methods that place zero coefficients on potentially irrelevant factors, the GPR is a flexible non-parametric specification that enables us to determine the role of non-linearity more generally for inflation forecasting, by admitting non-sparse solutions. Table 1.5 is partitioned vertically into six panels presenting the results for our EM European countries. The first row of each panel is the MSFEs of the AR model, and all other MSFEs are presented as ratios to the MSFE of the AR model. In the second row of each panel we record the best-MSFE outcome for a given forecast horizon across all the constant parameter Specifications (1 to 6). The values for the best of all models are emboldened.

An inspection of Table 1.5 shows that most of the entries are smaller than one, which indicates that the TVP-models have a superior forecasting performance to the benchmark AR model. Furthermore, it can be seen that the forecast improvements provided by the TVP-models are also statistically significant compared to the AR, based on application of the DM test. The accuracy gains from implementing TVP models are increasing with the forecast horizon. Apart from a few short horizons, where either ENET or VBVDS delivers the smallest ratios, the GPR method is the overall winner, being superior to the other time-varying parameters and shrinkage models for the majority of forecast horizons and countries. In particular, recall that we have a total of 48 cases (eight forecast horizons and six countries): the GPR is the MSFE-best model in 20 of the 48 cases, suggesting that it is possible to improve on the constant-parameter models. The outstanding performance of the GPR model suggests that taking non-linearities into account is key to improving inflation forecasts. The fact that the GPR computes the probability distributions from all suitable functions that fit the data (function view), rather than defining the distributions over specific function parameters, makes it a very flexible way to capture the potential non-linearities between the factors and inflation. There are several sources of non-linearity (as pointed out by Medeiros et al., 2021) which might account for the good performance of the GPR model. The relation between inflation and the local macro factors might be non-linear if it depends on the degree of economic slackness. Economic uncertainty is another possible reason, raising the prospect of choosing to delay irreversible economic decisions (Bloom, 2009). In the presence of such uncertainties, key macroeconomic variables may well have non-linear effects on inflation. We do however find that the GPR performance deteriorates at short horizons, suggesting that the benefits of introducing non-linearity may be limited for shorter horizons.

Taken together, sparsity-inducing methods do not provide marked gains compared to the models without shrinkage, supporting the notion of "the illusion of sparsity" in economic forecasting, as discussed by Giannone et al., 2018; Fava and Lopes, 2020; Cross et al., 2020. For example, we find that among the 'sparse' models, ENET is the best, but achieves the best performance overall in only 5 of the 48 cases outperforming the competing models. The VBVDS performs poorly, and generates the MSFE-best outcome in only one case.[24] Furthermore, Table 1.6 summarizes the MSFE-best models from Table 1.5. For each country and forecast horizon, it shows the pair of model specification (in terms of factors) and factor selection-modelling method (constant parameter, TVP or GPR) which gives the lowest MSFE. It is clear that the superiority of the GPR model comes from its coupling with

[24]In Table A23, we report the results of the same forecasting exercise for the rolling window procedure. Overall, the story is similar, as the GPR method attains the top rank in 28 out of 48 cases, followed by the VBVDS algorithm. This evidence again strongly supports the use of GPR methods for inflation forecasting because of the potential non-linearities.

Table 1.5: MSFEs based on the use of different dimension-reduction and shrinkage methods - Recursive forecasting

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
MSFE Best w/o shrinkage	**0.955**	**0.811*****	**0.690*****	0.547***	0.495***	0.503***	0.490***	**0.315*****
GPR	0.981	0.851***	0.708***	**0.542*****	**0.492*****	**0.502*****	**0.469*****	0.360***
VBDVS	1.058	0.936*	0.835**	0.735**	0.669**	0.640**	0.500**	0.536**
ENET	0.987	0.814***	0.703***	0.566***	0.525***	0.534***	0.496**	0.401***
LASSO	0.976	0.817***	0.699***	0.567***	0.523***	0.531***	0.497**	0.404***
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
MSFE Best w/o shrinkage	1.035	0.938	0.825***	0.796**	0.693***	0.601***	0.487***	0.379***
GPR	1.019	1.004	0.851**	**0.756****	**0.644*****	**0.563*****	0.460***	**0.370*****
VBDVS	**0.987**	1.008	0.969	0.930	0.890	0.865	0.754*	0.702*
ENET	1.009	**0.925**	**0.817*****	0.799**	0.687***	0.600***	0.462***	0.413***
LASSO	1.013	0.931	0.831***	0.798**	0.695***	0.604***	**0.459*****	0.413***
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
MSFE Best w/o shrinkage	0.894***	0.807**	**0.759*****	**0.662*****	0.575***	**0.482****	**0.238****	**0.155****
GPR	0.896***	**0.801****	0.763***	0.677***	**0.572*****	0.508**	0.248**	0.158**
VBDVS	0.991	0.852***	0.913**	0.814*	0.688**	0.673**	0.488**	0.430**
ENET	**0.894*****	0.818***	0.773***	0.682***	0.613***	0.518**	0.253**	0.158**
LASSO	0.899***	0.816***	0.772***	0.679***	0.605***	0.509**	0.248**	0.156**
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
MSFE Best w/o shrinkage	0.935	**0.870**	**0.776****	0.705**	0.638**	**0.573****	0.332**	**0.266****
GPR	**0.934**	0.880*	0.793**	**0.701****	**0.638****	0.584**	**0.307****	0.275**
VBDVS	1.098	0.962	0.975	0.863	0.826	0.770*	0.564**	0.478**
ENET	0.957	0.884	0.799**	0.722**	0.663**	0.604**	0.350**	0.284**
LASSO	0.950	0.893	0.800**	0.721**	0.664**	0.606**	0.354**	0.285**
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
MSFE Best w/o shrinkage	0.882*	0.798***	0.730***	**0.695*****	0.614***	**0.445*****	0.295***	**0.268*****
GPR	**0.882***	0.877**	0.774***	0.726***	0.624***	0.475***	**0.263*****	0.299***
VBDVS	1.024	0.936	0.933	0.822***	0.849*	0.799**	0.716**	0.543**
ENET	0.890*	**0.791*****	0.738***	0.715***	**0.610*****	0.462***	0.316***	0.322***
LASSO	0.890*	0.809***	**0.724*****	0.718***	0.611***	0.470***	0.313***	0.323***
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
MSFE Best w/o shrinkage	1.072	1.022	**0.928**	0.833**	0.741***	0.710***	**0.483*****	**0.538*****
GPR	1.072	**0.997**	0.940	**0.831****	**0.716*****	**0.655*****	0.530***	0.648***
VBDVS	1.060	1.005	0.947*	0.930	0.873**	0.967	0.824	0.939
ENET	1.080	1.033	0.941	0.839***	0.757***	0.737***	0.552***	0.598***
LASSO	1.089	1.045	0.939	0.844***	0.742***	0.735***	0.551***	0.594***

Notes: The entries are MSFEs, with the model that gives the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. The entries in the second row of each panel deliver the best-MSFE outcome for a given forecast horizon across all constant parameter Specification types, which are highlighted in bold in Table 1.2. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test.

Table 1.6: Summary of best-MSFEs models and dimension reduction methods across countries

	Recursive Forecasting							
	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Bulgaria	Spec-6	Spec-6	Spec-6	GPR-6	GPR-6	GPR-6	GPR-2	Spec-3
Czech R.	VBDVS-6	ENET-2	ENET-4	GPR-2	GPR-2	GPR-2	LASSO-3	GPR-6
Greece	ENET-6	GPR-2	Spec-2	Spec-4	GPR-6	Spec-3	Spec-6	Spec-3
Hungary	GPR-3	Spec-6	Spec-6	GPR-6	GPR-6	Spec-6	GPR-6	Spec-6
Poland	GPR-4	ENET-6	LASSO-6	Spec-6	ENET-6	Spec-6	GPR-6	Spec-6
Romania	AR	GPR-3	Spec-3	GPR-6	GPR-6	GPR-3	Spec-6	Spec-6

Notes: Abbreviations; Specification type-1 = “1”, Specification type-2 = “2”, Specification type-3 = “3”, Specification type-4 = “4”, Specification type-5 = “5”, Specification type-6 = “6”. For instance, GPR-6 means that when the Specification-6 is estimated with the GPR model, it yields the lowest MSFE across all TVP models and constant parameter models for a given country.

Specification-6. That is, when Specification-6 is estimated by the GPR method, the MSFE-best forecasts are obtained more often than not.

Finally, we pay special attention to the GPR model and compare the importance of global and local factors for the GPR. To measure each factors' importance, we follow the approach of Medeiros et al., 2021 and compute the relative importance measure by multiplying the average coefficient size with the respective standard deviations. Figure 1.3 presents the influence of each of the factor groups (local macro, local CPI and global CPI) on inflation for the GPR method. The values in the graphs are normalized to sum one. Figure 1.3 reveals that the relative importance of the factor groups varies across country and forecast horizon. For instance, in Hungary, global CPI factors are gaining importance as the forecast horizon increases where relative importance measure reaches to 0.58 (for h=6) from the initial level 0.10 (for h=1). On the other hand, local and global factors seem to equally important across the forecast horizons for Czech Republic. Despite these differences, overall we find the relative importance of the global factor is generally as important as the local CPI factor for all countries with the exception of Greece. And in addition, the importance of local macro factors group is low for almost all countries and forecast horizons. This is consistent with our forecasting findings, that Specification-1 (+LocalMACRO) is generally not as good as the models with inflation factors (local or global). If we interpret the model with local macro factors as an approximation[25] to a Phillips Curve-type relationship, then our findings favour global inflation explanations of EM national inflation rates.

1.6.3 Forecast informativeness: How far can we forecast?

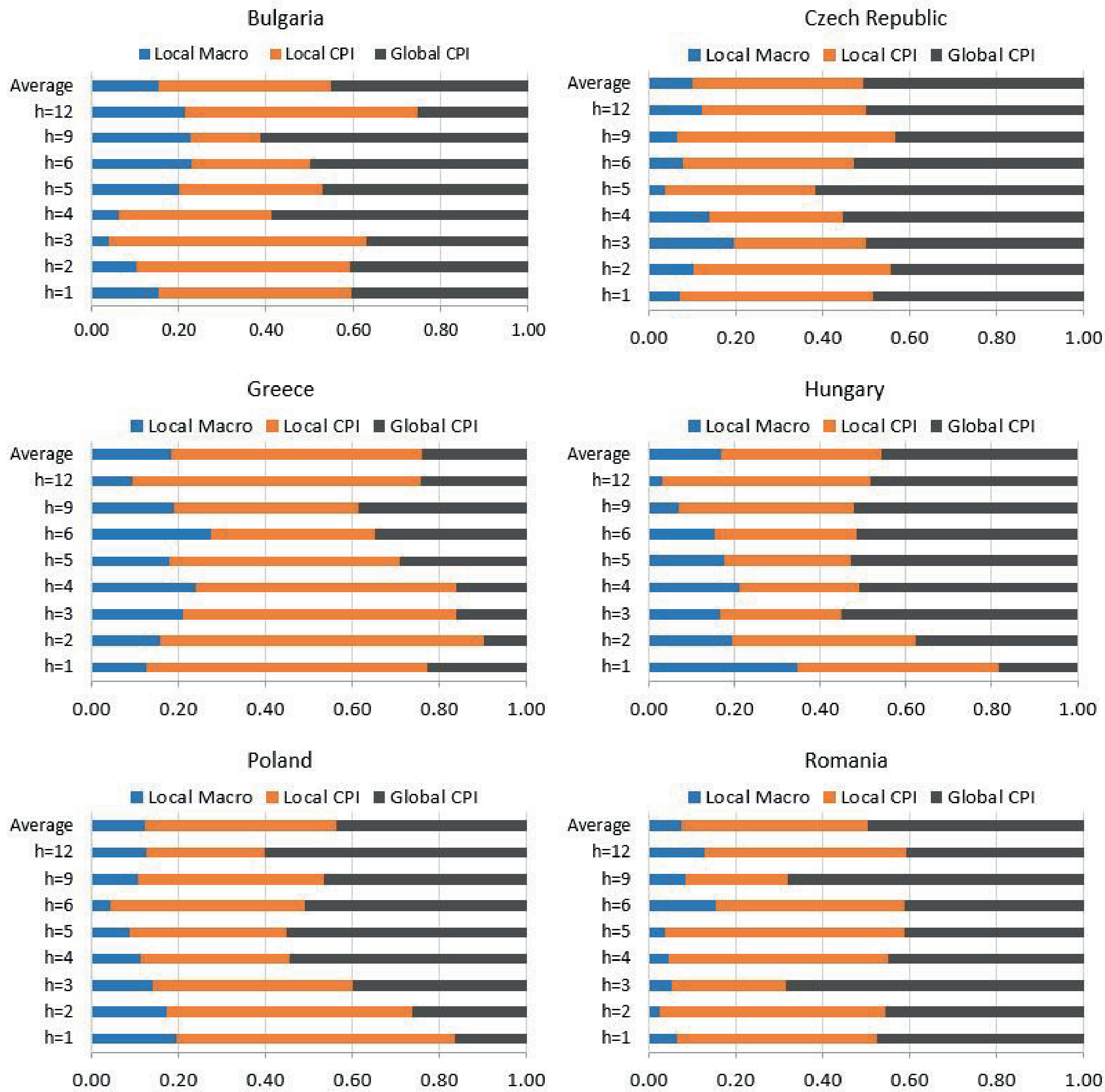
In some instances, the policy maker may be interested in a relatively long-horizon, and of interest is how far ahead our models can forecast. Forecasts are said to be informative up to the horizon at which the forecast error variance is no longer smaller than the unconditional variance of the target variable. (The assumption being that the forecasting model, which makes use of forecast-origin information, will initially fare better than the unconditional mean, but that the relative advantage will diminish in the forecast horizon as the role of the conditioning data wanes). In our context, it seems reasonable to suppose that long-horizon forecast performance will measure the ability of the models to forecast core inflation, and that short-horizon performance will bear more on the ability to forecast more cyclical or short-acting components such as food.

Following the work of Breitung and Knüppel, 2021, we test that the forecast $\hat{y}_{t+h|t}$ is not informative for y_{t+h} using the null hypothesis:

$$H_0: \quad \mathbb{E}\left(e^2_{t+h|t}\right) \geq \mathbb{E}\left(y_{t+h} - \mu\right)^2 \tag{1.19}$$

[25] An 'approximation' in the sense that it includes a wide range of domestic variables in addition to a simple activity variable such as the unemployment rate or the output gap.

Figure 1.3: The importance of global and local factor groups for the GPR method.



Notes: The sub-graphs plot the importance of each factor group for the GPR method for all horizons across the countries. The values in the graphs are normalized to sum one. h is the forecasting horizon.

where $e_{t+h|t} = y_{t+h} - \hat{y}_{t+h|t}$ is the forecast error. Then, the maximum forecast horizon h^* can be defined as $h^* = h_{\min} - 1$ where $h_{\min}$ is the lowest forecast horizon which satisfies the condition given in the null hypothesis. In other words, we sequentially test the H_0 for $h = 1, 2, \ldots, h_{\max}$ until the H_0 is not rejected for the first time. Then, we select the previous horizon as maximum forecast horizon. Equivalently, we can write our null hypothesis as:

$$H_0' : \quad \mathbb{E}\left(y_{t+h} - \mu\right)\left(\hat{y}_{t+h|t} - \mu\right) = 0 \tag{1.20}$$

This means that the forecast is rational if $\mathbb{E}\left(y_{t+h} - \hat{y}_{t+h|t} \mid \hat{y}_{t+h|t}\right) = 0$. Subsequently, we can reject the null hypothesis if y_{t+h} and $\hat{y}_{t+h|t}$ are positively correlated. This leads to a one sided t-test of the null hypothesis $\beta_{1,h} = 0$ against the alternative $\beta_{1,h} > 0$ with the constant $\alpha_{0,h} = \mu$ is left unrestricted in the Mincer-Zarnowitz regression defined in Mincer and Zarnowitz, 1969. Hence, this test can be interpreted as an encompassing test – whether the model forecast adds useful information relative to simply using the unconditional mean (estimated by the sample average).

Table 1.7 presents the maximum forecast horizons h^*, suggested by the encompassing test, for all our models (for headline inflation), to determine the extent to which the inclusion of the different factors extends the horizon at which our models are informative about the inflation outlook. The results demonstrate that the AR model forecasts are not informative beyond 9-months when the recursive forecasting scheme is employed. The encompassing test also implies smaller values of h^* for the AR model if the rolling window approach is adopted, which renders inflation forecasts uninformative beyond 6-months ahead for any country.

Table 1.7: Maximum forecast horizons in months determined by encompassing test

A) Recursive Forecasting						
	Bulgaria	Czech	Greece	Hungary	Poland	Romania
AR	6	9	6	6	6	9
Specification -1	12	12	12	12	12	9
Specification -2	12	12	12	12	12	9
Specification -3	12	12	12	12	12	12
Specification -4	12	12	12	12	12	12
Specification -5	12	12	12	12	12	12
Specification -6	12	12	12	12	12	12
B) Rolling Forecasting						
	Bulgaria	Czech	Greece	Hungary	Poland	Romania
AR	6	6	6	6	6	6
Specification -1	9	12	12	12	12	6
Specification -2	12	12	12	12	12	6
Specification -3	12	12	12	12	12	6
Specification -4	12	12	12	12	12	6
Specification -5	12	12	12	12	12	6
Specification -6	12	12	12	12	12	6

Notes: The table shows maximum forecast horizons in months for all forecast horizons determined by the encompassing test.

By way of contrast, the models augmented with factors produce informative forecasts at horizons greater than the maximum forecast horizon of the AR model in most of the cases. For Romania, there is no improvement in h^* (from 9 months) if only local factors are added (recursive scheme), but the horizon increases to 12 when global factors are included. For all other countries, the informative horizon is at the maximum of 12 for all specifications. This finding supports the view that inflation is largely a global phenomenon and highlights the role of global inflation in local inflation dynamics (Duncan and Martınez-Garcıa, 2015). However, the maximum horizon of 12 is reached for all specifications, so that we are not able to determine the extent to which informativeness is sensitive to the different measures of global inflation.

Note that none of the specifications leads to an increase in the maximum forecast horizon for Romania under the rolling window scheme, which confirms our previous finding that a recursive scheme leads to superior forecasts in these classes of model. However, for all other countries the results do not depend on whether we adopt a rolling or recursive scheme.

1.7 Estimating Global Inflation Factor Through International Inflation Spillovers

Up to this point, we have worked with a pre-determined designation of countries as developed or emerging market when we construct the global inflation factors, but this may not correspond to an economic grouping. In this section, we make use of a measure of economic connectedness to determine the group structure. We utilize the time-varying parameter VAR (TVP-VAR) model of Antonakakis et al. (2020) to identify inflation spillovers across countries.[26] We calculate a pairwise directional connectedness (spillover) index for every pair of countries, based on the share of the 10-step ahead forecast error variance of a country's inflation rate that is accounted for by shocks to the other country. [27]

In Figure 1.4, we depict the network analysis of inflation spillovers for each country. Each edge between two nodes denotes the net pairwise spillovers between two countries, the arrow's direction indicates which country received shocks from which country on average. The thickness of the edge between two countries shows the strength of the propagation of shocks between countries. Similarly, each node's size represents the overall magnitude of net total directional connectedness for each country, implying that a larger node size has a significant role as sender/receiver of shocks within the network. We highlight with red (green) if a country is a net transmitter (receiver) of the shocks within the system.

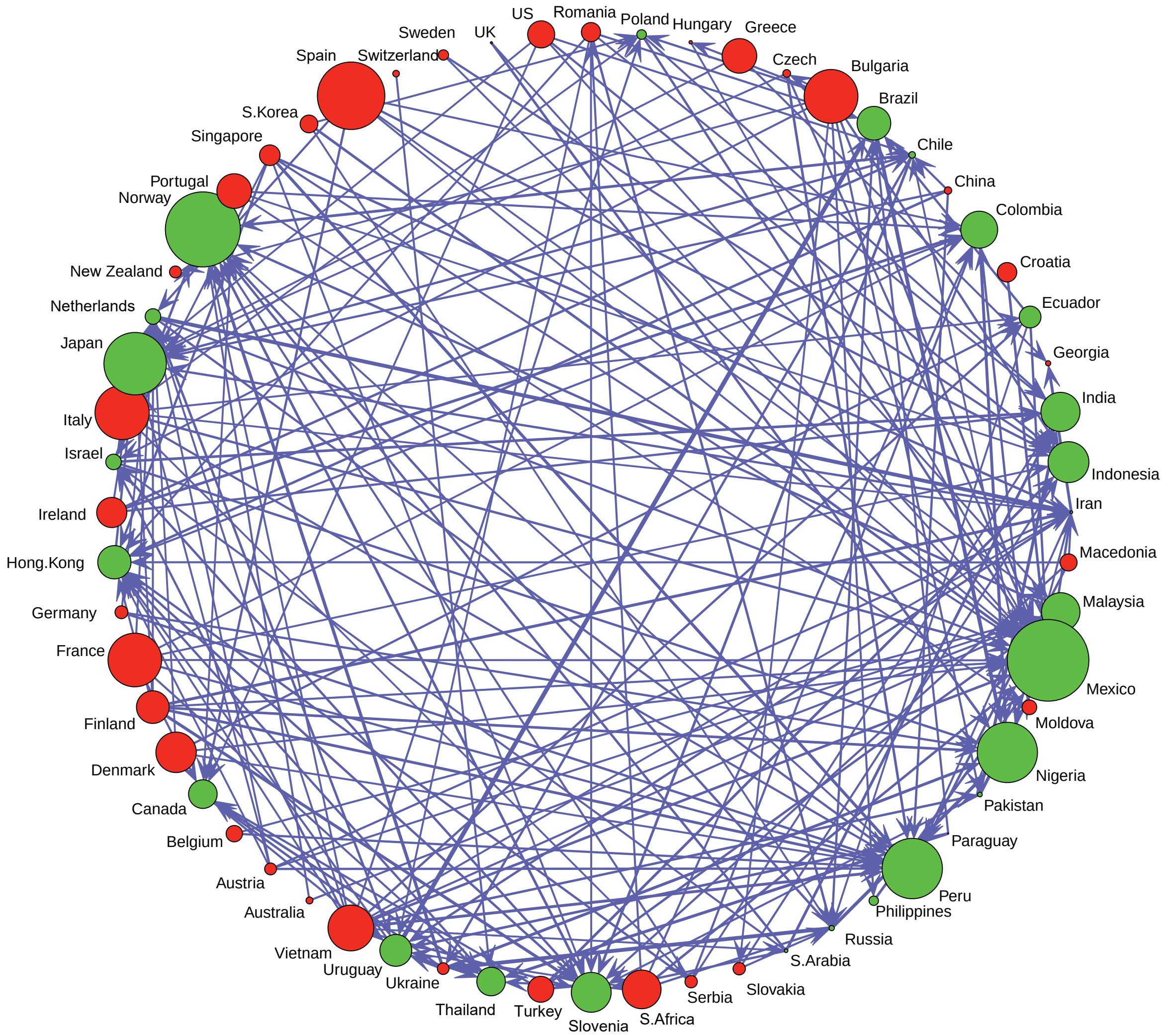
Our results highlight the global nature of the spillovers of the inflation shocks from European countries (especially; Spain, Italy, France) to the rest of the world. On the contrary, Japan, Norway and Mexico are the highest net receivers of inflation shocks in the network.[28] We identify the top 40 countries in terms of the transmission of inflation shocks to the EM European countries in our sample. We generate four different PLS factors using

[26]Technical details of TVP-VAR model and connectedness measures are provided in a supplementary online appendix.

[27]We also calculated the time-varying total connectedness of the network where its average sample value is 90.1%, implying that there is significant convergence in inflation rates across countries.

[28]Auer et al. (2019) analyze the synchronization of producer price inflation (PPI) across a large set of countries. They find considerable global co-movement in PPI, similar to the findings for CPI in previous studies (Neely and Rapach, 2011b; Mumtaz et al., 2011; Auer and Mehrotra, 2014; Bäurle et al., 2021). Akin to these studies, Ciccarelli and Garcıa (2015) examine the spillover of inflation expectations in the Euro area, US and UK.

Figure 1.4: Network analysis of inflation spillovers across countries



Notes: Each edge between two nodes demonstrates the net pairwise inflation spillovers between countries, and the arrow's direction indicates which country transmits the shocks to another country. The thickness of the edge between countries represents the strength of the spillovers between countries. Each node's size denotes the overall magnitude of net total directional spillovers. The red (green) node indicates whether a country is a net transmitter (receiver) of the shocks within the system. For better visualization, we report the pairwise spillovers greater than 0.05. Moreover, we run the model with 60 countries due to the need for a high-power computer.

Table 1.8: MSFEs based on the use of different global factors based on inflation spillovers - Recursive forecasting

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
ALL	**0.955**	**0.811*****	**0.690*****	**0.547*****	**0.495*****	**0.503*****	**0.503*****	**0.347*****
Top 10	1.175	0.930*	0.773***	0.743***	0.694***	0.666***	0.688***	0.497***
Top 20	1.156	0.925	0.845***	0.797***	0.715***	0.653***	0.544**	0.445***
Top 30	1.104	0.891***	0.792***	0.696***	0.636***	0.627***	0.614**	0.426***
Top 40	1.113	0.894***	0.798***	0.777**	0.694**	0.623**	0.640**	0.419***
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
ALL	1.113	1.046	1.005	0.980	0.899	0.723***	0.530***	0.404***
Top 10	1.043	**0.931**	**0.864***	**0.801***	**0.735***	**0.595****	**0.524****	0.440***
Top 20	1.078	1.022	0.914	0.902	0.864	0.685**	0.569**	0.441**
Top 30	1.083	1.034	0.984	0.985	1.010	0.805*	0.603**	**0.354*****
Top 40	1.144	1.091	0.925	0.964	0.984	0.835	0.553**	0.368***
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
ALL	0.912**	0.837**	0.789***	0.698***	0.574***	**0.485****	0.238**	**0.174****
Top 10	0.906**	0.820**	0.781**	0.720**	0.617**	0.513**	0.243**	0.209**
Top 20	0.906**	0.809**	0.767***	0.755**	0.663**	0.602**	**0.233****	0.188**
Top 30	**0.883****	0.809**	0.803***	0.729***	0.630**	0.540**	0.299**	0.191**
Top 40	0.887***	**0.795****	**0.748*****	**0.661*****	**0.572****	0.505**	0.304**	0.185**
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
ALL	**0.981**	**0.870**	**0.776****	**0.705****	**0.638****	**0.573****	**0.332****	**0.266****
Top 10	1.052	0.986	0.880	0.810	0.756	0.776	0.440**	0.320**
Top 20	1.074	1.013	0.839*	0.710**	0.685*	0.676*	0.350**	0.298**
Top 30	1.052	0.946	0.871	0.865	0.788	0.745	0.411**	0.315**
Top 40	1.075	0.950	0.845	0.808	0.733*	0.700*	0.437**	0.299**
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
ALL	0.887*	0.798***	0.730***	0.695***	**0.614*****	**0.445*****	**0.295*****	0.268***
Top 10	0.897*	0.869**	0.861*	0.842*	0.750**	0.639**	0.375***	0.334***
Top 20	0.907	0.851**	0.780***	0.723***	0.660***	0.599***	0.390***	**0.268*****
Top 30	0.921	0.875**	0.832**	0.778**	0.695**	0.620***	0.386***	0.343**
Top 40	**0.853****	**0.776*****	**0.709*****	**0.672*****	0.617***	0.507***	0.345***	0.396**
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
ALL	1.146	1.094	0.953	0.833**	**0.741*****	**0.710*****	**0.483*****	**0.538*****
Top 10	1.058	1.045	0.943	0.888	0.936	0.955	0.770**	0.745**
Top 20	**0.990**	0.970	0.914	0.884	0.887	0.863*	0.618***	0.686***
Top 30	1.039	**0.966**	**0.897***	**0.823****	0.858**	0.867**	0.654***	0.679***
Top 40	1.084	1.003	0.916	0.850**	0.895**	0.886**	0.691***	0.703**

Notes: The entries are MSFEs, with the model that gives the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of the AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than the AR model. The entries in the second row of each panel deliver the MSFE outcome for the model where factors are extracted from all the countries taken together, which are reported in Table 1.2. Top 10, Top 20, Top 30, and Top 40 report the MSFEs results of the Specification - 6 where global factors are estimated considering the Top 10, Top 20, Top 30, and Top 40 countries with the highest inflation shock propagation for a given country, respectively. Based on the DM forecast accuracy test, entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model.

the set of top 10, top 20, top 30, and top 40 countries. Then, we estimate the Specification - 6 using these "tailored" global factors.

Table 1.8 reports the results. The second row of each panel records the MSFE outcome when factors are extracted from all the countries taken together (i.e., emerging and developed) as in Section 2.2.3. The results show that choosing a subset of countries by considering the pairwise inflation spillovers across countries, before construction of the global factors, provides forecast improvement for the Czech Republic, Poland, and Romania. In particular, the forecast gains are primarily obtained for short and medium horizons (h= 1, 2, 3, 4), but not the longer horizons, indicating the importance of using information related to all countries for longer forecast horizons. Moreover, none of the competing models improve on the Section 2.2.3 strategy for Bulgaria and Hungary.

1.8 The Role of Country Characteristics in Explaining the Importance of the Global Inflation Factors

The channels through which global shocks are propagated and affect countries' inflation rates are numerous, and their interactions complex. But to shed some light on this question, we seek to uncover some of the country characteristics that tend to increase the importance of the effects global factors have on local inflation rates. We collect a candidate set of explanatory variables, consisting of time-varying country-specific variables, that might explain the (not-necessarily mutually exclusive) channels which influence effect of global factors on domestic consumer prices, either directly or indirectly.

To investigate the relationship between the country characteristics and the strength of the effect of the global factor on domestic inflation, we consider the following set of variables: (1) Current account balance to GDP (CAB); (2) Budget Balance to GDP (BB); (3) Household consumption to GDP (HCONS); (4) Unemployment rate (UNR); (5) FX reserves to GDP (FXR); (6) Uncertainty (UNC); (7) Real GDP growth (RGDP); (8) 5-years Credit Default Swap (CDS); (9) Real effective exchange rate (REER); (10) Exports to GDP (EXP); (11) Imports to GDP (IMP).[29] We estimate the following panel regression, allowing for country-specific fixed effects (the α_i) to capture time-invariant cross-country differences:

$$\begin{aligned}
\mathrm{CPI}_{i,t} = \alpha_i &+ \theta F_{it}^{LocalMACRO} + \gamma F_{it}^{LocalCPI} + \beta F_{it}^{GlobalCPI} \\
&+ \beta_1 F_{it}^{GlobalCPI} \times CAB_{it} + \beta_2 F_{it}^{GlobalCPI} \times BB_{it} \\
&+ \beta_3 F_{it}^{GlobalCPI} \times HCONS_{it} + \beta_4 F_{it}^{GlobalCPI} \times UNR_{it} \\
&+ \beta_5 F_{it}^{GlobalCPI} \times FXR_{it} + \beta_6 F_{it}^{GlobalCPI} \times UNC_{it} \\
&+ \beta_7 F_{it}^{GlobalCPI} \times RGDP_{it} + \beta_8 F_{it}^{GlobalCPI} \times CDS_{it} \\
&+ \beta_9 F_{it}^{GlobalCPI} \times REER_{it} + \beta_{10} F_{it}^{GlobalCPI} \times EXP_{it} \\
&+ \beta_{11} F_{it}^{GlobalCPI} \times IMP_{it} + e_{i,t}.
\end{aligned} \tag{1.21}$$

The dependent variable is the quarterly average value of the year-over-year inflation rates of European emerging countries. The country characteristics listed above appear as

[29] Table A24 of the appendix presents detail on these variables and data sources.

interaction terms with the global factor. This setup allows us to determine whether the effects of the global factor change with the country characteristics by simply testing for the significance of the interaction terms.

Table 1.9: Determinants of importance of global factor - Panel regression results

VARIABLES	(1) CPI	(2) CPI
$LocalMACRO$	0.133	0.125
	(0.135)	(0.132)
$LocalCPI$	1.302***	1.261***
	(0.135)	(0.130)
$GlobalCPI$	1.100***	1.100***
	(0.098)	(0.097)
$GlobalCPI \times CAB$	0.729***	0.577**
	(0.204)	(0.223)
$GlobalCPI \times BB$	0.0086	-0.056
	(0.091)	(0.091)
$GlobalCPI \times HCONS$	0.700***	0.643***
	(0.192)	(0.187)
$GlobalCPI \times UNR$	-0.084	-0.012
	(0.128)	(0.130)
$GlobalCPI \times FXR$	0.343***	0.103
	(0.104)	(0.114)
$GlobalCPI \times UNC$	-0.016	0.035
	(0.068)	(0.067)
$GlobalCPI \times RGDP$	0.0311	0.0301
	(0.097)	(0.091)
$GlobalCPI \times CDS$	0.005	-0.053
	(0.066)	(0.068)
$GlobalCPI \times REER$	-0.127	-0.057
	(0.078)	(0.099)
$GlobalCPI \times EXP$	-2.141**	
	(0.843)	
$GlobalCPI \times IMP$	2.127***	
	(0.685)	
$GlobalCPI \times EXP\_EU$		-2.183***
		(0.764)
$GlobalCPI \times IMP\_EU$		2.147***
		(0.645)
$GlobalCPI \times EXP\_NonEU$		0.329
		(0.239)
$GlobalCPI \times IMP\_NonEU$		0.103
		(0.202)
$Constant$	3.016***	3.018***
	(0.078)	(0.075)
Observations	369	369
F-stat prob.	0.00	0.00
Adjusted R^2	0.848	0.855

Notes: Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) denote significant levels. Robust standard errors are reported in parentheses. All explanatory variables are used in standardized forms.

Table 1.9 presents the panel regression results. Column 1 of Table 1.9 suggests that the relative importance of the global factor is positively associated with the current account balance and government debt. As suggested by Kılınç et al. (2016), higher current account deficits may result in larger currency depreciation in emerging market countries, amplifying the relationship between domestic inflationary pressures and current account deficits. Similarly, a higher level of household consumption may create greater dependency on imported goods, making a country more open to global shocks. The significant coefficients of the exports and imports variables indicate that the degree of trade openness is key to explaining the transmission of global shocks onto the headline inflation rate. In particular, a growing share of imports from other countries will increase the pass-through of supply chain shortages, energy and raw material prices, onto domestic inflation rates. These results are in line with the recent research suggesting that global production networks play a significant role in the transmission of shocks (Carvalho, 2014; Auer et al., 2017; Auer et al., 2019; Carvalho et al., 2021). We also modify the baseline model by splitting exports and imports into EU and Non-EU. Column 2 of Table 1.9 shows that imports from the EU are highly significant, but imports from Non-EU countries become insignificant. The reason might be that the EU has a single customs union with a single trade policy and tariff system, and that the EM European countries are more connected to the advanced countries in the EU than to the rest of the world.

Overall, our results suggest a number of plausible propagation channels for global factors on domestic inflation. We surmise that the potency of these channels may have increased in recent years, with policy rates being close to the lower bound of zero, diminishing the effectiveness of countries' own monetary policies.

1.9 Conclusion

We present a comprehensive empirical investigation into the forecasting performance of global factors for European EM countries' national inflation rates. We consider a variety of different models, forecasting schemes, forecast horizons and evaluation techniques, to include in our investigation the breadth of approaches in the literature. Naturally our results do not always give consistent findings across countries, models and horizons, but nevertheless some general patterns emerge.

Our empirical findings based on the outcomes of the forecasting exercises firmly support the contention that 'inflation is a global phenomenon' is true for the European EM countries' national inflation rates, and not just for developed, high-income economies. The support comes from comparing the forecast performance of models with global inflation factors to models with either local macro factors, which we contend generalise Phillips Curve-type models, and to models which may in addition include local inflation factors. Because our models with global inflation factors also include all the information in the models with local macro and inflation factors, we are able to show the incremental effect of 'global inflation'. This is important, because otherwise we might attribute to global inflation predictive ability which stems from domestic factors, recognising that in practice domestic variables will respond to the global situation and it might be difficult to separately disentangle the effects of the two sets of factors on national inflation rates. Our approach shifts the onus to global factors adding something over and above that provided by domestic factors.

We provide some insight as to why global factors are an important determinant of domestic inflation, by considering the country-level characteristics which tend to increase the importance of global factors over domestic. Perhaps not surprisingly the degree of openness of a country is a key determinant, but other factors, such as a high level of government debt also matter, and work in the same direction. Tailoring the global inflation factor to the particular EM country also matters for some countries - that is, forming the global factor by extracting a factor on the subset of countries which are closely connected to the EM countries.

We use factors throughout to condense the information in large sets of variables, both for domestic variables, and for foreign variables, consistent with a large body of literature on factor modelling. Where we depart from some of the literature on 'global inflation' is to calculate the factors in a way that ensures their relevance for the variable being forecast, that is, by PLS rather than PCA. We show that this has noticeable effects on our results. While our main set of results use linear factor forecasting models, we also establish that our findings are robust to factor-selection methods that enforce sparsity, as well as a machine-learning method that allows for a non-linear relationship between national inflation rates and the sets of factors. The latter serves to further enhance the forecasting improvements that result from the global inflation factors.

We also consider whether the findings for national headline inflation rates carry over to core inflation, which excludes food and energy, recognising that these elements of the domestic consumption basket will likely be directly influenced by global price movements. While global factors still play an important role in determining European emerging market core inflation rates, local factors are now found to play a more prominent role than they did for headline inflation.

Forecast performance can be evaluated in a number of ways. We compare the models' forecasts at each forecast horizon, using standard tests of equal forecast accuracy, as is often done in the literature. However, the evaluation of forecast paths, or of subsets of forecast paths, would likely be of greater interest to policy makers, as well as being a way of handling the multiple-testing problem that arises from comparing two models at a number of horizons. Generally we find that global factors dominate local factors at the shorter horizons. We also pay particular attention to the horizon at which the factor models lose their edge over the 'long-horizon' or unconditional mean forecast, and show that the factor models generally extend this horizon relative to the benchmark AR model.

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Appendix A: Additional Tables and Figures

Table A1: Share of inflation variance explained by each individual factor: PLS vs PCA

	PLS					PCA				
Bulgaria	1^{st} factor	2^{nd} factor	3^{rd} factor	4^{th} factor	*Total*	1^{st} factor	2^{nd} factor	3^{rd} factor	4^{th} factor	*Total*
Local Macro	0.69	0.09	0.08	0.03	0.89	0.09	0.59	0.03	0.02	0.73
Local CPI	0.74	0.21	0.03	0.01	0.99	0.60	0.30	0.01	0.00	0.92
EM CPI	0.83	0.10	0.02	0.01	0.97	0.79	0.01	0.03	0.01	0.84
DM CPI	0.61	0.17	0.09	0.02	0.89	0.57	0.00	0.06	0.01	0.65
Global CPI	0.79	0.14	0.02	0.02	0.98	0.75	0.01	0.00	0.00	0.77
Czech Republic										
Local Macro	0.58	0.12	0.09	0.05	0.85	0.00	0.09	0.09	0.16	0.34
Local CPI	0.85	0.08	0.04	0.02	0.98	0.51	0.32	0.00	0.00	0.84
EM CPI	0.65	0.21	0.07	0.03	0.96	0.53	0.11	0.03	0.01	0.67
DM CPI	0.55	0.17	0.09	0.02	0.83	0.52	0.01	0.05	0.02	0.59
Global CPI	0.65	0.21	0.07	0.03	0.95	0.55	0.09	0.04	0.01	0.69
Greece										
Local Macro	0.84	0.08	0.01	0.01	0.94	0.00	0.73	0.04	0.10	0.87
Local CPI	0.81	0.14	0.02	0.01	0.98	0.77	0.10	0.00	0.02	0.89
EM CPI	0.63	0.20	0.09	0.03	0.95	0.52	0.11	0.08	0.00	0.70
DM CPI	0.60	0.24	0.03	0.01	0.88	0.52	0.00	0.28	0.02	0.82
Global CPI	0.65	0.20	0.08	0.02	0.95	0.55	0.12	0.00	0.05	0.72
Hungary										
Local Macro	0.63	0.10	0.06	0.04	0.83	0.02	0.23	0.36	0.04	0.66
Local CPI	0.84	0.09	0.04	0.00	0.98	0.78	0.00	0.06	0.01	0.85
EM CPI	0.53	0.32	0.07	0.03	0.94	0.36	0.04	0.26	0.01	0.67
DM CPI	0.43	0.24	0.09	0.03	0.79	0.35	0.01	0.19	0.05	0.60
Global CPI	0.52	0.33	0.07	0.03	0.94	0.39	0.06	0.06	0.14	0.65
Poland										
Local Macro	0.55	0.24	0.06	0.05	0.90	0.01	0.00	0.01	0.64	0.66
Local CPI	0.84	0.10	0.03	0.01	0.99	0.78	0.00	0.07	0.04	0.90
EM CPI	0.54	0.33	0.06	0.03	0.95	0.37	0.03	0.19	0.14	0.73
DM CPI	0.43	0.27	0.08	0.03	0.82	0.34	0.11	0.10	0.08	0.63
Global CPI	0.52	0.34	0.05	0.04	0.95	0.38	0.03	0.03	0.29	0.73
Romania										
Local Macro	0.56	0.25	0.08	0.04	0.92	0.07	0.00	0.36	0.19	0.63
Local CPI	0.87	0.10	0.01	0.00	0.99	0.85	0.04	0.05	0.01	0.96
EM CPI	0.64	0.29	0.03	0.02	0.98	0.29	0.52	0.06	0.05	0.92
DM CPI	0.40	0.39	0.09	0.02	0.90	0.25	0.06	0.37	0.02	0.70
Global CPI	0.59	0.33	0.04	0.02	0.98	0.30	0.47	0.00	0.12	0.90

Table A2: Share of variance in each data groups explained by each individual factor: PLS vs PCA

	PLS					PCA				
Bulgaria	1^{st} factor	2^{nd} factor	3^{rd} factor	4^{th} factor	$Total$	1^{st} factor	2^{nd} factor	3^{rd} factor	4^{th} factor	$Total$
Local Macro	0.22	0.26	0.06	0.05	0.58	0.32	0.17	0.08	0.05	0.61
Local CPI	0.41	0.10	0.04	0.05	0.60	0.42	0.10	0.07	0.06	0.64
EM CPI	0.38	0.07	0.07	0.06	0.58	0.38	0.11	0.08	0.06	0.63
DM CPI	0.56	0.07	0.04	0.04	0.71	0.56	0.10	0.08	0.06	0.80
Global CPI	0.41	0.06	0.08	0.04	0.58	0.41	0.10	0.07	0.06	0.64
Czech Republic										
Local Macro	0.11	0.25	0.18	0.07	0.60	0.36	0.14	0.09	0.07	0.65
Local CPI	0.18	0.13	0.06	0.04	0.40	0.20	0.13	0.10	0.07	0.49
EM CPI	0.37	0.10	0.07	0.05	0.58	0.38	0.11	0.08	0.06	0.63
DM CPI	0.56	0.07	0.04	0.07	0.74	0.56	0.10	0.08	0.06	0.80
Global CPI	0.40	0.09	0.06	0.05	0.60	0.41	0.10	0.07	0.06	0.64
Greece										
Local Macro	0.17	0.09	0.24	0.06	0.56	0.27	0.18	0.08	0.06	0.59
Local CPI	0.47	0.06	0.04	0.03	0.59	0.47	0.06	0.06	0.05	0.63
EM CPI	0.37	0.10	0.06	0.06	0.59	0.38	0.11	0.08	0.06	0.63
DM CPI	0.56	0.09	0.04	0.06	0.74	0.56	0.10	0.08	0.06	0.80
Global CPI	0.40	0.09	0.05	0.05	0.59	0.41	0.10	0.07	0.06	0.64
Hungary										
Local Macro	0.18	0.26	0.16	0.06	0.66	0.34	0.18	0.11	0.05	0.68
Local CPI	0.29	0.08	0.05	0.10	0.52	0.29	0.13	0.10	0.06	0.57
EM CPI	0.37	0.09	0.07	0.07	0.59	0.38	0.11	0.08	0.06	0.63
DM CPI	0.55	0.08	0.04	0.06	0.74	0.56	0.10	0.08	0.06	0.80
Global CPI	0.40	0.08	0.07	0.05	0.60	0.41	0.10	0.07	0.06	0.64
Poland										
Local Macro	0.18	0.24	0.06	0.05	0.53	0.36	0.13	0.09	0.06	0.64
Local CPI	0.32	0.08	0.04	0.06	0.50	0.33	0.10	0.09	0.07	0.58
EM CPI	0.37	0.09	0.08	0.06	0.59	0.38	0.11	0.08	0.06	0.63
DM CPI	0.55	0.09	0.05	0.05	0.75	0.56	0.10	0.08	0.06	0.80
Global CPI	0.40	0.07	0.07	0.05	0.59	0.41	0.10	0.07	0.06	0.64
Romania										
Local Macro	0.24	0.19	0.06	0.05	0.54	0.34	0.14	0.10	0.08	0.67
Local CPI	0.66	0.06	0.04	0.03	0.79	0.66	0.07	0.05	0.04	0.81
EM CPI	0.34	0.15	0.06	0.04	0.59	0.38	0.11	0.08	0.06	0.63
DM CPI	0.54	0.10	0.04	0.07	0.75	0.56	0.10	0.08	0.06	0.80
Global CPI	0.38	0.13	0.06	0.03	0.59	0.41	0.10	0.07	0.06	0.64

Table A3: Point forecast performance: Recursive forecasting - Euro area sovereign debt crisis

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.502	0.898	1.205	1.594	1.996	2.378	3.547	4.675
Specification -1	**0.987**	0.902	**0.692*****	0.639***	0.516***	0.411***	0.696***	0.673***
Specification -2	1.310	0.920*	0.779***	0.717***	0.633***	0.433***	0.580***	0.259***
Specification -3	1.334	**0.819***	0.782**	0.651***	0.466***	0.314***	0.499***	**0.170*****
Specification -4	1.845	1.182	0.915	0.585***	0.512***	0.466***	0.569***	0.196***
Specification -5	1.606	0.950	0.896**	0.583***	**0.435*****	**0.268*****	0.767*	0.354***
Specification -6	1.426	0.856**	0.738***	**0.567*****	0.443***	0.318***	**0.465*****	0.179***
CZECH REPUBLIC								
AR	0.345	0.484	0.656	0.716	0.801	0.963	1.111	1.123
Specification -1	1.282	1.448	1.180	1.069	**0.887****	**0.602****	0.613**	0.816
Specification -2	1.332	1.368	1.254	1.278	1.051	0.670	0.476***	0.511***
Specification -3	1.684	1.933	1.790	1.730	1.220	0.828	0.730***	0.664***
Specification -4	1.686	1.960	1.399	1.132	0.954	0.910	0.464***	**0.453*****
Specification -5	1.898	1.920	1.560	1.368	1.228	0.909	**0.293*****	0.464***
Specification -6	1.791	2.068	1.779	1.722	1.265	0.839	0.614***	0.534***
GREECE								
AR	0.629	0.876	1.022	1.137	1.150	1.164	1.060	1.308
Specification -1	1.071	1.011	0.929	0.893**	1.045	1.068	1.059	0.874*
Specification -2	0.954	0.839**	0.853***	0.786***	0.856**	1.016	0.849**	0.545***
Specification -3	0.992	1.051	**0.798*****	**0.702*****	**0.571*****	0.546***	0.458***	0.389***
Specification -4	**0.930**	**0.799*****	0.927	0.824***	0.681***	0.546***	0.764	0.463***
Specification -5	1.004	0.924	0.808*	0.830*	0.656***	**0.475*****	0.395***	**0.335*****
Specification -6	0.967	0.900	0.989	1.002	0.855	0.807*	**0.276*****	0.346***
HUNGARY								
AR	0.493	0.747	0.883	0.975	1.078	1.189	1.514	1.581
Specification -1	**0.840**	**0.842***	**0.861***	1.035	1.012	1.189	1.123	0.992
Specification -2	1.568	1.508	1.272	1.127	1.055	0.916**	0.572***	**0.339*****
Specification -3	1.202	1.151	1.071	1.038	0.947	**0.799*****	0.507***	0.508***
Specification -4	1.580	1.528	1.187	0.995	1.119	1.126	0.511***	0.554**
Specification -5	1.361	1.290	1.108	**0.875***	**0.923**	0.967	**0.509*****	0.713**
Specification -6	1.544	1.512	1.089	1.008	1.024	1.027	0.525***	0.635***
POLAND								
AR	0.485	0.616	0.685	0.674	0.971	1.040	1.144	1.105
Specification -1	0.838***	**0.721*****	0.705***	0.674***	0.670***	0.631***	0.535***	0.835***
Specification -2	0.799***	0.899	0.742*	0.498***	**0.376*****	**0.274*****	0.479***	0.742***
Specification -3	**0.796*****	0.942	0.760*	0.602***	0.467***	0.383***	0.441***	**0.492*****
Specification -4	0.800***	0.922	0.662***	**0.436*****	0.444***	0.461***	0.425***	0.992
Specification -5	0.829***	0.982	**0.621*****	0.571***	0.518***	0.380***	**0.373*****	0.965
Specification -6	0.814***	0.958	0.736**	0.542***	0.462***	0.387***	0.405***	0.515***
ROMANIA								
AR	0.892	1.525	2.040	2.403	2.667	2.917	3.517	3.488
Specification -1	1.105	1.102	1.098	1.057	1.035	1.003	0.808*	0.673***
Specification -2	0.924	0.706***	0.602***	0.561***	0.622***	0.645***	0.710*	0.804*
Specification -3	**0.847****	**0.641****	**0.478*****	**0.377*****	**0.443*****	**0.525*****	0.784**	0.460***
Specification -4	0.987	0.901	0.810*	0.752**	0.721***	0.692***	0.632**	0.660***
Specification -5	0.884*	0.740*	0.586**	0.530***	0.481***	0.542***	**0.623****	**0.287*****
Specification -6	0.931	0.672***	0.525***	0.414***	0.489***	0.603***	0.737**	0.297***

Notes: The entries are MSFEs, with the Specification types that yields the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A4: Headline Inflation - Commodity Augmented: Recursive forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
$LocalMACRO + LocalCPI + Commodity$	1.038	0.839***	0.728***	0.607***	0.554***	0.523***	**0.495*****	0.360***
$Specification-6$	**0.955*****	0.811***	0.690***	0.547***	0.495***	0.503***	0.503***	**0.347*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.977	**0.806*****	**0.680*****	**0.539*****	**0.492*****	**0.494*****	0.518***	0.377***
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
$LocalMACRO + LocalCPI + Commodity$	1.105	1.017	**0.952***	**0.861*****	**0.745*****	**0.626*****	**0.493*****	0.397***
$Specification-6$	1.113	1.046	1.005	0.980	0.899	0.723***	0.530***	0.404***
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.130	1.099	1.054	1.017	0.935	0.738**	0.537***	**0.378*****
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
$LocalMACRO + LocalCPI + Commodity$	0.916**	**0.820****	**0.772****	0.727**	0.645**	0.577**	0.276**	0.203**
$Specification-6$	**0.912****	0.837**	0.789***	**0.698*****	**0.574*****	**0.485****	**0.238****	**0.174****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.929*	0.839**	0.795***	0.711***	0.599***	0.490**	0.260**	0.181**
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
$LocalMACRO + LocalCPI + Commodity$	1.018	0.949	0.822	0.775*	0.718*	0.673*	0.440**	0.296**
$Specification-6$	**0.981**	**0.870**	**0.776****	**0.705****	**0.638****	**0.573****	**0.332****	**0.266****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.008	0.901	0.801**	0.722**	0.656**	0.582**	0.370**	0.267**
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
$LocalMACRO + LocalCPI + Commodity$	0.937	0.876**	0.802***	0.727***	0.648***	0.579***	0.362***	0.312***
$Specification-6$	**0.887****	**0.798*****	0.730***	**0.695*****	**0.614*****	**0.445*****	0.295***	**0.268*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.905*	0.806***	**0.727*****	0.696***	0.615***	0.454***	**0.294*****	0.269***
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
$LocalMACRO + LocalCPI + Commodity$	1.098	1.116	1.089	1.066	1.020	0.974	0.882	0.878
$Specification-6$	1.146	1.094	**0.953**	**0.833*****	**0.741*****	**0.710*****	**0.483*****	**0.538*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.157	1.143	1.015	0.898*	0.774***	0.743***	0.515***	0.559***

Notes: The entries are MSFEs, with the Specification types that yields the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test. Specification types explanations: Specification -6: +GlobalCPI.

Table A5: Headline Inflation - Commodity Augmented: Rolling forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.429	0.770	1.015	1.257	1.489	1.719	2.576	3.585
$LocalMACRO + LocalCPI + Commodity$	1.088	0.983	0.871***	0.695***	0.620***	0.597***	**0.612****	0.443***
$Specification-6$	1.117	0.938	0.731***	**0.628*****	**0.582*****	**0.596*****	0.675*	**0.424*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.083	**0.930**	**0.716*****	0.652***	0.600***	0.617***	0.720*	0.432***
CZECH REPUBLIC								
AR	0.348	0.497	0.638	0.770	0.875	0.981	1.252	1.586
$LocalMACRO + LocalCPI + Commodity$	1.088	1.023	0.984	0.921	**0.791***	**0.675*****	**0.515*****	**0.395*****
$Specification-6$	1.157	1.063	**0.954**	**0.861***	0.846**	0.835*	0.603***	0.407***
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.148	1.075	0.996	0.907	0.892	0.887	0.616***	0.406***
GREECE								
AR	0.523	0.680	0.809	0.939	1.125	1.334	2.204	3.107
$LocalMACRO + LocalCPI + Commodity$	**0.936**	0.896	0.842*	0.786**	0.691**	0.629**	0.308**	**0.236****
$Specification-6$	0.944	**0.873**	**0.815*****	**0.748*****	**0.659****	**0.506****	0.321**	0.255**
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.957	0.893	0.830**	0.753***	0.681**	0.538**	**0.299****	0.270**
HUNGARY								
AR	0.473	0.745	0.976	1.220	1.434	1.656	2.280	2.916
$LocalMACRO + LocalCPI + Commodity$	1.080	1.013	0.935	0.955	0.936	0.822	0.474*	**0.346****
$Specification-6$	1.011	**0.913**	0.839*	**0.820**	**0.738***	0.636*	**0.366****	0.363**
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.037	0.919	**0.808***	0.824	0.756	**0.630***	0.490*	0.356**
POLAND								
AR	0.308	0.508	0.705	0.881	1.063	1.202	1.586	2.023
$LocalMACRO + LocalCPI + Commodity$	0.864**	0.866**	0.834**	0.746**	0.723***	0.642***	0.431***	0.403***
$Specification-6$	**0.856****	**0.813*****	**0.787*****	**0.736*****	**0.640*****	**0.497*****	**0.409*****	**0.336*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.869**	0.836***	0.815**	0.738***	0.677***	0.510***	0.424***	0.345***
ROMANIA								
AR	0.636	0.966	1.307	1.540	1.780	2.010	2.895	3.900
$LocalMACRO + LocalCPI + Commodity$	1.155	1.273	1.260	1.196	1.082	0.986	0.848	0.617**
$Specification-6$	1.160	1.135	0.914	**0.730*****	**0.617*****	0.634***	**0.708***	**0.460*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.164	1.144	**0.903**	0.753***	0.631***	**0.620*****	0.720*	0.474***

Notes: The entries are MSFEs, with the Specification types that yields the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test. Specification types explanations: Specification -6: +GlobalCPI.

Table A6: Giacomini and White, 2006 test results for PLS approach in a recursive window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.06	0.35	0.45	0.03	0.01	0.01	0.02	0.02
Specification - 2	0.36	0.00	0.00	0.00	0.00	0.01	0.01	0.01
Specification - 3	0.89	0.06	0.01	0.00	0.00	0.01	0.04	0.01
Specification - 4	0.21	0.00	0.00	0.00	0.01	0.01	0.02	0.01
Specification - 5	0.53	0.60	0.19	0.01	0.01	0.01	0.09	0.01
Specification - 6	0.35	0.01	0.00	0.00	0.00	0.01	0.02	0.01
CZECH REPUBLIC								
Specification - 1	0.31	0.85	0.74	0.35	0.22	0.11	0.15	0.16
Specification - 2	0.69	0.57	0.18	0.06	0.01	0.01	0.02	0.02
Specification - 3	0.09	0.56	0.80	0.70	0.16	0.06	0.01	0.03
Specification - 4	0.64	0.47	0.01	0.07	0.44	0.27	0.02	0.02
Specification - 5	0.08	0.23	0.98	0.42	0.19	0.05	0.03	0.05
Specification - 6	0.26	0.65	1.00	0.79	0.38	0.03	0.01	0.03
GREECE								
Specification - 1	0.83	0.61	0.59	0.51	0.24	0.15	0.07	0.05
Specification - 2	0.04	0.04	0.01	0.03	0.04	0.06	0.04	0.04
Specification - 3	0.19	0.14	0.02	0.02	0.03	0.04	0.04	0.04
Specification - 4	0.01	0.04	0.01	0.01	0.02	0.04	0.04	0.04
Specification - 5	0.10	0.31	0.05	0.01	0.01	0.03	0.05	0.04
Specification - 6	0.05	0.08	0.01	0.01	0.02	0.04	0.04	0.04
HUNGARY								
Specification - 1	0.99	0.89	0.50	0.23	0.20	0.16	0.13	0.09
Specification - 2	0.95	0.59	0.20	0.15	0.14	0.15	0.08	0.05
Specification - 3	0.60	0.20	0.08	0.07	0.07	0.05	0.05	0.05
Specification - 4	0.87	0.55	0.14	0.12	0.16	0.18	0.09	0.05
Specification - 5	0.99	0.94	0.17	0.06	0.04	0.03	0.07	0.06
Specification - 6	0.85	0.22	0.05	0.06	0.06	0.05	0.05	0.04
POLAND								
Specification - 1	0.05	0.08	0.04	0.01	0.00	0.00	0.00	0.01
Specification - 2	0.34	0.05	0.00	0.00	0.01	0.01	0.00	0.01
Specification - 3	0.20	0.01	0.00	0.00	0.00	0.00	0.00	0.01
Specification - 4	0.12	0.04	0.03	0.04	0.03	0.03	0.01	0.02
Specification - 5	0.20	0.05	0.02	0.03	0.01	0.00	0.02	0.02
Specification - 6	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.01
ROMANIA								
Specification - 1	0.04	0.02	0.03	0.07	0.72	0.84	0.28	0.17
Specification - 2	0.09	0.32	0.64	0.92	0.93	0.63	0.34	0.29
Specification - 3	0.17	0.80	0.38	0.11	0.01	0.00	0.00	0.00
Specification - 4	0.01	0.01	0.09	0.36	0.73	0.24	0.01	0.04
Specification - 5	0.10	0.18	0.83	0.28	0.06	0.01	0.00	0.00
Specification - 6	0.02	0.30	0.57	0.04	0.00	0.00	0.00	0.00

Notes:This table reports p-values based on Giacomini and White, 2006 forecast accuracy test results where factor extracting using the PLS-approach. Point forecasts are obtained from recursive window forecasting exercise. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A7: Giacomini and White, 2006 test results for PLS approach in a rolling window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.14	0.35	0.87	0.07	0.02	0.02	0.04	0.05
Specification - 2	0.16	0.70	0.18	0.00	0.00	0.00	0.05	0.01
Specification - 3	0.25	0.21	0.00	0.01	0.01	0.01	0.16	0.02
Specification - 4	0.18	0.60	0.39	0.00	0.00	0.00	0.09	0.01
Specification - 5	0.02	0.26	0.66	0.05	0.12	0.03	0.34	0.04
Specification - 6	0.22	0.34	0.00	0.00	0.00	0.00	0.12	0.02
CZECH REPUBLIC								
Specification - 1	0.46	0.80	0.54	0.39	0.24	0.23	0.20	0.11
Specification - 2	0.62	0.91	0.79	0.61	0.11	0.02	0.01	0.02
Specification - 3	0.08	0.48	0.93	0.59	0.09	0.04	0.01	0.02
Specification - 4	0.32	0.94	0.36	0.18	0.62	0.31	0.01	0.05
Specification - 5	0.03	0.39	0.93	0.31	0.09	0.08	0.04	0.07
Specification - 6	0.08	0.59	0.67	0.18	0.09	0.14	0.01	0.02
GREECE								
Specification - 1	0.90	0.90	0.92	0.88	0.42	0.25	0.06	0.05
Specification - 2	0.11	0.15	0.09	0.06	0.04	0.07	0.03	0.04
Specification - 3	0.53	0.37	0.16	0.11	0.10	0.08	0.04	0.05
Specification - 4	0.01	0.16	0.02	0.01	0.02	0.04	0.04	0.04
Specification - 5	0.32	0.45	0.05	0.04	0.05	0.05	0.04	0.05
Specification - 6	0.27	0.22	0.03	0.02	0.03	0.04	0.04	0.04
HUNGARY								
Specification - 1	0.93	0.96	0.76	0.38	0.31	0.22	0.17	0.16
Specification - 2	0.71	0.89	0.63	0.62	0.59	0.38	0.09	0.08
Specification - 3	0.74	0.75	0.49	0.66	0.47	0.31	0.09	0.14
Specification - 4	0.66	0.99	0.49	0.31	0.36	0.16	0.08	0.09
Specification - 5	0.72	0.57	0.58	0.56	0.21	0.06	0.08	0.09
Specification - 6	0.92	0.36	0.17	0.24	0.20	0.15	0.07	0.09
POLAND								
Specification - 1	0.27	0.17	0.04	0.02	0.00	0.00	0.00	0.01
Specification - 2	0.03	0.03	0.03	0.01	0.02	0.03	0.00	0.01
Specification - 3	0.05	0.01	0.20	0.17	0.00	0.01	0.00	0.02
Specification - 4	0.10	0.13	0.05	0.01	0.00	0.01	0.02	0.03
Specification - 5	0.07	0.01	0.01	0.00	0.00	0.01	0.04	0.04
Specification - 6	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.02
ROMANIA								
Specification - 1	0.02	0.02	0.09	0.46	0.87	0.47	0.05	0.02
Specification - 2	0.09	0.14	0.15	0.22	0.66	0.83	0.24	0.01
Specification - 3	0.13	0.91	0.22	0.05	0.03	0.01	0.04	0.00
Specification - 4	0.06	0.03	0.50	0.71	0.26	0.15	0.14	0.03
Specification - 5	0.27	0.54	0.45	0.24	0.20	0.01	0.09	0.00
Specification - 6	0.00	0.18	0.42	0.00	0.00	0.00	0.14	0.00

Notes: This table reports p-values based on Giacomini and White, 2006 forecast accuracy test results where factor extracting using the PLS-approach. Point forecasts are obtained from rolling window forecasting exercise. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A8: Giacomini and White, 2006 test results for PCA approach in a recursive window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.66	0.81	0.72	0.66	0.60	0.61	0.54	0.56
Specification - 2	0.04	0.10	0.09	0.14	0.13	0.15	0.68	0.46
Specification - 3	0.06	0.14	0.10	0.13	0.12	0.15	0.50	0.98
Specification - 4	0.13	0.23	0.25	0.14	0.06	0.04	0.28	0.84
Specification - 5	0.17	0.74	0.42	0.40	0.04	0.01	0.27	0.49
Specification - 6	0.00	0.03	0.01	0.02	0.04	0.06	0.28	0.66
CZECH REPUBLIC								
Specification - 1	0.92	0.28	0.28	0.40	0.41	0.40	0.17	0.06
Specification - 2	0.03	0.18	0.33	0.22	0.18	0.08	0.01	0.06
Specification - 3	0.00	0.27	0.52	0.71	0.30	0.14	0.00	0.00
Specification - 4	0.00	0.01	0.01	0.03	0.04	0.05	0.05	0.09
Specification - 5	0.00	0.00	0.01	0.02	0.02	0.04	0.08	0.19
Specification - 6	0.01	0.16	0.26	0.47	0.33	0.25	0.07	0.08
GREECE								
Specification - 1	0.39	0.71	0.71	0.88	0.98	0.97	0.93	0.96
Specification - 2	0.73	0.95	0.82	0.72	0.55	0.54	0.45	0.46
Specification - 3	0.27	0.58	0.42	0.44	0.67	0.61	0.16	0.12
Specification - 4	0.69	0.76	0.88	0.87	0.38	0.37	0.26	0.12
Specification - 5	0.30	0.29	0.38	0.42	0.43	0.79	0.19	0.14
Specification - 6	0.17	0.31	0.16	0.18	0.36	0.79	0.19	0.12
HUNGARY								
Specification - 1	0.50	0.50	0.62	0.74	0.73	0.72	0.77	0.72
Specification - 2	0.31	0.38	0.52	0.81	0.85	0.81	0.86	0.34
Specification - 3	0.15	0.34	0.13	0.35	0.28	0.23	0.79	0.31
Specification - 4	0.23	0.36	0.58	0.93	0.93	0.88	0.70	0.42
Specification - 5	0.28	0.47	0.31	0.64	0.42	0.30	0.57	0.29
Specification - 6	0.42	0.86	0.60	0.87	0.95	0.98	0.39	0.24
POLAND								
Specification - 1	0.02	0.06	0.08	0.12	0.10	0.08	0.63	0.26
Specification - 2	0.07	0.11	0.22	0.49	0.52	0.55	0.95	0.36
Specification - 3	0.79	0.60	0.58	0.80	0.70	0.61	0.34	0.76
Specification - 4	0.73	0.78	0.76	0.51	0.47	0.52	0.61	0.75
Specification - 5	0.73	0.60	0.59	0.37	0.41	0.77	0.46	0.58
Specification - 6	0.96	0.85	0.81	0.58	0.73	0.75	0.53	0.66
ROMANIA								
Specification - 1	0.45	0.35	0.43	0.40	0.29	0.24	0.07	0.01
Specification - 2	0.09	0.05	0.08	0.07	0.06	0.05	0.07	0.06
Specification - 3	0.32	0.04	0.04	0.03	0.03	0.03	0.02	0.02
Specification - 4	0.01	0.00	0.01	0.01	0.02	0.04	0.07	0.03
Specification - 5	0.07	0.00	0.01	0.00	0.01	0.01	0.02	0.01
Specification - 6	0.08	0.00	0.01	0.00	0.01	0.01	0.01	0.01

Notes: This table reports p-values based on Giacomini and White, 2006 forecast accuracy test results where factor extracting using the PCA-approach. Point forecasts are obtained from recursive window forecasting exercise. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A9: Giacomini and White, 2006 test results for PCA approach in a rolling window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.14	0.32	0.29	0.44	0.46	0.47	0.45	0.32
Specification - 2	0.12	0.11	0.10	0.08	0.06	0.04	0.02	0.08
Specification - 3	0.23	0.03	0.00	0.00	0.00	0.00	0.00	0.32
Specification - 4	0.04	0.08	0.11	0.02	0.03	0.05	0.12	0.47
Specification - 5	0.20	0.07	0.00	0.00	0.00	0.01	0.01	0.10
Specification - 6	0.16	0.03	0.01	0.00	0.00	0.00	0.01	0.62
CZECH REPUBLIC								
Specification - 1	0.99	0.77	0.59	0.61	0.40	0.30	0.40	0.76
Specification - 2	0.04	0.15	0.25	0.09	0.17	0.09	0.00	0.03
Specification - 3	0.00	0.00	0.00	0.11	0.28	0.08	0.09	0.02
Specification - 4	0.06	0.22	0.16	0.11	0.14	0.16	0.11	0.26
Specification - 5	0.00	0.02	0.03	0.02	0.10	0.07	0.31	0.53
Specification - 6	0.02	0.06	0.07	0.10	0.18	0.16	0.31	0.06
GREECE								
Specification - 1	0.53	0.21	0.31	0.44	0.64	0.69	0.52	0.68
Specification - 2	0.18	0.22	0.38	0.45	0.69	0.98	0.64	0.55
Specification - 3	0.01	0.06	0.04	0.08	0.07	0.04	0.18	0.14
Specification - 4	0.07	0.03	0.09	0.14	0.49	0.92	0.34	0.12
Specification - 5	0.00	0.02	0.03	0.09	0.09	0.01	0.54	0.20
Specification - 6	0.02	0.02	0.02	0.04	0.05	0.11	0.23	0.13
HUNGARY								
Specification - 1	0.43	0.55	0.73	0.47	0.44	0.44	0.55	0.26
Specification - 2	0.22	0.22	0.18	0.28	0.39	0.62	0.96	0.97
Specification - 3	0.05	0.12	0.01	0.04	0.09	0.13	0.29	0.26
Specification - 4	0.16	0.18	0.22	0.23	0.17	0.13	0.64	0.65
Specification - 5	0.09	0.13	0.01	0.00	0.04	0.04	0.65	0.45
Specification - 6	0.08	0.09	0.01	0.05	0.12	0.14	0.53	0.64
POLAND								
Specification - 1	0.40	0.51	0.47	0.65	0.60	0.58	0.68	0.34
Specification - 2	0.74	0.30	0.14	0.07	0.09	0.12	0.07	0.01
Specification - 3	0.87	0.68	0.26	0.08	0.10	0.38	0.86	0.53
Specification - 4	0.32	0.29	0.53	0.28	0.22	0.33	0.17	0.27
Specification - 5	0.98	0.47	0.19	0.07	0.13	0.61	0.64	0.40
Specification - 6	0.61	0.65	0.25	0.02	0.03	0.10	0.58	0.11
ROMANIA								
Specification - 1	0.14	0.12	0.18	0.20	0.07	0.05	0.02	0.01
Specification - 2	0.04	0.00	0.00	0.00	0.00	0.00	0.09	0.10
Specification - 3	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.49
Specification - 4	0.01	0.00	0.00	0.01	0.01	0.09	0.74	0.98
Specification - 5	0.02	0.01	0.01	0.00	0.00	0.03	0.88	0.63
Specification - 6	0.00	0.00	0.00	0.00	0.01	0.02	0.10	0.40

Notes: This table reports p-values based on Giacomini and White, 2006 forecast accuracy test results where factor extracting using the PCA-approach. Point forecasts are obtained from rolling window forecasting exercise. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A10: Harvey et al., 1997 test results for PLS approach in a recursive window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.95	0.79	0.26	0.03	0.02	0.01	0.03	0.02
Specification - 2	0.78	0.00	0.00	0.00	0.01	0.01	0.02	0.01
Specification - 3	0.55	0.05	0.02	0.01	0.01	0.01	0.04	0.01
Specification - 4	0.86	0.00	0.00	0.01	0.01	0.02	0.03	0.01
Specification - 5	0.71	0.33	0.13	0.01	0.01	0.02	0.07	0.02
Specification - 6	0.21	0.01	0.01	0.00	0.01	0.01	0.03	0.01
CZECH REPUBLIC								
Specification - 1	0.81	0.57	0.39	0.21	0.15	0.09	0.11	0.12
Specification - 2	0.64	0.31	0.12	0.06	0.01	0.01	0.02	0.02
Specification - 3	0.93	0.69	0.59	0.37	0.11	0.05	0.02	0.03
Specification - 4	0.66	0.27	0.01	0.06	0.25	0.17	0.03	0.03
Specification - 5	0.93	0.85	0.51	0.24	0.13	0.05	0.03	0.05
Specification - 6	0.84	0.65	0.50	0.41	0.23	0.03	0.02	0.03
GREECE								
Specification - 1	0.43	0.33	0.32	0.29	0.16	0.11	0.06	0.05
Specification - 2	0.04	0.04	0.02	0.03	0.04	0.06	0.04	0.04
Specification - 3	0.13	0.10	0.02	0.02	0.03	0.04	0.04	0.04
Specification - 4	0.01	0.04	0.02	0.01	0.02	0.04	0.04	0.04
Specification - 5	0.07	0.19	0.05	0.02	0.01	0.03	0.04	0.04
Specification - 6	0.05	0.06	0.02	0.01	0.02	0.04	0.04	0.04
HUNGARY								
Specification - 1	0.49	0.45	0.28	0.15	0.13	0.11	0.10	0.08
Specification - 2	0.52	0.32	0.13	0.10	0.10	0.11	0.07	0.05
Specification - 3	0.33	0.14	0.07	0.06	0.06	0.05	0.05	0.05
Specification - 4	0.56	0.30	0.10	0.09	0.11	0.12	0.08	0.05
Specification - 5	0.50	0.53	0.12	0.05	0.04	0.03	0.06	0.06
Specification - 6	0.44	0.15	0.05	0.05	0.05	0.05	0.05	0.04
POLAND								
Specification - 1	0.05	0.07	0.04	0.02	0.00	0.00	0.01	0.02
Specification - 2	0.20	0.04	0.00	0.00	0.01	0.01	0.01	0.02
Specification - 3	0.14	0.01	0.00	0.00	0.00	0.00	0.01	0.02
Specification - 4	0.09	0.04	0.03	0.04	0.03	0.03	0.02	0.03
Specification - 5	0.13	0.04	0.02	0.03	0.01	0.01	0.03	0.02
Specification - 6	0.10	0.01	0.00	0.01	0.01	0.00	0.01	0.02
ROMANIA								
Specification - 1	0.04	0.02	0.03	0.07	0.72	0.84	0.28	0.17
Specification - 2	0.09	0.32	0.64	0.92	0.93	0.63	0.34	0.29
Specification - 3	0.17	0.80	0.38	0.11	0.01	0.00	0.00	0.00
Specification - 4	0.01	0.01	0.09	0.36	0.73	0.24	0.01	0.04
Specification - 5	0.10	0.18	0.83	0.28	0.06	0.01	0.00	0.00
Specification - 6	0.02	0.30	0.57	0.04	0.00	0.00	0.00	0.00

Notes: This table reports p-values based on Harvey et al., 1997 forecast accuracy test results where factor extracting using the PLS-approach. Point forecasts are obtained from recursive window forecasting exercise. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A11: Harvey et al., 1997 test results for PLS approach in a rolling window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.90	0.79	0.44	0.06	0.02	0.02	0.04	0.05
Specification - 2	0.89	0.63	0.12	0.00	0.00	0.00	0.05	0.02
Specification - 3	0.84	0.14	0.01	0.01	0.01	0.01	0.12	0.03
Specification - 4	0.88	0.68	0.23	0.01	0.00	0.01	0.07	0.02
Specification - 5	0.98	0.84	0.35	0.04	0.09	0.03	0.21	0.04
Specification - 6	0.85	0.21	0.01	0.00	0.00	0.01	0.09	0.02
CZECH REPUBLIC								
Specification - 1	0.74	0.59	0.30	0.23	0.16	0.15	0.14	0.09
Specification - 2	0.66	0.46	0.41	0.33	0.08	0.02	0.02	0.02
Specification - 3	0.93	0.73	0.53	0.32	0.07	0.04	0.01	0.02
Specification - 4	0.81	0.48	0.21	0.12	0.34	0.19	0.01	0.05
Specification - 5	0.97	0.77	0.47	0.19	0.07	0.06	0.04	0.06
Specification - 6	0.93	0.68	0.36	0.12	0.08	0.10	0.02	0.03
GREECE								
Specification - 1	0.54	0.54	0.54	0.45	0.24	0.16	0.06	0.05
Specification - 2	0.08	0.11	0.07	0.05	0.04	0.06	0.04	0.04
Specification - 3	0.29	0.22	0.11	0.08	0.08	0.07	0.04	0.05
Specification - 4	0.01	0.11	0.02	0.01	0.02	0.04	0.04	0.04
Specification - 5	0.19	0.26	0.04	0.04	0.05	0.05	0.04	0.05
Specification - 6	0.17	0.14	0.03	0.03	0.03	0.04	0.04	0.04
HUNGARY								
Specification - 1	0.53	0.48	0.39	0.22	0.19	0.15	0.12	0.11
Specification - 2	0.62	0.45	0.34	0.33	0.32	0.23	0.08	0.07
Specification - 3	0.61	0.39	0.27	0.35	0.27	0.19	0.08	0.10
Specification - 4	0.65	0.50	0.27	0.19	0.21	0.12	0.07	0.08
Specification - 5	0.62	0.69	0.32	0.31	0.14	0.06	0.07	0.08
Specification - 6	0.53	0.21	0.12	0.16	0.13	0.11	0.06	0.07
POLAND								
Specification - 1	0.98	0.98	0.93	0.74	0.44	0.27	0.05	0.03
Specification - 2	0.93	0.90	0.89	0.85	0.65	0.43	0.16	0.02
Specification - 3	0.91	0.54	0.14	0.05	0.03	0.01	0.04	0.01
Specification - 4	0.95	0.97	0.72	0.37	0.17	0.11	0.11	0.04
Specification - 5	0.83	0.70	0.26	0.16	0.13	0.02	0.07	0.00
Specification - 6	0.99	0.88	0.24	0.01	0.00	0.01	0.10	0.01
ROMANIA								
Specification - 1	0.04	0.02	0.03	0.07	0.72	0.84	0.28	0.17
Specification - 2	0.09	0.32	0.64	0.92	0.93	0.63	0.34	0.29
Specification - 3	0.17	0.80	0.38	0.11	0.01	0.00	0.00	0.00
Specification - 4	0.01	0.01	0.09	0.36	0.73	0.24	0.01	0.04
Specification - 5	0.10	0.18	0.83	0.28	0.06	0.01	0.00	0.00
Specification - 6	0.02	0.30	0.57	0.04	0.00	0.00	0.00	0.00

Notes: This table reports p-values based on Harvey et al., 1997 forecast accuracy test results where factor extracting using the PLS-approach. Point forecasts are obtained from rolling window forecasting exercise. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A12: Harvey et al., 1997 test results for PCA approach in a recursive window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.65	0.58	0.62	0.65	0.67	0.67	0.70	0.69
Specification - 2	0.96	0.92	0.93	0.90	0.90	0.89	0.64	0.26
Specification - 3	0.95	0.90	0.92	0.91	0.91	0.89	0.72	0.51
Specification - 4	0.90	0.85	0.84	0.90	0.95	0.96	0.82	0.57
Specification - 5	0.88	0.61	0.76	0.77	0.96	0.99	0.83	0.72
Specification - 6	0.99	0.97	0.99	0.97	0.96	0.95	0.82	0.35
CZECH REPUBLIC								
Specification - 1	0.54	0.17	0.17	0.23	0.24	0.24	0.88	0.95
Specification - 2	0.97	0.88	0.80	0.86	0.88	0.94	0.98	0.94
Specification - 3	1.00	0.83	0.71	0.63	0.81	0.90	0.99	1.00
Specification - 4	1.00	0.98	0.98	0.97	0.96	0.95	0.95	0.93
Specification - 5	1.00	1.00	0.99	0.98	0.98	0.96	0.93	0.87
Specification - 6	0.99	0.89	0.84	0.73	0.80	0.84	0.94	0.93
GREECE								
Specification - 1	0.77	0.63	0.63	0.55	0.49	0.49	0.53	0.52
Specification - 2	0.62	0.48	0.42	0.38	0.30	0.30	0.26	0.27
Specification - 3	0.83	0.69	0.76	0.75	0.64	0.33	0.11	0.09
Specification - 4	0.64	0.61	0.55	0.44	0.22	0.22	0.17	0.09
Specification - 5	0.82	0.82	0.78	0.76	0.75	0.59	0.13	0.10
Specification - 6	0.88	0.81	0.89	0.88	0.78	0.41	0.13	0.10
HUNGARY								
Specification - 1	0.72	0.72	0.67	0.61	0.62	0.62	0.60	0.62
Specification - 2	0.81	0.78	0.71	0.58	0.57	0.58	0.56	0.79
Specification - 3	0.90	0.80	0.90	0.79	0.82	0.85	0.41	0.19
Specification - 4	0.85	0.78	0.68	0.53	0.47	0.45	0.37	0.24
Specification - 5	0.83	0.74	0.81	0.65	0.76	0.82	0.31	0.18
Specification - 6	0.76	0.56	0.68	0.44	0.52	0.51	0.23	0.16
POLAND								
Specification - 1	0.02	0.05	0.06	0.09	0.08	0.06	0.34	0.83
Specification - 2	0.06	0.08	0.14	0.28	0.29	0.30	0.48	0.78
Specification - 3	0.41	0.32	0.32	0.41	0.37	0.33	0.21	0.40
Specification - 4	0.62	0.60	0.61	0.71	0.73	0.71	0.67	0.39
Specification - 5	0.62	0.68	0.68	0.78	0.76	0.60	0.74	0.68
Specification - 6	0.48	0.57	0.58	0.68	0.62	0.61	0.29	0.35
ROMANIA								
Specification - 1	0.75	0.79	0.75	0.77	0.82	0.84	0.94	0.98
Specification - 2	0.93	0.95	0.93	0.94	0.95	0.95	0.94	0.94
Specification - 3	0.80	0.96	0.96	0.97	0.97	0.97	0.97	0.98
Specification - 4	0.99	0.99	0.98	0.98	0.98	0.96	0.94	0.96
Specification - 5	0.94	0.99	0.99	0.99	0.99	0.99	0.98	0.99
Specification - 6	0.93	0.99	0.99	0.99	0.99	0.99	0.99	0.99

Notes: This table reports p-values based on Harvey et al., 1997 forecast accuracy test results where factor extracting using the PCA-approach. Point forecasts are obtained from recursive window forecasting exercise. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A13: Harvey et al., 1997 test results for PCA approach in a rolling window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.90	0.81	0.82	0.75	0.74	0.73	0.74	0.80
Specification - 2	0.91	0.92	0.92	0.94	0.95	0.96	0.98	0.93
Specification - 3	0.85	0.97	1.00	1.00	1.00	1.00	0.99	0.80
Specification - 4	0.96	0.93	0.92	0.97	0.97	0.95	0.91	0.73
Specification - 5	0.87	0.94	0.99	1.00	1.00	0.99	0.98	0.92
Specification - 6	0.89	0.97	0.99	1.00	1.00	0.99	0.99	0.66
CZECH REPUBLIC								
Specification - 1	0.50	0.40	0.32	0.33	0.24	0.19	0.23	0.60
Specification - 2	0.96	0.89	0.84	0.93	0.88	0.92	0.99	0.97
Specification - 3	1.00	0.99	0.99	0.91	0.82	0.93	0.93	0.97
Specification - 4	0.95	0.85	0.89	0.92	0.90	0.89	0.92	0.83
Specification - 5	1.00	0.98	0.97	0.97	0.92	0.94	0.81	0.71
Specification - 6	0.98	0.95	0.94	0.92	0.87	0.89	0.81	0.94
GREECE								
Specification - 1	0.71	0.86	0.81	0.75	0.66	0.64	0.71	0.64
Specification - 2	0.88	0.86	0.77	0.75	0.64	0.51	0.34	0.31
Specification - 3	0.98	0.95	0.96	0.94	0.94	0.96	0.12	0.10
Specification - 4	0.94	0.97	0.93	0.90	0.73	0.54	0.21	0.09
Specification - 5	0.99	0.97	0.97	0.93	0.93	0.98	0.30	0.14
Specification - 6	0.98	0.98	0.98	0.96	0.96	0.91	0.15	0.10
HUNGARY								
Specification - 1	0.75	0.70	0.62	0.73	0.75	0.75	0.69	0.83
Specification - 2	0.86	0.85	0.88	0.83	0.77	0.67	0.48	0.49
Specification - 3	0.96	0.91	0.99	0.96	0.93	0.90	0.82	0.17
Specification - 4	0.89	0.88	0.85	0.85	0.88	0.90	0.66	0.35
Specification - 5	0.93	0.90	0.99	1.00	0.96	0.96	0.35	0.26
Specification - 6	0.93	0.93	0.98	0.96	0.91	0.90	0.70	0.34
POLAND								
Specification - 1	0.23	0.28	0.26	0.35	0.32	0.32	0.64	0.79
Specification - 2	0.61	0.82	0.90	0.94	0.93	0.91	0.94	0.99
Specification - 3	0.44	0.64	0.83	0.93	0.92	0.78	0.44	0.70
Specification - 4	0.80	0.82	0.70	0.83	0.85	0.80	0.88	0.83
Specification - 5	0.49	0.73	0.87	0.94	0.90	0.67	0.66	0.76
Specification - 6	0.33	0.65	0.84	0.98	0.97	0.92	0.68	0.91
ROMANIA								
Specification - 1	0.90	0.91	0.88	0.87	0.94	0.95	0.98	0.99
Specification - 2	0.96	1.00	1.00	1.00	1.00	0.99	0.93	0.92
Specification - 3	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.72
Specification - 4	0.99	1.00	1.00	0.99	0.98	0.93	0.61	0.49
Specification - 5	0.98	0.98	0.99	1.00	0.99	0.97	0.55	0.34
Specification - 6	1.00	1.00	1.00	1.00	0.99	0.98	0.92	0.76

Notes: This table reports p-values based on Harvey et al., 1997 forecast accuracy test results where factor extracting using the PCA-approach. Point forecasts are obtained from rolling window forecasting exercise. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A14: Point forecast performance: Rolling forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.429	0.770	1.015	1.257	1.489	1.719	2.576	3.585
Specification -1	1.150	1.063	0.990	0.883**	0.815***	0.771***	**0.605****	0.567**
Specification -2	1.197	1.031	0.917*	0.705***	0.645***	0.620***	0.637**	0.419***
Specification -3	1.071	**0.911**	0.732***	0.686***	0.649***	0.601***	0.709*	**0.395*****
Specification -4	1.157	1.064	0.939	0.726***	0.632***	0.631***	0.680**	0.491***
Specification -5	1.203	1.114	0.944	0.731**	0.762*	0.706**	0.809	0.443**
Specification -6	1.117	0.938	**0.731*****	**0.628*****	**0.582*****	**0.596*****	0.675*	0.424***
CZECH REPUBLIC								
AR	0.348	0.497	0.638	0.770	0.875	0.981	1.252	1.586
Specification -1	1.051	1.023	0.947	0.910	0.882	0.847	0.783*	0.696**
Specification -2	1.049	**0.984**	0.961	0.919	**0.780****	**0.667*****	0.511***	**0.385*****
Specification -3	1.169	1.091	1.011	0.931	0.837**	0.745**	0.557***	0.399***
Specification -4	1.076	0.993	**0.917**	0.863*	0.931	0.860	**0.505*****	0.529**
Specification -5	1.255	1.086	0.990	0.889	0.829**	0.791**	0.629**	0.549**
Specification -6	1.157	1.063	0.954	**0.861***	0.846**	0.835*	0.603***	0.407***
GREECE								
AR	0.523	0.680	0.809	0.939	1.125	1.334	2.204	3.107
Specification -1	1.010	1.014	1.013	0.982	0.878	0.756	0.433**	0.406**
Specification -2	0.919**	0.857*	0.832**	0.765**	0.647**	0.563**	0.299**	**0.207****
Specification -3	0.967	0.918	0.874*	0.805**	0.707**	0.586**	0.324**	0.208**
Specification -4	**0.903*****	**0.854***	**0.776*****	**0.674*****	**0.587*****	**0.489****	**0.287****	0.223**
Specification -5	0.960	0.933	0.831**	0.766**	0.735**	0.618**	0.318**	0.229**
Specification -6	0.944	0.873	0.815***	0.748***	0.659**	0.506**	0.321**	0.255**
HUNGARY								
AR	0.473	0.745	0.976	1.220	1.434	1.656	2.280	2.916
Specification -1	1.006	0.995	0.959	0.839	0.776	0.693	0.582*	0.573*
Specification -2	1.052	0.981	0.927	0.908	0.880	0.790	0.427**	**0.360****
Specification -3	1.038	0.974	0.923	0.933	0.869	0.793	0.430**	0.456*
Specification -4	1.060	0.999	0.906	0.841	0.806	0.662*	0.391**	0.378**
Specification -5	1.047	1.049	0.952	0.923	0.791*	**0.619****	0.417**	0.384**
Specification -6	1.011	**0.913**	**0.839***	**0.820**	**0.738***	0.636	**0.366****	0.363**
POLAND								
AR	0.308	0.508	0.705	0.881	1.063	1.202	1.586	2.023
Specification -1	0.951	0.923*	0.889**	0.850***	0.790***	0.735***	0.581***	0.603***
Specification -2	0.858***	0.863**	0.828***	0.739***	0.683***	0.629***	0.438***	0.385***
Specification -3	0.859**	0.828***	0.904*	0.900*	0.753***	0.631***	**0.362*****	0.416***
Specification -4	0.876**	0.885**	0.811**	**0.721*****	0.672***	0.629***	0.450***	0.430**
Specification -5	0.880**	0.840***	**0.779*****	0.797***	0.713***	0.625***	0.548**	0.432**
Specification -6	**0.856****	**0.813*****	0.787***	0.736***	**0.640*****	**0.497*****	0.409***	**0.336*****
ROMANIA								
AR	0.636	0.966	1.307	1.540	1.780	2.010	2.895	3.900
Specification -1	1.094	1.144	1.098	1.042	0.989	0.938	0.775***	0.720***
Specification -2	1.138	1.241	1.225	1.145	1.046	0.971	0.812	0.588***
Specification -3	1.077	1.009	**0.874**	0.818**	0.754**	0.712***	**0.695****	0.496***
Specification -4	1.140	1.225	1.072	0.961	0.867	0.794*	0.736*	0.654**
Specification -5	1.074	1.050	0.920	0.868	0.832*	0.718***	0.713**	0.553***
Specification -6	1.160	1.135	0.914	**0.730*****	**0.617*****	**0.634*****	0.708*	**0.460*****

Notes: See notes to Table A5.

Table A15: Point forecast performance: Recursive forecasting - Factors are extracted using the PCA approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
Specification -1	1.021	1.019	1.044	1.069	1.094	1.107	1.145	1.135
Specification -2	1.140	1.141	1.173	1.196	1.223	1.209	1.036	**0.919**
Specification -3	1.108	1.110	1.126	1.166	1.203	1.220	1.072	1.008
Specification -4	1.132	1.162	1.224	1.252	1.322	1.358	1.151	1.036
Specification -5	1.067	1.020	1.094	1.078	1.158	1.206	1.094	1.080
Specification -6	1.143	1.159	1.179	1.210	1.276	1.337	1.125	0.954
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
Specification -1	**0.997**	**0.954**	**0.954**	**0.968**	**0.964**	**0.964**	1.123	1.285
Specification -2	1.067	1.062	1.066	1.092	1.122	1.172	1.482	1.573
Specification -3	1.101	1.056	1.055	1.053	1.186	1.330	1.463	1.453
Specification -4	1.117	1.191	1.278	1.438	1.562	1.612	1.593	1.536
Specification -5	1.158	1.233	1.369	1.401	1.451	1.368	1.435	1.322
Specification -6	1.138	1.106	1.097	1.093	1.169	1.259	1.391	1.350
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
Specification -1	1.018	1.017	1.029	1.017	0.999	0.995	1.010	1.009
Specification -2	1.012	**0.996**	**0.977**	**0.951**	0.918	0.901	0.866	0.875
Specification -3	1.042	1.054	1.103	1.121	1.049	0.944	0.602*	0.578*
Specification -4	1.014	1.027	1.019	0.977	**0.885**	**0.865**	0.807	0.701*
Specification -5	1.072	1.147	1.154	1.186	1.133	1.029	0.637*	0.594*
Specification -6	1.064	1.112	1.185	1.226	1.116	0.962	**0.599***	**0.547***
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
Specification -1	1.038	1.049	1.057	1.042	1.053	1.071	1.054	1.049
Specification -2	1.068	1.068	1.075	1.031	1.030	1.043	1.029	1.083
Specification -3	1.077	1.049	1.124	1.113	1.180	1.202	0.963	0.796
Specification -4	1.099	1.079	1.069	1.010	**0.984**	**0.969**	0.907	0.823
Specification -5	1.064	1.055	1.079	1.043	1.108	1.158	0.894	0.765
Specification -6	1.046	1.010	1.034	**0.988**	1.005	1.005	**0.836**	**0.726**
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
Specification -1	**0.917*****	**0.877****	**0.858****	**0.862***	**0.851****	**0.853****	0.979	1.101
Specification -2	0.930**	0.906*	0.896	0.917	0.909	0.903	0.986	1.151
Specification -3	0.976	0.956	0.955	0.975	0.956	0.930	**0.779**	0.935
Specification -4	1.012	1.030	1.045	1.104	1.129	1.124	1.148	0.920
Specification -5	1.026	1.039	1.053	1.103	1.108	1.045	1.203	1.124
Specification -6	0.997	1.024	1.030	1.060	1.039	1.039	0.857	**0.908**
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
Specification -1	1.015	1.023	1.030	1.053	1.105	1.145	1.221	1.287
Specification -2	1.056	1.119	1.152	1.219	1.294	1.350	1.502	1.632
Specification -3	1.054	1.204	1.331	1.478	1.601	1.732	1.825	1.825
Specification -4	1.116	1.243	1.248	1.359	1.406	1.463	1.560	1.798
Specification -5	1.068	1.217	1.301	1.419	1.471	1.552	1.630	1.679
Specification -6	1.064	1.198	1.279	1.425	1.551	1.691	1.830	1.964

Notes: See the notes to Table 1.2.

Table A16: Point forecast performance: Rolling forecasting - Factors are extracted using the PCA approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.429	0.770	1.015	1.257	1.489	1.719	2.576	3.585
Specification -1	1.050	1.041	1.081	1.099	1.133	1.164	1.190	1.244
Specification -2	1.117	1.192	1.211	1.358	1.507	1.642	1.430	1.248
Specification -3	1.140	1.316	1.372	1.473	1.548	1.543	1.457	1.146
Specification -4	1.119	1.108	1.097	1.169	1.305	1.385	1.234	1.102
Specification -5	1.125	1.178	1.277	1.329	1.392	1.393	1.433	1.246
Specification -6	1.210	1.375	1.411	1.448	1.509	1.505	1.326	1.064
CZECH REPUBLIC								
AR	0.348	0.497	0.638	0.770	0.875	0.981	1.252	1.586
Specification -1	0.999	**0.982**	**0.959**	**0.951**	**0.908**	**0.886**	**0.906**	1.035
Specification -2	1.096	1.103	1.106	1.208	1.220	1.284	1.415	1.388
Specification -3	1.285	1.321	1.229	1.203	1.185	1.375	1.404	1.351
Specification -4	1.101	1.091	1.182	1.366	1.411	1.460	1.391	1.220
Specification -5	1.251	1.304	1.426	1.509	1.344	1.257	1.309	1.163
Specification -6	1.270	1.377	1.377	1.358	1.253	1.308	1.239	1.253
GREECE								
AR	0.523	0.680	0.809	0.939	1.125	1.334	2.204	3.107
Specification -1	1.024	1.076	1.105	1.110	1.071	1.064	1.082	1.062
Specification -2	1.067	1.133	1.145	1.137	1.061	1.003	0.927	0.911
Specification -3	1.150	1.171	1.266	1.309	1.231	1.147	**0.664***	**0.588***
Specification -4	1.122	1.279	1.245	1.219	1.091	1.017	0.811	0.691*
Specification -5	1.207	1.318	1.363	1.362	1.273	1.215	0.840	0.673*
Specification -6	1.154	1.244	1.378	1.426	1.295	1.146	0.682	0.630*
HUNGARY								
AR	0.473	0.745	0.976	1.220	1.434	1.656	2.280	2.916
Specification -1	1.043	1.033	1.027	1.062	1.087	1.093	1.075	1.110
Specification -2	1.087	1.091	1.105	1.100	1.099	1.061	0.993	0.997
Specification -3	1.116	1.126	1.241	1.264	1.351	1.308	1.107	**0.835**
Specification -4	1.129	1.120	1.128	1.143	1.192	1.205	1.105	0.906
Specification -5	1.125	1.152	1.248	1.245	1.245	1.251	**0.937**	0.851
Specification -6	1.124	1.171	1.276	1.271	1.289	1.244	1.075	0.911
POLAND								
AR	0.308	0.508	0.705	0.881	1.063	1.202	1.586	2.023
Specification -1	0.956	**0.955**	**0.947**	**0.965**	**0.953**	**0.948**	1.048	1.123
Specification -2	1.017	1.069	1.128	1.245	1.300	1.277	1.339	1.398
Specification -3	0.984	1.036	1.145	1.239	1.210	1.099	**0.968**	1.104
Specification -4	1.080	1.091	1.055	1.091	1.125	1.129	1.276	1.179
Specification -5	0.995	1.053	1.169	1.254	1.159	1.068	1.105	1.162
Specification -6	**0.948**	1.030	1.107	1.246	1.279	1.215	1.106	1.231
ROMANIA								
AR	0.636	0.966	1.307	1.540	1.780	2.010	2.895	3.900
Specification -1	1.043	1.078	1.084	1.096	1.167	1.215	1.264	1.230
Specification -2	1.122	1.254	1.274	1.292	1.329	1.346	1.235	1.227
Specification -3	1.104	1.216	1.267	1.410	1.494	1.488	1.157	1.048
Specification -4	1.141	1.310	1.292	1.347	1.302	1.217	1.057	0.997
Specification -5	1.115	1.256	1.346	1.480	1.470	1.405	1.026	**0.928**
Specification -6	1.111	1.255	1.273	1.447	1.473	1.452	1.138	1.101

Notes: See notes to Table A5.

Table A17: Multi-horizon foecast comparison: Rolling forecasting - Factors are extracted using the PCA approach -

	short horizon		medium horizon		long horizon		all horizon	
BULGARIA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA
Spec.2 against Spec.1	-1.07	-1.02	-0.98	-0.75	0.74**	1.50**	-1.07	0.21
Spec.3 against Spec.2	-0.10	0.10	0.80**	0.87*	-0.93	-0.94	-0.93	-0.14
Spec.4 against Spec.2	0.76**	0.95*	0.47	0.85*	0.03	0.28	0.03	0.63
Spec.5 against Spec.4	-1.11	-0.40	1.93***	2.33***	-0.85	-0.34	-1.11	0.92*
Spec.6 against Spec.5	-2.50	-2.19	-2.86	-2.73	-0.89	-0.61	-2.86	-1.73
Spec.6 against Spec.2	-1.75	-1.58	-0.53	-0.14	-0.68	-0.61	-1.75	-0.63
CZECH REPUBLIC								
Spec.2 against Spec.1	-2.02	-1.91	-2.24	-2.12	-2.26	-1.53	-2.26	-2.05
Spec.3 against Spec.2	-0.31	-0.17	0.04	0.13	-0.94	-0.83	-0.94	-0.41
Spec.4 against Spec.2	-0.60	-0.48	-1.49	-1.32	-0.40	-0.10	-1.49	-0.70
Spec.5 against Spec.4	-0.16	0.29	1.10***	1.69**	-0.57	-0.18	-0.57	1.58**
Spec.6 against Spec.5	-0.29	-0.11	0.09	0.16	-0.91	-0.53	-0.91	-0.20
Spec.6 against Spec.2	-0.20	-0.13	0.14	0.23	-1.20	-0.79	-1.20	-0.23
GREECE								
Spec.2 against Spec.1	1.45***	1.55**	1.28***	1.34**	2.05***	2.91***	1.28***	2.14**
Spec.3 against Spec.2	-0.18	1.62**	0.25	0.58	0.33	0.40	-0.18	0.75
Spec.4 against Spec.2	-1.36	-0.28	-2.56	-2.16	-1.17	-0.86	-2.56	-1.39
Spec.5 against Spec.4	0.63*	1.43**	1.85***	2.14**	2.65***	3.15***	0.63***	2.98***
Spec.6 against Spec.5	-1.79	-1.32	-0.23	0.13	-0.96	-0.98	-1.79	-0.64
Spec.6 against Spec.2	-2.52	-0.07	0.12	0.38	0.75*	0.97*	-2.52	0.60
HUNGARY								
Spec.2 against Spec.1	0.86**	1.14**	0.53	0.57	1.36**	2.03**	0.53**	1.48**
Spec.3 against Spec.2	-0.42	-0.05	-0.64	-0.27	-4.22	-3.31	-4.22	-2.04
Spec.4 against Spec.2	-2.92	-1.53	-0.42	-0.21	0.03	0.04	-2.92	-0.28
Spec.5 against Spec.4	-0.02	0.16	0.94**	1.10**	0.12	0.35	-0.02	0.74*
Spec.6 against Spec.5	0.23	0.59	-1.60	-1.27	-3.26	-2.62	-3.26	-1.91
Spec.6 against Spec.2	-0.63	-0.35	-0.64	-0.23	-4.02	-3.17	-4.02	-2.29
POLAND								
Spec.2 against Spec.1	-0.75	-0.20	-0.56	-0.42	0.36	0.73*	-0.75	0.12
Spec.3 against Spec.2	1.71***	3.33***	1.58***	1.84**	1.13***	1.31**	1.13***	2.03***
Spec.4 against Spec.2	-1.12	-0.55	0.21	0.29	-0.76	-0.72	-1.12	-0.43
Spec.5 against Spec.4	1.30***	2.91***	1.21***	2.23***	2.15***	3.11***	1.21***	3.58***
Spec.6 against Spec.5	-0.20	0.45	-0.67	-0.51	-3.17	-2.46	-3.17	-1.73
Spec.6 against Spec.2	0.56**	2.88***	0.48*	0.87*	-1.29	-0.79	-1.29	0.44
ROMANIA								
Spec.2 against Spec.1	-1.65	-1.53	-1.30	-0.88	1.87***	2.42***	-1.65	0.60
Spec.3 against Spec.2	1.41**	2.10**	1.18***	1.98***	-1.94	-1.60	-1.94	1.01*
Spec.4 against Spec.2	1.74***	1.94**	0.96**	1.33**	-0.09	0.06	-0.09	0.92*
Spec.5 against Spec.4	-0.76	-0.04	0.88**	0.98**	-0.82	-0.24	-0.82	0.47
Spec.6 against Spec.5	0.26	0.58	-0.62	0.09	-0.93	-0.78	-0.93	-0.26
Spec.6 against Spec.2	1.60***	2.28**	1.38***	2.20***	-1.45	-1.16	-1.45	1.39**

Notes: Specification types explanations: Spec.1: +LocalMACRO; Spec.2: +LocalCPI; Spec.3: +emCPI; Spec.4: +dmCPI; Spec.5: +em_dmCPI; Spec.6: +GlobalCPI.

Table A18: Mincer-Zarnowitz regressions for recursive forecasting exercise where factors are extracted using the PLS

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	12.21***	14.10***	17.67***	16.66***	17.88***	23.55***	32.34***	41.83***
Specification - 2	5.54*	2.31	1.10	1.33	5.94**	7.81**	10.25***	23.66***
Specification - 3	1.75	1.04	0.09	0.32	1.78	10.81***	26.66***	16.87***
Specification - 4	5.12*	3.80	4.73*	19.57***	27.43***	33.42***	19.48***	42.62***
Specification - 5	5.35*	2.11	0.17	0.49	4.80*	26.72***	26.05***	13.71***
Specification - 6	1.33	1.57	0.38	0.27	2.86	10.54***	26.25***	29.42***
CZECH REPUBLIC								
Specification - 1	0.64	1.19	1.42	2.30	2.74	4.06	14.03***	12.73***
Specification - 2	0.76	1.15	0.47	0.83	0.19	1.94	0.11	1.76
Specification - 3	2.25	1.66	0.70	1.01	5.43*	6.12**	1.95	5.13*
Specification - 4	0.03	1.63	0.32	4.67*	9.99***	8.14**	1.97	10.35***
Specification - 5	2.76	5.38*	2.92	1.31	0.38	1.75	19.37***	20.27***
Specification - 6	2.19	1.25	0.36	0.24	3.07	4.98*	1.99	3.83
GREECE								
Specification - 1	13.99***	23.09***	26.53***	48.10***	69.92***	101.82***	39.39***	31.97***
Specification - 2	3.78	8.18**	9.72***	16.18***	39.58***	50.29***	18.97***	29.22***
Specification - 3	6.20**	10.52***	8.35**	7.52**	12.40***	15.06***	12.22***	10.20***
Specification - 4	4.83*	6.64**	7.02**	7.89**	24.16***	36.14***	43.01***	29.96***
Specification - 5	7.78**	9.88***	8.05**	6.30**	10.08***	19.04***	27.16***	16.84***
Specification - 6	5.07*	6.42**	5.19*	4.91*	11.90***	22.87***	10.89***	17.37***
HUNGARY								
Specification - 1	2.55	0.77	0.76	0.49	1.93	4.57*	19.82***	23.46***
Specification - 2	4.70*	1.84	1.59	2.95	2.52	2.04	6.93**	19.58***
Specification - 3	5.31*	3.43	4.35	5.74*	14.12***	16.87***	12.54***	4.08
Specification - 4	5.72*	2.54	2.07	2.17	2.16	2.98	20.50***	40.31***
Specification - 5	4.93*	6.24**	8.62**	10.24***	12.33***	6.19**	32.77***	25.33***
Specification - 6	7.75**	4.57*	2.96	2.21	5.27*	7.47**	8.60***	3.37
POLAND								
Specification - 1	1.33	3.39	5.15*	5.85**	6.40**	6.90**	6.11**	6.65**
Specification - 2	7.16**	7.76**	8.31**	6.78**	7.48**	11.43***	1.91	2.13
Specification - 3	2.36	4.43	2.17	1.38	2.32	0.27	0.12	8.89***
Specification - 4	6.87**	2.01	0.40	0.88	5.50*	19.23***	19.97***	7.32**
Specification - 5	5.29*	2.57	0.77	0.07	0.93	4.65*	52.96***	5.00*
Specification - 6	4.24	3.51	1.05	0.27	1.21	1.28	1.40	8.76***
ROMANIA								
Specification - 1	1.61	3.32	4.34	5.42*	6.53**	6.67**	5.51*	13.89***
Specification - 2	6.94**	9.20***	11.69***	15.69***	18.38***	17.08***	9.10***	27.06***
Specification - 3	3.40	4.41	4.38	6.43**	7.93**	9.85***	3.13	7.06**
Specification - 4	7.72**	10.85***	11.68***	14.03***	14.51***	9.54***	10.04***	26.81***
Specification - 5	3.72	8.12**	11.35***	14.63***	13.86***	14.91***	18.47***	21.95***
Specification - 6	3.68	3.41	2.63	2.78	3.14	3.49	7.90**	5.86**

Notes: This table presents the p-values and chi-square test statistics with two degrees of freedom for Mincer-Zarnowitz efficiency test. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) imply that competing model forecasts are not efficient compared to those of AR model. Specification types explanations: Specification - 1: +LocalMACRO; Specification - 2: +LocalCPI; Specification - 3: +emCPI; Specification - 4: +dmCPI; Specification - 5: +em_dmCPI; Specification -6: +GlobalCPI.

Table A19: Mincer-Zarnowitz regressions for rolling forecasting exercise where factors are extracted using the PLS

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	12.81***	10.52***	9.33***	8.12**	10.35***	20.07***	7.81**	13.87***
Specification - 2	18.83***	26.43***	23.77***	9.10***	4.64*	5.29*	9.24***	3.53
Specification - 3	6.27**	2.86	0.72	2.00	1.60	9.53***	46.90***	2.92
Specification - 4	10.86***	15.47***	15.58***	13.63***	9.20***	14.52***	23.63***	14.91***
Specification - 5	8.32**	4.25	1.26	0.33	1.44	29.35***	50.59***	4.22
Specification - 6	7.00**	2.83	0.24	0.65	0.25	6.96**	59.98***	7.86**
CZECH REPUBLIC								
Specification - 1	1.18	1.73	1.88	2.12	1.13	1.73	12.54***	14.53***
Specification - 2	3.35	2.54	0.54	1.59	1.36	0.39	1.53	1.74
Specification - 3	4.23	2.65	1.36	3.22	8.28**	8.08**	0.31	1.15
Specification - 4	7.49**	6.68**	4.30	10.06***	20.91***	12.32***	0.24	7.03**
Specification - 5	9.54***	7.36**	3.01	9.40***	4.89*	6.72**	15.44***	17.62***
Specification - 6	3.58	1.44	0.16	0.89	6.06**	6.77**	5.16*	1.35
GREECE								
Specification - 1	14.24***	26.61***	30.60***	50.20***	78.60***	123.85***	33.57***	36.42***
Specification - 2	3.70	8.24**	7.79**	9.48***	17.67***	30.91***	15.83***	43.64***
Specification - 3	2.01	4.76*	5.70*	10.01***	20.61***	26.08***	19.16***	25.56***
Specification - 4	6.21**	8.61***	7.49**	6.76**	18.24***	32.02***	23.64***	27.17***
Specification - 5	2.79	3.84	1.33	2.62	15.50***	19.96***	28.90***	18.39***
Specification - 6	1.72	1.19	0.80	3.92	16.68***	18.68***	17.99***	50.46***
HUNGARY								
Specification - 1	2.87	2.87	2.73	2.75	6.25**	8.13**	23.31***	27.18***
Specification - 2	2.38	3.48	11.66***	14.11***	9.92***	8.60***	2.72	2.04
Specification - 3	3.66	6.64**	10.90***	24.20***	15.60***	14.58***	13.25***	7.22**
Specification - 4	0.68	3.01	10.13***	9.92***	6.42**	5.38*	7.50**	20.23***
Specification - 5	4.80*	12.59***	12.32***	26.09***	10.84***	2.92	13.16***	15.12***
Specification - 6	2.65	2.07	8.37***	16.40***	10.66***	7.27**	13.70***	8.15**
POLAND								
Specification - 1	1.15	2.07	3.35	4.98*	6.76**	8.42***	8.48***	13.16***
Specification - 2	4.82*	13.76***	24.83***	25.86***	20.29***	13.34***	4.36	6.11**
Specification - 3	2.58	7.70**	15.02***	17.44***	15.04***	8.98***	0.14	5.73*
Specification - 4	2.91	5.66*	11.58***	6.47**	7.52**	12.31***	43.04***	27.61***
Specification - 5	5.52**	5.36*	7.65**	6.28**	3.38	7.40**	109.18***	9.26***
Specification - 6	1.01	2.73	6.49**	7.05**	6.84**	3.45	4.43	13.57***
ROMANIA								
Specification - 1	8.53***	11.16***	18.01***	25.55***	46.03***	58.02***	52.02***	48.17***
Specification - 2	17.18***	21.55***	35.29***	54.99***	63.37***	59.15***	83.60***	45.16***
Specification - 3	4.70*	6.43**	9.41***	30.39***	23.00***	16.15***	38.50***	27.84***
Specification - 4	13.61***	18.78***	22.26***	32.60***	47.95***	32.54***	66.83***	70.91***
Specification - 5	11.01***	22.22***	24.09***	38.80***	40.36***	22.36***	60.90***	26.62***
Specification - 6	5.12*	3.21	2.28	16.26***	4.71*	6.85**	47.33***	31.47***

Notes: See notes to Table A18.

Table A20: Mincer-Zarnowitz regressions for recursive forecasting exercise where factors are extracted using the PCA

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	8.31**	12.01***	17.36***	22.07***	26.46***	32.18***	117.43***	542.19***
Specification - 2	19.37***	23.03***	29.75***	36.98***	47.48***	65.77***	88.47***	111.84***
Specification - 3	18.30***	31.89***	40.82***	50.61***	62.59***	78.46***	93.77***	327.32***
Specification - 4	8.84***	11.30***	20.84***	56.49***	95.50***	135.97***	110.49***	266.19***
Specification - 5	1.88	7.21**	21.53***	49.98***	120.49***	193.55***	160.38***	195.90***
Specification - 6	30.76***	49.41***	66.49***	103.16***	122.76***	149.57***	119.28***	143.41***
CZECH REPUBLIC								
Specification - 1	1.11	1.66	3.09	6.07**	8.12**	10.55***	20.41***	136.39***
Specification - 2	2.51	4.78*	7.25**	15.22***	22.34***	31.17***	47.32***	340.31***
Specification - 3	4.20	4.92	9.18***	21.18***	49.37***	92.24***	102.71***	100.65***
Specification - 4	6.86**	17.41***	28.70***	46.86***	70.89***	91.29***	102.27***	461.52***
Specification - 5	8.31**	7.37**	11.76***	18.33***	33.70***	50.18***	105.44***	111.60***
Specification - 6	1.68	1.66	4.62*	17.88***	42.34***	79.10***	128.73***	133.47***
GREECE								
Specification - 1	4.16	5.91**	7.52**	15.33***	25.60***	50.33***	143.75***	264.27***
Specification - 2	0.23	0.25	0.67	1.10	6.34**	27.24***	155.90***	270.34***
Specification - 3	0.24	0.48	0.11	4.23	12.47***	23.00***	39.91***	77.21***
Specification - 4	1.28	1.25	6.02**	11.01***	18.52***	52.69***	226.36***	197.66***
Specification - 5	0.12	0.04	1.34	7.70**	21.23***	43.29***	79.32***	113.79***
Specification - 6	0.18	1.02	5.02*	17.14***	29.06***	47.63***	54.62***	83.94***
HUNGARY								
Specification - 1	1.35	5.63**	10.66***	17.45***	24.81***	32.75***	43.54***	76.69***
Specification - 2	0.49	0.77	2.30	5.56**	10.82***	18.57***	39.84***	322.46***
Specification - 3	9.04***	10.29***	14.98***	12.41***	15.48***	20.78***	26.61***	47.80***
Specification - 4	0.98	0.09	0.37	2.35	5.28*	11.36***	40.53***	109.45***
Specification - 5	5.04*	3.45	3.12	3.21	9.98***	20.44***	46.15***	101.02***
Specification - 6	5.30*	4.87*	9.28 ***	9.18***	13.62***	19.00***	16.60***	33.68***
POLAND								
Specification - 1	0.79	0.27	0.28	0.87	2.09	4.78*	23.05***	94.02***
Specification - 2	4.31	6.95**	13.50***	17.21***	24.66***	30.26***	44.38***	133.30***
Specification - 3	2.16	3.68	15.67***	29.05***	48.70***	55.30***	42.26***	87.22***
Specification - 4	13.39***	22.41***	36.66***	42.08***	58.12***	68.21***	95.44***	107.86***
Specification - 5	2.21	7.14**	17.72***	27.51***	53.13***	68.81***	163.02***	163.02
Specification - 6	3.90	2.36	5.45*	10.22***	20.98***	29.94***	45.72***	127.56***
ROMANIA								
Specification - 1	1.53	4.06	7.20**	10.98***	16.00***	22.54***	71.43***	160.00***
Specification - 2	3.88	7.22**	10.14***	16.32***	26.05***	41.60***	108.30***	159.73***
Specification - 3	3.03	3.68	8.54***	20.14***	44.70***	76.99***	147.05***	203.31***
Specification - 4	5.58*	9.83***	13.86***	23.92***	41.35***	51.79***	84.11***	259.10***
Specification - 5	2.12	2.85	5.34*	14.78***	33.85***	56.60***	102.60***	197.00***
Specification - 6	3.72	4.80*	8.21**	17.11***	41.50***	81.52***	151.63***	244.71***

Notes: See notes to Table A18.

Table A21: Mincer-Zarnowitz regressions for rolling forecasting exercise where factors are extracted using the PCA

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	2.03	2.43	3.50	11.24***	24.93***	37.07***	75.98***	324.45***
Specification - 2	16.49***	30.24***	34.20***	57.70***	96.75***	159.12***	187.02***	207.17***
Specification - 3	13.35***	31.09***	49.00***	100.16***	134.48***	167.31***	229.51***	433.34***
Specification - 4	5.35*	12.36***	19.01***	38.81***	62.22***	89.96***	107.26***	179.47***
Specification - 5	2.24	8.74***	24.09***	57.15***	132.74***	225.23***	224.73***	254.56***
Specification - 6	8.61***	16.95***	24.42***	53.85***	101.35***	151.75***	170.13***	270.25***
CZECH REPUBLIC								
Specification - 1	0.96	1.79	2.89	2.73	2.65	3.82	8.58***	60.36***
Specification - 2	10.31***	12.49***	19.86***	36.69***	41.28***	51.98***	62.32***	382.43***
Specification - 3	3.27	4.89*	7.78**	14.10***	21.90***	73.11***	102.01***	127.88***
Specification - 4	5.27*	12.26***	28.26***	51.15***	72.43***	87.41***	101.61***	185.82***
Specification - 5	13.23***	10.42***	23.74***	42.89***	33.40***	39.95***	113.55***	111.80***
Specification - 6	0.57	2.08	11.49***	23.09***	25.26***	55.06***	73.95***	88.50***
GREECE								
Specification - 1	1.57	5.41*	6.69**	12.24***	20.07***	44.35***	160.43***	299.14***
Specification - 2	0.52	0.40	1.04	3.76	11.74***	42.36***	119.73***	281.01***
Specification - 3	1.21	1.87	6.61**	19.82***	47.26***	70.35***	74.03***	84.04***
Specification - 4	0.85	4.20	8.76***	19.00***	30.35***	68.29***	129.17***	205.20***
Specification - 5	4.09	12.51***	18.28***	32.09***	57.99***	88.15***	193.23***	353.65***
Specification - 6	2.57	4.08	15.21***	44.70***	73.77***	98.24***	93.72***	99.56***
HUNGARY								
Specification - 1	6.69**	15.01***	18.55***	26.65***	33.49***	44.23***	43.99***	55.48***
Specification - 2	3.92	5.30*	7.05**	10.32***	16.98***	22.28***	28.25***	119.67***
Specification - 3	1.43	3.84	10.01***	17.25***	23.91***	24.28***	42.56***	37.03***
Specification - 4	7.78**	5.71*	6.93**	6.16**	13.44***	27.32***	76.13***	90.96***
Specification - 5	6.36**	7.83**	15.56***	22.29***	29.10***	37.00***	46.74***	100.29***
Specification - 6	4.91*	4.45	7.77**	11.59***	17.64***	22.32***	45.89***	71.07***
POLAND								
Specification - 1	3.07	2.69	3.91	9.70***	15.17***	21.40***	44.20***	92.61***
Specification - 2	2.16	7.14**	13.41***	16.33***	26.34***	38.13***	114.09***	233.45***
Specification - 3	2.39	14.66***	38.49***	37.42***	37.34***	38.66***	49.44***	114.66***
Specification - 4	4.02	11.25***	19.11***	14.54***	19.25***	28.70***	99.44***	130.38***
Specification - 5	3.86	18.37***	39.22***	25.94***	17.37***	21.65***	87.79***	119.27***
Specification - 6	6.54**	12.00***	20.72***	20.28***	28.91***	41.12***	79.62***	206.83***
ROMANIA								
Specification - 1	6.46**	9.91***	19.88***	32.79***	62.63***	93.47***	189.59***	215.47***
Specification - 2	8.84***	18.44***	32.96***	49.93***	76.52***	110.50***	176.48***	216.22***
Specification - 3	2.10	6.28**	13.36***	45.29***	77.38***	97.01***	151.52***	167.11***
Specification - 4	6.51**	18.82***	33.83***	56.34***	82.77***	77.36***	139.43***	159.02***
Specification - 5	3.26	8.18***	19.06***	52.20***	58.29***	58.22***	129.51***	172.54***
Specification - 6	4.34	12.13***	23.60***	59.81***	77.25***	98.14***	135.97***	148.13***

Notes: See notes to Table A18.

Table A22: Core Inflation: Rolling forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.312	0.498	0.657	0.795	0.908	1.057	1.511	2.159
Specification -1	1.022	0.969	0.887**	0.799***	0.745***	0.677***	0.526***	**0.375*****
Specification -2	1.029	0.924*	0.850**	**0.743*****	**0.690*****	0.612***	0.517***	0.382***
Specification -3	1.096	0.951	0.830**	0.748***	0.703***	**0.584*****	**0.462*****	0.468***
Specification -4	1.098	0.995	0.997	0.970	0.891	0.693***	0.495***	0.454***
Specification -5	1.179	1.018	0.920	0.888	0.878	0.741***	0.588***	0.555***
Specification -6	1.042	**0.898**	**0.825****	0.750***	0.691***	0.595***	0.464***	0.402***
CZECH REPUBLIC								
AR	0.224	0.340	0.425	0.499	0.565	0.627	0.775	0.893
Specification -1	1.339	1.332	1.075	**0.929**	**0.802*****	**0.702*****	0.619***	0.615***
Specification -2	1.187	1.181	1.106	1.069	0.895	0.751***	**0.613*****	**0.422*****
Specification -3	1.165	1.163	1.209	1.261	1.093	0.990	0.686**	0.470***
Specification -4	1.181	1.154	1.038	1.012	0.859**	0.842*	0.651**	0.569***
Specification -5	1.151	1.158	1.248	1.296	1.212	1.033	0.744*	0.598***
Specification -6	1.185	1.226	1.219	1.194	0.971	0.951	0.682**	0.511***
GREECE								
AR	0.594	0.729	0.829	0.869	1.001	1.107	1.741	2.261
Specification -1	0.884**	0.811	0.748**	0.713**	0.646***	0.541***	0.343***	**0.252*****
Specification -2	**0.765*****	**0.622****	**0.580*****	0.557***	**0.551*****	**0.471*****	**0.301*****	0.257***
Specification -3	0.829***	0.706**	0.651**	0.524***	0.567***	0.546***	0.389***	0.261***
Specification -4	0.803***	0.668**	0.631***	**0.514*****	0.599***	0.541***	0.344***	0.299***
Specification -5	0.858**	0.747*	0.679**	0.602***	0.644***	0.660**	0.348***	0.286***
Specification -6	0.813***	0.689**	0.615***	0.529***	0.639***	0.606***	0.321***	0.304***
HUNGARY								
AR	0.274	0.413	0.506	0.616	0.709	0.794	1.116	1.433
Specification -1	1.190	1.166	1.073	0.994	0.943	0.869	0.630**	0.538***
Specification -2	1.240	**0.994**	0.859	0.820	0.952	0.827	**0.549****	0.443***
Specification -3	1.194	1.060	0.891	0.843*	0.940	0.770	0.632**	0.366***
Specification -4	1.161	1.065	0.884	0.876	0.967	0.679**	0.635**	0.554***
Specification -5	1.191	1.072	0.936	0.826**	0.941	0.714*	0.823	0.415***
Specification -6	1.176	1.072	**0.852***	**0.809*****	**0.871**	**0.651****	0.569**	**0.355*****
POLAND								
AR	0.256	0.387	0.495	0.595	0.688	0.755	0.939	1.096
Specification -1	1.041	0.990	0.840**	0.777***	0.732***	0.683***	0.599***	0.545***
Specification -2	0.919	0.844***	**0.664*****	**0.568*****	**0.494*****	**0.517*****	0.438***	**0.426*****
Specification -3	0.866**	0.817***	0.708***	0.625***	0.564***	0.582***	0.591***	0.470***
Specification -4	0.920	0.879**	0.724***	0.609***	0.536***	0.597***	**0.428*****	0.426***
Specification -5	0.899**	0.868**	0.789***	0.669***	0.605***	0.707***	0.562***	0.501***
Specification -6	**0.836*****	**0.790*****	0.736***	0.628***	0.547***	0.570***	0.502***	0.430***
ROMANIA								
AR	0.321	0.467	0.640	0.824	0.973	1.096	1.386	1.595
Specification -1	1.128	1.192	1.153	1.141	1.118	1.078	1.013	0.837*
Specification -2	1.092	1.120	1.032	1.025	0.997	0.910	**0.759****	0.643***
Specification -3	1.188	1.190	1.031	0.889	0.994	1.130	0.849	0.504***
Specification -4	1.083	1.077	1.065	1.013	0.937	**0.834**	1.015	1.020
Specification -5	1.172	1.152	**0.941**	**0.768****	**0.893**	0.953	0.856	0.545***
Specification -6	1.276	1.268	0.963	0.825**	0.924	1.021	0.761*	**0.495*****

Notes: See notes to Table A5.

Table A23: MSFEs based on the use of different dimension-reduction and shrinkage methods - Rolling forecasting

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.429	0.770	1.015	1.257	1.489	1.719	2.576	3.585
MSFE Best w/o shrinkage	1.071	**0.911**	0.731***	0.628***	**0.582*****	0.596***	0.605**	**0.395*****
GPR	1.050	0.954	**0.714*****	**0.604*****	0.590***	**0.585*****	**0.564****	0.447**
VBDVS	1.057	0.951	0.765***	0.840***	0.755***	0.725***	0.608***	0.550***
ENET	5.068	2.779	1.954	1.355	0.972	0.904	0.622**	0.406***
LASSO	5.029	2.796	1.924	1.350	0.973	0.886	0.630**	0.397***
CZECH REPUBLIC								
AR	0.348	0.497	0.638	0.770	0.875	0.981	1.252	1.586
MSFE Best w/o shrinkage	1.049	**0.984**	0.917	0.861*	0.780**	0.667***	0.505***	**0.385*****
GPR	1.041	1.014	**0.914**	**0.813****	**0.731****	**0.603*****	**0.478*****	0.398***
VBDVS	**0.963**	0.992	0.989	0.899	0.881	0.791**	0.784*	0.686*
ENET	1.376	1.113	1.030	0.946	0.837**	0.757**	0.597**	0.453***
LASSO	1.390	1.110	1.054	0.951	0.851**	0.763**	0.596**	0.456**
GREECE								
AR	0.523	0.680	0.809	0.939	1.125	1.334	2.204	3.107
MSFE Best w/o shrinkage	0.903***	0.854*	0.776***	**0.674*****	**0.587*****	**0.489****	0.287**	0.207**
GPR	**0.902*****	**0.841****	**0.773*****	0.681***	0.608***	0.512**	**0.265****	**0.199****
VBDVS	1.007	0.901**	0.911**	0.845*	0.747**	0.709*	0.477**	0.416**
ENET	1.891	1.295	1.227	1.219	1.064	0.830	0.356**	0.273**
LASSO	1.850	1.285	1.206	1.251	1.087	0.848	0.371**	0.277**
HUNGARY								
AR	0.473	0.745	0.976	1.220	1.434	1.656	2.280	2.916
MSFE Best w/o shrinkage	1.006	0.913	**0.839***	0.820	0.738*	**0.619****	0.366**	0.360**
GPR	**0.964**	**0.909**	0.846*	**0.793***	**0.722***	0.623**	**0.345****	**0.359****
VBDVS	1.089	0.954	0.952	0.893	0.862	0.792*	0.560**	0.507**
ENET	1.811	1.070	1.501	1.222	1.044	0.896	0.690	0.409**
LASSO	1.787	1.080	1.502	1.228	1.052	0.905	0.693	0.407**
POLAND								
AR	0.308	0.508	0.705	0.881	1.063	1.202	1.586	2.023
MSFE Best w/o shrinkage	**0.856****	**0.813*****	**0.779*****	**0.721*****	0.640***	0.497***	0.362***	0.336***
GPR	0.867**	0.857**	0.781***	0.744***	**0.633*****	**0.496*****	**0.358*****	**0.319*****
VBDVS	0.997	0.897**	0.907**	0.819***	0.757***	0.726***	0.818*	0.524**
ENET	1.739	1.135	1.174	1.015	0.892	0.755**	0.591**	0.447***
LASSO	1.741	1.150	1.156	1.012	0.904	0.751**	0.601**	0.445***
ROMANIA								
AR	0.636	0.966	1.307	1.540	1.780	2.010	2.895	3.900
MSFE Best w/o shrinkage	1.074	1.009	0.874	0.730***	**0.617*****	0.634***	0.695**	**0.460*****
GPR	1.074	**0.988**	**0.859****	**0.805****	0.733***	**0.595*****	0.679**	0.517***
VBDVS	1.025	1.008	0.888***	0.906*	0.843**	0.823*	**0.596*****	0.686**
ENET	3.332	2.115	1.508	1.083	0.852*	0.861	0.759	0.562***
LASSO	3.282	2.139	1.528	1.104	0.834*	0.872	0.778	0.561***

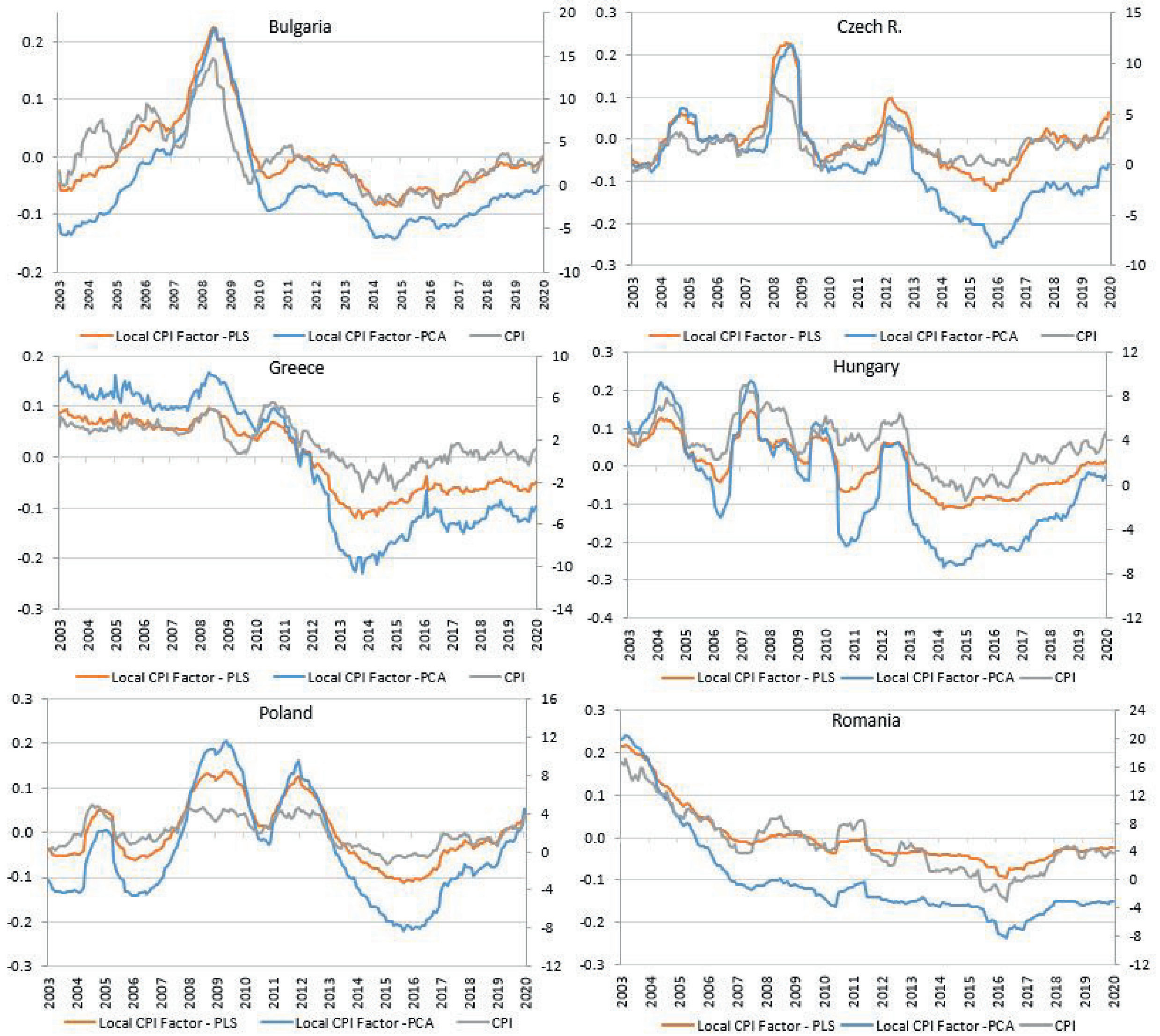
Notes: See notes to Table 1.5.

Table A24: Variables definitions and data sources - Panel regression

Variables	Definition	Source
Current Account Balance	Current Account Balance / GDP	Bloomberg
Budget Balance	Budget Balance / GDP	Bloomberg
Households Cons.	Household consumption /GDP	Bloomberg
Unemployment Rate	Unemployment rate	Bloomberg
Real GDP Growth	Real GDP Growth year over year	Bloomberg
CDS	5-Year Credit Default Swaps	Bloomberg
Exports	Total exports / GDP	Bloomberg
Imports	Total imports / GDP	Bloomberg
Uncertainty	Country specific uncertainty Index	St Louis FRED
REER	Real effective exchange rate	BIS
FX Reserves	FX Reserve / GDP	IMF

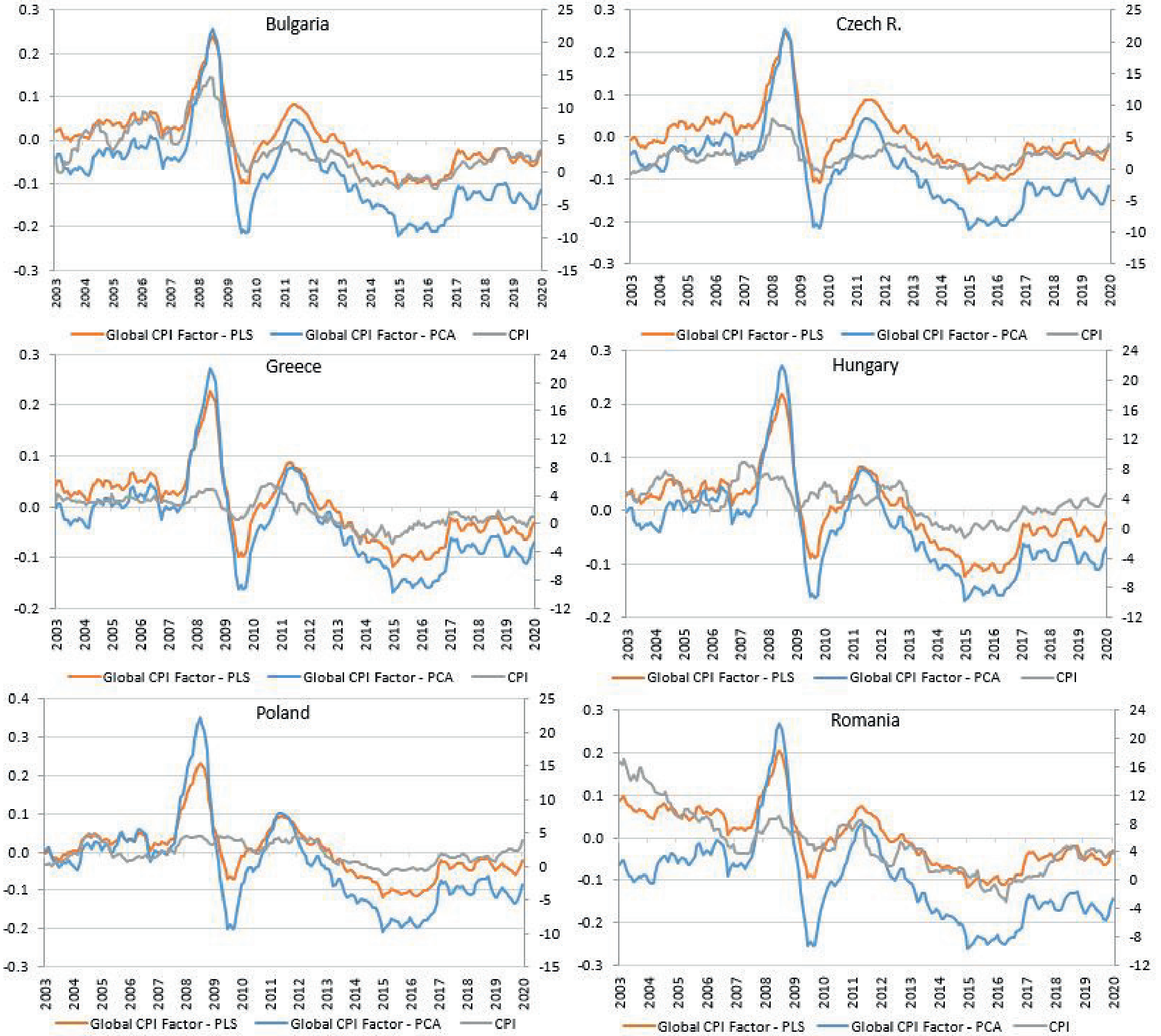
Notes: Uncertainty index determines uncertainty using the frequency of the selfsame word in the quarterly Economist Intelligence Unit country reports. Real effective exchange rates are calculated as weighted averages of bilateral exchange rates adjusted by relative consumer prices.

Figure A1: Time series evolution of Local CPI factors along with headline inflation rates



Notes: This figure shows the time series plots of first Local CPI factors along with headline inflation rate of corresponding EM European country, where factors are obtained from using the PLS and PCA factor extraction methods.

Figure A2: Time series evolution of Global CPI factors along with headline inflation rates



Notes: This figure shows the time series plots of first Global CPI factors along with headline inflation rate of corresponding EM European country, where factors are obtained from using the PLS and PCA factor extraction methods.

Appendix B: TVP-VAR-Based Dynamic Connectedness Approach

To construct inflation connectedness measures, we run the following TVP-VAR model:

$$x_t = D_t x_{t-1} + u_t \qquad e_t, \sim N(0, S_t) \tag{1.22}$$

$$vec(D_t) = vec(D_{t-1}) + v_t, \qquad u_t \sim N(0, R_t) \tag{1.23}$$

where x_t, x_{t-1} and e_t are $k \times 1$ dimensional vector and D_t and S_t are $k \times k$ dimensional matrices. $vec(D_t)$ and u_t are $k^2 \times 1$ dimensional vectors whereas R_t is a $k^2 \times k^2$ dimensional matrix.[30] Then, we first transform the TVP-VAR to its vector moving average (VMA) representation using the following equation: $x_t = \sum_{i=1}^{p} D_{it} x_{t-i} + e_t = \sum_{j=0}^{\infty} A_{jt} e_{t-j}$. Secondly, we compute the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD). Hence, $\tilde{\phi}^g_{ij,t}(H)$ represents the influence country j inflation rate has on the inflation rate of country i with regard to its forecast error variance share which can be defined as:

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\iota'_i A_t S_t \iota_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\iota_i A_t S_t A'_t \iota_i)}, \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k} \phi^g_{ij,t}(H)}$$

where $\sum_{j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = k$, and ι_i corresponds to a selection vector with unity on the ith position and zero otherwise. Then, we compute the total connectedness index (TCI) through the use of the GFEVD as follows:

$$TO_{jt} = \sum_{i=1, i \neq j}^{k} \tilde{\phi}^g_{ij,t}(H) \tag{1.24}$$

$$FROM_{jt} = \sum_{i=1, i \neq j}^{k} \tilde{\phi}^g_{ji,t}(H) \tag{1.25}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{1.26}$$

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt}. \tag{1.27}$$

$$NPDC_{ij,t} = \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H) \tag{1.28}$$

where $\tilde{\phi}^g_{ij,t}(H)$ represents the impact a shock in inflation rate of country j has on the country i 's inflation. Eq. (1.24) illustrates the aggregated impact a shock in a country inflation rate j has on all *other* countries inflation rates which is defined as *total directional connectedness to others*. Eq. (1.25) indicates the aggregated influence all *other* countries have on country j (*total directional connectedness from others*). Eq. (1.26) subtracts the impact of country

[30] The optimal 1-lag length is selected by the Bayesian information criterion (BIC).

j has on others from the influences of *others* have on country j, resulting in the *net total directional connectedness* which provides information whether a country is a net transmitter or a net receiver of shocks. Country j is a net transmitter (*receiver*) of inflation shocks - and hence driving (*driven by*) the network - when the impact of a country j has on others is larger (*smaller*) than the influence all others have on country j, $NET_{jt} > 0$ ($NET_{jt} < 0$). Eq. (1.27) shows the TCI_t that is the average impact one country has on all *others*. Higher values of this measure implies a higher inter-connectedness of the network, suggesting that a inflation shock in one country will influence other countries. Finally, Eq. (1.28) defines *net pairwise directional connectedness ($NPDC_{ij,t}$)* which indicates whether a shock to country j inflation is driving country i domestic inflation rate or vice versa.

Chapter 2

Geography of Housing Sentiment over Business Cycles

Oguzhan Cepni & Natalia Khorunzhina

Abstract

We construct state-level housing-sentiment indices using regional variations in consumer attitudes and expectations about home-buying conditions. Our state-level housing-sentiment index is a stronger predictor of future state-level house-price growth than a range of key state-level housing-market determinants and is a stronger and more accurate predictor than the national housing-sentiment index. We find housing sentiment has a greater effect on house-price growth during recessions, high economic-policy uncertainty, bubble periods, and in states with greater activity of speculative investors, higher foreclosure rates, and inelastic housing supply.

2.1 Introduction

Within the same country, house prices vary considerably between regions. The differences in local house prices can be attributed to differences in local productivity, labor income levels, regional policies, regulatory constraints, and geographical environment and barriers. Moreover, regional differences in house prices continue expanding. Van Nieuwerburgh and Weill, 2010 document a steep rise in the dispersion of house prices across regions, manifested in an almost four-fold increase in the cross-sectional coefficient of variation in regional house prices between 1975 and 2007. The recent evidence in Tang et al., 2020 suggests the rising trend in the dispersion of the regional house prices persists further. On the one hand, heterogeneous growth in fundamental regional factors, such as the dispersion of regional productivity shocks and labor income, coupled with the rigidity of tightly regulated local housing supply, help explain the dispersion in regional house prices (Van Nieuwerburgh and Weill, 2010). On the other hand, the evidence in Kuchler and Zafar, 2019 suggests past experiences of local house-price movements can generate diverse expectations about future changes in house prices, which themselves can further drive the dispersion in regional house prices (Case et al., 2012). Whereas people's beliefs and opinions are shown to be a strong predictor of future house prices at the national level (Bork et al., 2020; Case et al., 2012), the rising dispersion in regional house prices makes the national-level forecast less relevant for predicting the diverse movements in local house prices.

In this paper, we construct state-level housing-sentiment indices using consumer attitudes and expectations about home-buying conditions from the Survey of Consumers of the University of Michigan. We exploit the regional identifier of the survey, which allows for extracting regional variation in sentiment composition. Using partial least squares (PLS), we construct state-level housing-sentiment indices by linking the regional variation in sentiment composition with the target variable of the state-level house-price growth. A basic analysis of the importance of the particular sentiments in the state-level housing-sentiment index supports the diversity in opinions and beliefs about local housing markets in a cross section of the states and over business-cycle phases. For example, whereas large weights are put on survey questions related to unfavorable buying conditions in North Dakota and Vermont, beliefs about favorable buying conditions receive higher weights in Utah and Colorado. Further analysis of the importance of specific sentiments in high- and low-sentiment periods reveals different sentiments are prevalent in these periods. Households have a positive outlook on the housing market during times of high sentiment, because they expect house prices will continue to increase, and consider real estate a good investment. However, households are pessimistic and choose the survey question "times are bad/can't afford to buy" most frequently in low-sentiment periods. In general, households seemingly pay more attention to the level of prices than borrowing conditions when forming their sentiment related to house-buying conditions.

Similar to the relationship between the housing-sentiment index and house-price dynamics at the national level (Bork et al., 2020), our state-level housing-sentiment index has more power to explain future state-level house-price growth than the macroeconomic variables that are commonly used to forecast changes in house prices. An in-sample forecast regression conducted with quarterly observations of the Federal Housing Finance Agency's all-transactions state-level house-price index from 1999:Q2 to 2021:Q1 shows the local housing-sentiment index yields an R^2 of 37%. The second-highest R^2 is 27% for the state-level building permits, whereas other typical house-price predictors such as income, employment, mortgage rate, and the index of economic activity yield R^2 values between only 1% and 5%. In bi-variate regressions with state-level housing sentiment and an additional housing-market predictor, we detect only minor increases in R^2 when incorporating macroeconomic indicators of house prices into a regression model that already includes state-level housing sentiment, which can indicate state-level housing sentiment captures some of the information contained in economic fundamentals.

Furthermore, we explore the relative importance of local and national housing-sentiment indices in predicting local house-price growth. Despite national housing sentiment being a powerful predictor of house-price growth at the state level (as shown in Bork et al., 2020), the coefficient of the orthogonalized state-level sentiment with respect to national-level sentiment still remains significant, underscoring the significance of considering sentiment variations at the state level in predictive analyses of the housing market. On average, a one-standard-deviation rise in the state-level housing sentiment is linked to a 0.40% growth in state house prices at the one-quarter horizon.

Understanding the relationship between housing market sentiment and future house prices is crucial for policymakers to formulate effective interventions during business cycles (Jordà et al., 2016). For instance, positive sentiment during an upswing might prompt regulators to implement measures to prevent overheating and excessive lending. On the other hand, during a downturn, policymakers can assess the depth of negative sentiment and implement targeted stimulus packages to revive the market. Investigating this connection aids in crafting timely and appropriate policies to support sustainable growth and prevent financial crises. In this regard, using variation in the timing of state-specific recessionary periods, obtained from a Zillow Research report (Tucker, 2019), we find the relationship between sentiment and future house-price growth is amplified in economic downturns. For the forecast horizon of two to three quarters ahead, on average, a one-standard-deviation decrease in the housing sentiment predicts an almost two-times-larger decrease in house prices in recessions than in non-recessionary periods, whereas the results for one- and four-period forecast horizons are only marginally significant or inconclusive. For the special case of the COVID-19 recession, our findings are mixed and depend on the forecast horizon, likely reflecting pandemic-related volatility in house prices and the short period for the COVID-19 recession captured in our data. For a short forecast horizon, lowered sentiment during the COVID-19 pandemic predicts an increase in house prices, capturing the pandemic-related volatility in house prices, whereas for longer horizons, the prediction of sentiment on future house prices is in line with the results for other recessions: a decrease in sentiment predicts a large decrease in house prices during the recessions relative to non-recessionary periods.

We test further the predictive relationship between housing sentiment and subsequent changes in house prices in states experiencing greater financial distress, that is, more short sales, foreclosure sales, and a higher rate of deed in lieu of foreclosure. To do so, we use the information on subprime adjustable-rate mortgage-loan foreclosures, and divide the states into two groups according to their share of foreclosure sales in total housing sales. As an alternative measure of distressed home sales, we use information from CoreLogic on the share of existing home sales that are distressed. We find the relation between future house-price growth and housing sentiment is stronger in states that are experiencing greater financial distress, that is, have a higher fraction of foreclosures or a higher share of home sales under the distressed sale conditions (short-sales and deeds in lieu).

The general consensus is that the Great Recession of 2007-2009 was triggered by the mortgage-default crisis arising from the bursting of the housing bubble. The geographic variation in the factors responsible for the formation of the housing bubble suggests substantial differences in the starting period and the duration of the housing bubbles over states. We empirically identify regional housing bubbles by utilizing a recursive unit root test proposed in Phillips et al., 2015 and examine whether the forecasting ability of the housing sentiment for fluctuations in house prices can differ over the bubble and non-bubble periods. We find the housing sentiment predicts generally larger future housing returns during bubble periods than during non-bubble periods, and is almost twice as large when we control for other macroeconomic housing-market determinants.

We find housing returns are predicted to be lower during the recessionary periods in the states with greater speculative activity. Further, we test the predictive power of sentiment in states with high levels of housing speculation, focusing on recessionary episodes in these states, and find some evidence for a stronger relationship between housing sentiment and the subsequent changes in the house prices during the recessionary periods in the states with greater speculative activity. Overall, we show housing sentiment has a greater effect on house prices in the states with more speculative activity. This finding agrees with the study of Soo, 2018, who documents the impact of news sentiment on housing returns is larger in cities experiencing greater housing speculative activity. Relatedly, Møller et al., 2023 show the ability of the housing search index to forecast changes in the house-price movements is positively linked to speculative activity.

Our additional findings are related to the heterogeneity across the states in housing-supply elasticity and economic-policy uncertainty (EPU) and its effect on the predictive ability of housing sentiment for future house-price movements. We examine the extent to which the housing-sentiment index impacts house prices in states with a limited housing supply elasticity. To do so, we use the measure of land-supply elasticity constructed in Saiz, 2010 based on a combination of natural land constraints and the intensity of local growth-control policies, aggregated to the state level by Chetty et al., 2017. We divide the states into groups with high and low housing-supply elasticity, and find the housing-sentiment index has a stronger predictive ability for house prices in the states where the housing supply is less elastic. On average, a one-standard-deviation increase in the housing sentiment predicts a two-times-larger increase in house prices in less elastic states than in more elastic ones. Given that the demand for housing is often largely driven by the sentiments (Case and Shiller, 2003), our finding is in line with the results in Møller et al., 2023 that house prices are more strongly influenced by changes in local housing demand in metropolitan areas with more constrained supply of housing. Finally, recognizing that each state has its own vision about how to define the economic and administrative environment via various state policies, EPU might vary substantially across states. Therefore, examining how the forecasting ability of housing sentiment for future state-level house prices changes with EPU is interesting. Using the state-level measure of economic and policy-related uncertainty of Baker et al., 2022, we find the predictive power of sentiment on subsequent changes in house prices is higher in the states with a higher index of economic and policy-related uncertainty, indicating the high uncertainty amplifies the impact of sentiment on future house prices.

Our findings that sentiment predicts larger changes in house prices during housing busts and recessions than in non-recessionary periods are in line with the psychological literature that reports people's reactions to news are sharper during times of anxiety and fear (Smith and Ellsworth, 1985; Tiedens and Linton, 2001; Gino et al., 2009). Overall, we contribute to the literature studying the role of market sentiment, often driven by news content, in moving the market prices. Berardi, 2021 shows the effect of sentiment on asset returns can be amplified through uncertainty, because investors can be particularly pessimistic about something they do not know for sure. Relatedly, Garcıa, 2013 argues investors' sensitivity to news is most pronounced during recessionary periods. Garcıa, 2013 finds the link between media content, as a proxy for sentiment, and stock returns is stronger during recessions: sentiment predicts larger changes in the stock market index in recessions than in expansions. We find house prices are predicted to be significantly lower during recessions when the sentiment is lower, suggesting the finding of Garcıa, 2013 on the link between sentiment and the stock market index being stronger in recessions is also valid for the housing markets. In housing markets, sentiment about home-buying conditions is instrumental in forming house-price expectations, which consumers act upon when trading homes. Chauvet et al., 2016 points out negative sentiments were prevalent in the US housing market during the recession of 2007-2009. This recession was preceded by a remarkable increase in house prices, when abundant liquidity and the belief that housing-price growth would continue to escalate led to an unprecedented rise in the purchasing of non-owner-occupied homes (Haughwout et al., 2011; Chinco and Mayer, 2016; Badarinza and Ramadorai, 2018; Nathanson and Zwick, 2018; Garcıa, 2022). Gao et al., 2020 find higher speculative activity during a housing boom, driven by the extrapolative expectations of past housing price increases, can cause a more substantial decrease in home values and a more severe economic downturn during the following housing-market crash. Our finding that during the recession periods housing returns are predicted to be lower in the states with greater speculative activity confirms the geographically nuanced ZIP-code results in Gao et al., 2020 for the aggregate state-level data considered in this article.

Our paper enriches the relatively new but growing literature on constructing and using indices of consumers' attention for the prediction of local house-price growth. Møller et al., 2023 build a housing search index measuring online queries for specific keywords relevant to the home-buying process, and use it to study the importance of housing search activity for predicting house prices across Metropolitan Statistical Areas (MSA). By conducting a textual analysis of the qualitative tone in local newspaper articles, Soo, 2018 creates a media-sentiment index to study its predictive power for future house prices in selected cities across the US. Zhu et al., 2022 build sentiment indices for cities in China by utilizing semantic results obtained by language-processing techniques. Unlike these articles focusing on city-level housing markets, we construct a housing-sentiment index at the state level and use it to study heterogeneity in the predictive ability of housing sentiment across the US states. That is, one of the novelties of this paper is in presenting a new intermediate geographical dissection (between national and city levels) in the predictive ability of the housing sentiment for future house-price movements. Furthermore, Google search-query data, used in Møller et al., 2023, are only available since 2004 (see also Chauvet et al., 2016) and are limited for studying the predictive ability of consumers' attention toward house-price growth over the business cycles. By contrast, our state-level housing-sentiment indices are estimated consistently over a longer period of time. The longer data series allows for investigating the explanatory power of housing sentiment on future house prices over business-cycle phases and during boom and bust periods, which constitutes another novel information reported in this study.

One significant aspect of our research is the focus on the state level in constructing the housing sentiment index, as opposed to MSA or city-level indices, which enable us to capture a broader representation of housing sentiment while still acknowledging and incorporating regional heterogeneities. Firstly, the construction of a state-level housing sentiment index presents a more holistic view of housing market sentiment. MSAs are typically comprised of a central city and its surrounding, tightly linked suburban counties. While this granularity provides detailed insights into urban housing markets, it may overlook sentiments in rural or less densely populated regions that are not included in the MSA. Secondly, state-level measures are often more suitable for policy analysis. Most housing policies are determined at the state level. Therefore, measuring housing sentiment at the same level allows us to more directly associate policy impacts with sentiment shifts. It also enables us to better understand how varying state-level regulations and policies contribute to differences in housing sentiment. Thirdly, most key macroeconomic and housing-related variables, such as employment levels, income, housing supply indicators, mortgage rates, and broader economic activity, are commonly reported and reliably maintained at the state level. As a result, state-level indices allow for more robust controls and a more thorough and nuanced examination of the various factors driving housing prices[1]. This, in turn, strengthens the analytical rigor and validity of our study.

The rest of the paper is organized as follows. Section 2 describes the construction of the state-level housing-sentiment indices. Section 3 compares the explanatory power of the state-level housing sentiment for changes in house prices with that of the standard housing-market determinants. Section 4 examines heterogeneity in the predictive power of the housing-sentiment index on future house-price growth over business cycle phases and across the state characteristics that can magnify the strength of business-cycles. Section 5 conducts a range of robustness checks to validate the study's findings further. Finally, Section 6 concludes.

2.2 State-Level Housing Sentiment Index

2.2.1 Survey Data

To construct a state-level housing-sentiment index, we use questions about consumer attitudes and expectations from the Survey of Consumers of the University of Michigan. The sample of 500 consumers for the surveys is designed to be representative of the households in the US, excluding those living in Alaska and Hawaii. The survey covers various areas of consumer sentiment and include questions appraising present housing market conditions. In particular, Table 41 of the survey summarizes the responses to the question, "Generally speaking, do you think now is a good or bad time to buy a house?" Respondents choose

[1]Edelstein and Tsang, 2007 show that housing fundamentals, such as employment growth and interest rates, play a crucial role in determining the cycles of the residential real estate market.

one of three options: “yes,” “no,” or “do not know.” Then, the follow-up question “Why do you say so?” invites the respondents to provide their reasoning. The following reasons for opinions about house-buying conditions are summarized in Table 42 of the surveys:

1. Bad time to buy: prices are high
2. Bad time to buy: interest rates are high/credit is tight
3. Bad time to buy: times are bad/can’t afford to buy
4. Bad time to buy: bad times ahead/uncertain future
5. Bad time to buy: bad investment
6. Good time to buy: prices are low/good buys available
7. Good time to buy : prices will not come down/are going higher
8. Good time to buy: interest rates are low
9. Good time to buy: borrow in advance of rising interest rates
10. Good time to buy: times are good/prosperity
11. Good time to buy: good investment

We form the housing-sentiment index by focusing on the responses to this follow-up question, because we aim at extracting information about household beliefs for housing-market dynamics. The survey has a regional identifier, which allows for variation in sentiment composition at the level of four regions: Northeast, Midwest, South and West. Our data are quarterly and covers the period 1999:Q2 - 2021:Q1, where the sample starting date is determined by the availability of the state-level data.

2.2.2 Housing and Economic Data

We collect quarterly house-price indices for the US states constructed by the US Federal Housing Finance Agency (FHFA), which is a weighted, repeat-sales index based on transactions involving single-family homes.

Additionally, we collect variables commonly used to elucidate house-price fluctuations: building permits, mortgage rate, stock index, employment, income, and economic activity index. We use state-level building permits from the US Census Bureau as a proxy for changes in housing supply. We also use the employment levels by state from the Bureau of Labor Statistics (BLS) to control for the local labor market factors that can determine the demand for homes (Rosen and Smith, 1983; Mankiw and Weil, 1989; Nakajima et al., 2011). The

Table 2.1: Summary statistics of housing sentiment and macroeconomic data

Variable	Transformation	Obs	Mean	Std. Dev.	Min	Max	Corr
House-price index	Log difference	4,400	0.004	0.007	-0.046	0.052	0.58
Building permits	Log level	4,400	7.682	1.306	2.079	11.07	0.37
Mortgage rate	Difference	4,350	-0.050	0.261	-1.180	0.740	0.17
Stock index	Log difference	4,400	0.026	0.101	-0.719	0.621	0.05
Employment	Log level	4,400	4.122	0.077	3.826	4.292	0.18
Leading index	Log difference	4,400	0.492	2.782	-53.82	28.79	0.14
Per-capita income	Log difference	4,350	0.035	0.027	-0.105	0.144	0.10
Housing-sentiment index	Level	4,400	0.000	0.107	-0.225	0.161	1.00

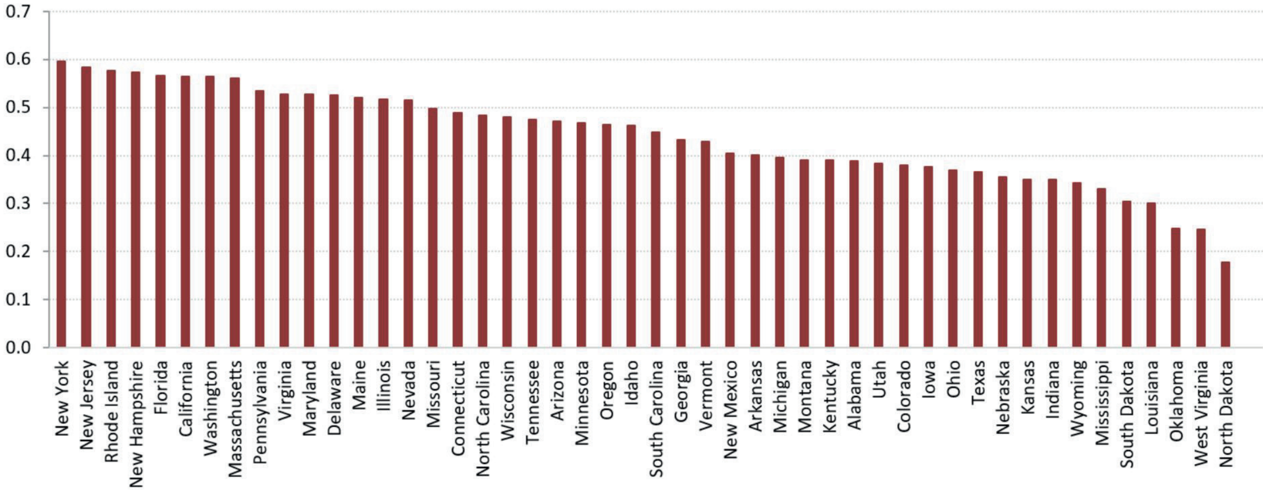
Notes: The table below displays the summary statistics of the macroeconomic control variables and housing-sentiment index. The number of observations, mean, standard deviation, and minimum and maximum value are included for each variable. "Corr" represents the pairwise correlation coefficient with the housing-sentiment index. The column name with transformation shows how the variables are made stationary if needed.

spatial-equilibrium model of Rosen and Smith, 1983 shows personal income is a powerful housing-demand shifter; therefore, we include the state-level per-capita income from the Bureau of Economic Analysis (BEA) into our analysis. Several studies highlight that low borrowing rates lead to a rise in the demand for housing and a subsequent increase in house prices (Himmelberg et al., 2005; Gelain et al., 2018), which motivates us to collect the state-level 30-year conventional mortgage rate to control for the borrowing conditions and the interest rate fluctuations. To capture the heterogeneous economic-activity conditions, we use Philadelphia Fed's State leading index. This index is based on the VAR model, which includes the interest-rate spread between the 3-month Treasury bill and 10-year Treasury bond, the Institute for Supply Management (ISM) manufacturing survey data, and the insurance claims (Crone and Clayton-Matthews, 2005). Finally, Shiller, 2015 notes stock market booms are more likely to coincide with booms in the housing market; therefore, we use the Bloomberg state-level stock index computed as the capitalization-weighted index consisting of equities domiciled in a given state. Table 2.1 denotes summary statistics for the macroeconomic variables and house-price index, described above.

2.2.3 Construction of the State-Level Housing-Sentiment Index

We implement a partial least squares (PLS) approach to summarize the information in the responses to 11 survey questions in a state-level housing-sentiment index and filter out the idiosyncratic noise that is less relevant for the dynamics of the housing returns and common components (Kelly and Pruitt, 2013; Kelly and Pruitt, 2015; Huang et al., 2015; Bork et al., 2020). In doing so, we extract the latent common component that summarizes the most important information in the regional survey responses by directly exploiting the covariance between the common component and a target variable. Our target variable is the state-level house-price growth, computed from the FHFA house-price index.

Figure 2.1: Explanatory power of housing sentiment for house-prices growth across US states



Notes: This figure displays the R^2 values from the regressions of state-level house-prices growth on the estimated state-level housing-sentiment index.

To build the state-level housing-sentiment index, we utilize the SIMPLS algorithm developed by De Jong, 1993. The estimated housing-sentiment index is a linear combination of the 11 survey responses, which maximizes the covariance with the house-price changes. In particular, the state-level housing-sentiment index at time t is computed by $S_{it} = s_{rt}w_i$, where s_{rt} is a vector of survey responses capturing the sentiment at time t in region r, where state i is located. The vector of weights w_i for state i is computed as

$$w_i = \arg\max \quad w_i' s_{rt} h_{it} h_{it} s_{rt}' w_i \tag{2.1}$$

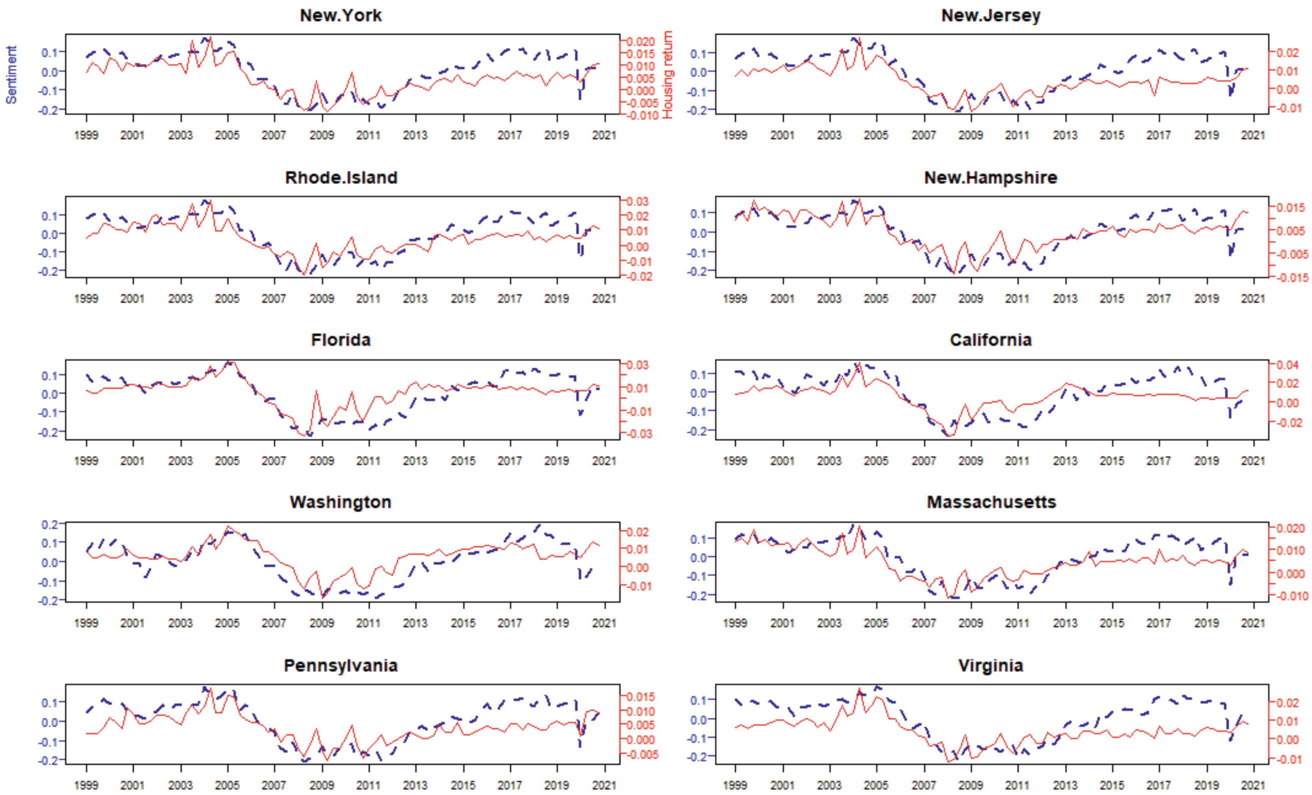
subject to $w_i' w_i = 1$, and h_{it} denotes the house-price growth for state i in period t.[2]

Table 2.1 presents descriptive statistics for the state-level housing-sentiment index. Figure 2.1 displays the R^2 values from the regressions of state-level house-price changes on the estimated state-level housing-sentiment index. The explanatory power of the housing-sentiment index ranges between 0.18 and 0.60 across states, implying the regional house-price dynamics are highly heterogeneous. Figures 2.2-2.3 present time series of the FHFA house-price changes and housing sentiment for the top and bottom 10 states, where housing-sentiment has the highest and lowest explanatory power, respectively. These figures show housing-sentiment indices and house-price growth have a strong co-movement over time. The housing-sentiment index accurately captures turning points around the house-price decline of 2009-2010 following the collapse of the mortgage market and around the subsequent recovery and steady house-price increase in recent years. Although many macroeconomic

[2]We recognize the limitation imposed by using survey data at the regional level to generate state-level sentiment indices. Indeed, the usage of regional survey data to form state-level indices assumes that states within each region share certain characteristics in terms of sentiment towards the housing market. While this assumption presents a limitation, it is important to note that our approach still enables us to capture a significant level of variation across states, as the weights in the PLS index are state-specific.

indicators declined during the COVID-19 pandemic, house prices have risen due to the low-interest-rate environment and supply-chain disruptions, resulting in higher costs of construction materials. After the post-pandemic period, housing-sentiment indices display an upward trend and remain high, reflecting the housing-market dynamics relatively well.

Figure 2.2: Housing-sentiment index and house-price changes for the top 10 states with highest R^2 values

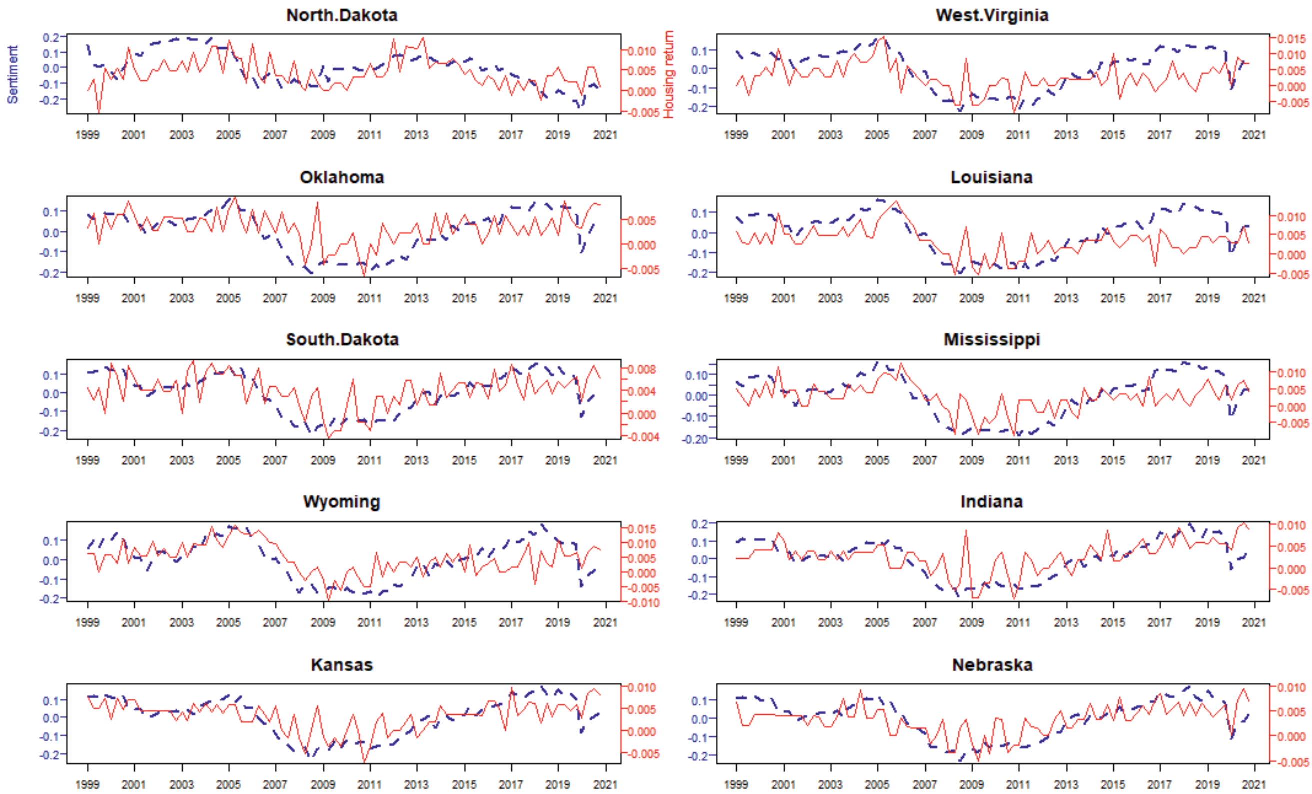


Notes: This figure plots the house-price changes and the housing-sentiment index for the top 10 states where housing sentiment has the lowest explanatory power.

2.2.4 Sentiment Decomposition

We examine PLS weights assigned to the sentiment variables to obtain insights into the importance of different survey questions used in the construction of state-level housing-sentiment indices. To investigate the differences across state-level housing-sentiment indices, we present the absolute value of the PLS weights for each of 11 survey questions in Figure 2.4. The figure shows a significant variation in PLS weights, confirming diversity in opinions and beliefs about local housing markets. For instance, whereas PLS puts large weights on survey questions related to unfavorable buying conditions (questions under the label "bad time to buy") in North Dakota and Vermont, we observe higher weights on series capturing

Figure 2.3: Housing-sentiment index and house-price changes for the bottom 10 states with lowest R^2 values



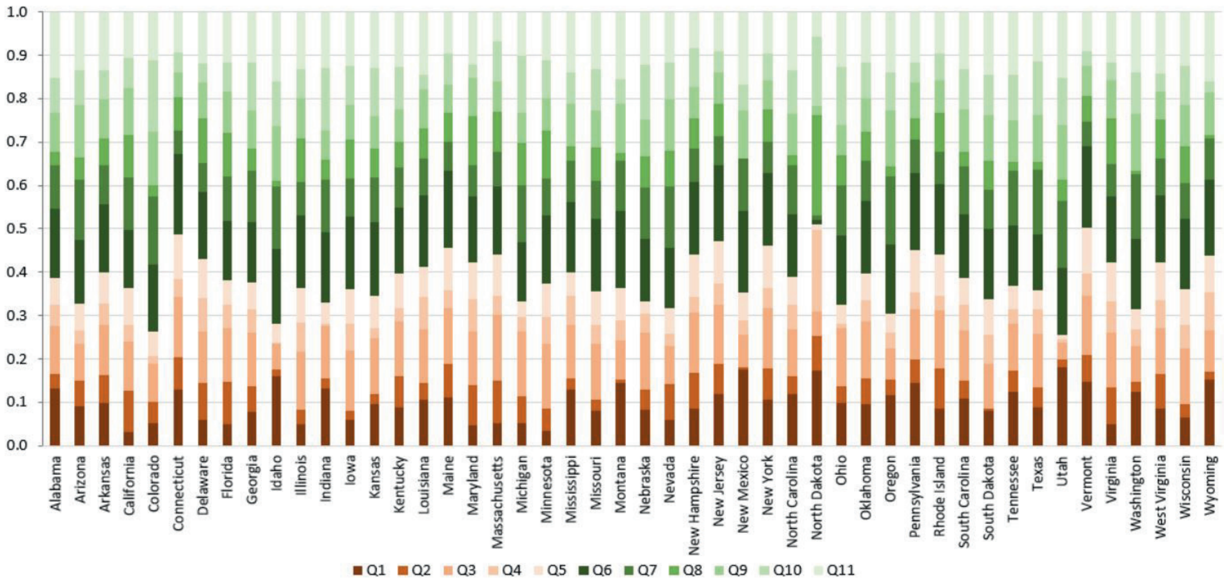
Notes: This figure plots the house-price changes and the housing-sentiment index for the bottom 10 states where housing sentiment has the lowest explanatory power.

the household belief about favorable buying conditions (questions under the label "good time to buy") in Utah and Colorado.[3]

Furthermore, we compute the variable of importance (VIP) score for survey questions, showing the importance of each component in a PLS model (Wold et al., 2001; Chong and Jun, 2005). Variables with a VIP score above 1 are deemed relevant for the PLS model. Figure A3 in appendix shows sentiment components, considered a VIP in constructing state-level housing-sentiment indices. The answer "prices are low/good buys available" is the major component of the housing-sentiment indices because it is selected as a VIP variable in almost all states, followed by the answers "good investment" (in 39 states), "times are bad/ can't afford to buy" (in 37 states), and "prices are high" (in 22 states). By contrast, the survey answers about uncertainty and interest rates, such as "bad times ahead/uncertain future" and "interest rates are high/credit is tight," are not selected as VIP variables in all but one state. These findings suggest that although many factors contribute to housing-

[3]Figures A1 - A2 in appendix show the weight decomposition of sentiment variables when the housing-sentiment index reached its highest and lowest values, respectively.

Figure 2.4: PLS weights of individual survey questions across states



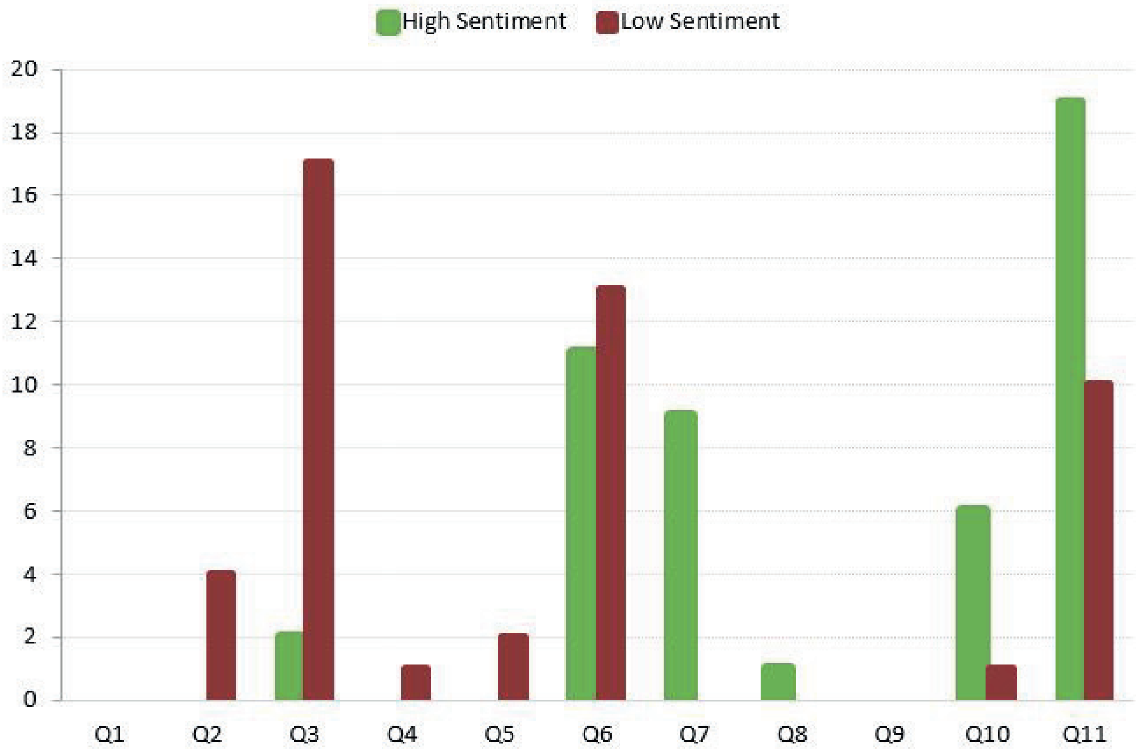
Notes: This figure displays the absolute values of the PLS weights for the construction of housing-sentiment indices across states computed using eq. (3.1).

sentiment indices, households seemingly pay attention to the level of house prices rather than borrowing conditions when forming sentiment related to house-buying conditions.

Finally, we examine the frequency with which the individual sentiments become important contributors to the sentiment index during high- and low-sentiment periods. In doing so, we decompose the housing-sentiment index into its components obtained by multiplication of PLS weights and corresponding sentiment values for periods in which the housing-sentiment index has reached its highest and lowest values. Figure 2.5 illustrates the most important components driving the housing-sentiment index in high- and low-sentiment periods. We observe that the components related to survey questions “good investment,” “prices are low/good buys available,” and “prices will not come down/are going higher” receive higher values in high-sentiment periods, indicating households have a positive outlook on the housing market because they expect house prices will continue to increase, and consider real estate a good investment. Indeed, this finding is in line with the behavioral channel suggesting investors weight the recent past too heavily when they form their views about future developments in financial markets (Campbell and Sharpe, 2009) and aggregate economic conditions (Kuchler and Zafar, 2019). During the periods of low sentiment, households are pessimistic about the housing markets and choose the survey answer “times are bad/can’t afford to buy” most frequently. Figure 2.5 shows this sentiment is the most crucial component in low-sentiment periods for 17 states.[4] Notably, the sentiment “prices

[4]For more insights into how the values of sentiment components change over time, see Figures A4 - A5 in appendix, where we plot time-series patterns in the sentiment components for New York and North Dakota, respectively.

Figure 2.5: Frequency of individual sentiments in high- and low-sentiment periods



Notes: This figure displays how many times an individual sentiment receives the highest value (in absolute terms) in the state-level housing-sentiment indices for high and low sentiment periods.

are low/good buys available" is almost as frequent in both high- and low-sentiment periods, likely reflecting positive expectations about housing market growth in high-sentiment periods and simply describing housing markets being in a depressed low-price state in low-sentiment periods.

2.3 House Prices and Sentiment

2.3.1 Sentiment and Predictability of House Prices

We explore how well our newly created state-level housing-sentiment index explains the future house prices and compare its predictive ability with a variety of other variables that are commonly used to explain house-price changes. We begin with estimating in-sample univariate predictive panel regressions:

$$h_{it+1} = \alpha_i + \beta X_{it} + \epsilon_{it+1}, \tag{2.2}$$

where h_{it+1} is the growth of the FHFA house-price index for state i in period $t+1$ and X_{it} includes either the housing-sentiment index (S) or one of the common housing-market determinants in state i in quarter t. We consider the one-quarter-ahead forecast horizon.

Table 2.2: In-sample predictive ability of the housing-sentiment Index

	Panel A: Univariate			Panel B: Bivariate				
Variables	β	t	R^2	β	t	δ	t	R^2
Housing-sentiment	0.0040	6.97	0.368					
Mortgage rate	0.0007	0.29	0.016	0.0041	7.30	-0.0020	-1.27	0.375
Stock index	-0.0042	-0.83	0.019	0.0041	7.24	-0.0057	-1.57	0.375
Building permits	0.0048	6.93	0.272	0.0031	5.21	0.0020	2.88	0.393
Employment	0.0248	1.75	0.036	0.0042	6.74	-0.0131	-1.13	0.373
Leading index	0.0001	0.56	0.019	0.0041	7.09	-0.0001	-0.37	0.369
Per-capita income	0.0471	2.37	0.050	0.0039	7.00	0.0248	1.76	0.377

Notes: Panel A presents the univariate regression results obtained from $h_{it+1} = \alpha_i + \beta X_{it} + \epsilon_{it+1}$, where h_{it+1} is the growth of the FHFA house-price index for state i in period $t+1$, and X_{it} includes either the housing-sentiment index (S) or one of the housing-market determinants discussed in section 2.2.2. We use the one-quarter-ahead forecast horizon. Panel B reports the bi-variate regression results from predictive model $h_{it+1} = \alpha_i + \beta S_{it} + \delta X_{it} + \epsilon_{it+1}$, where X_{it} is one of the housing-market determinants. For each regression, the table summarizes slope estimates, the corresponding t-statistics, and adjusted R^2 values. Standard errors are double-clustered by state and quarter. All variables are used in standardized form.

Panel A of Table 2.2 denotes the slope estimates, the corresponding t-statistics, and the proportion of the variance explained by the independent variable (R^2). Housing sentiment appears to be the most powerful predictor according to both the degree of explanatory power and statistical significance. In particular, the positive and statistically significant coefficient on housing sentiment indicates future house prices tend to rise when current sentiment for the housing market is high. A one-standard-deviation increase in the housing sentiment on average is associated with a 0.40% growth in house prices at the one-quarter horizon. The R^2 of 0.37 demonstrates the explanatory power of housing sentiment is substantial for future house-price movements. Building permits have the second-highest statistical significance with an R^2 of 0.27, implying it does not account for as much variation in house prices as housing sentiment. None of the remaining housing-market determinants come close to matching the explanatory power of the state-level housing sentiment, with much lower R^2 values between 0.01 and 0.05.

Next, we investigate whether housing sentiment includes information in addition to what is the other predictive variables already contain. Panel B of Table 2.2 reports the estimation results from the following bi-variate panel-regression model:

$$h_{it+1} = \alpha_i + \beta S_{it} + \delta X_{it} + \epsilon_{it+1}, \tag{2.3}$$

where S_{it} represent the period t housing- entiment in state i, and X_{it} is one of the standard housing-market determinants used in the literature on aggregate house-price dynamics. The results show only small increases in R^2 values when other housing fundamentals are included in a predictive regression in addition to housing sentiment. This result suggests housing sentiment contains useful information about future house-price growth that common housing-market predictors do not contain. Moreover, the size of the coefficient on S_{it}

in the estimated equation (2.3) does not change much compared with the univariate model with housing sentiment being the single predictor (equation (2.2)), and it still maintains a high level of statistical significance.

2.3.2 State-Level versus National-Level Housing Sentiment

An active debate in the literature concerns whether local or national factors determine house prices (Del Negro and Otrok, 2007; Gyourko et al., 2013; Cepni et al., 2021). In a recent paper, Bork et al., 2020 construct a national-level housing-sentiment index from the responses to selected questions about house-buying conditions from the Surveys of Consumers of the University of Michigan.[5] They show national housing sentiment includes predictive information for house-price growth at the state level. However, given that the housing markets are heterogeneous and highly segmented, investigating how much both local and national housing sentiments explain heterogeneity in house prices across the US states is important. To explore the importance of local and national housing-sentiment indices in predicting local house-price growth, we run the following panel data regression:

$$h_{it+1} = \alpha_i + \beta_S S_{it}^{State} + \delta X_{it} + \epsilon_{it+1}, \tag{2.4}$$

where S_{it}^{State} represents our newly constructed state-specific housing sentiment, also denoted as S_{it}, and the vector X_{it} includes all housing-market factors described in section 2.2.2. Subsequently, we substitute S_{it}^{State} with $S_t^{National}$, which signifies the national housing-sentiment index constructed following Bork et al., 2020. Standard errors are double-clustered by time and state.

Table 2.3 presents the estimation results of equation (2.4). The results in columns (1)-(2) with state-level housing sentiment and in columns (3)-(4) with the national housing sentiment show both the state and national housing-sentiment indices individually have a strong power to predict state house prices. The forecasting ability of national housing sentiment for state house-price growth is insightful regarding why boom and bust episodes in house-price cycles across the states occur at similar times. On the other hand, as shown in columns (5)-(6) of Table 2.3, the coefficient of the orthogonalized state-level sentiment ($S^{\perp}$) with respect to national-level sentiment shows positive and significant slope coefficients, even with the inclusion of control variables. This finding suggests that S_{it}^{State} offers complementary, non-overlapping insights regarding future house prices that are not otherwise captured by $S_t^{National}$, underscoring the importance of capturing sentiment variations at the state level in predictive housing market analyses.[6] This result implies housing-market dynamics are

[5] In their analysis, Bork et al., 2020 use selected questions from Table 42 of the Surveys of Consumers of the University of Michigan, whereas we use all 11 questions.

[6] To obtain an orthogonalized version of the state-level housing sentiment, we calculate the residuals from regressing the state-level sentiment on the national-level sentiment.

Table 2.3: Predicting local house prices with state-level and national housing sentiments

Variables	(1)	(2)	(3)	(4)	(5)	(6)
S	0.0040***	0.0035***				
	(0.0006)	(0.0006)				
$National\ S$			0.0038***	0.0033***		
			(0.0006)	(0.0006)		
$S^{\perp}$					0.0012***	0.0011***
					(0.0004)	(0.0003)
Control variables		✓		✓		✓
Observations	4,176	4,128	4,176	4,128	4,176	4,128
Number of states	48	48	48	48	48	48
Adj. R^2	0.361	0.405	0.328	0.379	0.037	0.299

Notes: This table reports results from estimation of the model $h_{it+1} = \alpha_i + \beta_S S_{it}^{State} + \delta X_{it} + \epsilon_{it+1}$, where S_{it}^{State} is state-specific housing sentiment (also denoted as S_{it}), and X_{it} includes other macroeconomic variables discussed in section 2.2.2. Furthermore, $S_t^{National}$ denotes the national housing-sentiment index constructed following Bork et al., 2020. $S^{\perp}$ is the part of S_{it}^{State} that is orthogonal to $S_t^{National}$. For each regression, the table reports slope coefficients, significance-level asterisk(s) (*** 1% level; ** 5% level; * 10% level), and standard errors in parentheses, clustered at the state and quarter level. All variables are used in standardized form.

strongly predicted by local housing sentiment, in line with the findings in Del Negro and Otrok, 2007, Glaeser et al., 2014, and Møller et al., 2023.

2.3.3 Out of sample forecasting performance

Up to this point, our in-sample regression analysis suggests a significant relationship between housing sentiment and future housing prices; however, a potential over-fitting issue arises when predictive regressions use all sample data. Therefore, we use an out-of-sample forecasting exercise with an expanding estimation window to reduce the risk of look-ahead bias. The housing sentiment index and all parameters are estimated recursively using only the data available at the forecast time. We divide the sample period evenly, with the initial half dedicated to training, whilst the latter half is reserved for out-of-sample forecasting and generate forecasts for h-quarter-ahead horizons, where h= 1, 2, 3, 4, 5, 6, 9, 12.

We build a benchmark model first, which uses information from economic variables like building permits, the stock market, employment, and the coincident index as outlined in the Section 2.2.2. Next, we supplement the benchmark model with state-level housing sentiment to create the Local Sentiment Model (Specification - 1). Then, we adjust the same model by replacing the state-level housing sentiment with a national sentiment index, resulting in the National Sentiment Model (Specification - 2).

- **Specification 0**: Benchmark Model
  $h_{t+h} = \mu + \beta X_t + \varepsilon_{t+h}$

- **Specification - 1**: Local Sentiment Model
  $h_{t+h} = \mu + \beta_S S_t + \delta X_t + \varepsilon_{t+h}$
- **Specification - 2**: National Sentiment Model
  $h_{t+h} = \mu + \beta_{NS} NS_t + \delta X_t + \varepsilon_{t+h},$

where h_t is housing price growth. While Specification - 1 allows us to explore the significance of the local housing sentiment index by controlling for housing market fundamentals, Specification - 2 offers a way to measure the predictive performance of the national housing sentiment index. To assess the forecast performance of these models, we adopt the out-of-sample R^2 (R^2_{OoS}) statistics, as defined by Campbell and Thompson, 2008.[7] For each state, the R^2_{OoS} values are computed relative to a benchmark model that capture the role of macroeconomic variables in house-price growth. Then, we test the null hypothesis, $R^2_{\text{OoS}} \leq 0$, against the alternative, $R^2_{\text{OoS}} > 0$, using the Clark and West, 2007 test, thereby enabling an examination of predictive accuracy in nested models.

The results from Table 2.4 highlight the comparative out-of-sample predictive performance of the Local Sentiment Model and the National Sentiment Model. The R^2_{OoS} values across different forecast horizons indicate that both models outperform the benchmark model, particularly in the short term. A closer examination reveals that the average R^2_{OoS} values of the local sentiment model are positive and consistently higher than those of the national sentiment model for almost all horizons (except for h=1), highlighting the role local sentiment plays in accurately predicting housing price growth. In particular, at longer forecast horizons (e.g., h=12), the Local Sentiment Model retains its forecasting ability with an R^2_{OoS} of 0.050, while the National Sentiment Model falls into negative territory (-0.064), implying that it performs worse than the benchmark model. These results suggest that local housing sentiment captures unique regional information not encompassed by national sentiment, which contributes to the improved forecasting ability, especially for longer forecast horizons. Hence, this finding provides empirical evidence for the role of local sentiment in predicting housing prices, indicating its potential utility as a practical tool in real estate market analysis and policy-making.

Table A1 of the appendix provides a detailed presentation of the R^2_{OoS} values for each state, as obtained from the Specification - 1, offering in-depth perspective on the out-of-sample efficacy of the local sentiment model at the state level. The results from the Clark and West, 2007 test provide strong evidence rejecting the null hypothesis of $R^2_{\text{OoS}} \leq 0$ across a majority of states and numerous forecast horizons. For instance, the forecasting

[7] R^2_{OoS} is defined as $R^2_{OoS} = 1 - \frac{\sum_{t=1}^{T}(r_t - \widehat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2}$ where $\widehat{r}_t$ denotes the forecasts derived from the prediction model, whereas $\bar{r}_t$ represents the forecasts made using the benchmark model. Hence, a positive out-of-sample R^2 indicates that the forecasting regression yields smaller prediction errors compared to the benchmark model.

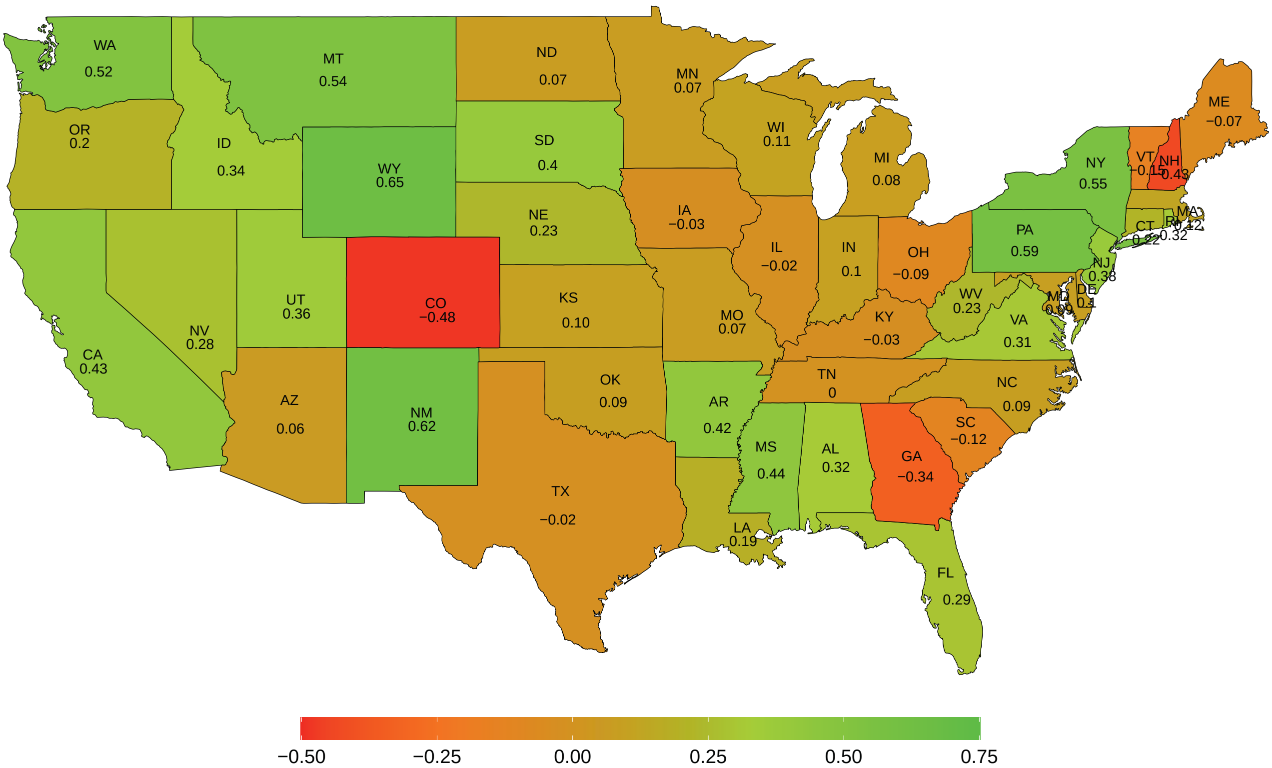
gain reaches its peak at h=4 for New York, where a significant R^2_{OoS} value of 64% is achieved. To summarize the results in a more holistic approach, in Figure 2.6, we present the average R^2_{OoS} values for all states, considering all forecast horizons. The overall takeaway from this analysis is that housing sentiment at the state level can serve as a valuable source of information, enabling the accurate prediction of house prices in a vast majority of states.

Table 2.4: Comparison of out of sample predictive ability - R^2_{OoS} statistics

Specification	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Local sentiment model	0.311	0.121	0.191	0.267	0.222	0.149	0.056	0.050
National sentiment model	0.317	0.106	0.160	0.253	0.208	0.120	0.014	-0.064

Notes: This table shows average R^2_{OoS} values across states for a given forecast horizon h. We compare the predictive performance of the models by leveraging the out-of-sample R^2 (R^2_{OoS}), as proposed by Campbell and Thompson, 2008. For every state, we compute these R^2 values in relation to the benchmark model.

Figure 2.6: Forecast performance compared to the benchmark model: Average R^2_{OoS} values



Notes: This figure displays average R^2_{OoS} values across states and forecast horizons computed from Local sentiment model versus benchmark.

2.4 Predicting House-Price Growth over the Business Cycle

2.4.1 Recessions and Housing Speculation

The psychological literature finds people's reactions to news are sharper during times of anxiety and fear (Smith and Ellsworth, 1985; Tiedens and Linton, 2001; Gino et al., 2009). Relatedly, Garcıa, 2013 argues investors' sensitivity to news is most pronounced during recessionary periods. Garcıa, 2013 finds the link between media content, as a proxy for sentiment, and Dow Jones Industrial Average (DJIA) returns is stronger during recessions: sentiment predicts larger changes in the stock market index in recessions than in expansions. In a related study, Akerlof and Shiller (2010, p.2) write, "We conceive of the link between changes in confidence and changes in income as being especially large and critical when economies are going into a downturn, but not so important at other times." Motivated by these studies, we explore th sentiment-business-cycle relationship by controlling for recession periods in US states. Different states enter and leave recessions in varying times. To capture this variation, we use the state-specific recession dates obtained from the Zillow Research report (Tucker, 2019).

One of the recessions in our period of study, the Great Recession of 2007 - 2009, was preceded by a remarkable increase in house prices. Abundant liquidity and anticipation of persistent growth stemming from prior housing price rises led to an unprecedented increase in non-owner-occupied home purchases (homeowners purchasing properties other than their primary residence) and to the boom in house prices of the 2000s (Haughwout et al., 2011; Chinco and Mayer, 2016; Badarinza and Ramadorai, 2018; Nathanson and Zwick, 2018; Garcıa, 2022).[8] Gao et al., 2020 demonstrate that the eager buying of non-owner-occupied properties by investors can amplify local economic circumstances during a housing boom, leading to larger drops in home prices and more intense economic contractions during the subsequent housing-market busts. We test the predictive power of sentiment in states with high levels of housing speculation, focusing on recessionary episodes in these states. Following Gao et al., 2020, we use the Home Mortgage Disclosure Act (HDMA) dataset, which reports the individual-level mortgage transactions in all US states, and measure the state-specific housing speculation as a fraction of non-owner-occupied home purchases in all house purchases in a given state. With the help of this information, we extend our baseline sentiment-housing-market relation with controls for recessionary episodes and housing speculation and estimate the following panel regression:

[8] Overall, during 2000-2005, real house-price growth reached 34%, which more than doubles any five-year rate in the preceding 30 years. Some metropolitan areas saw an even more rapid increase in their property values: in 2004 alone, housing prices in Las Vegas saw a soaring 35% increase, whereas in Los Angeles, West Palm Beach, and Miami, they rose by more than 20%.

$$h_{it+h} = \alpha_i + \beta S_{it} + \beta_R S_{it} \times I_{it}^{Reces} + \beta_S S_{it} \times I_i^{Spec} + \beta_{RS} S_{it} \times I_{it}^{Reces} \times I_i^{Spec} + \gamma I_{it}^{Reces} \times I_i^{Spec} + \delta X_{it} + \epsilon_{it+h}, \tag{2.5}$$

where I_i^{Spec} is a dummy equal to 1 if the housing speculation in state i is above the median, and I_{it}^{Reces} is a dummy equal to 1 if a state i is in a recession at time t. We consider four different forecast horizons, namely, $h = 1, 2, 3, 4$ quarters ahead.

Panel A of Table 2.5 shows the estimation results. We find the predictive coefficient on S is significant for all forecast horizons, representing the baseline effect of sentiment for states with low speculative activity during non-recessionary periods. The positive and statistically significant coefficient on the interaction term $S \times I^{Reces}$ (specifically, for h =2, 3) demonstrates housing sentiment is a significant predictor of future housing returns across business cycles. We find the relationship between the housing market and sentiment is indeed concentrated around economic downturns. The positive coefficient on $S \times I^{Reces}$ indicates house prices are predicted to be significantly lower during recessions when the sentiment is lower (see, e.g., the dynamics of sentiment plotted for New York and North Dakota in Figures A4 - A5 in the appendix), suggesting the finding of Garcıa, 2013 on the link between sentiment and the stock market index being stronger in recessions is also valid for the housing markets.

Our results show that, during the recessionary periods, housing returns are predicted to be lower in the states with greater speculative activity, as indicated by the negative and statistically significant coefficient on $I^{Reces} \times I^{Spec}$. This finding is in line with the results in Gao et al., 2020. Overall, we find a more pronounced impact of housing sentiment on house prices in the states with more speculative activity, as indicated by the positive and marginally significant coefficient on $S \times I^{Spec}$ in specifications for one- and two-period-ahead forecast horizons. This finding agrees with the study of Soo, 2018, who documents the effect of news sentiment on housing prices is larger in cities experiencing greater housing speculative activity. If investors are extrapolating prices from earlier house-price growth and actively buying non-owner-occupied properties, the predictive capacity of the sentiment index can be associated with the increased number of second-home purchases. Relatedly, Møller et al., 2023 show the forecasting ability of the housing search index for future house-price movements is positively linked to speculative activity.

One of the sharpest recessions in the US was caused by the COVID-19 pandemic, which is present in our data at the end of the study period. During the short but steep COVID-19 recession, house prices have risen within months to their record levels, reaching a 19% increase in one year from the start of the pandemic. The staggering increase in house prices during this recession was in sharp contrast to the steep decline of house prices triggered by the subprime bust of the Great Recession of 2007-2009. The search for housing was driven

Table 2.5: Housing sentiment during periods of recession, bubble, and economic distress

Variables	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
Panel A: Recession Periods and Housing Speculation								
S	0.0031***	0.0028***	0.0029***	0.0029***	0.0026***	0.0024***	0.0028***	0.0029***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$S \times I^{Reces}$	0.0015	0.0025**	0.0021**	0.0016*	0.0017*	0.0023**	0.0017**	0.0011
	(0.0012)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0009)
$S \times I^{Spec}$	0.0008*	0.0007**	0.0005	0.0004	0.0007*	0.0007**	0.0005	0.0004
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
$I^{Reces} \times I^{Spec.}$	-0.0011	-0.0016*	-0.0019*	-0.0015	-0.0016**	-0.0016*	-0.0017*	-0.0012
	(0.0009)	(0.0009)	(0.0011)	(0.0011)	(0.0007)	(0.0008)	(0.0009)	(0.0010)
$S \times I^{Reces} \times I^{Spec}$	0.0011*	0.0006	0.0006	0.0008	0.0007	0.0005	0.0006	0.0007
	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Adj. R^2	0.390	0.385	0.360	0.330	0.432	0.421	0.390	0.351
Panel B: Non-pandemic Recession Periods and COVID-19 Recession								
S	0.0037***	0.0034***	0.0033***	0.0031***	0.0032***	0.0029***	0.0031***	0.0031***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$S \times I^{Reces}$	0.0020	0.0028**	0.0026**	0.0023**	0.0022*	0.0027***	0.0021**	0.0016
	(0.0014)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0010)
$S \times I^{Covid-19}$	-0.0032***	-0.0011	0.0018	0.0030***	-0.0037***	-0.0009	0.0019	0.0029***
	(0.0006)	(0.0016)	(0.0012)	(0.0004)	(0.0007)	(0.0017)	(0.0012)	(0.0005)
Stringency	0.0052***	0.0073***	0.0112***		0.0043***	0.0064***	0.0100***	
	(0.0005)	(0.0015)	(0.0015)		(0.0012)	(0.0017)	(0.0029)	
Adj. R^2	0.409	0.402	0.372	0.325	0.439	0.426	0.388	0.348
Panel C: Bubble Periods								
S	0.0039***	0.0038***	0.0037***	0.0037***	0.0034***	0.0033***	0.0035***	0.0034***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
$S \times I^{Bubble}$	0.0034**	0.0027*	0.0026*	0.0012	0.0037**	0.0030*	0.0031**	0.0017
	(0.0015)	(0.0015)	(0.0014)	(0.0013)	(0.0016)	(0.0016)	(0.0015)	(0.0012)
Adj. R^2	0.367	0.343	0.327	0.304	0.412	0.393	0.371	0.340
Panel D: Foreclosure								
S	0.0035***	0.0034***	0.0034***	0.0033***	0.0031***	0.0029***	0.0031***	0.0030***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
$S \times I^{Foreclosure}$	0.0011*	0.0010*	0.0009*	0.0008*	0.0010*	0.0010*	0.0010**	0.0008*
	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.0004)
Adj. R^2	0.367	0.344	0.327	0.307	0.411	0.394	0.371	0.342
Panel E: Distressed Sales								
S	0.0032***	0.0031***	0.0032***	0.0032***	0.0029***	0.0028***	0.0030***	0.0030***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.000478)
$S \times I^{Distressed}$	0.0016***	0.0015**	0.0012**	0.0010**	0.0015**	0.0013**	0.0011**	0.0010**
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0005)
Adj. R^2	0.375	0.350	0.331	0.309	0.417	0.397	0.373	0.344
Common Information for Panels A - E								
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,176	4,128	4,080	4,032	4,128	4,080	4,032	3,984
Number of states	48	48	48	48	48	48	48	48

Notes: Panel A reports the estimation results of the regression model: $h_{it+h} = \alpha_i + \beta S_{it} + \beta_R S_{it} \times I_{it}^{Reces} + \beta_S S_{it} \times I_i^{Spec} + \gamma I_{it}^{Reces} \times I_i^{Spec} + \beta_{RS} S_{it} \times I_{it}^{Reces} \times I_i^{Spec} + \delta X_{it} + \epsilon_{it+h}$, where I_i^{Spec} is a dummy equal to 1 if the housing speculation in state i is above the median, and I_{it}^{Reces} is a dummy equal to 1 if a state i is in a recession at time t. Panel B presents the estimation results of the regression model: $h_{it+h} = \alpha_i + \beta S_{it} + \beta_R S_{it} \times I_{it}^{Reces} + \beta_C S_{it} \times I_t^{Covid-19} + \delta X_{it} + \epsilon_{it+h}$, where $I_t^{Covid-19}$ is a dummy equal to 1 for the period from 2020:Q1 to 2021:Q1. Panel C presents the estimation results of the regression model: $h_{it+h} = \alpha_i + \beta S_{it} + \beta_B S_{it} \times I_{it}^{Bubble} + \delta X_{it} + \epsilon_{it+h}$, where I_{it}^{Bubble} is a dummy equal to 1 for the date-stamping bubble periods detected by the approach in Phillips et al., 2015. Panel D shows the estimation results of regression model: $h_{it+h} = \alpha_i + \beta S_{it} + \beta_F S_{it} \times I_i^{Foreclosure} + \delta X_{it} + \epsilon_{it+h}$, where $I_i^{Foreclosure}$ is a dummy equal to 1 if the fraction of foreclosures in state i is above the median. Panel E shows the estimation results of the regression model: $h_{it+h} = \alpha_i + \beta S_{it} + \beta_D S_{it} \times I_i^{Distressed} + \delta X_{it} + \epsilon_{it+h}$, where $I_i^{Distressed}$ is a dummy equal to 1 if the share of distressed home sales in state i is above the median. The vector X_{it} includes housing-market determinants listed in section 2.2.2; *Stringency* is the COVID-19 stringency measure from Hale et al., 2021. For each regression, the table presents the estimates of slopes and standard errors clustered at the state and quarter level in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. All variables are used in standardized form.

by the demands of remote working and for more socially distanced living options away from densely populated areas and was accommodated by liquidity transfers and unemployment benefits, low mortgage interest rates, and favorable monetary policy. Housing supply, which normally moderates house-price pressure through new construction, has been muted time by the pandemic-related supply constraints such as supply-chain disruptions and restrictions on work practices. We investigate whether the housing-sentiment index is still a predictor of house-price dynamics during the COVID-19 recession, controlling for housing supply proxied by building permits and the state-specific COVID-19 stringency measures (Hale et al., 2021) related to cancellation of public events, closing of workplaces and public transportation, self-isolation requirements, and so on. We estimate the following panel regression:

$$h_{it+h} = \alpha_i + \beta S_{it} + \beta_R S_{it} \times I_{it}^{Reces} + \beta_C S_{it} \times I_t^{Covid-19} + \delta X_{it} + \epsilon_{it+h}, \tag{2.6}$$

where $I_t^{Covid-19}$ is a dummy equal to 1 for the period from 2020:Q1 to 2021:Q1, which is the end of our sample period, and X_{it} contains the state-specific COVID-19 stringency measure of Hale et al., 2021 and a set of control variables discussed in section 2.2.2, including state-specific building permits.

Panel B of Table 2.5 summarizes the results for the COVID-19 recession. Coefficient estimates on housing sentiment and the interaction term $S \times I^{Reces}$ are similar over specifications in Panels A and B and our previous conclusion is not changed: housing sentiment is still a significant predictor of future house-price changes across business cycles. The findings for the interaction term $S \times I^{Covid-19}$ are mixed, likely reflecting pandemic-related volatility in house prices and the short period for the COVID-19 recession captured in our data. For a short forecast horizon ($h = 1$), lowered sentiment during COVID-19 pandemic (see, e.g., the dynamics of sentiment at the end of our sample period plotted for New York and North Dakota in Figures A4 - A5 in the appendix) predicts increase in house prices, reflecting pandemic-related volatility in house prices. However, for longer forecast horizons ($h = 4$), the prediction of the effect of sentiment on house prices is in line with the results for other recessions: an increase in sentiment predicts a larger increase in house prices during the recessions than during non-recessionary periods. The coefficient of the stringency index could only be estimated for forecast horizons $h = 1, 2, 3$ because of the limited number of COVID-19 recession observations. The coefficient of the stringency index is positive and statistically significant, suggesting states that implemented more stringent lockdown measures exacerbated already radical COVID-19-related housing-supply restrictions, allowing house-prices to soar.

2.4.2 Bubble Periods

A general consensus is that the mortgage-default crisis arising from the bursting of the housing bubble triggered the Great Recession of 2007-2009. The primary causes of the housing bubble, identified by the financial literature, are the low interest rates, the relaxed standards for mortgage loans, and irrationally optimistic expectations about the future house prices. The influence of these factors on the dynamics of local house prices varies substantially because of the geographical segmentation of the housing markets. McDonald and Stokes (2013) show the effect of the low-interest-rate policy of the Federal Reserve Bank on the house-price index in major metropolitan areas is far from uniform. The regional differential effect of lax mortgage lending standards is illustrated in Mian and Sufi, 2009: geographical concentration of subprime borrowers in certain US ZIP codes allows these authors to show the unprecedented expansion of mortgage credit in these localities and to link this expansion to the higher rate of mortgages sold in private securitizations. Finally, geographical heterogeneity in the irrational exuberance, defined in Shiller, 2015 as a heightened state of speculative fervor, is supported by the state-specific variation in housing speculation, used in this paper. House-price growth expectations driven by irrational optimistic views are also likely to differ between states because of differences in housing-supply elasticities and the possibility to make quick adjustments in the quantity of housing stock to any upward pressure on house prices in areas with elastic housing supply. The geographic variation in the factors responsible for the formation of the housing bubble suggests substantial differences can exist in the starting period and the duration of the housing bubbles over states.

We empirically identify regional housing bubbles by utilizing a recursive unit root test proposed in Phillips et al., 2015, and examine whether the predictive ability of the housing-sentiment index for the fluctuations in house prices can differ in housing-bubble periods in the following panel regression:

$$h_{it+h} = \alpha_i + \beta S_{it} + \beta_B S_{it} \times I_{it}^{Bubble} + \delta X_{it} + \epsilon_{it+h}, \tag{2.7}$$

where is I_{it}^{Bubble} is a dummy equal to 1 for the date-stamping bubble period detected in state i following the approach in Phillips et al., 2015.[9] The vector X_{it} includes housing-market-related control variables described in Section 2.2.2. In testing for bubbles, we examine the explosiveness of the price-rent ratio instead of directly assessing prices, as focusing on the price-rent ratio allows us to control for fundamentals and aligns with established literature (Engsted et al., 2016; Pedersen and Schütte, 2020; Hald Hansen et al., 2022). To measure rents, we utilize the BLS indices specifically designed for primary residence rentals. These indices are accessible on a monthly basis and are categorized by region (West, North Central,

[9]Phillips et al., 2015 propose a recursive flexible-window approach that is suitable for long historical time series. A simulation study shows the method considerably enhances discriminatory power of bubbles and provides a consistent date-stamping technique for beginning and ending dates of multiple bubbles.

Northeast, and South), and hence we map each state with its corresponding region based on its geographical location.[10]

Panel C of Table 2.5 suggests the effect of sentiment on future housing returns is generally larger during bubble periods than during the non-bubble periods, and almost twice as large during bubble periods when we control for other housing-market determinants, especially for forecast horizons $h = 2, 3$, as shown by the coefficients on $S \times I^{Bubble}$. This result suggests stronger sentiment during bubble periods is linked to the anticipation of even larger future house-price changes, which is consistent with the overvaluation of house-price growth during a bubble period.[11]

2.4.3 Foreclosures and Distressed Sales

The evidence in Mian and Sufi, 2009 suggests expansionary mortgage credit policies and lax lending standards in 2002-2005 resulted in higher mortgage lending to subprime borrowers. However, when a significant shock strikes the economy, and many homeowners default at the same time, the theory predicts the fire sales of foreclosed homes could result in a further decline in home values, negatively affecting residential investment and consumer demand in the long run (Krishnamurthy, 2003; Krishnamurthy, 2010). Investors' pessimism and negativity are exacerbated when the markets perform poorly during a period of turmoil (Akhtar et al., 2011). Chauvet et al., 2016 note, such negative sentiments were prevalent in the US housing market during the mortgage crisis of 2007-2009. We anticipate the relation between future house-price growth and housing sentiment will be stronger in states that experience greater financial distress. Furthermore, if subprime lenders target certain borrowers based on their credit profiles, they likely reach buyers who are more susceptible to market sentiment. Therefore, buyers who are more misinformed and susceptible to sentiment are also more inclined to take out risky, subprime loans.

We use information on subprime adjustable-rate mortgage-loan foreclosures accessed at Bloomberg that follows properties for which mortgage payments have gone into arrears and the lender is trying to reclaim the loan balance from the borrower by seizing the property and forcing its sale. We test whether the forecasting ability of sentiment for subsequent changes in the house prices varies with the fraction of subprime adjustable-rate mortgage-

[10] As the BLS rental indices are starting from 1984, we identify the bubble periods over the period 1984:Q1 to 2021:Q1.

[11] One potential concern when testing directly on the price-rent ratio is that rent alone may not encompass all pertinent fundamentals influencing house prices. To address this issue, Shi and Phillips, 2023 propose an alternative strategy, which involves breaking down the price-rent ratio into a fundamental and a non-fundamental element, and subsequently examining the explosiveness in the non-fundamental component. To do so, we initially regress the price-rent ratio onto our set of control variables and then apply the Phillips et al., 2015's test on the resulting residuals. The results reported in Table A2 indicate that our conclusion is robust, even when applying alternative strategies for testing bubbles.

loan foreclosures across states, using the following linear framework:

$$h_{it+h} = \alpha_i + \beta S_{it} + \beta_F S_{it} \times I_i^{Foreclosure} + \delta X_{it} + \epsilon_{it+h}, \tag{2.8}$$

where $I_i^{Foreclosure}$ is a dummy equal to 1 if the fraction of foreclosures in state i is above the median, and X_{it} is a set of control variables described in section 2.2.2.

Panel D of Table 2.5 shows the results based on the differences in fraction of subprime loan foreclosures across states. Our findings indicate the ability of housing-sentiment to predict future changes in house prices is stronger in states with higher ratios of subprime foreclosures. In particular, at the one-period-forecast horizon, the effect of a one-standard-deviation increase in the housing sentiment on future house-price growth on average is $0.35\% + 0.11\% = 0.46\%$ in states with more subprime foreclosures, indicating states with higher rates of subprime foreclosures experience a greater influence of housing sentiment on future housing returns.

Campbell et al., 2011 find foreclosed houses are sold at a discount of 27% on average, though the discounts may vary based on the nature of the housing market or the disposition method used for forced sales (e.g., real-estate owned vs. short sale). Given the large discount associated with distressed sales, changes in the share of distressed versus non-distressed home sales may shape household home-buying decisions. As a robustness check, we re-estimate eq. (2.8), replacing $I_i^{Foreclosure}$ with the dummy for distressed sales $I_i^{Distressed}$. To construct $I_i^{Distressed}$, we divide the states into two groups based on the median value of the share of existing home sales that are distressed, including the short sales, foreclosure sales, and deed in lieu of foreclosure, using the information on distressed sales from CoreLogic. This measure enables us to determine the potential impact of distressed sales on local housing markets through affecting the housing sentiment. Panel E of Table 2.5 indicates our results are robust to various measures of financial distress. Overall, our analysis reveals a stronger association between housing sentiment and subsequent changes in house prices in states with a higher proportion of distressed sales.

2.4.4 Local-Housing-Supply Elasticity

Using the housing search index based on Google trends, Møller et al., 2023 document that house prices are more strongly influenced by changes in local housing demand in metropolitan areas with a more constrained supply of housing. Following Møller et al., 2023, we investigate whether the housing-sentiment index has a greater influence on house prices in states where the housing supply is relatively inelastic. We use the measure of land-supply elasticity constructed in Saiz, 2010 based on a combination of natural land constraints and the intensity of local growth-control policies. In particular, using the housing-supply-elasticity measure, aggregated to the state level by Chetty et al., 2017, we divide the states

Table 2.6: Predicting local house-price changes with housing sentiment: the importance of housing-supply elasticity and economic-policy uncertainty

Variables	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
Panel A: Supply Elasticity								
S	0.0028***	0.0028***	0.0028***	0.0028***	0.0024***	0.0024***	0.0026***	0.0026***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$S \times I^{Elasticity}$	0.0029***	0.0026***	0.0023***	0.0021***	0.0028***	0.0024***	0.0021***	0.0019***
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Control variables					✓	✓	✓	✓
Adj. R^2	0.413	0.381	0.351	0.322	0.455	0.432	0.397	0.360
Number of s tates	40	40	40	40	40	40	40	40
Observations	3,480	3,440	3,400	3,360	3,440	3,400	3,360	3,320
Panel B: Economic-Policy Uncertainty								
S	0.0031***	0.0030***	0.0030***	0.0030***	0.0026***	0.0026***	0.0028***	0.0027***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$S \times I^{HighEPU}$	0.0019***	0.0018***	0.0016***	0.0015***	0.0019***	0.0017***	0.0015***	0.0016***
	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.0004)
Control variables					✓	✓	✓	✓
Adj. R^2	0.381	0.356	0.336	0.315	0.425	0.404	0.379	0.350
Number of States	48	48	48	48	48	48	48	48
Observations	4,176	4,128	4,080	4,032	4,128	4,080	4,032	3,984

Notes: Panel A presents the results of regression model: $h_{it+h} = \alpha_i + \beta S_{it} + \beta_E S_{it} \times I_i^{Elasticity} + \delta X_{it} + \epsilon_{it+h}$, where $I_i^{Elasticity}$ is a dummy equal to 1 if the supply elasticity in state i is below the median. Panel B reports the results from the regression: $h_{it+h} = \alpha_i + \beta S_{it} + \beta_H S_{it} \times I_i^{HighEPU} + \delta X_{it} + \epsilon_{it+h}$, where is $I_i^{HighEPU}$ is a dummy equal to 1 if the economic-policy uncertainty in state i is above the median. The vector X_{it} includes housing market determinants listed in Section 2.2.2. For each regression, the table presents the estimates of slopes and standard errors clustered at the state and quarter level in parentheses; *, ** and *** denote 10%, 5% and 1% significance levels, respectively. All variables are used in standardized form.

into groups with high and low housing-supply elasticity. With the help of the following panel predictive regression, we investigate whether the impact of housing sentiment depends on the supply elasticity of the local housing market:

$$h_{it+h} = \alpha_i + \beta S_{it} + \beta_E S_{it} \times I_i^{Elasticity} + \delta X_{it} + \epsilon_{it+h}, \tag{2.9}$$

where $I_i^{Elasticity}$ is a dummy equal to 1 if the supply elasticity in state i is below the median, and X_{it} is a set of control variables described in section 2.2.2. In this specification, β_E measures the incremental effect of housing sentiment on house prices in more constrained states according to housing-supply elasticity, and β captures the baseline effect of sentiment for more elastic states. This specification is based on the intuition that housing sentiment may have a weaker impact on house prices in areas where new houses can be quickly built to accommodate the additional housing demand. By contrast, in areas where land is scarce or zoning regulations are strict, house prices have to increase to clear the market in response to growing demand because housing supply is constrained.

Panel A of Table 2.6 reports the results from estimation of eq. (2.9) for different forecasting horizons. The estimated predictive coefficient on the housing sentiment is significant for all horizons. The incremental effect of the sentiment interacted with the housing-supply-elasticity dummy on house prices is also significant, and its magnitude reveals a substantial difference between the high and low housing-supply-elasticity states. In particular, the coefficient estimate β_E suggests a one-standard-deviation change in sentiment predicts an additional 0.28% increase in house prices for the one-quarter-ahead horizon for the less elastic states when we control for economic fundamentals. That is, a one-standard-deviation increase in the housing sentiment on average predicts a two-times-larger increase in house prices in less elastic states than in more elastic ones. The values of adjusted R^2 for the one-quarter-ahead forecast horizon are 0.41-0.46 and indicate the predictive power of the sentiment is substantial. Our finding of a larger impact of the sentiment in less elastic housing markets provides empirical evidence for studies highlighting the role of housing-supply elasticities in housing booms and busts (Glaeser et al., 2008; Glaeser et al., 2012; Guerrieri et al., 2013).

2.4.5 State-Level Economic-Policy Uncertainty

The US states vary not only in terms of economic and social characteristics, but also in terms of state laws and economic policies. Each state has its own vision on how to define the economic and administrative environment via various state policies related to government expenditure, subsidies, taxes, and so on. Therefore, EPU is likely to differ from state to state because of the specific political choices made at the state level. Further, state-level EPU is likely to affect the consumption and investment decisions of economic agents (Francis et al., 2010; Pástor and Veronesi, 2012; Pástor and Veronesi, 2013; Jurado et al., 2015). Considering that EPU might vary substantially across states, examining how the predictive power of housing sentiment on house prices changes with the EPU is of interest.

Berardi, 2021 investigates one possible mechanism on how uncertainty-amplified shocks can affect the link between sentiment and asset returns. The author shows the effect of sentiment can be amplified through uncertainty, capturing the insight that investors can be particularly optimistic or pessimistic about something they do not know for sure. Using a theoretical framework describing investors' decisions, Berardi, 2021 shows higher uncertainty leads to boosting sentimental and psychological attitudes, resulting in higher asset prices.

To investigate the predictive ability of housing sentiment on future house prices under higher economic uncertainty, we use the state-level measure of economic and policy-related uncertainty of Baker et al., 2022 to sort the states based on the level of their EPU, denoting a state with an EPU index above the median as a high-EPU state. Then we run the following panel regression:

$$h_{it+h} = \alpha_i + \beta S_{it} + \beta_H S_{it} \times I_i^{HighEPU} + \delta X_{it} + \epsilon_{it+h}, \tag{2.10}$$

where is $I_i^{HighEPU}$ is a dummy equal to 1 if the EPU index in state i is above the median.[12] The vector X_{it} includes housing-market-related control variables described in section 2.2.2.

[12]Based on nearly 3,500 local newspapers in each state that can be accessed using the online archives, Baker et al., 2022 compute a state-level EPU index by counting the number of articles containing the terms

Panel B of Table 2.6 summarizes the results across high- and low- (baseline) EPU states. We find the forecasting power of sentiment on future subsequent house prices is more substantial in high-EPU states, indicating high uncertainty amplifies the effect of sentiment on future housing prices.

2.5 Robustness Checks

2.5.1 Controlling for time fixed effects

The potential presence of common time-varying factors at the country level could concurrently drive the relation between sentiment and prices. Hence, our model can further benefit from the inclusion of time fixed effects, which might assist in controlling for unobserved common shocks or nationwide trends affecting all states equally. Notably, these might encompass shifts in national monetary policy, country-wide economic trends, or even significant global events. As we navigate the complex dynamics between housing sentiment and price growth across various states and periods, incorporating these time fixed effects ensures that we do not inadvertently attribute the impact of these nationwide phenomena to our primary variable of interest - housing sentiment. Hence, we re-estimate the equation 2.3 with all control variables and saturating the model with state and time fixed effects, which yields a more nuanced understanding of our subject matter.

In Table A3 of the appendix, we provide the results of our model re-estimation incorporating both state and time fixed effects. Our state level sentiment measure remains significant across all forecast horizons (h=1 to h=4), indicating that the relationship between sentiment and future house prices is robust to controlling for time fixed effects.The adjusted R^2 values further corroborate the strength and validity of our model, with values ranging from 0.594 to 0.620, implying that our model explains a substantial portion of the variation in house prices.

2.5.2 Sub-sample analysis

The global financial crisis, triggered by the bursting of the US housing bubble, presents an extreme case of a sharp downturn in the housing market. During this time, a pervasive pessimistic sentiment might have been a significant factor contributing to the rapid decline in house prices. Therefore, examining the predictive power of the sentiment index across different sub-samples can shed light on the dynamics of sentiment-house price relationship under different market conditions, which is critical for verifying the robustness of our findings.

"economy," "economic," "uncertainty," "city council," "mayor," "state senate," and so on. We would like to thank the authors for sharing the state-level uncertainty data with us.

To further analyze the predictive power of the sentiment index under different market conditions, we divide our sample into three distinct sub-periods: the pre-crisis period (1999-2006), the crisis period (2006-2009), and the post-crisis period (2010-2021). In each of these sub-periods, we run the predictive regression model described in equation 2.3, controlling for the variables introduced in section 2.2.2, to examine the predictive power of the state-level sentiment index.

Table A4 of the appendix presents the results. Coefficients of the housing sentiment are significant and positive across all three periods, indicating a consistent positive relationship between sentiment and future house prices across these time frames. Interestingly, while the magnitude of the coefficients varies across different periods, the housing sentiment exhibits a stronger relationship during the crisis period (2006-2009) compared to the pre and post-crisis periods. Hence, our empirical findings align well with the theoretical underpinnings discussed in the previous sections of the paper. Previous studies suggest that people's reactions to news are more intense during times of anxiety and fear, which is quite synonymous with crisis periods (Smith and Ellsworth, 1985; Tiedens and Linton, 2001; Gino et al., 2009). For instance, Garcıa, 2013 argues that investors' sensitivity to news is particularly pronounced during recessionary periods. Thus, the empirical results corroborate the theoretical predictions, solidifying our conclusions and inferences about the relationship between sentiment, house price growth, and the business cycle.

2.5.3 Comparison with MSA-level measures

Møller et al., 2023 quantify housing demand through the lens of internet search activity. By leveraging data from Google Search Volume Index, they develop a Housing Search Index (HSI) at the Metropolitan Statistical Area (MSA) level, which provides a granular view of housing demand trends.

On the other hand, our state-level housing sentiment measure offers an intermediate level of aggregation which, in some respects, may provide a more balanced view of the housing market dynamics. This is particularly relevant as, while MSA-level measures have the advantage of reflecting localized housing market conditions, they might miss broader statewide trends that can significantly influence the housing market. These trends could be legislative changes, statewide economic conditions, or shifts in population demographics which are all critical factors in the housing market. Additionally, the state-level sentiment index accounts for the state's overall housing market sentiment, which is likely to be reflected in all the MSAs within that state. Given the fact that state-level policies and economic conditions tend to have a broad influence on the housing market conditions across all MSAs within the state, it is plausible to consider the state-level housing sentiment as an important predictor of housing returns at the MSA level.

To substantiate this hypothesis, we empirically test the predictive power of our state-level sentiment index for MSA level housing returns when we control the HSI measure and housing market fundamentals. By juxtaposing the state-level sentiment measure with MSA-level measures in this way, we aim to offer compelling insights into the relative predictive strengths of these differing scales of analysis. In particular, we run the following regression:

$$h^{MSA}_{it+h} = \alpha_i + \beta_S S_{it} + \beta_{HSI} HSI_{it} + \delta X_{it} + \gamma_t + \epsilon_{it+h}, \tag{2.11}$$

where is h^{MSA}_{it+h} is the growth of the Freddie Mac house price index for MSA i in period $t+1$.

Table 2.7: State-Level Sentiment vs HSI: Predicting MSA Housing Returns

Variables	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
HSI	0.0023***	0.0022***	0.0019***	0.0016***	0.0021***	0.0020***	0.0018***	0.0015***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
S	0.0042***	0.0036***	0.0034***	0.0026***	0.0040***	0.0033***	0.0030***	0.0023**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0009)
Control variables					✓	✓	✓	✓
MSA and Time FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	5,092	5,016	4,940	4,864	5,092	5,016	4,940	4,864
Number of MSAs	76	76	76	76	76	76	76	76
Adj. R^2	0.652	0.643	0.636	0.620	0.665	0.657	0.651	0.638

Notes: The dependent variable is the growth of the Freddie Mac house price index for each MSA in the given period. HSI refers to the housing search index at the MSA level, and S refers to the state-level housing sentiment index. Control variables include other housing market fundamentals. The "h" in the header row corresponds to the horizon of the forecast. For instance, $h = 1$ refers to a one-period-ahead forecast, $h = 2$ refers to a two-period-ahead forecast, and so on. For each regression, the table presents the estimates of slopes and standard errors double clustered at the state and quarter level in parentheses; *, ** and *** denote 10%, 5% and 1% significance levels, respectively. All variables are used in standardized form.

Table 2.7 present the results, highlighting the significant predictive power of both the state-level sentiment measure and the housing search index for forecasting MSA-level housing returns across different forecast horizons (h=1 to h=4). Interestingly, the coefficient of the state-level sentiment is consistently larger than that of the HSI across all horizons, suggesting that state-level sentiment plays a more substantial role in influencing MSA-level housing returns, even after controlling for search activity and market fundamentals. This finding underscores the importance of macro-level factors that are captured in the state-level sentiment that may be overlooked when focusing only on the MSA level. Understanding these statewide trends is crucial as they can significantly influence the housing market conditions across all MSAs within a state.

2.5.4 Considering Cross-Sectional Spatial Dependence

While our standard errors are clustered by both state and time, we delve deeper into the potential influence of spatial correlation on the computed standard errors since the existence of spatial correlation across our measures could dramatically understate the standard errors computed, thus potentially skewing our conclusions (Foote, 2007).

To mitigate this concern, we employ the non-parametric estimator for the covariance matrix introduced by Driscoll and Kraay, 1998, which yields standard errors that robustly withstand different forms of spatial and temporal dependence, heteroskedasticity, and auto-correlation.The coefficient estimates remain statistically significant even when considering potential spatial correlation, as shown in Table A5 in the appendix. This evidence supports the robustness of our findings to cross-sectional dependence, thereby reinforcing the validity and robustness of our initial insights regarding the relationship between housing sentiment and price growth.

2.5.5 Controlling for AR component

Housing markets are often characterized by frictions and illiquidity, leading to positive serial correlation in house price changes, as documented in the previous studies (Ghysels et al., 2013; Soo, 2018; Møller et al., 2023). This tendency might arise due to the slow reaction of market participants to new information, the time it takes for a transaction to be completed, or the procedure employed in the construction of the house price indices. Hence, we enrich our model described in equation 2.3 by controlling for the autoregressive (AR) component in house prices, which allows us to capture the inherent inertia in house prices. Furthermore, it mitigates the potential risk of omitted variable bias, which may arise if we fail to account for the influence of past house price growth rates. Following the approach recommended by Soo, 2018, we select four lags for the AR component in our model, which controls the significant auto-correlation present in the quarterly changes in house prices.

As presented in Table A6, when controlling for the autoregressive component, our state-level sentiment measure retains its strong statistical significance across all time horizons. Although the magnitude of the coefficients diminishes somewhat after accounting for the AR component, the economic magnitude of its predictability for future house price growth remains substantial. Hence, this finding reinforces our main argument that the sentiment in the housing market holds essential predictive power, providing insights not fully encompassed by the autoregressive component.

2.6 Conclusion

Unlike the stock market, the housing market has a greater proportion of individual investors, it is highly localized and fragmented, and is characterized by a higher degree of information asymmetry and short-sell constraints, all of which make the housing market more susceptible to investor sentiment. In this paper, we construct state-level housing-sentiment indices based on households' beliefs about home-buying conditions, and show these indices explain a large part of variation in house prices at the state level. We find the effect of sentiment on house prices persists in successive quarters, even after controlling for important economic fundamentals. Therefore, our state-level housing-sentiment index provides a valuable tool for policymakers and investors who are keenly interested in tracking changes in investor sentiment and future house prices. Furthermore, accurate predictions of local house-price dynamics over the business cycles can give valuable insights to real-estate agents and financial institutions working in the housing markets about timely adjustments of portfolios containing real estate.

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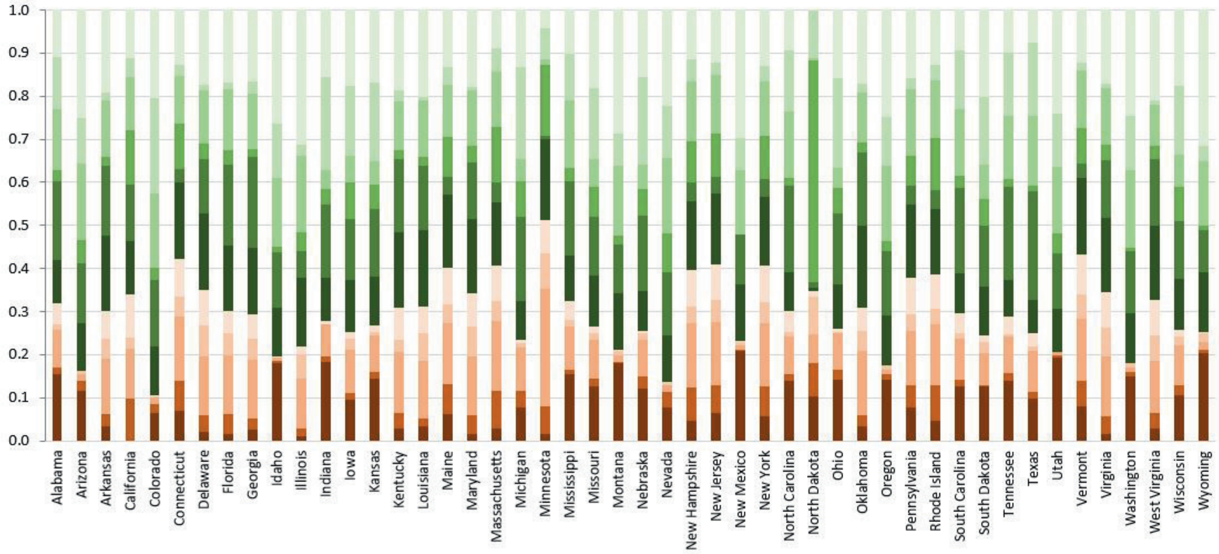
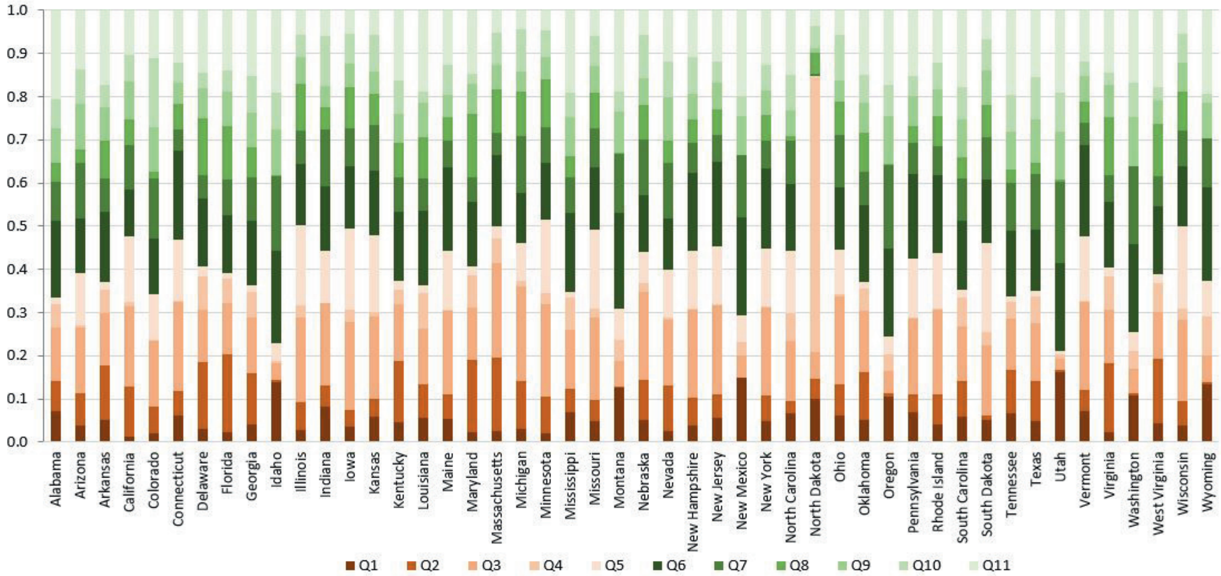
Appendix : Additional Tables and Figures

Figure A1: PLS weights - High-sentiment period



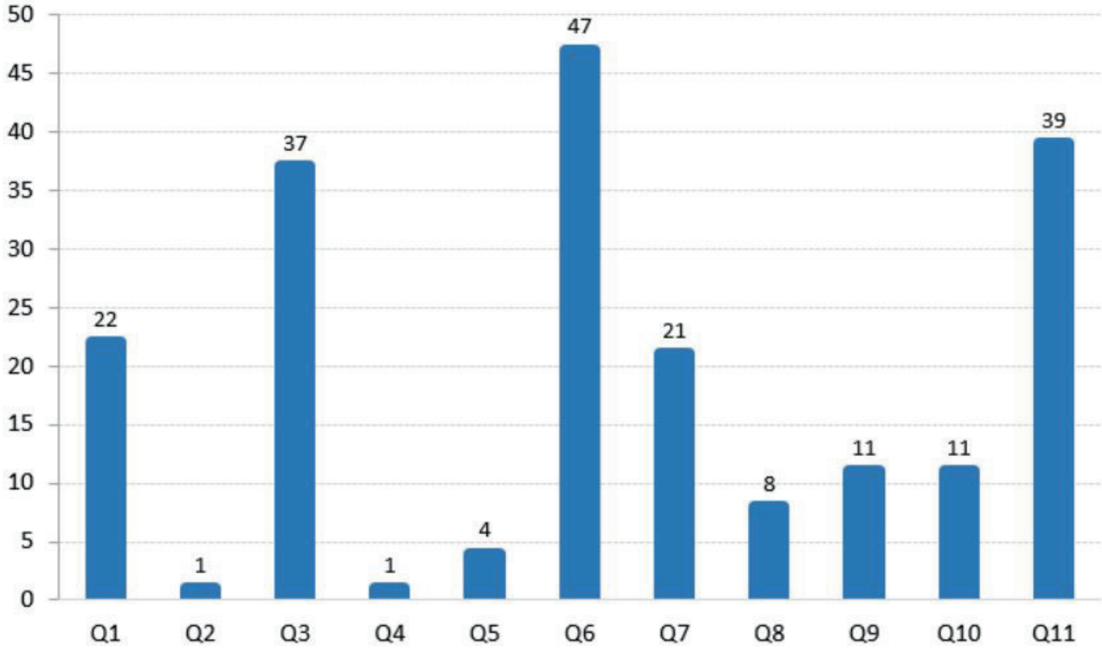
Notes: This figure displays the absolute value of the PLS weights used in constructing housing-sentiment indices across states when the corresponding state-level housing-sentiment index attains its maximum value.

Figure A2: PLS weights - Low-sentiment period



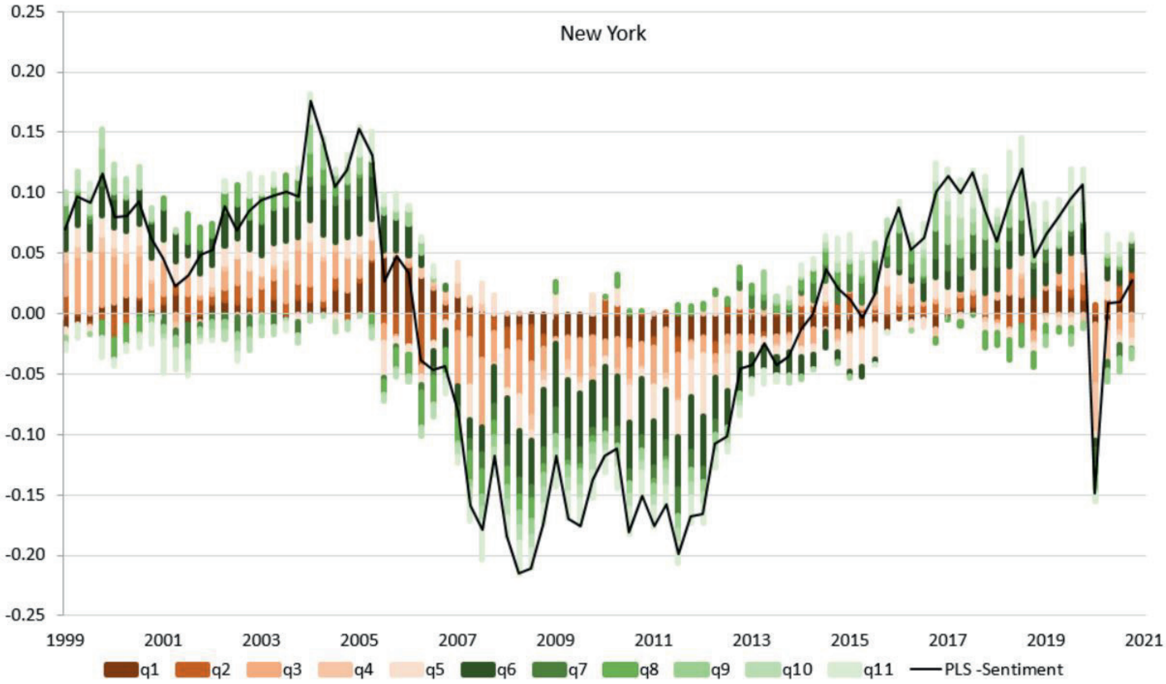
Notes: This figure displays the absolute value of the PLS weights used in constructing housing-sentiment indices across states when the corresponding state-level housing-sentiment index attains its minimum value.

Figure A3: Frequencies of survey variables selected as VIP in the PLS method



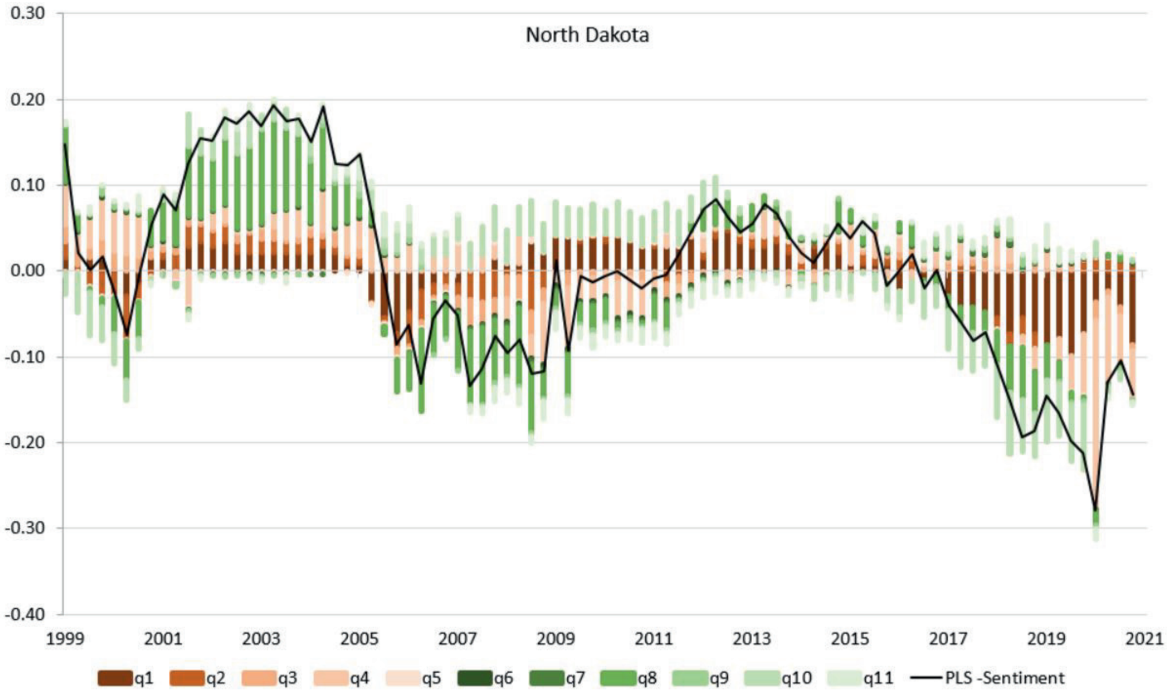
Notes: This figure displays the frequencies of each survey question selected as VIP in constructing state-level sentiment indices.

Figure A4: Decomposition of housing-sentiment index over time - New York



Notes: This figure displays time-series patterns in the sentiment components for New York.

Figure A5: Decomposition of housing-sentiment index over time - North Dakota



Notes: This figure displays time-series patterns in the sentiment components for North Dakota.

Table A1: State-level R^2_{OoS} values obtained from the local sentiment model across different forecast horizons

State	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Alabama	0.46*	0.22***	0.27***	0.42***	0.39***	-0.02***	0.41**	0.39**
Arizona	0.04	-0.19	0.05*	-0.51	-0.50	0.12***	0.70***	0.77***
Arkansas	0.28	0.01**	0.35**	0.47***	0.37***	0.49***	0.77***	0.65***
California	0.59*	0.50***	0.64***	0.65***	0.60***	0.45***	-0.08***	0.07**
Colorado	0.08	-0.23	-0.28	-0.42	-1.01	-1.48	-0.53	0.01*
Connecticut	0.41**	0.38***	0.41***	0.41***	0.28***	-0.06***	-0.09*	0.01**
Delaware	0.38	0.22	0.62**	0.75**	0.71**	0.59**	-1.63	-0.86
Florida	0.25	0.12**	0.32***	0.47***	0.49***	0.72***	0.78***	-0.82***
Georgia	0.18	-0.52	-0.58	0.16	-0.09	-0.51	-1.47	0.13***
Idaho	0.38	-0.07	0.18***	0.24*	0.10*	0.25*	0.73***	0.90***
Illinois	0.08	-0.06	-0.03**	0.16***	0.04*	-0.13	-0.25	0.01*
Indiana	0.59	0.11***	0.14***	0.31***	-0.13	0.17**	-0.42	0.02
Iowa	0.37**	0.12***	0.28***	0.50***	0.30***	0.12**	-1.02	-0.88
Kansas	0.35	0.13***	0.24***	0.27***	0.10**	0.09**	-0.34	-0.04
Kentucky	0.22***	0.15***	0.22***	0.49***	0.26***	-0.09*	-0.67	-0.81
Louisiana	-0.31	-0.25	-0.15**	0.17**	0.34***	0.47***	0.50***	0.73***
Maine	0.71	0.04**	-0.55	-0.72	-0.36	-0.14	0.06*	0.43***
Maryland	0.51**	0.48**	0.63***	0.73***	0.65***	-0.12***	-1.38***	-0.77
Massachusetts	0.11	-0.17	-0.12	0.11*	0.18**	0.21***	0.11***	0.55***
Michigan	0.16	-0.01	-0.03	-0.09	0.04**	0.09***	0.13***	0.37***
Minnesota	0.13	-0.03	0.00	0.09***	0.09***	0.05***	0.26***	-0.01
Mississippi	0.45*	0.25***	0.33***	0.48***	0.36***	0.57***	0.46***	0.63***
Missouri	0.01**	0.02**	0.14***	0.24***	0.24***	0.04*	-0.01*	-0.09
Montana	0.31	0.24***	0.38***	0.44***	0.51***	0.67***	0.84***	0.91***
Nebraska	0.10**	0.04*	0.17**	0.25***	0.32***	0.37***	0.49***	0.11***
Nevada	-0.32***	0.09***	0.35**	0.62**	0.65**	0.43***	-0.10	0.49***
New Hampshire	0.18	-0.13*	-1.11	-1.82	-0.58	-0.42	0.00	0.43***
New Jersey	0.64	0.22***	0.41***	0.54***	0.44***	0.43***	0.14***	0.26***
New Mexico	0.71	0.05***	0.33***	0.62***	0.67***	0.76***	0.91***	0.92***
New York	0.61**	0.45***	0.50***	0.64***	0.62***	0.62***	0.51***	0.46***
North Carolina	0.65	0.28***	0.34***	0.44***	0.11***	0.02***	-0.23***	-0.91***
North Dakota	-0.15	0.05***	0.06***	0.13***	0.15***	0.16***	0.12***	0.07**
Ohio	0.28*	0.03	0.07**	0.40**	0.11*	-0.19	-1.12	-0.27
Oklahoma	0.30*	-0.03*	0.14***	0.18***	0.02**	-0.08*	-0.07**	0.22***
Oregon	0.32*	0.01*	0.12**	0.09**	0.09**	0.05**	0.27***	0.64***
Pennsylvania	0.74	0.56**	0.73**	0.80**	0.69***	0.61***	0.69***	-0.12**
Rhode Island	0.72	0.51*	0.60***	0.75***	0.67***	0.66***	0.60***	-1.98
South Carolina	0.17**	-0.01**	0.21***	0.34***	0.11**	-0.66	-0.16*	-0.97
South Dakota	0.34**	0.25***	0.33***	0.48***	0.46***	0.36***	0.54***	0.42***
Tennessee	0.27**	0.24**	0.41**	0.52**	0.15*	-1.07	-0.70	0.17*
Texas	0.12*	-0.04	-0.04	-0.33	-0.30	-0.30	0.13**	0.58***
Utah	0.16*	0.07**	0.24**	0.42***	0.45***	0.54***	0.50***	0.49***
Vermont	0.59	-0.01***	-0.32***	-0.37***	-0.46***	-0.25***	-0.10	-0.23
Virginia	0.47	0.40**	0.53***	0.52***	0.57***	0.79***	0.49***	-1.30
Washington	0.52	0.31***	0.35***	0.37***	0.42***	0.53***	0.81***	0.82***
West Virginia	0.26*	0.33***	0.42***	0.34***	0.48***	0.50***	0.53***	-0.99***
Wisconsin	0.34*	0.14**	0.18***	0.35***	0.10*	0.00	-0.17	-0.07
Wyoming	0.16***	0.54***	0.69***	0.68***	0.76***	0.75***	0.77***	0.87***

Notes: This table reveals the R^2_{OoS} values derived from the local sentiment model over a range of forecast horizons, denoted as h. Asterisk(s) (*** 1% level; ** 5% level; * 10% level) shows the significance level of testing the null hypothesis of $R^2_{\text{OoS}} \leq 0$, against the alternative $R^2_{\text{OoS}} > 0$ applying the Clark and West, 2007 statistics, which allows us to assess the predictive accuracy in nested models.

Table A2: Different bubble testing strategies

Variables	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
S	0.0036***	0.0034***	0.0033***	0.0032***	0.0028***	0.0027***	0.0028***	0.0031***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0005)
$S \times I^{Bubble}$	0.0013	0.0013*	0.0006	-0.0003	0.0018**	0.0021**	0.0015**	0.0004
	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0008)	(0.0008)	(0.0007)	(0.0006)
Adj. R^2	0.344	0.326	0.302	0.279	0.438	0.435	0.426	0.424
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,120	3,072	3,024	2,976	3,120	3,072	3,024	2,976
Number of states	48	48	48	48	48	48	48	48

Notes: This table presents the estimation results of the regression model: $h_{it+h} = \alpha_i + \beta S_{it} + \beta_B S_{it} \times I_{it}^{Bubble} + \delta X_{it} + \epsilon_{it+h}$, where I_{it}^{Bubble} is a dummy equal to 1 for the date-stamping bubble periods detected by the approach in Phillips et al., 2015. To obtain bubble periods in the non-fundamental component of the price-rent ratio, we initially regress the price-rent ratio onto our set of control variables and then apply the Phillips et al., 2015's test on the resulting residuals. For each regression, the table presents the estimates of slopes and standard errors clustered at the state and quarter level in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. All variables are used in standardized form. Given that our control variables begin from from 1999:Q2, we identify the bubble periods over the period 1999:Q2 to 2021:Q1.

Table A3: Controlling for time fixed effects

Variables	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
S	0.0062***	0.0054***	0.0050***	0.0040**	0.0057***	0.0049***	0.0044***	0.0034**
	(0.0016)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0014)
Control variables					✓	✓	✓	✓
State and Time FEs	✓	✓	✓	✓	✓	✓	✓	✓
Number of states	48	48	48	48	48	48	48	48
Observations	4,958	4,884	4,810	4,736	4,958	4,884	4,810	4,736
Adj. R^2	0.597	0.595	0.598	0.594	0.620	0.616	0.620	0.617

Notes: The dependent variable in each model is the growth of the house price index in each state at the given horizon (h=1, 2, 3, or 4). S refers to the state-level housing sentiment index. The inclusion of both state and time fixed effects in the model is indicated by a checkmark. For each regression, the table presents the estimates of slopes and standard errors clustered at the state and quarter level in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. All variables are used in standardized form.

Table A4: Sub-sample analysis

Variables	Pre -Crisis (1999-2005)	Around Crisis (2006-2009)	Post Crisis (2010-2021)	Pre -Crisis (1999-2005)	Around Crisis (2006-2009)	Post Crisis (2010-2021)
S	0.0060***	0.0082**	0.0025***	0.0056***	0.0082***	0.0024***
	(0.0014)	(0.0029)	(0.00087)	(0.0014)	(0.0028)	(0.0008)
Control variables				✓	✓	✓
State and Time FEs	✓	✓	✓	✓	✓	✓
Number of states	48	48	48	48	48	48
Observations	592	1,184	3,182	592	1,184	3,182
Adj. R^2	0.646	0.645	0.696	0.652	0.651	0.699

Notes: The dependent variable in each model is the growth of the house price index in each state during the specified sub-periods: pre-crisis (1999-2005), crisis (2006-2009), and post-crisis (2010-2021). State and time fixed effects (FEs) were accounted for in all models. For each regression, the table presents the estimates of slopes and standard errors double clustered at the state and quarter level in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. All variables are used in standardized form.

Table A5: Considering cross-sectional spatial dependence

Variables	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
S	0.0040***	0.0039***	0.0038***	0.0037***	0.0035***	0.0034***	0.0036***	0.0034***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Control variables					✓	✓	✓	✓
SE: DK approach	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,176	4,128	4,080	4,032	4,128	4,080	4,032	3,984
Number of states	48	48	48	48	48	48	48	48
R^2	0.239	0.212	0.198	0.141	0.466	0.425	0.385	0.359

Notes: The dependent variable in each model is the growth of the house price index in each state at the given horizon (h=1, 2, 3, or 4). S refers to the state-level housing sentiment index. The values in parentheses are standard errors computed using the Driscoll and Kraay, 1998 approach, which is robust to different forms of spatial and temporal dependence, heteroskedasticity, and auto-correlation. The h in the header row refers to the forecast horizon, with h=1, 2, 3, or 4 corresponding to a forecast for one, two, three, or four periods ahead, respectively. For each regression, ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. All variables are used in standardized form.

Table A6: Controlling for AR component

Variables	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
S	0.0005	0.0009**	0.0016***	0.0015***	0.0015***	0.0022***	0.0025***	0.0023***
	(0.0003)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Control variables					✓	✓	✓	✓
Controlling AR	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,662	4,588	4,514	4,440	4,662	4,588	4,514	4,440
Number of states	48	48	48	48	48	48	48	48
Adj. R^2	0.616	0.479	0.327	0.246	0.732	0.621	0.502	0.463

Notes: The dependent variable in each model is the growth of the house price index, and the main explanatory variable (S) is the state-level housing sentiment index. The check-marks denote models where control variables and the autoregressive (AR) component have been included. The control variables are other factors that could influence housing prices, while the AR component controls for the auto-correlation in the house price series. For each regression, the table presents the estimates of slopes and standard errors double clustered at the state and quarter level in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. All variables are used in standardized form.

Chapter 3

Fifty Shades of the US States: News Media Coverage and Predictability of House Prices

Oguzhan Cepni

Abstract

This paper introduces new housing-media-attention indices for the 50 US states based on the Bloomberg Terminal News Trends (NT) function, which collects articles from various news and social media sources and identifies their content using artificial intelligence tools. The results indicate the state-level housing-media-attention index explains a significant portion of the total variation in future house prices, even when economic fundamentals are considered. Additionally, I find the impact of housing media attention on future house prices is stronger in states with non-recourse mortgage laws, greater land-use regulations, and higher social connectedness among individuals of both low and high socioeconomic status. Out-of-sample forecasting results further suggest that housing media attention has the potential to act as an early indicator of the direction of the housing market.

3.1 Introduction

In light of recent advancements in digital and telecommunication technology, news media platforms have emerged as a rapid avenue for disseminating information. As a result, the public now has access to more information pertaining to financial markets. The news media coverage can influence asset prices by shaping individuals' expectations about future returns. As Shiller, 2002 notes, the news media has a significant impact in triggering market movements and can determine market sentiment based on what is reported, even if it is mostly hype. Accordingly, many studies have investigated the role of news media on financial markets through various dimensions, such as reducing information asymmetry (Tetlock, 2010), creating incentives for manipulation (Gurun and Butler, 2012), driving investor attention (Barber and Odean, 2008; Fang and Peress, 2009; Solomon et al., 2014; Kaniel and Parham, 2017), and forming market sentiment (Tetlock, 2007; Garcıa, 2013; Calomiris and Mamaysky, 2019; Jeon et al., 2022). However, little is known about the effect of news media on real asset markets, particularly the housing market, even though real estate investments have traditionally represented a significant portion of an individual's wealth.[1] Considering the lower informational efficiency of housing market prices and shorting constraints relative to those of the stock market (Case and Shiller, 1989), how news media coverage affects price fluctuations in this asset class and determines price formation relative to other markets remains an open question.[2]

In this paper, I present a new approach for constructing housing-media-attention indices for the 50 US states using the Bloomberg Terminal News Trends (NT) function. The NT function is a powerful tool that analyzes the volume of news published in a vast archive of news stories and social media posts from over 150,000 sources, leveraging AI methods to assign content codes to thousands of news stories in real time.[3] Hence, it functions as a stand-in for widely disseminated news articles and provides more in-depth coverage than many of the alternatives used in earlier research.[4] With the help of the NT function of

[1]According to the first quarter of 2021 Financial Accounts data of the US, residential estate accounts for approximately 27.4% of total household net worth and 84.2% of total household non-financial assets, see: `https://www.federalreserve.gov/releases/z1/`

[2]The housing market presents an ideal environment for exploring the informational role of news media for the following reasons: first, the market is dominated by individual investors who have limited information processing capabilities, and second, short-sale constraints in the housing market are stringent.

[3]The Bloomberg Terminal news feed gathers articles from a variety of news and social media sources, including but not limited to The Wall Street Journal, The Financial Times, Business Insider, The New York Times, Reddit, and Twitter, among others.

[4]The vast majority of the earlier research that utilizes news media relies on a single source, such as social media platforms (Chen et al., 2014; Lee et al., 2015), Reddit forums (Corbet et al., 2022), online message boards (Antweiler and Frank, 2004; Das and Chen, 2007), Wall Street Journal (WSJ) (Tetlock, 2007; Manela and Moreira, 2017), New York Times (Garcıa, 2013), Dow Jones newswire (Chen et al., 2022b), and financial news releases (Bali et al., 2018; Glasserman and Mamaysky, 2019; Boudoukh et al., 2019; Huang et al., 2020; Fraiberger et al., 2021).

Bloomberg Terminal, I quantify news media coverage by counting the number of news stories and social posts if their content is related to the housing market at the state level. To capture the common variation in news count on housing-related topics, I employ the partial least squares (PLS) method and construct state-level housing-media-attention indices.[5] This is achieved by combining the state-level variation in news counts with the target variable of state-level house-price growth rates. My state-level housing-media-attention indices accurately capture the heterogeneity in the local house-price dynamics and demonstrate higher explanatory power compared to other housing market fundamentals. In particular, the results of in-sample panel predictive regression indicate housing media coverage explains a substantial portion of future house-price fluctuations, as evidenced by an adjusted R^2 of 0.29. This result is significantly higher than other house-price predictors such as mortgage rate, income, employment, and economic-activity-related variables. A one-standard-deviation increase in the housing-attention index in the current quarter on average leads to a 0.37% increase in the growth rate of house prices in the next quarter, as indicated by the magnitude of the slope coefficient.

Furthermore, I also construct a national-level housing-media-attention index by collecting the news media coverage at the national level and examine the predictive capabilities of both the national- and state-level attention indices for future house-price growth. The results indicate that although national-level housing-market attention has a significant impact on local housing price growth, which helps explain the synchronized occurrence of booms and busts in house-price cycles across different states, the state-level attention index still retains its significant predictive power even when controlling for national-level attention and other housing-market fundamentals. This result suggests state-level media coverage may contain useful information about the local dynamics of the housing market that national-level attention does not capture. The results from the out-of-sample forecasting exercise further support this claim, because the state-level housing-attention indices exhibit a better out-of-sample predictive ability, as measured by a higher out-of-sample R^2 (R^2_{OoS}), than national-level media attention, This finding confirms the conclusion that housing markets are highly segmented and local in nature (Del Negro and Otrok, 2007; Glaeser et al., 2014;

[5]The interpretation of the constructed index as a measure of "attention" rather than merely a "measure of house price dynamics" stems from the underlying methodology and the conceptual framework guiding this study. The index is built upon the premise that media coverage on housing-related topics reflects the collective focus and interest of various stakeholders, including investors, policymakers, and the general public. It captures the intensity of news coverage related to specific housing market themes, which is posited as a proxy for the level of societal attention to the housing market at any given time. This interpretation recognizes that while news coverage might indeed correlate with house price dynamics, it also serves a more complex function in shaping perceptions, informing decisions, and potentially influencing market behavior. In other words, the housing-attention index not only mirrors the price dynamics but also encapsulates the information flows and cognitive processes that contribute to those dynamics. The term "attention" is thus used to reflect this broader, multifaceted relationship between news media and the housing market, acknowledging the role of media as both a respondent to and a shaper of market conditions.

Soo, 2018; Møller et al., 2023).

Using state-level housing-media attention indices, I further examine the relationship between news media coverage and changes in house-price growth through the lens of state characteristics, such as mortgage laws, land-use regulations, and levels of social connectedness, to assess whether state characteristics amplify the effects of news media coverage on future house-price movements. The findings of Nam and Oh, 2021 suggest non-recourse law contributes significantly to the rise in home prices by encouraging risk-shifting behavior among lenders, because lenders have no additional claim on mortgagors over the collateral value of the house in states governed by non-recourse mortgage law. I find the relationship between media coverage and future housing prices is stronger in non-recourse states than in the recourse states. Specifically, a one-standard-deviation increase in housing attention leads to an additional 0.13% rise in the housing prices in non-recourse states at the one-quarter-ahead forecast horizon, when controlling for all housing fundamentals. This result suggests media coverage may play a role in encouraging risk-shifting behavior in the residential housing market and ultimately drive an increase in future housing prices.

There are numerous forms of land use restrictions in the US, most of which are implemented at the local government level. Using the Residential Land Use Regulatory Index (WRLURI) developed by Gyourko et al., 2021, I aim to determine whether the impact of news media coverage on housing prices is more pronounced in states with highly regulated housing market. Indeed, my findings reveal the housing-market-attention index is a stronger predictor for future house prices in states with a highly regulated housing markets. More specifically, in more regulated states, a one-standard-deviation rise in the housing-attention index predicts an increase in housing prices that is two times bigger than in less regulated states. This result aligns with the findings of Møller et al., 2023, who document that changes in local housing demand have a greater impact on home prices in metropolitan areas with limited housing supply.

Shiller, 2002[p.84] emphasizes the significance of social connections in the housing market, stating that "significant market events generally occur only if there is similar thinking among large groups of people, and the news media are essential vehicles for the spread of ideas." Using the social-connectedness measure of Bailey et al., 2018b, which is based on the friendship links on Facebook, I investigate whether the housing-attention index is a stronger predictor of housing prices in more socially connected states. My findings provide supportive evidence that the housing-attention index has more substantial predictive power for house-price changes in more socially connected states, implying social media can significantly influence household behaviors through dissemination of information via social networks (Bailey et al., 2018a). In particular, I find that, at the one-quarter-ahead forecast horizon, a one-standard-deviation increase in housing attention predicts, on average, 0.15% more increase in housing prices in more socially connected states than in less socially connected ones. Furthermore, various theoretical studies show social connections with well-educated or wealthy individuals may facilitate knowledge transmission and reduce information asymmetry (Montgomery, 1991; Ambrus et al., 2014). Using data on 21 billion Facebook friendships, Chetty et al., 2022 develop a measure of economic connectedness that denotes the percentage of low socioeconomic status (SES) individuals who have high-SES friends in a given county. Given that high-SES individuals are more likely than low-SES individuals to learn new knowledge from the media, I examine how greater exposure to high-SES friends amplifies the predictive power of housing media attention for future house-price growth. I divide the states into groups with high and low economic connectedness and find the influence of media attention on future house prices is greater in states where low- and high-SES individuals are more connected through friendship.

The paper contributes to the literature exploring the role of media in financial markets, such as the cost of capital and debt (Fang and Peress, 2009; Gao et al., 2020), executive compensation (Core et al., 2008; Kuhnen and Niessen, 2012), firm value (Nguyen et al., 2020; Chen et al., 2020), stock markets (Garcıa, 2013; Peress, 2014; Ahmad et al., 2016; Drake et al., 2017; Ben-Rephael et al., 2017; Bali et al., 2018; Ozik et al., 2021; Jeon et al., 2022; Chen et al., 2022a), options market (Filippou and Garcia-Ares, 2020), bond market (Defond and Zhang, 2014; Bartov et al., 2022), and cryptocurrency market (Corbet et al., 2020; Ozdamar et al., 2022). Although the housing market is largely dominated by individual investors with limited access to comprehensive information, empirical studies examining the relationship between news media coverage and housing returns are scarce, due to a lack of measures for housing media attention. Additionally, the distinctive nature of the housing market, characterized by stringent short-selling constraints, high transaction costs, and substantial information asymmetries, creates a favorable environment to assess the influence of news media on house prices. I address this gap by constructing new measures of US state-level housing-attention indices, which is a novel contribution to the literature.

Soo, 2018 creates a media sentiment index for 34 cities across the US by conducting a textual analysis on the qualitative tone of local newspaper articles. Similarly, Zhu et al., 2022 build a city-level sentiment index for the four first-tier cities in China by utilizing text-mining techniques on a micro-blogging platform (Sina Weibo). In contrast to these limited number of city-level housing measures, I build a housing-media attention index at the state level and use it to explain variations in house prices across the 50 US states.[6] I also diverge from previous studies in terms of using comprehensive news coverage, by utilizing the Bloomberg Terminal news feed, which covers articles from well-known financial news blogs,

[6] As a robustness check, I construct a housing-media-attention index for the same 34 cities as in Soo, 2018 and show my newly constructed media-attention index continues to play a significant role in determining housing prices at both the state and city levels.

social media, and online newspapers rather than focusing on news from a single source.[7] This approach enhances the accuracy of the data in reflecting the depth of housing news coverage accessible to the general public, because individual investors have access to different media platforms. Furthermore, the study exploits the heterogeneity in state characteristics and finds housing attention has a more substantial predictive power in states with non-recourse mortgage laws, stronger land-use regulations, and higher social and economic connectedness. This finding constitutes another novel contribution of the study.

The state-level analysis conducted in this study offers a distinctive perspective on housing market dynamics that complements existing city-level analyses (for instance, Soo, 2018 and Zhu et al., 2022). While city-level indices can provide granular insights into localized housing market conditions, they may overlook broader regional trends and economic factors that often transcend city boundaries. By focusing on a state-level analysis, I capture a more comprehensive view of the housing market that incorporates regional economic policies, inter-city migration patterns, infrastructure developments, and other state-wide phenomena. This approach not only reflects the more extensive geographic scope of media coverage but also aligns with the decision-making frameworks of regional policymakers, investors, and large real estate firms that often operate at the state level. Furthermore, a state-level housing-attention index helps us bridge the gap between micro-level city dynamics and macro-level national trends. While a city-level index might more naturally represent the size of a specific housing market, it may miss interconnected dynamics between cities within the same state. Housing markets are not isolated entities; they interact and influence each other through various channels, such as labor mobility, supply chain relationships, and investment flows. Hence, my state-level index encapsulates these interconnected dynamics, offering a more holistic understanding of housing market behavior. In doing so, it augments city-level analyses by presenting a broader context within which local markets operate and contributes to our comprehension of the multifaceted nature of housing markets that can guide more effective policy interventions and investment strategies.

My study also enriches the existing literature on the predictability of house prices. Previous studies (Rapach and Strauss, 2009; Gupta and Das, 2010; Ghysels et al., 2013; Segnon et al., 2021; Gupta et al., 2021; Balcilar et al., 2021) have used economic variables such as employment, housing wealth-to-income ratios, and interest rates or uncertainty-related variables as predictors for house prices. However, as Lai and Van Order, 2010 indicate, these

[7] My study differs from the previous studies that have constructed housing sentiment indices using Google search activity and survey data (Dietzel et al., 2016; Chauvet et al., 2016; Møller et al., 2023). For example, Møller et al., 2023 build a housing search index using online queries for specific keywords related to the home-buying process and use it to study the relationship between housing search activity and house prices. Additionally, other studies have used survey-based sentiment indicators, such as those from the University of Michigan, to explain the fluctuations in house prices at both the national and state levels (Bork et al., 2020; Cepni and Khorunzhina, 2023).

variables only accounted for 10% of the variation in house prices between 2000 to 2011. By incorporating news media coverage in the analysis, this study seeks to demonstrate that it offers insights into future house prices beyond what traditional macroeconomic indicators typically reveal.

The rest of the paper is structured as follows: Section 2 describes the data used in this study. Section 3 outlines the development of the state-level housing-attention indices. Section 4 delves into the factors that influence media attention toward the housing market. Section 5 compares the predictive power of the attention indices with traditional housing-market variables and a national-level attention measure. Section 6 evaluates the out-of-sample predictability of the indices. Section 7 examines the variations in local housing markets and the interaction of the housing-attention measure with state-specific characteristics. Section 8 conducts a myriad of robustness checks to further validate the findings of the study. Section 9 presents additional analyses. Lastly, section 10 concludes.

3.2 Data

3.2.1 Control Variables and Housing Data

I gather quarterly data on the all-transactions house-price index for the 50 states in the US, obtained from the Federal Housing Finance Agency (FHFA). The index is calculated using a weighted approach that considers the repeat sales of single-family houses. To account for the housing market and macroeconomic conditions, I consider several state-level factors, including building permits, 30-year mortgage rate, per-capita income, stock market index, employment level, and economic-activity index. As a proxy for changes in housing supply, I use data from the US Census Bureau on building permits issued at the state level. To consider fluctuations in interest rates, I collect the 30-year fixed mortgage rate at the state level from `https://www.bankrate.com/mortgages/30-year-mortgage-rates/` because previous studies show low borrowing rates contribute to an increase in demand for houses (Himmelberg et al., 2005; Gelain et al., 2018).

As Rosen and Smith, 1983 suggest, I include the per-capita income from the Bureau of Economic Analysis (BEA) to control the shifts in housing demand due to the changes in income. In addition, Shiller, 2015 argues booms in the stock market often coincide with booms in the housing market. To account for this relationship, I utilize the Bloomberg state-level stock index, which is calculated as a capitalization-weighted index of publicly listed company shares domiciled in a given state. I also incorporate state-level employment data from the Bureau of Labor Statistics (BLS) to adjust for local labor-market conditions that might affect housing demand. Finally, I control for heterogeneous macroeconomic conditions using the Philadelphia Fed's State leading index (Crone and Clayton-Matthews, 2005).[8] The data, spanning from 2004:Q2 to 2021:Q1, are collected on a quarterly basis. The starting date of the sample is determined by the availability of media coverage data, which are introduced in the following section.

3.2.2 News Data

To quantify media attention to the housing market, I tally the number of articles available through the Bloomberg Terminal. The Bloomberg Terminal's news feed aggregates articles from a range of news and social media outlets, including The Financial Times, Business Insider, Wall Street Journal, New York Times, and Twitter. As a result, it serves as a comprehensive proxy for widely circulated news coverage, surpassing alternatives utilized in previous studies. To access data, I use the Bloomberg Terminal NT function, which allows me to search for specific topics and US states. The tool is based on a comprehensive library of news articles (over 150,000 sources) and social media posts and uses advanced AI methods to identify content from thousands of news stories and social media posts in real time. In contrast to previous studies that focused on a limited number of search categories, I construct search queries for a wide variety of topics related to the housing market, enhancing the possibility that the data accurately reflect the level of news coverage accessible to the general public.[9]

To create a comprehensive measure of the media attention on the housing market, I collect news counts on the following 20 related topics: "home sales," "home price," "housing price," "housing demand," "housing supply," "housing market," "housing cost," "home buyers," "home inventory," "homeownership," "real estate agencies," "real estate," "real estate listing," "mortgage rate," "mortgage demand," "mortgage credit," "subprime mortgage," "residential property price," "home foreclosure," and "mortgage affordability." These search phrases pertain to the housing market and serve as a reliable indicator of media attention. To obtain state-specific news counts on these topics, I include an additional filter by combining each search query with the US states, using the Boolean search operator "AND" in the NT function of Bloomberg.[10] I then calculate the quarterly sum of daily news counts. Note that if a news article is classified by the NT function as relating to more than one topic pertaining to the housing market for a given state, it will be counted more than once.

[8] This index is calculated using the VAR model, which takes into account the interest rate gap between the three-month Treasury bill and the 10-year Treasury bond, insurance claims, and Institute for Supply Management's (ISM) manufacturing survey.

[9] Wu and Brynjolfsson, 2015 use the volume of internet search queries on two categories, namely, "Real estate agencies" and "Real estate listings." Ruscheinsky et al., 2018 focus on news containing either the keywords "REIT" and/or "real estate" by searching four US leading papers. Using the NewsBank's Access World News (AWN) database, Cho, 2016 collects housing articles, including the keywords "housing price" and "housing market."

[10] For instance, to obtain news counts on home sales for California, I run the following search query in the NT function: "home sales" AND "California."

This desirable feature of my approach serves as a form of weighting, because it reflects the information intensity of the news on the housing market. If a news story covers multiple topics related to the housing market, it is likely to be more relevant and provide a more comprehensive picture of housing developments.

It is essential to recognize that the media's role extends beyond direct influence on buying behavior within a specific geographical region. When a non-local media outlet, such as the Los Angeles Times, publishes an article about the New York housing market, it indicates a trend or event in that market warranting broader attention. The inclusion of such articles in constructing the housing media attention index for New York does not aim to illustrate how readers in California might be encouraged to buy property in New York. Instead, it emphasizes how the news about New York's housing market has resonated within the media landscape, thereby capturing a phenomenon that may be regionally significant but has garnered national interest. By encompassing news pieces that pertain to specific states, regardless of the origin of the media outlet, my aim is to capture the information intensity of the news on the housing market, recognizing the interconnected nature of modern media where news on a particular topic might be published across various channels, both locally and nationally. Hence, my approach to create housing media attention index encapsulates not only the local dynamics but also the broader narrative surrounding the housing market, leading to a more robust and nuanced understanding.

3.3 Construction of the State - Level Housing-Attention Index

Following Kelly and Pruitt, 2013; Kelly and Pruitt, 2015, Huang et al., 2015, and Bork et al., 2020, I employ a PLS approach to eliminate idiosyncratic noise that is deemed less significant for the dynamics of housing prices and to identify common components to succinctly encapsulate the information contained in the news counts of various housing-related search topics. This methodology allows me to translate the information contained in the news counts of numerous topics into a single, easily interpretable index. To do so, I leverage the covariance between the common component and the target variable to directly extract the latent common component, effectively summarizing the most relevant information from the news counts for house-price growth. In my setup, the target variable is the state-level housing price growth, calculated from the FHFA house-price index.[11]

[11] The construction of the housing-attention index is indeed built on the premise that variation in news can act as a driving force in the housing market. The choice of search topics and the structure of the index aim to mirror what investors and the broader public are likely to pay attention to and learn about the housing market from news. It is based on the understanding that news media plays an essential role in disseminating information, shaping perceptions, and influencing decisions in the housing market. While

Subsequently, I utilize the SIMPLS algorithm proposed by De Jong (1993) to develop the state-level housing-attention index, which is derived from a linear combination of the news counts for 20 news topics and is designed to maximize the covariance with the state-level housing price growth. More specifically, the state-level housing-market attention index at time t is computed by $HAI_{it} = nc_{it}w_i$, where nc_{it} is a vector of standardized news counts on different search topics capturing the media attention at time t in state i. The vector of weights w_i for state i is computed as:

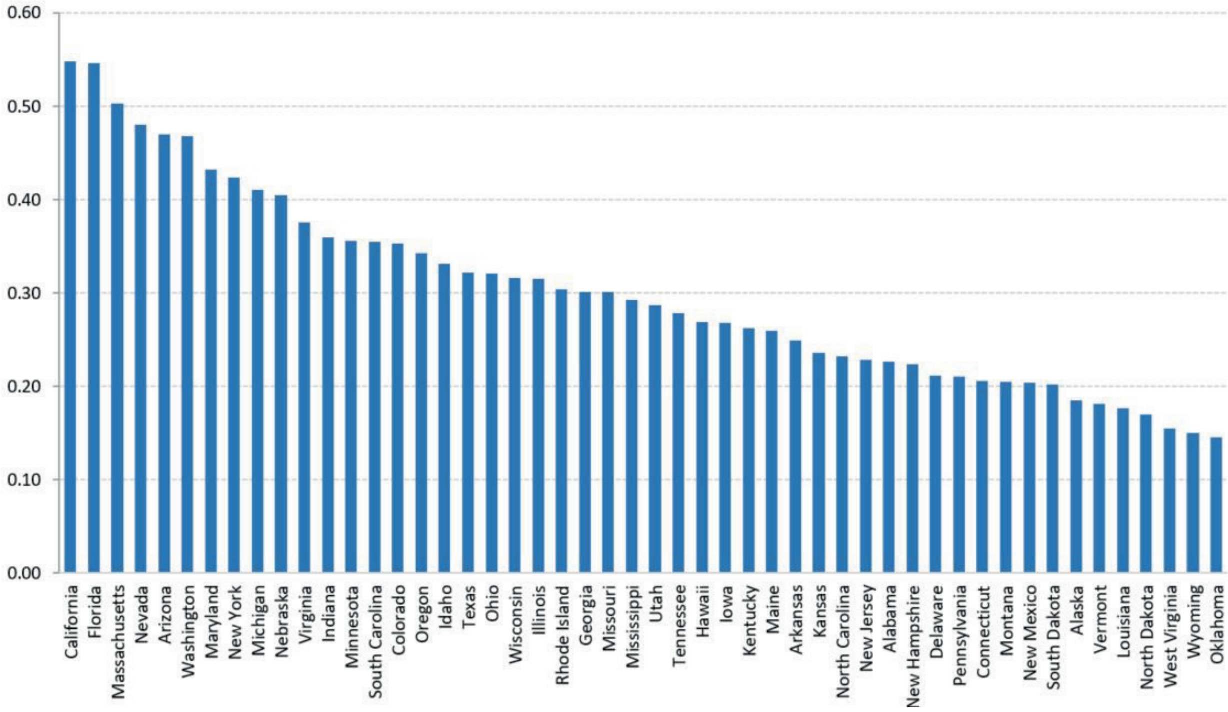
$$w_i = \arg\max \quad w_i' nc_{it} h_{it} h_{it}' nc_{it}' w_i \tag{3.1}$$

subject to $w_i' w_i = 1$, and h_{it} refers to the house-price growth for state i in period t.

Figure 3.1 plots the R^2 values obtained from the regressions of state-level house-price growth with state-level housing-attention indices. Given that the explanatory power of the housing-attention index ranges from 0.15 to 0.55 across states, one can infer that house-price dynamics are locally segmented and highly diverse. Furthermore, Figures 3.2 - 3.3 plot the time series of the housing-attention index along with the house-price growth for the top and bottom 10 states based on the explanatory power of the housing-attention index. A quick inspection of these figures suggests a strong co-movement between the housing-attention indices and house prices over time. In particular, the housing-attention index accurately reflects pivotal events in the housing market, such as the decrease in home prices in 2009 and 2010 after the collapse of the mortgage market and the subsequent rebound and steady growth in home prices in recent years. Another observation from these figures is that, although the COVID-19 pandemic caused a drop in many macroeconomic indices, the combination of low-interest rates and supply-chain interruptions resulted in greater costs of building materials, which in turn drove up home prices. Hence, in the aftermath of the pandemic, housing-attention indices have been on an upward trend and have remained strong.

acknowledging that the news may also reflect underlying housing market dynamics, the index is designed to encapsulate the proactive role of the media in guiding attention to specific aspects of the housing market. The observed association between news coverage and house prices supports the notion that media attention serves as more than a mere proxy for underlying variation but may actively contribute to shaping housing market trends.

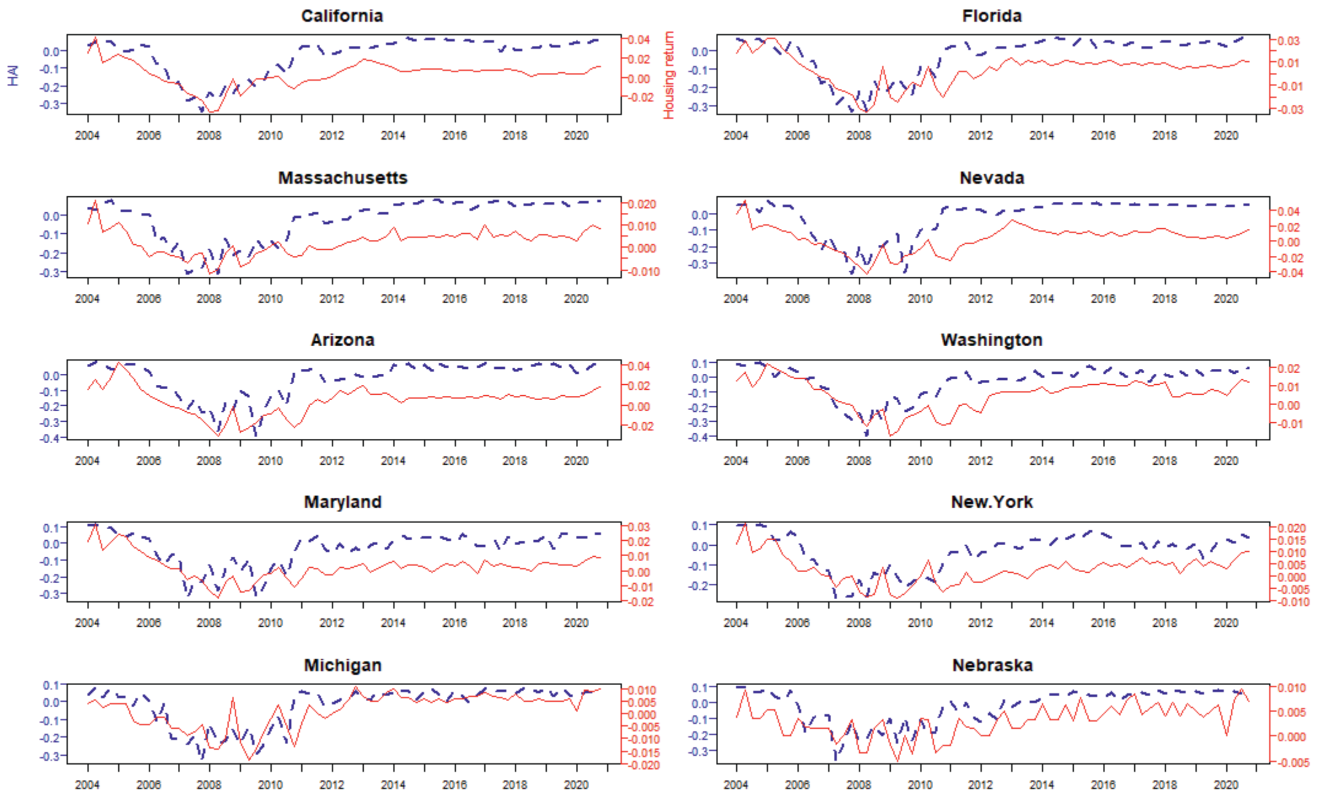
Figure 3.1: Explanatory power of housing media attention for variation in housing price growth



Notes: This figure displays the R^2 values from the regressions of each state-level house price growth rates onto each constructed state-level attention index.

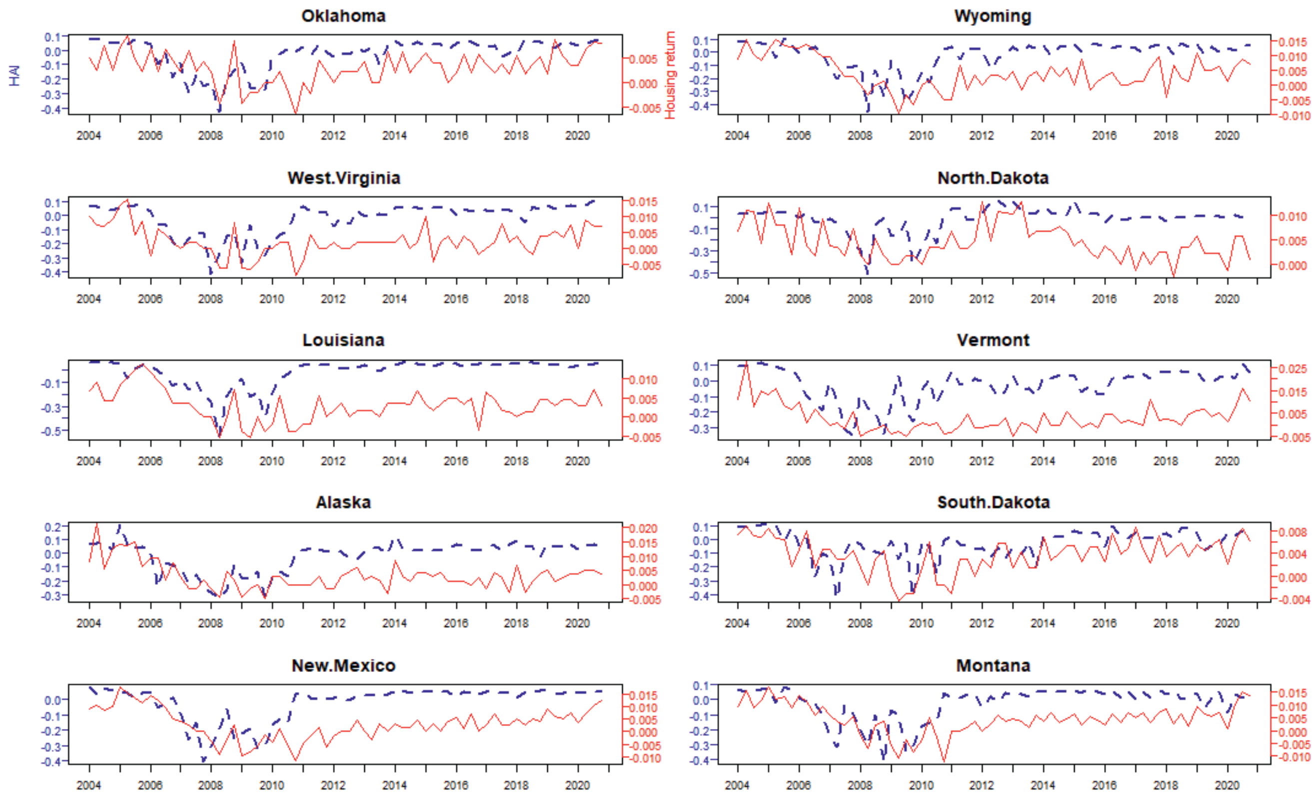
I further investigate the PLS weights assigned to different news topics in the construction of the state-level housing-media-attention indices to gain insight into their relative importance in shaping the housing-market attention. The results of this analysis are depicted in Figure 3.4, which displays the maximum, average, and minimum values of the PLS weights across states. The results demonstrate a significant variation in PLS weights, highlighting the varying importance of different news topics in determining the state-level housing market attention. For example, PLS assigns greater weights to news topics related to "price," such as "home price" and "housing price," suggesting these topics are important in shaping the state-level housing-market attention and media coverage. This is not surprising, given that changes in housing prices can greatly impact household decision-making. Additionally, the higher weights assigned to topics related to credit conditions, such as "mortgage credit," indicate credit availability may have a significant impact on home buying and selling activities, and the media may closely monitor the mortgage market and the conditions surrounding it. Finally, the PLS places more emphasis on topics reflecting housing-market stress, such as "subprime mortgage" and "home foreclosure," suggest high levels of subprime mortgage defaults and foreclosures can lead to a decline in home prices and further affect consumer sentiment and decision-making.

Figure 3.2: Housing-attention index along with housing price growth for top 10 states with highest R^2 values



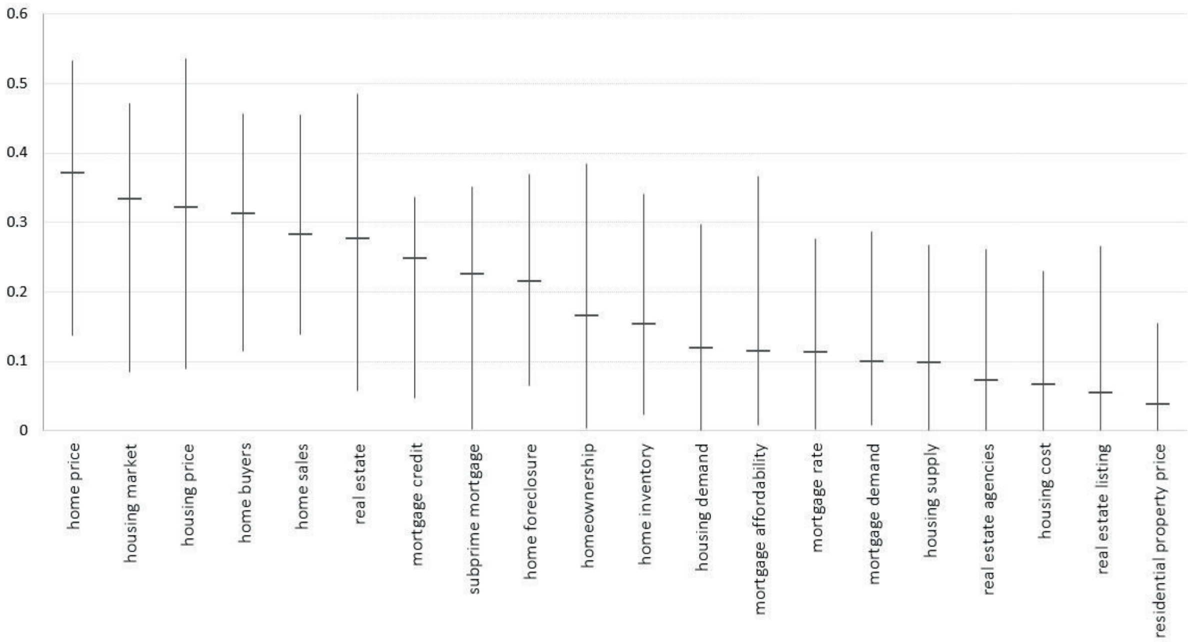
Notes: This figure plots the housing-attention index and housing price growth for top 10 states where housing attention has the highest explanatory power.

Figure 3.3: Housing-attention index along with housing price growth for bottom 10 states with lowest R^2 values



Notes: This figure plots the housing-attention index and housing price growth for bottom 10 states where housing attention has the lowest explanatory power.

Figure 3.4: PLS weights of housing market related news topics



Notes: This figure presents the variation of the partial least squares (PLS) weights for a specific housing market related news topic across different states. The bar graph shows the maximum, average, and minimum values of the PLS weights. The upper end of the bar represents the maximum weight, while the lower end of the bar depicts the minimum weight, calculated across all states. This visual representation provides a clear insight into how the housing market related news topic is weighted differently in various states, giving a comprehensive overview of the distribution of PLS weights.

Overall, these findings provide valuable insights into the relative importance of different news topics in shaping the state-level housing-market attention, which can inform future research and policy considerations.

3.4 Determinants of Media Attention on Housing Market

A range of other economic factors is likely to be connected to the amount of attention the media puts on the housing market. I aim to examine the relationship between the amount of attention paid to the housing market and the relevant economic factors that affect it. To do so, I perform a regression analysis by regressing the HAI on a set of housing-market fundamentals as described in section 3.2.1. This analysis provides a better understanding of the factors that drive the media's attention toward the housing market. The panel regression model to be estimated is as follows:

$$HAI_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}, \tag{3.2}$$

where HAI_{it} denotes housing attention in state i at time t and X_{it} alternatively contains the housing-market fundamentals. I also run a multivariate regression, including all variables simultaneously.

Table 3.1 presents both univariate and multivariate regression results. In the univariate regressions, building permits and mortgage rate are both statistically significant with substantial R^2 values of 34% and 28%, respectively. The relationship between the mortgage rate and media attention stands out the most. The estimated negative coefficient implies a decrease in mortgage rates corresponds to periods of high media attention. As demonstrated in my multivariate regression analysis using the comprehensive list of conventional housing-market factors (column (7)), I find housing-media attention is now significantly positively related to employment level, which aligns with the expectations. Despite including the entire list of typical housing-market factors, I am still only able to account for approximately 42% of the variance in the HAI. This finding indicates that a significant portion of the fluctuations in housing media attention is uncorrelated with standard predictors of the housing market.

Table 3.1: Determinants of housing media attention

	Dependent variable : Housing-attention index						
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Building Permits	1.139***						0.761***
	(0.0347)						(0.0414)
Mortgage Rate		-0.761***					-0.590***
		(0.0205)					(0.0422)
Stock Index			0.0433**				0.0177
			(0.0172)				(0.0143)
Employment				-0.476***			0.267***
				(0.0516)			(0.0595)
Per Capita Income					0.0724**		-0.00477
					(0.0335)		(0.0301)
Coincident Index						0.0802***	0.0250**
						(0.0121)	(0.00939)
Constant	-0.0182***	-0.500***	-0.216***	-0.312***	-0.194***	-0.216***	-0.246***
	(0.00610)	(0.00759)	(0.000835)	(0.0101)	(0.0159)	(0.000363)	(0.0143)
Observations	3,400	3,400	3,400	3,400	3,350	3,400	3,350
Adj. R^2	0.340	0.277	-0.012	0.032	-0.010	-0.001	0.419

Notes: This table reports the univariate and multivariate regression results from the following panel regression model: $HAI_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}$, where HAI_{it} denotes housing attention in state i at time t, and X_{it} is one of the housing market determinants introduced in section 3.2.1. For each regression, the table presents the estimates of β with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors clustered at the state level are reported in parentheses. All variables are used in standardized form to make it easier to compare the estimations.

3.5 The Role of Media Coverage on Housing Prices

3.5.1 Housing Media Attention and Predictability of House Prices

I first investigate the performance of the newly constructed state-level housing-attention index in explaining future house-price growth and compare its predictive abilities with other factors that are widely employed to understand fluctuations in house prices. To this end, I estimate the following predictive panel regression model:

$$h_{it+1} = \alpha_i + \beta X_{it} + \epsilon_{it+1}, \tag{3.3}$$

where X_{it} alternatively includes the housing-attention index (HAI) and housing-market-related variables introduced in section 3.2.1. h_{it+1} is the growth of the FHFA house-price index for state i in period $t+1$. I focus on the one-quarter-ahead forecast horizon to compare the in-sample predictive power of the housing-attention index to other relevant variables.

Table 3.2: In-Sample Forecasting Performance

	Panel A: Univariate			Panel B: Bivariate				
Variables	β	t	Adj. R^2	β	t	β	t	Adj. R^2
HAI	0.0037	6.40	0.29					
Mortgage Rate	-0.0019	-2.02	0.04	0.0041	6.58	0.0013	1.71	0.30
Stock Index	-0.0007	-1.06	0.01	0.0037	6.57	-0.0008	-1.89	0.30
Building Permits	0.0071	6.93	0.29	0.0023	4.22	0.0045	4.37	0.36
Employment	0.0006	0.36	0.01	0.0039	6.78	0.0024	1.95	0.31
Coincident Index	0.0003	0.57	0.01	0.0036	6.43	0.0001	0.19	0.29
Per Capita Income	0.0015	2.19	0.04	0.0036	6.57	0.0013	2.25	0.31

Notes: Panel A presents the univariate regression results obtained from $h_{it+1} = \alpha_i + \beta X_{it} + \epsilon_{it+1}$ where X_{it} alternatively includes the housing-attention index (HAI) and housing market related variables introduced in the section 3.2.1. h_{it+1} is the growth of the FHFA house-price index for state i in period $t+1$. I focus on one quarter ahead forecast horizon to compare the in-sample predictive power of the housing-attention index to other relevant variables. Panel B reports the bi-variate regression results from predictive model $h_{it+1} = \alpha_i + \beta HAI_{it} + \gamma Z_{it} + \epsilon_{it+1}$, where Z_{it} alternatively includes one of the housing market determinants introduced in section 3.2.1. For each regression, the table summarizes slope estimates, the corresponding t-statistics and adjusted R^2 values. Standard errors are double-clustered by state and quarter. All variables are used in standardized form.

Panel A of Table 3.2 reports the slope estimates together with the accompanying t-statistics and the fraction of the variance (R^2) explained by the independent variable. The results reveal housing-market attention is a powerful predictor based on the degree of explanatory power. The R^2 of 0.29 indicates media coverage explains a sizeable fraction of future house-price fluctuations. The positive and statistically significant coefficient on HAI suggests an increase in media coverage of the housing market is associated with higher future house prices. On average, a one-standard-deviation rise in the housing-attention index at time t results in a 0.37% increase in the growth rate of house prices in the next quarter.

These findings imply media has a significant impact on households' purchasing decisions, which in turn affects house-price movements.

Next, I examine whether HAI still keeps its superior predictive power when including other variables in the regression. To formally test this hypothesis, I run the following bi-variate panel regression model:

$$h_{it+1} = \alpha_i + \beta HAI_{it} + \gamma Z_{it} + \epsilon_{it+1}, \tag{3.4}$$

where HAI_{it} denotes housing attention in state i at time t, and Z_{it} is, alternatively, one of the housing-market determinants introduced in section 3.2.1. Panel B of the Table 3.2 indicates that when other housing factors are incorporated into the regression analysis alongside the housing-attention index, there is only a slight increase in the R^2 values. This result implies state-level housing-media-attention indices offer important information on future house prices beyond what is generally discovered through traditional housing-market factors. Additionally, the magnitude of the coefficient on HAI_{it} in equation (3.4) does not differ significantly from the univariate model, where housing attention is the only variable, and still maintains a high level of statistical significance.

3.5.2 Does Peer Attention Play a Role in Local Housing Price Growth?

Shiller, 2005[p.143] states, "People who inhabit the glamorous international cities of the world may, aided by the news media, become culturally closer to others in such distant cities (despite language barriers) than to rural people in their own country. It is not so surprising that the home prices in these cities often move together." The widespread availability of online news sources and advancements in technology have enabled the quick dissemination of housing-market expectations from one state to others that are spatially close. Two mechanisms for this phenomenon are possible: First, increased media coverage in neighboring states can incentivize households to purchase additional homes in their local area, and second, the housing demand can originate from adjacent cities. Chinco and Mayer, 2012 show, an increase in purchases made by distant speculators (but not by local speculators) has a strong correlation with increases in house prices. Considering these factors, I expect that news media coverage can bolster confidence in the local property market by continually highlighting developments in the housing market of neighboring states. To reflect this relationship, I introduce a new metric, the peer-attention index (PAI), which captures the shared variation in housing-market attention across adjacent states. To calculate the PAI for each state, I extract the first principal component from the housing-market-attention indices of neighboring states. Finally, I test the impact of media coverage of the housing market in neighboring states on local housing price growth by running the following panel predictive regression:

$$h_{it+1} = \alpha_i + \beta_1 HAI_{it} + \beta_2 PAI_{it} + \gamma Z_{it} + \epsilon_{it+1}, \tag{3.5}$$

where PAI_{it} denotes peer housing attention for state i at time t, and Z_{it} is the set of the housing fundamentals introduced in section 3.2.1.

The estimation results of equation (3.5) are presented in Table 3.3. The estimated coefficients in columns (1) to (2), which include the state-level housing-attention index, and columns (3) to (4), which include the peer-attention index, both show the state-level and adjacent-state attention indices have the ability to predict future house prices. Furthermore, column (6) of Table 3.3 indicates the peer-attention index has a statistically significant positive coefficient even when controlling for state-level housing attention and market fundamentals.[12] In particular, a one-standard-deviation increase in the peer-attention index at time t, on average, results in a 0.13% increase in the quarterly growth rate of house prices in the next quarter. Therefore, consistent with Shiller, 2005's hypotheses, my findings suggest the housing media attention in adjacent states has a cross-market effect on local housing price growth, highlighting the spillover channel of media attention.

Table 3.3: Predicting housing prices with peer attention and housing fundamentals

Variables	(1)	(2)	(3)	(4)	(5)	(6)
HAI	0.0037***	0.0029***			0.0023***	0.0019***
	(0.0006)	(0.0006)			(0.0005)	(0.0004)
PAI			0.0034***	0.0027***	0.0016***	0.0013**
			(0.0006)	(0.0006)	(0.0005)	(0.0005)
Control variables		✓		✓		✓
State FEs	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓
Number of States	50	50	48	48	48	48
Observations	3,350	3,350	3,216	3,216	3,216	3,216
Adj. R^2	0.288	0.410	0.280	0.405	0.307	0.424

Notes: This table reports results from estimation of the model $h_{it+1} = \alpha_i + \beta_1 HAI_{it} + \beta_2 PAI_{it} + \gamma Z_{it} + \epsilon_{it+1}$ where PAI_{it} denotes peer housing attention for state i at time t, and Z_{it} is the set of the housing fundamentals introduced in section 3.2.1. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors are clustered at the state and quarter level are reported in parentheses. All variables are used in standardized form.

Furthermore, Nathanson and Zwick, 2018 show speculation took place in not only the pre-existing housing market but also in the newly built housing market during the most recent housing boom. Building on this perspective, peer attention might not only affect housing demand, but also housing supply. To test this hypothesis, I examine whether media

[12]For this analysis, I omitted Alaska and Hawaii from the sample because they have no adjacent states.

attention in adjacent states affects the local housing supply in a given state. As a proxy for housing supply, I utilize building-permit data and re-estimate equation (3.5) with building permits as the dependent variable. The results in Table A1 of the appendix indicate peer attention has a significant impact on the number of building permits issued.

3.5.3 State-Level Attention versus National-Level Housing Media Attention

Previous studies have discussed the question of whether housing prices are influenced by local or national factors (Gyourko et al., 2013; Bork et al., 2020; Cepni et al., 2021). Although the housing-price cycles in the past have largely been confined to individual regions, the latest housing crisis was characterized by an unusual number of locations experiencing boom and bust phases simultaneously, indicating a possible national factor affecting various markets (Soo, 2018). Recently, using the Google Trends search volume data, Møller et al., 2023 investigate the extent to which local search dynamics affect housing markets relative to the national-level search activity. They show that even after adjusting for national-level housing search, local housing search continues to maintain its statistical significance across all prediction horizons. Building on these findings, I extend my primary regression model to investigate the role of national and local media coverage in explaining future house-price growth. Specifically, I examine the following:

$$h_{it+1} = \alpha_i + \beta_1 HAI_{it} + \beta_2 NHAI_{it} + \gamma Z_{it} + \epsilon_{it+1}, \tag{3.6}$$

where $NHAI_{i,t}$ represents the national-level housing attention at time t, constructed using the PLS method based on the news counts, which incorporate both the housing-market-related search topics discussed in section 3.2.2 and the term "United States."[13] As before, $Z_{i,t}$ encompasses the housing-market factors discussed in section 3.2.1. Standard errors are calculated using a double-clustering method by both state and time.

Table 3.4 presents the results of the estimation of equation (3.6). The findings show both the state- and national-level housing-attention indices have a positive and significant impact on local housing price growth, as demonstrated in columns (1) to (2) and (3) to (4), respectively. The significant effect of national-level housing-market attention on local housing price growth highlights the reasons why housing-price cycles in different states tend to experience boom and bust episodes at similar times. However, columns (5) to (6) in Table 3.4 reveal the estimated coefficient of the state-level attention index continues to remain significant even when controlling for national-level attention. This result suggests that although housing prices are influenced by national-level media attention, state-level

[13]In this case, my target variable is the national-level housing price growth, downloaded from the FHFA.

media coverage may contain additional information about the local dynamics of the housing market that the national-level attention does not capture.

Table 3.4: Predicting local housing prices with state level and national housing attention indices

Variables	(1)	(2)	(3)	(4)	(5)	(6)
HAI	0.0037***	0.0029***			0.0011**	0.0012**
	(0.0006)	(0.0006)			(0.0005)	(0.0005)
$NHAI$			0.0042***	0.0034***	0.0032***	0.0024***
			(0.0007)	(0.0006)	(0.0007)	(0.0007)
Control variables		✓		✓		✓
State FEs	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓
Number of States	50	50	50	50	50	50
Observations	3,350	3,350	3,350	3,350	3,350	3,350
Adj. R^2	0.288	0.410	0.328	0.428	0.334	0.434

Notes: This table reports results from estimation of the model $h_{it+1} = \alpha_i + \beta_1 HAI_{it} + \beta_2 NHAI_{it} + \gamma Z_{it} + \epsilon_{it+1}$ where, $NHAI_{it}$ denotes national level housing attention for at time t, and Z_{it} is the set of the housing fundamentals introduced in section 3.2.1. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors are clustered at the state and quarter level are reported in parentheses. All variables are used in standardized form.

3.5.4 Predictive Power at Longer Horizons

Buying a house is often a lengthy process, with many consumers balancing search costs with optimal decision-making over medium to long-term time-frames (Møller et al., 2023). This understanding necessitates a careful examination of predictive power at longer horizons, as it aligns with this practical consumer behavior, offering insights that reflect the real time-frames within which buyers and sellers operate. As home buyers naturally aim to minimize search costs without compromising decision quality, the predictability at various horizons assumes paramount importance.

To investigate the longer horizon predictive ability of the housing media attention index, I extend the predictive regression in equation 3.4 until a 12-quarter ahead forecast horizon using all control variables, helping to understand the temporal dynamics and the latent patterns governing housing prices. The results in Table 3.5 reveal the robustness of the HAI in predicting future housing prices, not just for the immediate next quarter but for subsequent periods up to nine quarters. The insignificance of the HAI after nine quarters merits particular examination and can be attributed to various factors. First, the time decay of information might cause the influence of media attention to diminish over time, making the data less relevant after nine quarters. Second, market adaptation might neutralize the HAI's predictive power over time, as market participants respond to identified trends. More interestingly, the coefficient on HAI reaches its peak at a forecast horizon of five quarters ($h = 5$), which is statistically significant at the 1% level. Since search costs may rise sharply after a certain period, consumers have an incentive to limit the search period to avoid excessively large search costs (Møller et al., 2023). Accordingly, the results suggest that a forecast horizon of five quarters is a critical point in the decision-making process, possibly representing a balance between the need for accurate forecasts and the desire to minimize search costs. My results also align with the findings of Soo, 2018, who shows that housing media sentiment leads housing prices by two years.

Table 3.5: Predictability at longer horizons

Variables	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
HAI	0.0029***	0.0027***	0.0026***	0.0028***	0.0030***	0.0024***	0.0016***	0.0010*	0.0010*	0.0008	0.0004	-0.0001
	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0004)	(0.0006)
State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Control variables	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Number of States	50	50	50	50	50	50	50	50	50	50	50	50
Observations	3,350	3,300	3,250	3,200	3,150	3,100	3,050	3,000	2,950	2,900	2,850	2,800
Adj. R^2	0.410	0.402	0.386	0.384	0.375	0.354	0.381	0.364	0.364	0.378	0.407	0.399

Notes: This table reports the regression results from predictive model $h_{it+1} = \alpha_i + \beta HAI_{it} + \gamma Z_{it} + \epsilon_{it+1}$, where Z_{it} includes all the housing market determinants introduced in section 3.2.1. For each regression, the table summarizes slope estimates, the corresponding t-statistics and adjusted R^2 values. Standard errors are double-clustered by state and quarter. All variables are used in standardized form.

3.6 Does Housing Media Attention Yield Better Out-of-Sample Forecasts?

Until now, the results of the in-sample regressions point to a significant connection between media attention on the housing market and future housing prices. However, over-fitting the data is a risk when using predictive regressions with the entire sample. To address this issue, I employ an out-of-sample forecasting approach based on an expanding estimation window. This approach allows me to reduce the likelihood of look-ahead bias, because the housing-media attention index and all parameters are estimated recursively using only the information available at the time of the forecast. The analysis consists of a 50 - 50 split of the sample period, with the first half used for training and the second half for out-of-sample forecasting. I produce forecasts for h-quarter-ahead horizons where h = 1, 2, 3, 4, 5, 6, and assess the forecast performance for each state. The specifications of the forecasting exercise are as follows:

- **Specification 1**: Local-attention model
  $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{HAI} HAI_t + \varepsilon_{t+h}$
- **Specification 2**: National-attention model
  $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{NAI} NAI_t + \varepsilon_{t+h}$

- **Specification 3**: Combined-attention model
  $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{HAI} HAI_t + \beta_{NAI} NAI_t + \varepsilon_{t+h}$,

where h_t is housing price growth, and L^p denotes the p-th order lag polynomial where the lag length p is decided based on Schwarz information criterion (SIC) criteria. Whereas the specification type 1 allows me to assess the significance of local housing media attention (HAI) in addition to the constant and lags of the house price growth, specification type 2 evaluates the predictive performance of national-media attention. Similarly, the specification type 3 is an extended version that incorporates both types of attention indices. To compare the predictive performance of the models, I use the out-of-sample R^2 (R^2_{OoS}) method proposed by Campbell and Thompson, 2008. For each state, the R^2_{OoS} values are calculated in relation to a benchmark $AR(p)$ model that captures the persistence behavior in the house-price growth. The null hypothesis, $R^2_{\text{OoS}} \leq 0$, is tested against the alternative, $R^2_{\text{OoS}} > 0$, by utilizing the approximate statistics from Clark and West, 2007, which enables me to examine the predictive accuracy in nested models.[14]

Table 3.6 reports the average R^2_{OoS} values across states for a given forecast horizon, h. The results indicate the HAI, on average, explains more than 46% of the out-of-sample variation for h=6, where the predictive power of local media attention reaches its peak. Given that the process of buying a house involves a considerable amount of searching and a thorough examination of the houses listed for sale (Møller et al., 2023), HAI is expected to exhibit superior predictive performance for long horizons. By contrast, the specification types that include national media attention, on average, yield lower R^2_{OoS} values for all forecast horizons, implying housing markets are inherently local and segmented. When the HAI in specification 1 is alternatively replaced with local housing fundamentals, in all cases, these variables generate negative or lower R^2_{OoS} values than the benchmark model, indicating they do not outperform the predictive performance of the $AR(p)$ model in many cases. However, as Table 3.6 shows, two exceptions are the mortgage rates and employment level. Whereas the former yields R^2_{OoS} values exceeding those of specification types 2-3, for forecast horizons h=1,2, the latter provides a positive R^2_{OoS} values for all forecast horizons.

[14] The out-of-sample R^2_{OoS} metric is given by $R^2_{OoS} = 1 - \frac{\sum_{t=1}^{T}(r_t - \widehat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2}$ where $\widehat{r}_t$ is the prediction from the model in consideration, and $\bar{r}_t$ is the forecast from the benchmark model. A positive R^2_{OoS} suggests the forecasting model provides more accurate estimates than the benchmark.

Table 3.6: Out of sample predictive ability

Specification	h=1	h=2	h=3	h=4	h=5	h=6
Local	0.160	0.256	0.305	0.335	0.415	0.461
National	0.104	0.154	0.242	0.294	0.363	0.434
Combined	0.116	0.180	0.277	0.319	0.399	0.446
Permits	0.053	0.034	0.136	-0.323	-0.267	0.111
Stock Index	-0.002	-0.060	-0.081	-0.019	-0.005	-0.015
Coincident Index	-2.692	0.045	0.052	0.051	0.024	0.020
Mortgage Rate	0.117	0.224	0.073	-0.228	0.105	0.193
Employment	0.016	0.079	0.146	0.119	0.233	0.309
Per Capita Income	-0.033	-0.072	-0.071	-0.082	-0.112	-0.08

Notes: This table reports average R^2_{OoS} values across states for a given forecast horizon h. While the Local (specification type-1) allow us to evaluate the relevance of local housing media attention (HAI) in addition to constant and lags of the house price growth rate, National (specification type-2) checks the predictive performance of national media attention. Similarly, the Combined (specification type-3) is the extended model including both types of attention indices. I compare the predictive performance of the models using Campbell and Thompson, 2008 out-of-sample R^2 (R^2_{OoS}), where R^2 values, for each state, are calculated relative to benchmark $AR(p)$ model that captures the persistence behaviour in the housing prices. The lag length p is decided based on Schwarz information criterion (SIC) criteria. Alternatively, I replace the HAI in the specification-1 with local housing fundamentals, namely; permits, stock index, coincident index, mortgage rate, employment, and per-capita income.

Table 3.7 presents the R^2_{OoS} values for each state obtained from specification type 1, offering further insight into the out-of-sample performance of the HAI at the state level.[15] The results show Clark and West, 2007 test strongly rejects the null hypothesis of $R^2_{\text{OoS}} \leq 0$ for almost all states and forecast horizons. For instance, the extent of predictability is highest at h=6 for New Jersey, with a statistically significant R^2_{OoS} of 82%. To provide a comprehensive summary of the findings, I display the average value of R^2_{OoS} for all forecast horizons across the states in Figure 3.5. The overall picture is that housing media attention provides information that can accurately predict house prices in the great majority of states. The only exceptions are North Dakota and Michigan, where the average values of R^2_{OoS} are negative.[16]

Next, I compare the predictive ability of the model including the HAI (specification type 1) with the $AR(p)$ employing forecast the encompassing test of Chong and Hendry, 1986. More specifically, I implement the test using the following regression:

$$h_{t+h} = \delta + \lambda_{AR}\hat{h}^{AR}_{t+h} + \lambda_{HAI}\hat{h}^{HAI}_{t+h} + u_{t+h}, \tag{3.7}$$

where h_{t+h} is the actual h-quarter-ahead housing price growth and $\hat{h}^{AR}_{t+h}$ is the forecast value of the benchmark $AR(p)$ model and $\hat{h}^{HAI}_{t+h}$ denotes the forecast obtained from specification type 1. If λ_{HAI} is significantly different from zero, the implication is that the forecast of specification type 1 encompasses the forecast of the benchmark $AR(p)$ model. In other words, HAI contains valuable information relative to the $AR(p)$.

[15]Tables A2 - A3 of the appendix reports the R^2_{OoS} values obtained from specification types 2-3.

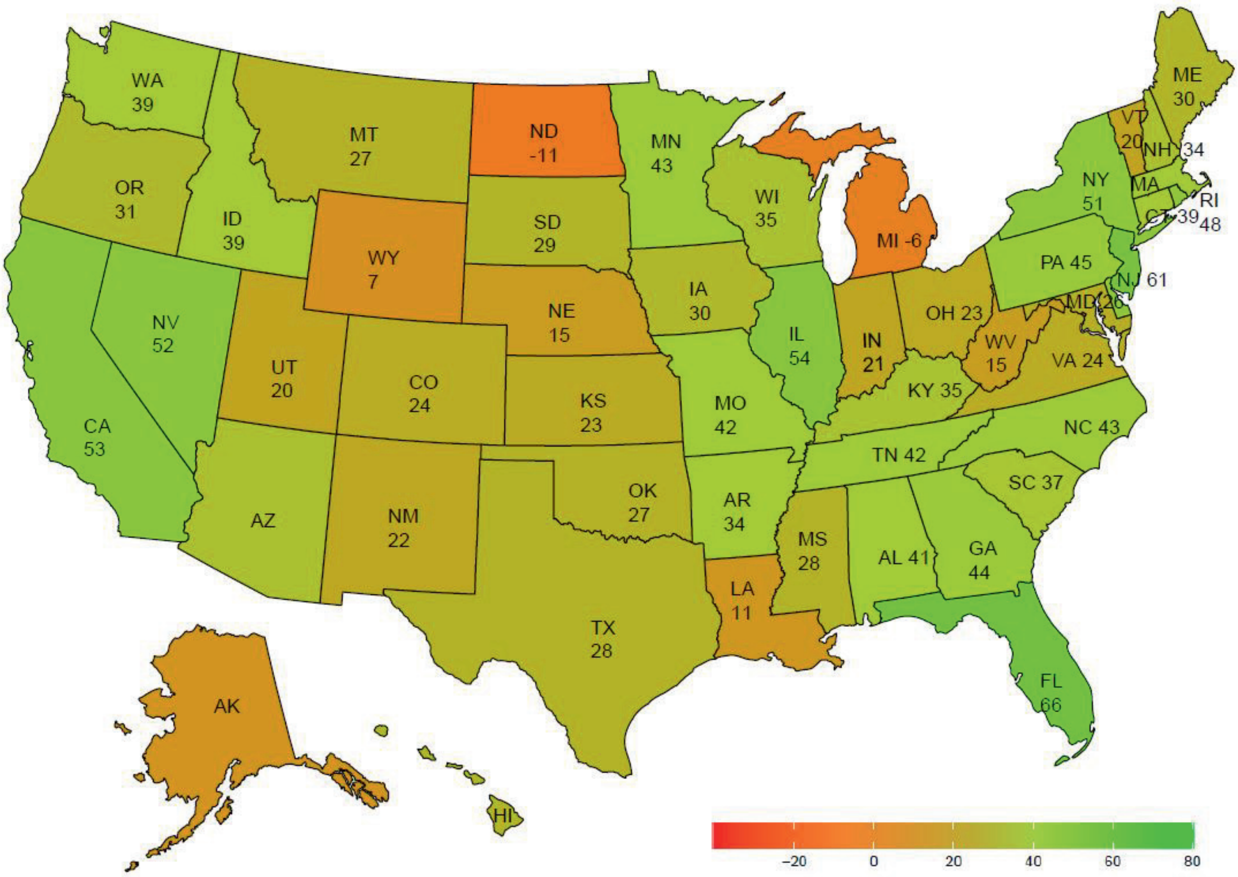
[16]Figures A1 and A2 present the average R^2_{OoS} values for all states and forecast horizons across the states obtained from specification types 2-3, respectively.

Table 3.7: R^2_{OoS} values across states calculated from "Local" attention model

State	h=1	h=2	h=3	h=4	h=5	h=6
Alabama	0.17**	0.33***	0.29***	0.50***	0.59***	0.60***
Alaska	0.09**	0.02	0.12**	0.09**	0.09**	0.14**
Arizona	-0.07	0.05***	0.40***	0.58***	0.70***	0.72***
Arkansas	0.17***	0.26***	0.28***	0.33***	0.50***	0.50***
California	0.21***	0.39***	0.52***	0.62***	0.69***	0.74***
Colorado	0.10**	0.26**	0.22***	0.30***	0.28***	0.30***
Connecticut	0.17***	0.33***	0.38***	0.39***	0.52***	0.53***
Delaware	0.18***	0.40***	0.47***	0.52***	0.69***	0.73***
Florida	0.26***	0.56***	0.71***	0.79***	0.84***	0.79***
Georgia	0.33***	0.28***	0.38***	0.44***	0.58***	0.62***
Hawaii	0.05*	0.09**	0.29***	0.37***	0.48***	0.51***
Idaho	0.12**	0.36***	0.48***	0.47***	0.46***	0.45***
Illinois	0.25***	0.51***	0.45***	0.50***	0.69***	0.81***
Indiana	0.14***	0.21***	0.22***	0.13**	0.25**	0.31***
Iowa	0.26***	0.34***	0.21***	0.25***	0.31***	0.43***
Kansas	0.26***	0.13**	0.14***	0.16**	0.36***	0.33***
Kentucky	0.24***	0.33***	0.30***	0.36***	0.45***	0.43***
Louisiana	0.10**	0.05*	0.05**	-0.11**	0.23***	0.33***
Maine	0.14***	0.24***	0.30***	0.41***	0.31***	0.39***
Maryland	0.06***	0.27***	0.20***	0.23***	0.37***	0.42***
Massachusetts	0.24***	0.42***	0.45***	0.43***	0.39***	0.47***
Michigan	-0.35	0.00	0.15*	0.06	-0.22	-0.01
Minnesota	0.31***	0.46***	0.46***	0.47***	0.39***	0.50***
Mississippi	0.21***	-0.02**	0.28***	0.29***	0.52***	0.40***
Missouri	0.26***	0.36***	0.31***	0.45***	0.52***	0.60***
Montana	0.14**	0.12***	0.23***	0.27***	0.38***	0.47***
Nebraska	0.14*	0.14**	0.12**	0.03	0.22**	0.25**
Nevada	0.21***	0.42***	0.57***	0.61***	0.64***	0.68***
New Hampshire	0.23***	0.35***	0.32***	0.28***	0.39***	0.48***
New Jersey	0.22***	0.56***	0.64***	0.68***	0.75***	0.82***
New Mexico	0.19***	0.18***	0.13***	0.28***	0.35***	0.19***
New York	0.25***	0.44***	0.52***	0.57***	0.59***	0.66***
North Carolina	0.24***	0.35***	0.37***	0.50***	0.54***	0.59***
North Dakota	0.00	-0.02	-0.02	-0.12	-0.16	-0.32
Ohio	0.17***	0.21***	0.23**	0.24***	0.23***	0.31***
Oklahoma	0.19**	0.25***	0.23***	0.24***	0.30***	0.41***
Oregon	0.14***	0.19***	0.32***	0.41***	0.41***	0.39***
Pennsylvania	0.16***	0.40***	0.46***	0.51***	0.57***	0.59***
Rhode Island	0.36***	0.42***	0.51***	0.47***	0.55***	0.60***
South Carolina	0.10**	0.32***	0.46***	0.32***	0.43***	0.59***
South Dakota	0.20**	0.35***	0.23***	0.23***	0.30***	0.43***
Tennessee	0.17**	0.30***	0.28***	0.53***	0.62***	0.63***
Texas	0.10**	0.19**	0.21**	0.34***	0.37***	0.47***
Utah	0.02	-0.11**	0.07***	0.19***	0.41***	0.64***
Vermont	0.13***	0.14***	0.19***	0.16***	0.31***	0.24***
Virginia	0.25**	0.22***	0.19***	0.15***	0.33***	0.31***
Washington	0.13**	0.23***	0.47***	0.46***	0.47***	0.58***
West Virginia	0.08 **	0.10**	0.15**	0.10**	0.20***	0.29***
Wisconsin	0.21***	0.35***	0.28***	0.31***	0.44***	0.51***
Wyoming	0.04	0.04**	0.04**	-0.03**	0.11***	0.18***

Notes: For a given forecast horizon h, this table reports R^2_{OoS} values across states calculated from Local attention model: $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{HAI} HAI + \varepsilon_{t+h}$. Asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level of testing the null hypothesis of $R^2_{\text{OoS}} \leq 0$, against the alternative $R^2_{\text{OoS}} > 0$ utilizing the Clark and West, 2007 statistics, which allows me to test predictive accuracy in nested models.

Figure 3.5: Out of sample forecasting: Forecast improvement compared to the benchmark AR model



Notes: This figure shows average R^2_{OoS} values across states and forecast horizons computed from Local attention model: $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{HAI} HAI + \varepsilon_{t+h}$ versus the benchmark AR(p) model.

Table A4 of the appendix presents the results. With the help of the Newey–West estimator, I make adjustments for heteroskedasticity and auto-correlation in the standard errors. The constraint $\lambda_{HAI} + \lambda_{AR} = 1$ is imposed to facilitate interpretation. The estimates of λ_{HAI} are statistically significant across most states and forecast horizons, indicating the HAI contains additional information beyond what the benchmark $AR(p)$ model captures. Put differently, specification type 1 is capable of encompassing the forecasts obtained from the benchmark model.

Taken together, the out-of-sample forecasting exercise affirms that the better in-sample forecast ability of the HAI also holds for out-of-sample predictive ability. This evidence suggests housing media attention may provide useful information about future house prices.

3.7 How Important Are State Characteristics in Determining the Effect of Media Attention on Housing Prices?

3.7.1 The Role of Mortgage Laws: Non-Recourse vs. Recourse States

Mortgage legislation in the US varies widely across states. One aspect of mortgage legislation is non-recourse law, which determines the extent of a lender's power to obtain a deficiency judgment if borrowers fail to make mortgage loan payments. Non-recourse law is particularly important in situations where borrowers are in negative equity, meaning that the value of the loan exceeds the value of the house. In these cases, borrowers may have an incentive to default on the loan, regardless of their ability to make payments, because non-recourse law gives them a "put option." As noted by Pavlov and Wachter, 2004, this allows borrowers to sell the property to the bank in case of substantial price drops and walk away, while still enjoying any capital gains from an increase in the property's value. Conversely, borrowers in recourse states are still responsible for the loan even after default, which prompts them to cut back on spending in order to avoid defaulting on the loan.

Previous studies have shown that the non-recourse law can promote risk-shifting behavior and play a significant role in the increase of home prices, particularly during boom periods (Nam and Oh, 2021). In line with these findings, Ghent and Kudlyak, 2011 find the non-recourse law impacts the default rates of mortgages, making the borrower less sensitive to negative equity. In particular, they show the default probability of borrowers is doubled in non-recourse states. As such, I hypothesize that house prices in non-recourse states respond more strongly than those in recourse states to media attention.

Subsequently, I analyze how the relationship between media coverage and future house prices changes based on the mortgage legislation of the state, using the following panel regression:

$$h_{it+h} = \alpha_i + \beta_R HAI_{it} + \beta_{NR} HAI_{it} \times I_i^{Non-recourse} + \delta Z_{it} + \epsilon_{it+h}, \tag{3.8}$$

where $I_i^{Non-recourse}$ is a dummy variable takes a value of 1 if the state is governed by non-recourse law.[17] The results of the panel regression allow me to determine whether the relationship between media attention and housing prices differs between states with non-recourse and recourse mortgage laws. The coefficient of the interaction term β_{NR} represents the differential effect that media attention has on housing prices in states with non-recourse

[17] The state classification is based on the data from https://www.financialsamurai.com/non-recourse-states-walk-away-from-mortgage/.

laws, relative to states with recourse laws. I investigate the predictive power at both long and short horizons, namely, $h = 1, 2, 3, 4$ quarters ahead.

The panel regression results in Panel A of Table 3.8 show the effect of media attention on future house prices is greater in non-recourse states than in the recourse states, as indicated by the significant and positive estimated coefficient β_{NR} across all forecast horizons. As shown in column (6) of Table 3.8, the impact of a one-standard-deviation increase in housing attention leads to an increase of 0.39% (0.26% + 0.13%) in future house prices in non-recourse states at the one-quarter-ahead forecast horizon when controlling for all housing fundamentals. The heightened responsiveness of house prices in non-recourse states to media attention may be due to several factors. First, the increased media attention might encourage risk-shifting behavior in non-recourse states, contributing to the rise in home prices. Second, Nam and Oh, 2021 find the share of non-owner-occupied home purchases is 20% higher in non-recourse states compared to recourse states, meaning media attention could boost speculative buying behavior, especially from distant speculators who are less informed about local market conditions. Hence, the media might reduce information asymmetries between local and non-local investors by disseminating developments in housing markets to a broader audience.[18]

3.7.2 The Role of Residential Land Use Regulations

The US has a wide range of land-use restrictions, primarily administered at the local level. Gyourko et al., 2021 analyze more than 2,500 primarily suburban communities and develop the Wharton Residential Land Use Regulatory Index (WRLURI) to rank states based on the restrictiveness of their regulations. The WRLURI index consists of 11 sub-indices, each providing a concise summary of a specific aspect of the regulatory environment.[19] Housing regulations might limit the supply of housing in several ways. One way is to put a restriction

[18]Mian et al., 2015 find foreclosures led to a significant drop in home values from 2007 to 2009 by utilizing state judicial requirements as an instrument for foreclosures. In states where judicial foreclosure is necessary, the lender must first submit a notice with the court, explaining the debt's amount, the borrower's delinquency, and why the borrower's default should provide the lender the right to sell the property. This notice must be filed within a certain amount of time after the delinquency occurs. According to Mian et al., 2015, 20 states are considered judicial foreclosure states. Hence, I also examine whether variation in housing prices reflects the role of media attention in judicial and non-judicial states. In particular, I replace the $I_i^{Non-recourse}$ variable in equation (3.8) with $I_i^{JudicialLaw}$ dummy, which takes the value of 1 if the state is governed by judicial law. The results presented in Table A5 show the estimated coefficient of $I_i^{JudicialLaw}$ is insignificant at all forecast horizons except h=4, implying the judicial foreclosure requirement is quite different from non-recourse legislation.

[19]They consider the following aspects related to the regulatory environment: (1) Local Political Pressure Index, (2) State Political Involvement Index, (3) Court Involvement Index, (4) Local Project Approval Index, (5) Local Zoning Approval Index, (6) Local Assembly Index, (7) Density Restriction Index, (8) Open Space Index, (9) Exactions Index, (10) Affordable Housing Index, (11) Approval Delay Index, (12) Supply Restrictions Index. Then, the WRLURI index is a linear combination of these 12 sub-indices where the weights are computed using factor analysis. The higher values of the index imply more regulation in the housing market.

Table 3.8: Predicting local housing prices with media attention: The role of state characteristics

Variables	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
Panel A: Non-Recourse Mortgage Law								
HAI	0.0033***	0.0032***	0.0033***	0.0034***	0.0026***	0.0024***	0.0023***	0.0025***
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)
$HAI \times I^{Non-recourse}$	0.0015*	0.0014*	0.0016**	0.0018**	0.0013*	0.0013*	0.0015**	0.0017**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0008)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Number of States	50	50	50	50	50	50	50	50
Adj. R^2	0.296	0.308	0.327	0.367	0.416	0.408	0.396	0.395
Panel B: Residential Land Use Regulation								
HAI	0.0024***	0.0023***	0.0024***	0.0026***	0.0018***	0.0016***	0.0015***	0.0018***
	(0.0004)	(0.0006)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$HAI \times I^{HighRegulation}$	0.0024***	0.0024***	0.0025***	0.0024***	0.0022***	0.0022***	0.0023***	0.0022***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,283	3,234	3,185	3,136	3,283	3,234	3,185	3,136
Number of States	49	49	49	49	49	49	49	49
Adj. R^2	0.320	0.332	0.350	0.388	0.437	0.429	0.417	0.414
Panel C: Social Connectedness								
HAI	0.0029***	0.0029***	0.0029***	0.0032***	0.0022***	0.0021***	0.0020***	0.0022***
	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
$HAI \times I^{SCI}$	0.0015**	0.0015**	0.0015**	0.0014**	0.0015**	0.0013**	0.0014**	0.0013**
	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Number of States	50	50	50	50	50	50	50	50
Adj. R^2	0.299	0.312	0.329	0.365	0.421	0.412	0.397	0.393
Panel D: Economic Connectedness								
HAI	0.0019***	0.0021***	0.0017***	0.0014***	0.0015***	0.0018***	0.0014***	0.0012***
	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
$HAI \times I^{EC}$	-0.0017**	-0.0014**	-0.0015**	-0.0012*	-0.0015**	-0.0013**	-0.0014**	-0.0012**
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Number of states	50	50	50	50	50	50	50	50
Adj. R^2	0.635	0.642	0.638	0.635	0.670	0.671	0.661	0.656

Notes: Panel A reports regression results from: $h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{NR} HAI_{it} \times I_i^{Non-recourse} + \delta Z_{it} + \epsilon_{it+h}$ where the $Non-recourse$ is the dummy variables takes value of 1 if the state is governed by non-recourse law. Panel B presents the results of regression model: $h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{HR} HAI_{it} \times I_i^{High-Regulation} + \delta Z_{it} + \epsilon_{it+h}$, where $I_i^{High-Regulation}$ is a dummy variable equal to 1 (0) if the WRLURI of the state i is above (below) the median values of all states, representing highly (lightly) regulated states. Panel C presents the results from the regression: $h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{SCI} HAI_{it} \times I_i^{SCI} + \delta Z_{it} + \epsilon_{it+h}$ where I_i^{SCI} is a dummy equal to 1 if the social connectedness level in state i is above the median. Panel D denotes the estimation results from the regression: $h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{EC} HAI_{it} \times I_i^{EC} + \delta Z_{it} + \epsilon_{it+h}$ where I_i^{EC} is a dummy variable equal to 1 (0) if the economic connectedness measure (EC) of the state i is below (above) the median values of all states, representing less (more) connectedness states. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors are clustered at the state and quarter level are reported in parentheses. All variables are used in standardized form.

on the number of new housing units that may be built.[20] Therefore, I examine whether the impact of HAI on housing prices is more substantial in states with a more heavily regulated housing market.

Next, I run the following panel predictive regression to test this effect:

$$h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{HR} HAI_{it} \times I_i^{High-Regulation} + \delta Z_{it} + \epsilon_{it+h}, \tag{3.9}$$

where $I_i^{High-Regulation}$ is a dummy variable equal to 1 (0) if the WRLURI of the state i is above (below) the median values of all states, representing highly (lightly) regulated states. I expect the media attention on house prices to be stronger in more regulated states.

Panel B of Table 3.8 shows the influence of housing attention on future home prices appears to be stronger in states with a more restrictive housing-market environment, as indicated by the positive and significant value of the coefficient β_{HR}. Specifically, whereas a one-standard-deviation increase in the HAI leads to a 0.18% increase in the next quarter's housing prices in lightly regulated states when controlling for all other variables (column (6)), the effect of media attention on future housing prices is more than double in highly regulated states (0.18% + 0.22% = 0.40%). Additionally, the strong predictive power of the HAI remains significant, with its explanatory power (measured by R^2) exceeding 40% across all forecast horizons. One possible explanation for this effect is that the media often discusses upcoming regulatory interventions early on, leading to faster dissemination of information about new regulations to a broader audience. As a result, investors may adjust their beliefs about future house prices and react to regulatory events early, contributing to the predictive power of the HAI for future house prices.

3.7.3 Social Networks and Housing-Market Attention

How Does Social Connectedness Amplify the Role of Housing-Market Attention?

Interest in examining the effects of social networks on investors' economic decision-making processes has been growing (Bailey et al., 2018a; Bailey et al., 2019). For instance, by constructing a Social Connectedness Index (SCI) based on the friendship links on Facebook, Bailey et al., 2018a show individuals' opinions about the housing market and their

[20] In the US, land-use and housing regulations predominantly originate at the local level, resulting in diverse regulatory landscapes across and even within states. While some areas have maintained relatively stable regulatory frameworks, such as Houston's consistent lax zoning laws, others like certain Californian cities have seen their regulations tighten over time. This variation is influenced by growing awareness of housing affordability challenges and the role of regulations therein. Notably, states like Oregon have recently made legislative shifts to address these concerns, emphasizing a push towards increased housing density. However, despite occasional changes, many regions exhibit a prevailing stability in their regulatory environment due to the complexities of the political landscape and the slow-moving nature of legislative changes.

investment behavior are significantly influenced by their social networks. The crucial role of social media in explaining the spread of house-price contagion in the US has also been emphasized by DeFusco et al., 2018. Due to the rapid and convenient nature of social media, housing-market news can quickly spread and amplify, potentially affecting property prices.

Given the significance of social interactions on individuals' expectations and investment behavior in the housing market, the forecasting efficacy of the housing-attention index might be related to the level of social connectedness in a state. To test this hypothesis, I divide states into two groups based on their social-connectedness levels, as measured by the state-level Social Connectedness Index (Bailey et al., 2018b).[21] This division allows me to examine whether house prices in states with higher levels of social connectedness show a stronger reaction to increased housing media attention. To do so, I estimate the following predictive panel regression model:

$$h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{SCI} HAI_{it} \times I_i^{SCI} + \delta Z_{it} + \epsilon_{it+h}, \tag{3.10}$$

where I_i^{SCI} is a dummy equal to 1 if the social-connectedness level in state i is above the median, β_{SCI} indicates the incremental effect of the housing-market-attention index on house prices in more socially connected states, and β captures the baseline effect of sentiment for less socially connected states. I consider four different forecast horizons, namely, $h = 1, 2, 3, 4$ quarters ahead.

Panel C of Table 3.8 reveals a a significant relationship between future growth rates of house prices and social connectedness for both states with high and low levels of social connectedness. However, the impact of housing media attention on future house prices seems to be more pronounced in states with higher levels of social connectedness relative to those with lower levels. In particular, column (6) shows that, at the one-quarter-ahead forecast horizon, the effect of a one-standard-deviation increase in the housing attention is $0.22\% + 0.15\% = 0.37\%$ in states with higher levels of social connectedness. This stronger response of housing prices in states with higher levels of social connectedness supports the notion that social media can significantly affect household behaviors by facilitating the dissemination of knowledge and ideas through social networks (Bailey et al., 2018b).

Media Attention and House Prices: The Role of Socioeconomic Status of Friends

Numerous theoretical studies have demonstrated that having connections to people who are more educated or affluent may be advantageous for knowledge transmission and shaping aspirations (Montgomery, 1991; Ambrus et al., 2014). In a recent study, Chetty et al.,

[21] Following the methodology of Bailey et al., 2018a, I compute the state-level social-connectedness index as a weighted average of county-level SCI measures within the same state.

2022 develop a measure of economic connectedness to examine the role of social capital on upward income mobility, using data on 21 billion friendships from Facebook. They find the percentage of low-SES individuals who have high-SES friends, referred to as economic connectedness, is one of the strongest indicators of upward income mobility to date. Inspired by this literature, I anticipate the impact of media attention on house prices may be stronger in states where low- and high-SES individuals are more connected. According to the "knowledge gap hypothesis" proposed by Tichenor et al., 1970, individuals in higher socioeconomic brackets are more likely to quickly acquire new information introduced into society via mass media than those in lower socioeconomic brackets. This situation creates a potential for the knowledge gap between different social groups to widen instead of narrow due to the flow of news media into society. Therefore, I expect that greater exposure to high-SES friends plays an informational role for low-SES individuals, thereby affecting their perceptions of property investments, because higher SES is associated with paying more attention to news media (McLeod and Perse, 1994).

To formally test this hypothesis, I utilize the following panel regressions:

$$h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{EC} HAI_{it} \times I_i^{EC} + \delta Z_{it} + \epsilon_{it+h} \tag{3.11}$$

where I_i^{EC} is a dummy variable equal to 1 (0) if the economic connectedness (EC) measure of the state i is below (above) the median values of all states, representing less (more) connectedness states. I compute the state-level EC measure by taking the average value of the standardized county-level EC values constructed by Chetty et al., 2022. Therefore, whereas the higher values of the state-level EC indicate low-SES people have a considerable number of high-SES friends, the lower values of EC imply the network among low-SES and high-SES individuals is limited. Hence, I divide the states into two groups by comparing their EC scores with the median values of all states. The coefficient of the interaction term $HAI_{it} \times I_i^{EC}$ captures the differential effect of media attention on house prices between more and less connected states.

Panel D of Table 3.8 supports the hypothesis that the impact of media attention on future house prices is greater in states where low-SES and high-SES individuals are more connected through friendship. This is reflected by the negative and significant value of the β_{EC}. In particular, as shown by the second column of Panel D, whereas a one-standard-deviation increase in the HAI leads to a 0.19% - 0.17% =0.02% increase in the house price in the next quarter in the less connected states, it has a greater impact in the more connected states. Furthermore, the adjusted R^2 value of 63.5% indicates the model used to capture the effect of media attention on housing prices explains a substantial portion of the variation in the data. The findings also provide evidence for the two-step flow hypothesis proposed by Katz and Lazarsfeld, 1955, which suggests the media first affects society's opinion leaders, who then affect the opinion followers. Hence, high-SES people might serve as opinion leaders in society. If the media influence the belief of the opinion leaders about housing markets, the views of opinions leaders can be shared with others, thereby boosting the effect of media on housing prices. Furthermore, Das et al., 2020 show an individual's socioeconomic status has a role in shaping their expectations about the macro-economy and find that higher-SES people tend to have a more positive outlook on future macroeconomic changes. Hence, SES-driven expectations might explain why the media attention has a more substantial positive effect on house prices in more connected states.[22]

3.8 Robustness Checks

3.8.1 Placebo Test

To further validate the relationship between housing media attention and future house prices, I conduct a simulation study that generates 10,000 bootstrapped samples from the list of housing-related news topics across states. I utilize a row-wise resampling method, in which news counts are randomly selected with replacement from the panel of housing-market-related topics. Then, I employ the PLS approach and construct a placebo state-level housing-media-attention index based on the re-sampled news counts. Finally, I re-estimate equation (3.3) by using the newly constructed placebo housing-attention index and save the adjusted R^2 values.

The results of the simulation study are summarized in Table A7 in the appendix. The findings reveal the adjusted R^2 values from the placebo regressions are consistently lower than the actual R^2 values. This result indicates that the probability of obtaining the same R^2 values from the random news-count data is virtually zero, suggesting the observed relationship between housing media attention and future house prices is highly unlikely to be a result of chance. Overall, these results provide robust evidence for the relationship between housing media attention and future house prices.

3.8.2 Driscoll and Kraay (1998) Standard Errors

Despite clustering the standard errors by both state and time, I further examine the potential impact of spatial correlation on the standard errors obtained. To address this concern, I adopt the non-parametric estimator for the covariance matrix proposed by Driscoll and Kraay, 1998, which provides standard errors that are robust to various forms of spatial

[22] As a robustness check, I also construct the state-level population-weighted measure of economic connectedness (ECW) by taking population-weighted average values of the county-level EC scores. Subsequently, I create a dummy variable I_i^{ECW}, which takes the value of 1 (0) if the ECW measure of the state i is below (above) the median values of all states. Table A6 of the appendix indicates that my results are robust to a different measure of social connectedness of high- and low-SES individuals.

and temporal dependence, as well as heteroskedasticity and auto-correlation. The results presented in Table A8 in the appendix indicate the coefficient estimates remain statistically significant, suggesting my findings are robust to cross-sectional dependence.

3.8.3 Lagged House Prices

Housing markets frequently exhibit attributes of sequential correlation and illiquidity, which naturally leads to positive patterns in successive price alterations. Such a trend, as evidenced in earlier studies (Ghysels et al., 2013; Soo, 2018; Møller et al., 2023), can stem from delayed market responses to new information, the inherent time required for transaction completions, or specific methodologies applied to house price index construction. To address these complexities and to grasp the latent inertia in housing prices, I include the autoregressive (AR) component of house prices in the predictive regression, which serves not only to encapsulate past price levels' influence on future house prices, but also minimizes the possibility of omitted variable bias due to overlooking past price growth rates. In alignment with the strategy outlined by Soo, 2018, I include four lags in the AR component, effectively managing the pronounced auto-correlation found in the quarterly shifts in house prices, as presented in Table A9 of the appendix. The results show that the HAI consistently retains its significant predictive power across all forecast horizons, although the coefficient's magnitude does observe a slight reduction. Furthermore, the lagged house prices, denoted by $L.HPR$ to $L4.HPR$, exhibit varied significance levels across different horizons, contributing to the overall understanding of price dynamics. For instance, the negative coefficients at certain lags may allude to potential corrections or adjustments in the market over time. Overall, the results confirm that HAI still has significant predictive power when accounting for past price patterns, and they underscore that HAI captures essential dynamics that are not fully revealed by merely observing the autoregressive component.

3.8.4 Controlling for Time Fixed Effects

The potential influence of common time-varying factors at the national level could simultaneously steer both state-level media attention and house prices. Nationwide dynamics, such as shifts in monetary policy, broad economic movements, or even international occurrences, might obscure the true relationship between housing media attention and house price trajectories. Therefore, incorporating time fixed effects into predictive regressions allows me to distinguish the genuine effects of state-specific HAI from these overarching national trends.

As illustrated in Table A10, when I include both state and time fixed effects, HAI retains its robustness and significance across all forecast periods (from h=1 to h=4), suggesting that its predictive power is consistent, even when accounting for time-varying factors. The HAI

maintains significance levels ranging from 1% to 5% across various horizons, highlighting that the relationship between housing media and ensuing house price fluctuations isn't just a byproduct of general time-specific influences. Rather, it possesses considerable predictive value in its own right. Additionally, the adjusted R^2 values, which range from 0.620 to 0.657, further strengthen the reliability of my findings. These metrics indicate that the enhanced model, encompassing both state and time fixed effects, aptly explains a sizable share of the variation in house prices, emphasizing the pivotal role housing media attention plays in forecasting upcoming house price trends.

3.8.5 Alternative Metrics for Tracking the Changes in Housing Price Growth

Until now, I have primarily concentrated on the FHFA all-transactions house-price index, a widely recognized metric in the housing market. To demonstrate the predictive power of the housing-attention index is not exclusive to the FHFA index, I also look at another frequently employed house-price index, specifically, the Freddie Mac house-price index for single-family homes. Although they serve a similar purpose, the FHFA and Freddie Mac house-price indices differ in their coverage and data sources. The FHFA index provides a comprehensive view of the entire US housing market, because it covers all home transactions in the country. On the other hand, the Freddie Mac index provides a more targeted outlook, only covering homes backed by Freddie Mac. Additionally, the FHFA index utilizes data from the Federal Home Loan Bank System and Ginnie Mae, whereas the Freddie Mac index uses its own loan data. This difference in data sources may result in differing values reported for the same homes at different locations and times. Despite these differences, both indices employ the repeat-sales methodology to calculate their house-price indexes.

The results presented in Table A11 demonstrate the robustness of the state-level housing-attention index as a predictor of housing price growth across different house-price measures. The results show the predictive power of the housing-attention index holds true across all house-price indices. However, note the impact of the housing-attention index on future house-price growth is slightly higher when using the Freddie Mac house-price index, which covers homes backed by Freddie Mac. These results suggest that whereas the type of house-price index used may affect the magnitude of the impact, the overall predictive power of the state-level housing-attention index remains unchanged.

3.9 Additional Analyses

3.9.1 City-Level Housing-Media Attention Index

Soo, 2018 makes a pioneering contribution to the field of housing-market analysis by constructing 34 city-specific housing sentiment indices for major metropolitan areas in the US using local newspapers. The study quantifies the tone of local housing media coverage and indicates the housing sentiment indices precede changes in housing prices. In this context, media attention to local housing markets provides valuable insights into the perceived importance and market trends of housing in different cities.

Building upon the findings of Soo, 2018, this study expands the analysis from the state to the city level to evaluate the feasibility of capturing the micro-level dynamics of the housing market. To do so, housing-media-attention indices are constructed using the same methodology for the 34 cities as in Soo, 2018, and the relationship between media attention and future house prices at the city level is explored by estimating the panel predictive regression of the form:

$$h_{it+1}^{city} = \alpha_i + \beta_c HAI_{it}^{city} + \gamma X_{it} + \epsilon_{it+1} \tag{3.12}$$

where h_{it+1}^{city} shows house price growth at the city level. HAI^{city} denotes the city-level media-attention index for city i at time t, constructed using the PLS approach based on the news counts of the 20 housing-market-related topics introduced in the section 3.2.2, and X_{it} is the set of control variables including the home-ownership rate, vacancy rate, rental vacancy rate, and employment level, all measured at the city level.[23]

Table 3.9 presents the results for the same sample period as the state-level analysis. The results from the city-level analysis reveal a similar pattern to that of the state-level analysis. The R^2 value obtained from the city-level analysis for the one-step-ahead forecast horizon is 0.32, which is slightly higher than the state-level analysis of 0.29. Similarly, a one-standard-deviation increase in the housing-attention index results in a 0.52% increase in the growth rate of house prices in the next quarter, which is higher than the state-level effect (0.37%). The effect of the housing-media-attention index on future house prices remains significant for all forecast horizons, even after controlling for other factors that may affect

[23]To obtain city-level news counts, I applied an additional filter to flag any news articles with housing-market-related topics that mention my sample of cities: Atlanta, Austin, Baltimore, Boston, Charlotte, Chicago, Cincinnati, Cleveland, Columbus, Dallas, Denver, Detroit, Indianapolis, Kansas City, Las Vegas, Los Angeles, Miami, Milwaukee, Minneapolis, New York City, Orlando, Philadelphia, Phoenix, Pittsburgh, Portland, Sacramento, San Antonio, San Diego, San Francisco, San Jose, Seattle, St. Louis, Tampa, and Washington D.C. However, in this case, my target variable is the city-level housing price growth, which is downloaded from the FHFA all-transaction index. Figure A3 plots the R^2 values obtained from the regression analysis of city-level housing price growth rates with city-level housing attention, with values ranging from 0.14 to 0.59. This result highlights the continued diversity and local segmentation of house-price dynamics even at the city level, which is a more granular level of analysis than the state-level analysis.

the housing market. Additionally, the rental vacancy, home-ownership, and vacancy rates have statistically significant coefficients, negatively affecting future house prices at different forecast horizons.

Overall, the results from the city-level analysis further validate the findings from the state-level analysis and show my newly constructed media-attention index continues to play a significant role in shaping housing prices at both the state and city levels.[24]

Table 3.9: Predicting local housing prices with media attention: city-level analysis

Variables	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
HAI^{city}	0.00519***	0.00516***	0.00510***	0.00501***	0.00386***	0.00388***	0.00372***	0.00358***
	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0007)	(0.0008)
Vacancy					-0.00249***	-0.00246***	-0.00223***	-0.00206***
					(0.0005)	(0.0005)	(0.0005)	(0.0005)
Rental vacancy					-0.00112*	-0.00105**	-0.000758	-0.000222
					(0.0006)	(0.0004)	(0.0005)	(0.0004)
Home-ownership					0.00034	-0.00021	-0.00135*	-0.00251***
					(0.0007)	(0.0007)	(0.0007)	(0.0009)
Employment					-0.00425	-0.00493	-0.00405	-0.00118
					(0.0054)	(0.0048)	(0.0045)	(0.0048)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓	✓	✓
Number of cities	34	34	34	34	34	34	34	34
Observations	2,278	2,244	2,210	2,176	2,132	2,098	2,064	2,030
Adj. R^2	0.318	0.339	0.334	0.328	0.373	0.392	0.382	0.385

Notes: This table reports regression results from: $h_{it+1} = \alpha_i + \beta_c HAI_{it}^{city} + \gamma X_{it} + \epsilon_{it+1}$ where HAI^{city} denotes city-level media attention index for city i at time t, and X_{it} is the set of controls variables including the home-ownership rate, vacancy rate, rental vacancy rate and employment level. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors clustered at the city and quarter level are reported in parentheses. All variables are used in standardized form.

3.9.2 Positive vs. Negative News: Which Has a Greater Impact on Housing Prices?

My results have so far shown media coverage of the housing market is a significant predictor of housing price growth, beyond standard housing-market indicators. A positive relationship exists between media coverage of the housing market and future house prices at the state level. In this regard, my findings align with the results of Cho, 2016, who shows the greater news intensity in the housing market leads to higher subsequent prices on housing invest-

[24] The results of the financial-literacy survey conducted by Lusardi and Mitchell, 2007 suggest households with lower incomes tend to have lower financial literacy and, as a result, they might be more greatly affected by media attention than those with higher incomes. The reason is that buyers with lower financial literacy might have limited access to adequate financial advice. To further explore this issue, I repeat the city-level analysis across different price tiers (low, medium, and high). This approach allows me to gain deeper insights into how media attention affects house prices in different segments of the housing market. I re-estimate equation (3.12) by replacing the dependent variable with low-, medium-, and high-tier house prices growth, respectively. The results in Table A12 of the appendix show the impact of media attention on house prices is positive and statistically significant across all price tiers. The highest magnitude of effect is observed in the low-tier segment houses, which implies low-income buyers are more susceptible to the influence of media attention than higher-income buyers.

ments.[25] One explanation for this phenomenon is that higher exposure to media sources creates heterogeneous beliefs about housing-market conditions, potentially increasing the number of households making buying or selling decisions. However, shorting restrictions limit the ability of homeowners to respond to negative signals in the housing market. By contrast, both homeowners seeking to buy a second home and non-owners who are in the market to purchase a house can respond to positive signals, creating a positive correlation between housing news media attention and future house prices. Additionally, Shiller, 2005 suggests news media can shape reader perceptions through their choice of tone and emphasis on specific positive or negative events.

To delve deeper into this explanation, I categorize articles as either positive or negative with respect to housing news and examine the distinct impacts of positive and negative media on future housing prices. To do so, I focus on news articles with the topic of the "housing market" and adopt the top 10 most frequently appearing negative and positive words in housing news from Table 2 of Soo, 2018. To identify news with a positive tone, I count the number of articles that include the following positive words: "up," "highs," "increasing," "rise," "great," "sustains," "most," "biggest," "frenziness," and "fastest." Similarly, to classify news with negative tone, I count the number of articles that include the following keywords: "downs," "low," "falling," "declining," "dropping," "foreclosing," "slow," "contract," "recession," and "bubble." Subsequently, I use the PLS method to construct separate positive and negative media attention indices.

As a result, more accurately comprehending and quantifying the impact of media tone on the housing market is now feasible. I run the following panel regression model:

$$h_{it+1} = \alpha_i + \beta_p HAI_{it}^{pos.} + \beta_n HAI_{it}^{neg.} + \gamma Z_{it} + \epsilon_{it+1} \tag{3.13}$$

where $HAI_{it}^{pos.}$ and $HAI_{it}^{neg.}$ denote positive and negative housing media attention, respectively, for state i at time t, and Z_{it} is the set of the housing fundamentals introduced in section 3.2.1.

Table A13 of the appendix provides a summary of the findings, which suggest positive news has a greater impact on future housing prices than negative news. Columns (2)-(3) show an increase in positive news leads to an increase in future housing prices for one-, two-, and three-quarter-ahead forecast horizons, whereas an increase in negative media attention has a negative impact on future housing price growth for one- and two-steps-ahead forecast

[25]Furthermore, previous studies on the stock market indicate investors tend to invest in stocks that receive media attention, resulting in an increase in demand for those stocks. Because investors are primarily concerned with future prices when making investment decisions, the information obtained through media plays a crucial role in their decision-making process. On the other hand, most individual investors rely solely on historical returns when deciding which stocks to sell (Hartzmark, 2015; Cziraki et al., 2021). This perspective aligns with the results of this study, which suggests news coverage in the housing market that receives the attention of investors can lead to an increase in house prices.

horizons. This finding implies negative news has a short-lived effect on future housing prices relative to positive news. The magnitude of the coefficient of positive news being larger than that of negative news suggests positive news has a greater impact on future housing prices than negative news. However, when I include housing-market indicators as control variables in the analysis, the effect of negative media attention on future housing prices becomes insignificant. On the other hand, the effect of positive media attention remains significant for one- and two-quarter-ahead forecast horizons, indicating the impact of positive news on future housing prices is still robust, even when other housing-market indicators are considered. The coefficient of positive media attention turns out to be negative for a longer forecast horizon (h=4), which suggests house prices might tend to move back toward their average levels due to the mean-reverting behavior of housing price growth. Overall, my results uncover a nuanced relationship where positive news seems to exert a more significant and lasting impact on future housing prices than negative news. This finding is consistent with the presence of shorting constraints, limiting the ability to sell in response to negative information, but does not exclude other explanations. I acknowledge that if media outlets prefer to publish negative news, the relationship between housing news and prices could vary. However, my analysis focuses on the observable patterns and correlations, rather than asserting a fixed causal relationship. By exploring both positive and negative news within the existing constraints and market characteristics, I aim to provide a more comprehensive understanding of how media coverage correlates with housing prices, without oversimplifying or overlooking the complexity of the issue.

My results differ from previous studies on the effects of positive and negative news on the stock market. For instance, Tetlock, 2007 utilizes a media factor derived from a prominent column in the Wall Street Journal to investigate the relationship between the media and stock market and shows negative or pessimistic news has the greatest predictive ability for stock market returns. Similarly, Da et al., 2015 also conclude negative terms are the most effective in indicating market sentiment, and thus only use negative words in constructing their stock market sentiment index. Therefore, my results suggest limitations on short-selling may play a role in explaining the differences in the impact of positive and negative news between the housing and stock markets.

3.10 Conclusion

A significant portion of an individual's wealth is traditionally represented by real estate investments, making a deeper understanding of house-price fluctuations crucial. Additionally, because the housing market is less informationally efficient than other financial markets, which present constant news in the form of daily price changes (Shiller, 2002), the housing market prices may be less informationally efficient, allowing news media coverage to play a more prominent role in shaping market information (Case and Shiller, 1989). In this study, I construct new state-level housing-attention indices and demonstrate these media-based measures effectively explain variations in house prices at the state level. Despite controlling for other key housing-market predictors, the impact of the news media on housing prices remains statistically significant in subsequent quarters. Furthermore, by exploiting the heterogeneity in state characteristics, I find the predictive power of housing attention is particularly pronounced in states with non-recourse mortgage laws, stronger land-use regulations, and higher levels of social and economic connectedness.

The results of this study underscore the considerable predictive power of housing media attention and suggest it should receive greater consideration when policymakers design real-estate-market policies or take actions to improve the functioning of the housing market. Accurate house-price estimates can furnish valuable insights not only for policymakers but also for households and real estate agents in the housing market, allowing them to make informed portfolio adjustments. In conclusion, this study helps shed light on the impact of news media coverage on housing prices and its role in price formation, thereby advancing our understanding of housing-market dynamics.

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Appendix: Additional Tables and Figures

Table A1: The effect of peer attention on housing supply

	Dependent variable : Building permits							
Variables	(1) $h=1$	(2) $h=2$	(3) $h=3$	(4) $h=4$	(5) $h=1$	(6) $h=2$	(7) $h=3$	(8) $h=4$
PAI	0.228***	0.245***	0.254***	0.266***	0.139***	0.145***	0.152***	0.178***
	(0.0297)	(0.0290)	(0.0320)	(0.0278)	(0.0293)	(0.0266)	(0.0290)	(0.0262)
HAI	0.112***	0.118***	0.121***	0.138***	0.0635***	0.0682***	0.0745***	0.0933***
	(0.0210)	(0.0228)	(0.0208)	(0.0228)	(0.0163)	(0.0163)	(0.0141)	(0.0181)
Mortgage rate					-0.425***	-0.464***	-0.451***	-0.377***
					(0.0662)	(0.0693)	(0.0697)	(0.0569)
Stock index					0.0257	0.00484	-0.0391	-0.0626***
					(0.0364)	(0.0188)	(0.0266)	(0.0166)
Employment					0.316**	0.310**	0.258**	0.114
					(0.122)	(0.121)	(0.120)	(0.0991)
Coincident index					-0.0365*	-0.0322**	-0.0310**	-0.00631
					(0.0196)	(0.0157)	(0.0136)	(0.0387)
Per capita income					0.0963**	0.0849**	0.0751**	0.0852***
					(0.0375)	(0.0331)	(0.0288)	(0.0316)
Constant	0.00170	0.0145	0.0250	0.0379	-0.0902**	-0.1000**	-0.101**	-0.0734**
	(0.0446)	(0.0434)	(0.0410)	(0.0368)	(0.0414)	(0.0420)	(0.0432)	(0.0337)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Number of States	50	50	50	50	50	50	50	50
Observations	3,216	3,168	3,120	3,072	3,216	3,168	3,120	3,072
Adj. R^2	0.816	0.833	0.841	0.866	0.861	0.883	0.892	0.910

Notes: This table reports results from estimation of the model $Permits_{it+1} = \alpha_i + \beta_1 HAI_{it} + \beta_2 PAI_{it} + \gamma Z_{it} + \epsilon_{it+1}$ where PAI_{it} denotes peer housing attention for state i at time t, and Z_{it} is the set of the housing fundamentals introduced in section 3.2.1. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors clustered at the state and quarter level are reported in parentheses. All variables are used in standardized form.

Table A2: R^2_{OoS} values across states calculated from "National" attention model

State	h=1	h=2	h=3	h=4	h=5	h=6
Alabama	0.10**	0.10**	0.18***	0.28***	0.37***	0.50***
Alaska	0.12**	-0.01*	0.03*	-0.03**	0.08**	-0.10*
Arizona	-0.24*	-0.25***	0.20***	0.52***	0.68***	0.74***
Arkansas	0.15**	0.25**	0.24***	0.30***	0.33***	0.44***
California	0.16***	0.34***	0.54***	0.68***	0.70***	0.70***
Colorado	-0.04	-0.04	0.13**	0.15**	0.08**	0.15**
Connecticut	0.18***	0.27***	0.28***	0.28***	0.40***	0.53***
Delaware	0.15**	0.30***	0.35***	0.39***	0.51***	0.66***
Florida	0.22***	0.48***	0.66***	0.75***	0.81***	0.79***
Georgia	0.14**	0.27**	0.34***	0.43***	0.53***	0.60***
Hawaii	0.02*	0.09**	0.17***	0.21***	0.34***	0.48***
Idaho	0.13***	0.12***	0.26***	0.34***	0.47***	0.60***
Illinois	0.18***	0.41***	0.40***	0.51***	0.61***	0.78***
Indiana	0.01	0.09*	0.17***	0.15***	0.18***	0.29***
Iowa	0.21**	0.26***	0.26***	0.31***	0.26***	0.36***
Kansas	0.17***	0.10**	0.14***	0.20***	0.31***	0.32***
Kentucky	0.16*	0.22**	0.26***	0.28***	0.32***	0.39***
Louisiana	0.09**	-0.14**	-0.06**	-0.25***	-0.02***	0.22***
Maine	0.18**	0.29***	0.29***	0.31***	0.43***	0.56***
Maryland	0.11***	0.25***	0.19***	0.13***	0.45***	0.60***
Massachusetts	0.08**	0.19***	0.40***	0.53***	0.52***	0.57***
Michigan	-0.45	-0.20	0.18*	0.37*	0.18**	0.41**
Minnesota	0.12*	0.22**	0.40***	0.44***	0.40***	0.48***
Mississippi	0.10**	-0.15**	0.16***	0.17***	0.43***	0.40***
Missouri	0.17**	0.34***	0.28***	0.36***	0.37***	0.59***
Montana	0.16**	-0.09**	0.19***	0.15***	0.36***	0.36***
Nebraska	0.04	0.04*	0.13**	0.12***	0.13***	0.22***
Nevada	0.01*	0.21***	0.39***	0.50***	0.55***	0.64***
New Hampshire	0.11**	0.23***	0.35***	0.50***	0.45***	0.57***
New Jersey	0.15***	0.34***	0.47***	0.55***	0.65***	0.75***
New Mexico	0.10***	0.08*	0.05**	0.17***	0.31***	0.17***
New York	0.23***	0.38***	0.43***	0.53***	0.57***	0.63***
North Carolina	0.20***	0.36***	0.27***	0.35***	0.43***	0.59***
North Dakota	-0.12	-0.06	-0.17	-0.42	-0.51	-0.66
Ohio	0.02	-0.03	0.12*	0.17***	0.17***	0.22***
Oklahoma	0.21***	0.06**	0.10**	0.21**	0.20***	0.28***
Oregon	0.11***	0.19***	0.33***	0.40***	0.46***	0.43***
Pennsylvania	0.13***	0.27***	0.34***	0.38***	0.45***	0.50***
Rhode Island	0.22***	0.33***	0.45***	0.48***	0.58***	0.63***
South Carolina	0.16***	0.38***	0.38***	0.36***	0.54***	0.59***
South Dakota	0.19**	0.28***	0.29***	0.31***	0.41***	0.38***
Tennessee	0.27**	0.25***	0.19***	0.51***	0.53***	0.59***
Texas	0.11**	0.16**	0.24***	0.34***	0.42***	0.44***
Utah	0.10**	-0.02***	0.21***	0.34***	0.51***	0.64***
Vermont	0.09**	0.11**	0.16***	0.12***	0.19***	0.26***
Virginia	0.08*	0.06	0.01	-0.05	0.25**	0.30***
Washington	0.18***	0.27***	0.51***	0.66***	0.59***	0.65***
West Virginia	0.12*	-0.10	0.07*	0.14**	0.15**	0.20***
Wisconsin	0.15**	0.29***	0.30***	0.32***	0.32***	0.50***
Wyoming	-0.03	-0.13	-0.20	-0.25*	-0.31*	-0.22**

Notes: For a given forecast horizon h, this table reports R^2_{OoS} values across states calculated from National attention model: $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{NHAI} NHAI + \varepsilon_{t+h}$. Asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level of testing the null hypothesis of $R^2_{\text{OoS}} \leq 0$, against the alternative $R^2_{\text{OoS}} > 0$ utilizing the Clark and West, 2007 statistics, which allows us to test predictive accuracy in nested models.

Table A3: R^2_{OoS} values across states calculated from "Combined" attention model

State	h=1	h=2	h=3	h=4	h=5	h=6
Alabama	0.12**	0.01**	0.28***	0.42***	0.55***	0.55***
Alaska	0.10**	0.00*	0.13**	0.06**	0.06**	-0.07**
Arizona	-0.31	-0.35***	0.03***	0.55***	0.70***	0.75***
Arkansas	0.07*	0.28***	0.31***	0.34***	0.50***	0.45***
California	0.20***	0.39***	0.53***	0.69***	0.71***	0.74***
Colorado	0.01	-0.04	0.21***	0.30***	0.15***	0.10*
Connecticut	0.13***	0.30***	0.34***	0.23***	0.59***	0.53***
Delaware	0.15**	0.35***	0.41***	0.33***	0.71***	0.73***
Florida	0.24***	0.57***	0.73***	0.81***	0.83***	0.79***
Georgia	0.18***	-0.35	0.37***	0.47***	0.60***	0.62***
Hawaii	-0.15	0.07**	0.16***	0.21***	0.41***	0.48***
Idaho	0.11**	0.15***	0.43***	0.45***	0.47***	0.56***
Illinois	0.24***	0.48***	0.45***	0.43***	0.63***	0.82***
Indiana	0.01	0.17***	0.20***	0.16**	0.20***	0.30***
Iowa	0.25***	0.35***	0.23***	0.33***	0.30***	0.43***
Kansas	0.12**	0.11**	0.13***	0.18***	0.23***	0.27***
Kentucky	0.24**	0.32***	0.28***	0.31***	0.44***	0.43***
Louisiana	-0.01	-0.35	-0.09	-0.27	-0.03	0.19
Maine	0.13**	0.20*	0.30**	0.37***	0.42**	0.57***
Maryland	0.05*	0.26***	0.14**	0.04***	0.25***	0.59***
Massachusetts	0.26***	0.44***	0.44***	0.51***	0.48***	0.56***
Michigan	-0.48	-0.09	0.12*	0.20*	-0.12	0.35**
Minnesota	0.23**	0.38***	0.47***	0.49***	0.42***	0.50***
Mississippi	0.14**	-0.15**	0.19***	0.17***	0.46***	0.37***
Missouri	0.18**	0.36***	0.32***	0.43***	0.51***	0.63***
Montana	0.13**	-0.09**	0.18***	0.26***	0.37***	0.23***
Nebraska	0.07	0.13**	0.13**	0.04	0.22*	0.26**
Nevada	-0.08	0.35***	0.44***	0.59***	0.62***	0.66***
New Hampshire	0.25***	0.39***	0.41***	0.50***	0.49***	0.59***
New Jersey	0.18***	0.47***	0.65***	0.67***	0.74***	0.82***
New Mexico	0.14***	0.13***	0.05**	0.26***	0.36***	-0.06
New York	0.23***	0.41***	0.45***	0.57***	0.58***	0.65***
North Carolina	0.26***	0.37***	0.36***	0.49***	0.50***	0.55***
North Dakota	-0.13	-0.06	-0.19	-0.41	-0.46	-0.69
Ohio	0.18***	0.13***	0.07*	0.24***	0.23***	0.26***
Oklahoma	0.08**	0.03*	0.14***	0.23***	0.27***	0.33***
Oregon	0.13***	0.18***	0.34***	0.44***	0.45***	0.44***
Pennsylvania	0.14***	0.38***	0.45***	0.52***	0.58***	0.58***
Rhode Island	0.33***	0.42***	0.52***	0.52***	0.60***	0.62***
South Carolina	0.17***	0.38***	0.49***	0.23***	0.54***	0.61***
South Dakota	0.23**	0.40***	0.30***	0.33***	0.41***	0.33***
Tennessee	0.25**	0.30***	0.26***	0.52***	0.61***	0.64***
Texas	0.11**	0.11**	0.21**	0.35***	0.26***	0.37***
Utah	0.10**	-0.08***	0.16***	0.22***	0.46***	0.61***
Vermont	0.10***	0.07**	0.19***	0.15***	0.28***	0.19***
Virginia	0.18**	0.12*	0.18***	0.13***	0.32***	0.26***
Washington	0.18***	0.27***	0.47***	0.63***	0.59***	0.64***
West Virginia	0.11**	-0.11	0.01	0.12**	0.18**	0.23***
Wisconsin	0.20***	0.31***	0.26***	0.14***	0.42***	0.51***
Wyoming	-0.08	-0.13	-0.16	-0.19*	-0.26*	-0.24***

Notes: For a given forecast horizon h, this table reports R^2_{OoS} values across states calculated from Combined attention model: $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{HAI} HAI + \beta_{NAI} NAI + \varepsilon_{t+h}$. Asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level of testing the null hypothesis of $R^2_{\text{OoS}} \leq 0$, against the alternative $R^2_{\text{OoS}} > 0$ utilizing the Clark and West, 2007 statistics, which allows us to test predictive accuracy in nested models.

Table A4: Out-of-sample forecasting comparison: Encompassing test results

State	h=1	h=2	h=3	h=4	h=5	h=6
Alabama	1.018***	0.980**	-0.043	0.978***	0.226	0.189
Alaska	6.141***	-2.148	3.231***	1.025**	-0.022	0.734
Arizona	1.397***	0.638***	-0.688***	0.459***	-0.007	-0.268***
Arkansas	3.401***	0.658*	0.648	0.538	1.322***	0.205
California	0.528**	0.845***	1.011***	0.962***	0.420***	0.110
Colorado	1.550***	1.448***	1.522***	2.006***	3.251***	3.264***
Connecticut	-0.210	-0.431	0.435	0.213	0.047	-0.373
Delaware	2.693***	-1.147*	-0.733	-0.003	-0.149	1.231***
Florida	0.911***	1.261***	0.759***	0.567***	0.083	1.033***
Georgia	2.391***	0.674**	0.661**	-0.058	2.087***	2.276***
Hawaii	-2.787**	0.790***	1.484***	1.511***	0.257	-0.221
Idaho	-7.888***	0.908***	0.453***	0.259*	1.046***	-0.035
Illinois	4.315***	1.626***	1.804***	3.419***	1.641***	1.277***
Indiana	0.565	0.212	0.601**	0.641**	0.633***	0.212**
Iowa	2.369***	1.284***	0.199	0.906***	1.621***	1.162***
Kansas	1.933***	0.686**	0.330	0.865***	1.861***	0.557*
Kentucky	1.254***	1.302***	1.547***	1.285***	1.574***	0.288
Louisiana	5.248***	2.799*	1.368	0.428	1.467***	1.136**
Maine	-0.325	0.382	1.096***	1.434***	-0.526	-0.049
Maryland	5.733***	1.419***	-0.242***	1.107***	0.730***	-0.190
Massachusetts	4.302***	1.704***	0.655***	2.240***	-0.067	1.156***
Michigan	-0.336**	-1.019***	0.342*	0.695	0.333***	1.632***
Minnesota	1.532***	0.613***	0.458	0.817***	1.130***	0.505***
Mississippi	3.306***	-0.377	1.166***	-1.041**	1.156***	-0.702***
Missouri	2.178***	1.047**	-0.428	2.001***	1.349***	0.466***
Montana	2.076***	0.999***	1.287***	0.748***	-0.368	0.870***
Nebraska	1.439*	0.753***	0.916***	0.235	1.206***	0.672***
Nevada	1.136*	2.547***	1.611***	1.130***	1.651***	1.895***
New Hampshire	1.353***	0.495***	0.639***	1.417***	0.861**	0.513***
New Jersey	-2.485***	1.841***	1.652***	0.999***	-0.257*	1.476***
New Mexico	1.120***	-0.160	-0.796	1.551***	1.692***	-7.813***
New York	0.674***	0.765***	0.413**	0.584***	0.476**	0.501***
North Carolina	3.362***	1.248**	0.290	1.597***	0.939***	0.665*
North Dakota	2.662***	-0.162	2.728***	1.035	-0.181	-0.147
Ohio	1.946***	0.969**	1.074**	1.356***	1.668***	0.558**
Oklahoma	2.164***	2.103***	1.864***	1.054*	1.232*	1.945***
Oregon	-0.232	-0.545**	-0.444	0.088	0.824***	-0.219
Pennsylvania	0.910***	0.305	0.186	-0.126	-0.176	-0.152
Rhode Island	0.092	0.546***	1.532***	0.898**	-0.053	0.325***
South Carolina	-0.820***	0.522*	1.242***	0.501*	-0.401*	0.626***
South Dakota	2.390***	0.728***	2.072***	2.308***	3.853***	1.389***
Tennessee	-0.547***	0.592***	-0.164	1.106***	0.308	0.371***
Texas	1.456***	1.981***	1.547***	1.458***	2.422***	2.613***
Utah	-0.179	0.448	0.244**	0.122	0.476***	0.178
Vermont	0.986**	0.569	1.542**	1.427	1.137**	-0.350
Virginia	1.706***	0.861***	0.240	0.009	0.844***	1.841***
Washington	0.221	0.675	0.895***	0.407***	0.330**	1.017***
West Virginia	2.682***	1.318***	2.080***	0.525	0.558	-0.343
Wisconsin	0.476*	0.264	1.610	1.156*	0.851***	0.448**
Wyoming	1.053**	1.912***	1.146***	1.087*	0.444	1.001***

Notes: The table presents results of forecast encompassing test of Chong and Hendry, 1986 using the following regression: $r_{t+h} = \delta + \lambda_{AR}\hat{r}^{AR}_{t+h} + \lambda_{HAI}\hat{r}^{HAI}_{t+h} + u_{t+1}$, where r_{t+h} is the actual h-quarter ahead housing price growth rate and $\hat{r}^{AR}_{t+h}$ is the forecast value of benchmark $AR(p)$ model and $\hat{r}^{HAI}_{t+h}$ denotes the forecast obtained from Local attention model (specification - 1). I test null hypothesis that λ_{HAI} is significantly differs from zero. The asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance levels.

Table A5: Judicial Law

$Variables$	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
HAI	0.0039***	0.0038***	0.0039***	0.0042***	0.0030***	0.0029***	0.0029***	0.0032***
	(0.0007)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)
$HAI \times I^{JudicialLaw}$	-0.0006	-0.0006	-0.0007	-0.0010*	-0.0004	-0.0004	-0.0006	-0.0009*
	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Number of States	50	50	50	50	50	50	50	50
Adj. R^2	0.289	0.302	0.318	0.359	0.410	0.402	0.388	0.388

Notes: This table reports regression results from: $h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{JL} HAI_{it} \times I_i^{JudicialLaw} + \delta X_{it} + \epsilon_{it+h}$ where the $JudicialLaw$ is the dummy variables takes value of 1 if the state is governed by judicial law. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors clustered at the state and quarter level are reported in parentheses. All variables are used in standardized form.

Table A6: Population weighted economic connectedness and housing prices

$Variables$	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
HAI	0.0024***	0.0026***	0.0022***	0.0020***	0.0019***	0.0022***	0.0018***	0.0017***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
$HAI \times I^{ECW}$	-0.0025***	-0.0023***	-0.0023***	-0.0021***	-0.0021***	-0.0020***	-0.0020***	-0.0020***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Number of States	50	50	50	50	50	50	50	50
Adj. R^2	0.654	0.660	0.655	0.652	0.680	0.682	0.672	0.668

Notes: This table denotes the estimation results from the regression: $h_{it+h} = \alpha_i + \beta HAI_{it} + \beta_{ECW} HAI_{it} \times I_i^{ECW} + \delta X_{it} + \epsilon_{it+h}$ where I_i^{ECW} is a dummy variable equal to 1 (0) if the population weighted economic connectedness measure (ECW) of the state i is below (above) the median values of all states, representing less (more) connectedness states. I compute the state-level ECW measure by taking the population weighted average value of the population standardized county-level EC values constructed by Chetty et al., 2022. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors clustered at the state and quarter level are reported in parentheses. All variables are used in standardized form.

Table A7: Placebo R^2 values

	h=1	h=2	h=3	h=4
Panel A: Actual R^2 values				
HAI	0.289	0.302	0.318	0.359
Panel B: Placebo R^2 values				
Mean	0.146	0.112	0.155	0.178
Max	0.181	0.145	0.197	0.220
Min	0.109	0.084	0.115	0.139

Notes: Panel A reports the actual R^2 values. In Panel B, I present mean, maximum and minimum of the placebo R^2 values obtained from re-estimation of the eq. (3.3) using the newly constructed Placebo housing-media attention index. I consider forecast horizons h= 1, 2, 3, 4.

Table A8: Driscoll and Kraay, 1998 standard errors

Variables	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
HAI	0.00365***	0.00357***	0.00365***	0.00383***	0.00288***	0.00273***	0.00263***	0.00283***
	(0.000395)	(0.000451)	(0.000437)	(0.000372)	(0.000574)	(0.000658)	(0.000763)	(0.000689)
Constant	0.00382***	0.00365***	0.00361***	0.00358***	0.00560***	0.00524***	0.00446***	0.00369***
	(0.000659)	(0.000573)	(0.000520)	(0.000460)	(0.000803)	(0.000721)	(0.000781)	(0.000895)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Number of states	50	50	50	50	50	50	50	50

Notes: For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Driscoll and Kraay, 1998 are reported in parentheses. All variables are used in standardized form. I consider forecast horizons h= 1, 2, 3, 4.

Table A9: Lagged house prices

Variables	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
HAI	0.0020***	0.0018***	0.0021***	0.0029***	0.0014***	0.0011**	0.0013**	0.0020***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0006)
$L.HPR$	0.0375	0.236**	0.533***	0.356***	0.0577	0.244***	0.525***	0.348***
	(0.0996)	(0.0918)	(0.0734)	(0.0853)	(0.0867)	(0.0881)	(0.0750)	(0.0883)
$L2.HPR$	0.208**	0.331***	-0.0684	-0.144	0.249***	0.343***	-0.0505	-0.100
	(0.102)	(0.0822)	(0.101)	(0.101)	(0.0887)	(0.0676)	(0.100)	(0.0971)
$L3.HPR$	0.363***	0.0502	0.103	0.289***	0.342***	0.0363	0.0915	0.282***
	(0.0840)	(0.0960)	(0.117)	(0.0783)	(0.0774)	(0.0902)	(0.111)	(0.0772)
$L4.HPR$	0.0006	-0.0568	-0.0984	-0.238***	0.0007	-0.0398	-0.0657	-0.205**
	(0.0785)	(0.111)	(0.0874)	(0.0828)	(0.0723)	(0.108)	(0.0765)	(0.0840)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Number of States	50	50	50	50	50	50	50	50
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Adj. R^2	0.550	0.536	0.515	0.441	0.576	0.572	0.551	0.463

Notes: The dependent variable in each model is the growth of the house price index (HPR), and the main explanatory variable (HAI) is the state-level housing media attention index. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Two way clustered standard errors are reported in parentheses. All variables are used in standardized form. I consider forecast horizons h= 1, 2, 3, 4.

Table A10: Controlling for time fixed effects

Variables	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
HAI	0.0009***	0.0012***	0.0008***	0.0007***	0.0006**	0.0010***	0.0006***	0.0005**
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Control variables					✓	✓	✓	✓
State and Time Fes	✓	✓	✓	✓	✓	✓	✓	✓
Number of States	50	50	50	50	50	50	50	50
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Adj. R^2	0.620	0.630	0.625	0.626	0.657	0.661	0.650	0.648

Notes: The dependent variable in each model is the growth of the house price index in each state at the given horizon (h=1, 2, 3, or 4). HAI refers to the state-level housing media attention. For each regression, the table presents the estimates of slopes and standard errors clustered at the state and quarter level in parentheses; ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. All variables are used in standardized form.

Table A11: Alternative measures of house price growths

	FHFA house price index				Freddie-Mac house price index			
Variables	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
HAI	0.00288***	0.00273***	0.00263***	0.00283***	0.00319***	0.00314***	0.00287***	0.00308***
	(0.000550)	(0.000669)	(0.000643)	(0.000661)	(0.000752)	(0.000823)	(0.000913)	(0.000899)
Constant	0.00560***	0.00524***	0.00446***	0.00369***	0.00485***	0.00340***	0.00373***	0.00437***
	(0.000645)	(0.000533)	(0.000554)	(0.000643)	(0.000874)	(0.000938)	(0.000952)	(0.000928)
Control variables	✓	✓	✓	✓	✓	✓	✓	✓
Number of states	50	50	50	50	50	50	50	50
Observations	3,350	3,300	3,250	3,200	3,350	3,300	3,250	3,200
Adj. R^2	0.410	0.402	0.386	0.384	0.330	0.285	0.287	0.319

Notes: For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Two way clustered standard errors are reported in parentheses. All variables are used in standardized form. I consider forecast horizons h= 1, 2, 3, 4.

Table A12: The effect of housing media attention on different segments of housing market

$Variables$	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
Panel A: Low-tier house prices								
HAI^{city}	0.0116***	0.0119***	0.0117***	0.0109***	0.00906***	0.00976***	0.00967***	0.00858***
	(0.00178)	(0.00166)	(0.00156)	(0.00189)	(0.00167)	(0.00165)	(0.00142)	(0.00190)
Adj. R^2	0.362	0.385	0.369	0.325	0.421	0.440	0.420	0.395
Panel B: Medium-tier house prices								
HAI^{city}	0.00853***	0.00859***	0.00829***	0.00759***	0.00670***	0.00688***	0.00651***	0.00556***
	(0.00119)	(0.00107)	(0.00102)	(0.00123)	(0.00111)	(0.00100)	(0.000872)	(0.00121)
Adj. R^2	0.409	0.425	0.399	0.342	0.489	0.494	0.471	0.421
Panel C: High-tier house prices								
HAI^{city}	0.00665***	0.00669***	0.00647***	0.00578***	0.00520***	0.00537***	0.00525***	0.00430***
	(0.00107)	(0.000994)	(0.000947)	(0.00109)	(0.000958)	(0.000947)	(0.000866)	(0.00115)
Adj. R^2	0.380	0.397	0.377	0.311	0.477	0.476	0.434	0.366
Common Information for Panels A - C								
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1,072	1,056	1,040	1,024	980	964	948	932
Number of states	16	16	16	16	16	16	16	16

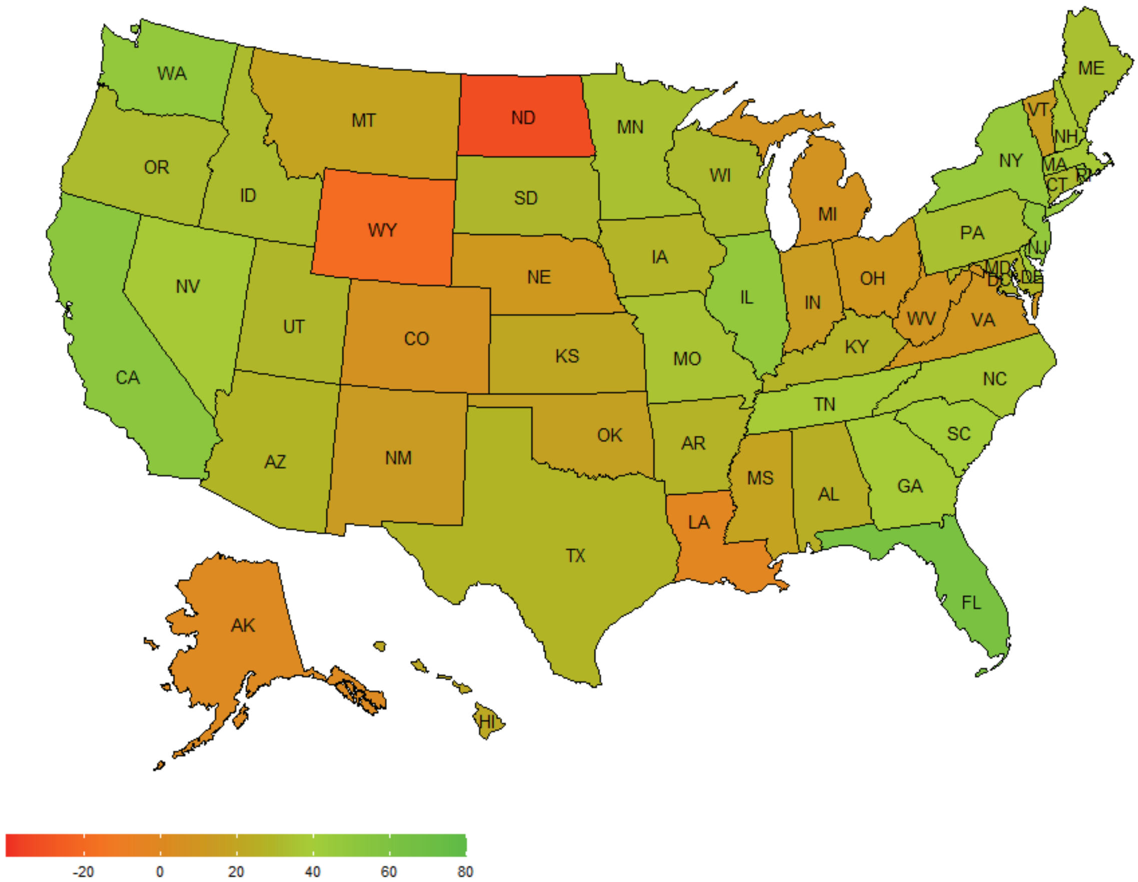
Notes: This table reports regression results from:$h_{it+1} = \alpha_i + \beta_c HAI_{it}^{city} + \gamma X_{it} + \epsilon_{it+1}$ where the h_{it+1} alternatively represents Case-Shiller house prices for low-, medium-, high-tier segment. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors clustered at the city and quarter level are reported in parentheses. All variables are used in standardized form. Since Case-Shiller house prices indices are available for only : Atlanta, Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle Tampa, Washington D.C., estimations results are limited to this sample.

Table A13: The impact of positive vs. negative news on future house prices

$Variables$	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
$HAI^{pos.}$	0.00801***	0.00670***	0.00373***	0.00198	0.00411**	0.00360**	0.00114	-0.00101
	(0.00192)	(0.00159)	(0.00136)	(0.00188)	(0.00176)	(0.00144)	(0.00133)	(0.00198)
$HAI^{neg.}$	-0.00491***	-0.00344**	-0.000212	0.00161	-0.00117	-0.000565	0.00197	0.00390**
	(0.00178)	(0.00133)	(0.00122)	(0.00180)	(0.00177)	(0.00139)	(0.00132)	(0.00189)
Control variables					✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
SE: double clustered	✓	✓	✓	✓	✓	✓	✓	✓
Number of states	50	50	50	50	50	50	50	50
Observations	3,216	3,168	3,120	3,072	3,216	3,168	3,120	3,072
Adj. R^2	0.260	0.290	0.312	0.326	0.412	0.417	0.404	0.379

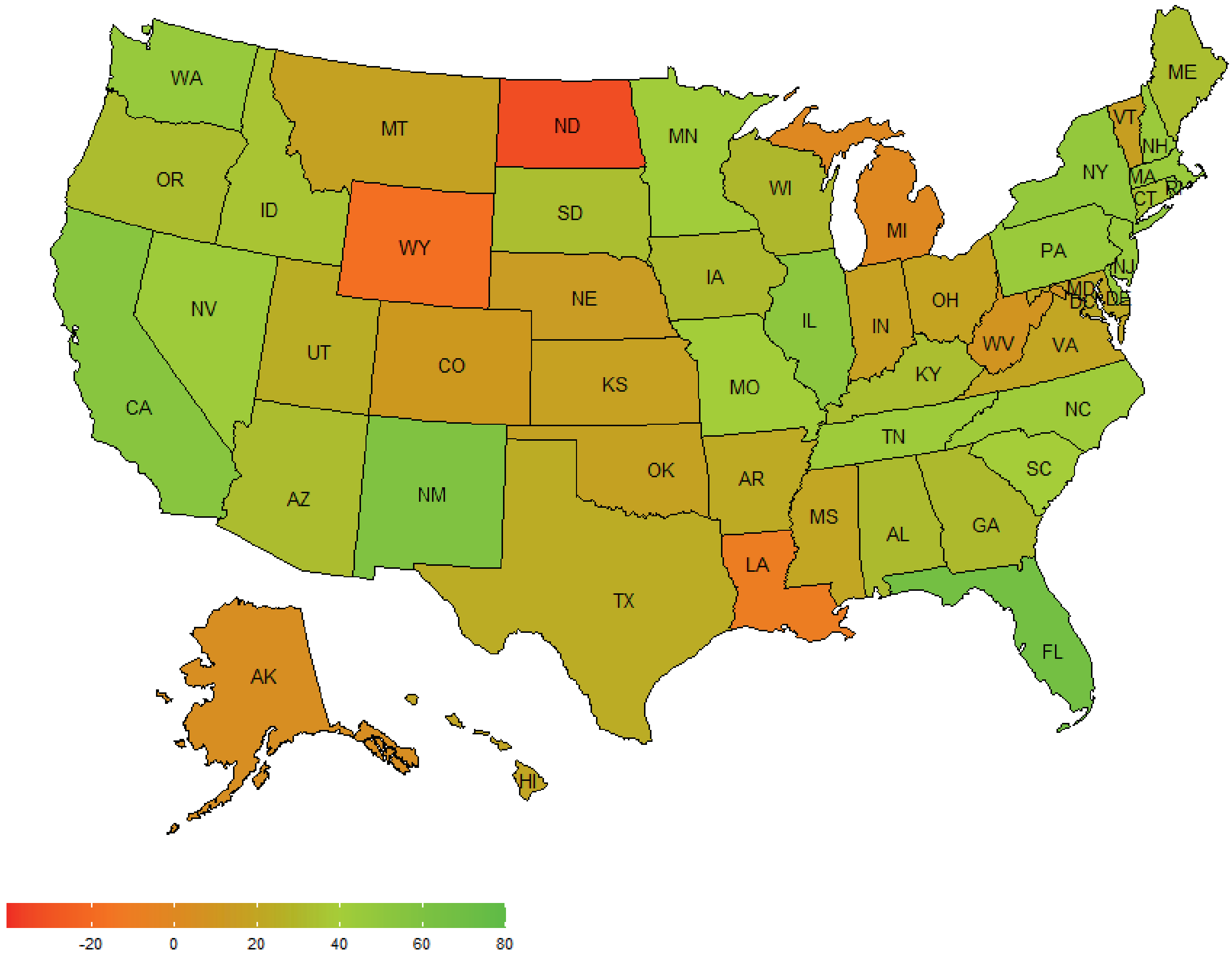
Notes: This table reports results from estimation of the model $h_{it+1} = \alpha_i + \beta_p HAI_{it}^{pos.} + \beta_n HAI_{it}^{neg.} + \gamma Z_{it} + \epsilon_{it+1}$ where, $HAI_{it}^{pos.}$ and $HAI_{it}^{neg.}$ denotes positive and negative housing media attention for state i at time t, and Z_{it} is the set of the housing fundamentals introduced in section 3.2.1. For each regression, the table presents the estimates of slopes with a corresponding significance levels where asterisk(s) (*** 1% level; ** 5% level; * 10% level) denotes the significance level. Standard errors are clustered at the state and quarter level are reported in parentheses. All variables are used in standardized form.

Figure A1: National attention model: Forecast improvement compared to the benchmark AR(p) model



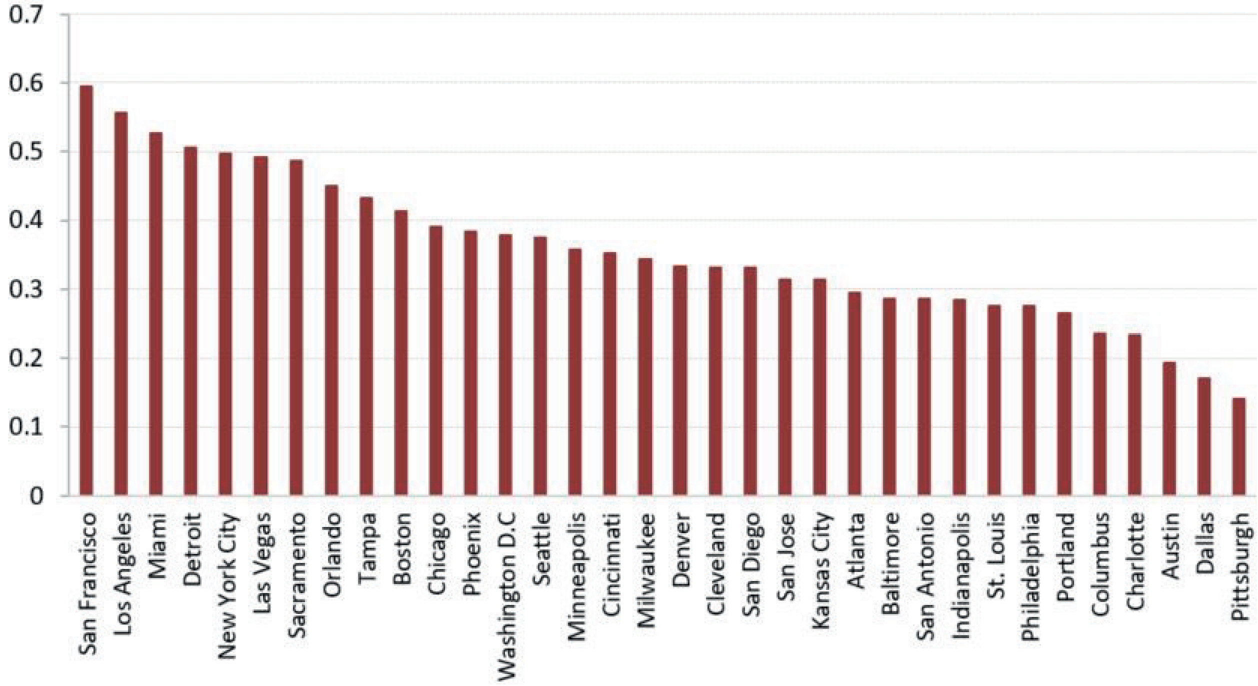
Notes: This figure shows average R^2_{OoS} values across states and forecast horizons computed from National attention model: $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{NHAI} NHAI + \varepsilon_{t+h}$ versus the benchmark AR(p) model.

Figure A2: Combined attention model: Forecast improvement compared to the benchmark AR(p) model



Notes: This figure shows average R^2_{OoS} values across states and forecast horizons computed from combined attention model: $h_{t+h} = \mu + \mathcal{L}^p h_t + \beta_{HAI} HAI + \beta_{NAI} NAI + \varepsilon_{t+h}$ versus the benchmark AR(p) model.

Figure A3: Explanatory power of city level housing media attention for variation in the city level house price growth



Notes: This figure displays the R^2 values from the regressions of each city-level house price growth rates onto each constructed city-level attention index.

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