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Personal Experience as the Driver of Heterogeneity in Inflation Expectations during Crises

An Empirical Assessment of the Michigan Survey of Consumers

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Abstract

This paper studies heterogeneity in consumers' inflation expectation during shocks using micro-level data from the University of Michigan's Survey of Consumers. By performing a linear regression, we validate suggested heterogeneity across demographic groups for our dataset ranging from 2000 to 2020. In detail, we document that women, non-college, low-income and older people have higher inflation expectations. Furthermore, we analyse how these tendencies change at the onset of an economic shock. The panel data feature of the survey allows us to build revision variables and conduct a first-difference regression while adding demographic explanatory variables to the model. Hereby, we isolate the impact of an economic shock and analyse three economic shocks individually. We find a significant heterogeneity across age groups during the Corona Crisis. Individuals between 18 and 25 years revise their inflation expectation by almost 170 basis points more compared to the reference group. In contrast, individuals who are at least 80 years old revise their inflation expectations significantly upwards compared to other age groups. The heterogeneity across age groups is tested by adding personal local experiences and personal lifetime experiences as predictors to the model. Personal local experiences, proxied by age-specific inflation rates derived from expenditure micro-evidence, do not explain the heterogeneity. Personal lifetime experiences, proxied by an individual crisis factor, partly offer an explanation. Our results have important implications for policymakers as the ignorance of the found heterogeneity may have a severe effect on the effectiveness of monetary policy especially during crises.

Keywords: Consumer inflation expectations, Survey Expectations, Heterogeneous Expectations, Personal experiences, Crises, COVID-19

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1 Introduction

> *Inflation is the tiger whose tail central banks control. [...] This tiger has been stirred by the extraordinary events and policy actions of the past 12 months.*
>
> — **Andy Haldane (2021)**
> Chief Economist at Bank of England

Though used by central bankers around the world, Hayek (1972) originally coined the metaphor by referring to inflation control as "trying to catch a tiger by its tail”. For many years, the tiger seemed to be asleep and did not give the faintest impression to wander around. The jungle, as the natural environment of the tiger, has adapted itself to live without its most feared inhabitant. However, the combined effects of unprecedentedly large shocks and policy measures may have woken him up and the metaphor holds true today more than ever. If the tiger indeed woke up, central banks would have to tame or even catch him to put the peacefulness of the jungle back in order. This is not an easy shot. The wild animal moves in such an agile way and is clearly advantageous in its natural environment. To gain a better understanding of the relationship between the tiger and its hunters, one must understand the precedent environment.

Following the aftermath of the Global Financial Crisis in 2008, interest rates in the majority of advanced countries approached their zero lower bound (Taylor, 2009). As a conventional monetary policy tool, low-interest rates were intended to bolster the economy (Bernanke, 2009). However, as inflation did not pick up, central banks ran out of standard ammunition with conventional practices and, inevitably, saw the management of inflation expectation as an avenue of escape (Yellen, 2016).

It is argued to be one of the mechanisms underlying the effectiveness of quantitative easing[1] and forward guidance[2]. Further, considerable effort has been devoted to anchoring inflation expectations - for instance, by announcing inflation targets. The ability of such unconventional policies to manage expectation in a low nominal rate environment is a valuable asset, as this is the only way of further reducing the real interest rate, and thereby households to spend more (Krugman et al., 1998). However, managing inflation expectations requires not just monitoring expectations but also understanding how these expectations are formed (Bernanke, 2004).

The examples from above show that inflation expectation is viewed by policymakers as a key determinant of actual inflation (Bernanke, 2007) and, therefore, has become central to macroeconomic models and monetary policy (Galí, 2008). In such models, inflation expectations drive a broad range of household decisions including consumption, borrowing, saving, wage bargaining, and investing (Woodford, 2011). For decades, consumers in macroeconomic models are mostly treated as rational agents who incorporate all information into their decision making and have biased-free forecasts (Muth, 1961). However, household surveys give evidence that consumers are far from rational and reveal substantial heterogeneity (Mankiw et al., 2003; Souleles, 2004). While previous empirical evidence has only shown that gender, education, income and age have explanatory power over a long time horizon, none of the studies explicitly looked at crisis periods. By using the panel component of the Michigan Survey of Consumers, our approach improves upon previous work by incorporating idiosyncratic heterogeneity and dynamic updating of each agent's inflation expectations. In this thesis, we clarify that there is substantial heterogeneity across age groups. We propose two hypotheses that address that consumers provide expectations about inflation based on observable inflation rates in the present or in the past (as in Malmendier and Nagel (2016)). Our results shed more light on the formation of inflation expectation and fill a gap in the rather sparse literature of heterogeneity. It helps economists and central bankers to improve their forecasts of future macroeconomic trends and formulate adequate monetary policy. The ability of central banks to make correct forecasts of inflation depends on their capability of understanding what determines the inflation expectations of the public. Or in other words "[...] an essential prerequisite to controlling inflation is controlling inflation expectations" (Bernanke, 2004).

[1] Mario Draghi (2015, March 23) summarized, "When inflation expectations go up with zero nominal rates, real rates go down. When real rates go down, investments and the economic activity improves. That's the reasoning [of QE]."

[2] Janet Yellen (2018, September 14) observed, "The strategy [of forward guidance] also potentially supports aggregate demand by raising inflation expectations, thereby lowering real long-term rates relative to a Taylor Rule type baseline.

1.1 Rationale and Research Question

The introduction from above sets the framework for our research question:

> *How do demographic groups revise their inflation expectations at the onset of an economic shock and does the idea of personal experience explain potential heterogeneity in interpretation?*

We put this research question at the centre of our thesis. It influences our choice of literature, the research design we follow, our data collection, as well as our methodology (Bell et al., 2018). The overall purpose of this thesis is to answer the research question above. In addition, we formulate the following subquestions as a guideline to create a structured response to the research question:

> 1) *Which demographic characteristics have explanatory power to describe the formation of inflation expectations?*

> 2) *Does a general heterogeneity with respect to inflation expectations among identified characteristics exist?*

> 3) *How can we isolate the impact of an economic shock on inflation expectations while allowing for individual-specific interpretation?*

These three subquestions help to answer how demographic groups revise their inflation expectation at the onset of an economic shock and, therefore, the first part of our research question.

> 4) *To what extent can personal local experiences in form of expenditure patterns explain the revisions?*

> 5) *To what extent can personal past experiences in form of lifetime experiences explain the revisions?*

Following the first three subquestions, 4) and 5) help to answer if personal experience explains potential heterogeneity in interpretation.

With the purpose of responding to the research question and to the stated subquestions, a quantitative research strategy through a multiple linear regression and a panel data regression is chosen (Saunders et al., 2019). The central part of this research strategy is the in-depth analysis of the Michigan Survey of Consumers, a large consumer survey in the US. The analysis follows a deductive and descriptive research approach (Bell et al., 2018) to gain an accurate picture of how individuals interpret economic crises. The Michigan Survey of Consumers with its rotating panel design and its rich information set about participants' socio-demographic characteristics, namely age, allows the collection of standardised data. Furthermore, it facilitates generating statistically representative findings for the US population. The applied econometric methods allow controlling for several factors that affect the formation of inflation expectations (Wooldridge, 2018). The hypotheses find their origin in the strand of literature on personal experiences and are empirically tested to reject or confirm the importance of the current theory (Bell et al., 2018). The statistical program language R has been used to plot the descriptive results and to perform the regressions.

1.2 Motivation

Since the introduction of rational expectations, academics have long left the stone of inflation expectations untouched. Significant attention has been paid to theoretically model expectations; however, the empirical work on micro-level expectations data has been rather sparse. Furthermore, barely any academic analysed inflation expectations during crises in-depth. As the Corona Crisis is an exogenous unprecedented shock to the global economy, it offers the unique opportunity to analyse how different socio-demographic groups revise their inflation expectation during crises. At the onset of the crises, a few empirical studies have been conducted but utilized data samples with a rather small number of observations (Binder, 2020; Meyer et al., 2021). In contrast, working with a large-scale consumer survey offers to obtain results with high external validity and, therefore, more general knowledge is detected. Such general knowledge is highly important from the perspectives of policymakers. It helps them to improve their inflation forecast and resulting policy choices. Combining the importance for policymakers with the obtained findings offers to conclude on the (in)efficiency of monetary policy. Thus, the rise of modelling the individual in a socio-demographic context (e.g. through personal lifetime experience or economic environment) and the shifted attention to the importance of micro-data surveys are key to our motivation.

1.3 Delimitations and scope of the paper

To keep sight of our research question, we delimit the scope of the thesis from certain aspects. The delimitations impact the external validity of the attained results but were either intentionally chosen by us or the consequence of data inaccessibility. As such, there are a few aspects that need to be pointed out. First and foremost, we only analysed one consumer survey. Even though the Michigan Survey of Consumers has been analysed and tested under various circumstances, other surveys offer wider panel dimensions[3]. Furthermore, the underlying survey represents the US population. In other advanced economies, namely Japan or the Euro-area, inflation expectation might be formed differently. Moreover, the thesis is limited to study the period from 2000 to 2020. Testing our two hypotheses on more historical crises, namely the 1980s recession or the stagflation period in the 1970s, might indicate further insights. Lastly, our thesis does not contrive a new theoretical approach. The strand of literature on personal experiences in all its theoretical facets provided the framework to formulate our hypotheses which we quantitatively and qualitatively extended by adjusting it to shocks. Besides these general remarks, it is worth mentioning that a few assumptions were made in our hypotheses. For the first one, it was assumed that all age groups face the same prices for the same goods and services. For the second one, it was assumed that there exists a clear threshold age (at age 18) at which an individual personally experiences a crisis.

1.4 Thesis Structure

This thesis is structured as follows. It starts with a thorough overview of the related work on inflation expectations in section 2. Besides putting the work of the thesis in a historical context, relevant theories and empirical studies are named. This section has two main objectives: On the one hand, it provides the academic framework and, on the other hand, it introduces the rationale behind the two

[3] Respondents of the Survey of Consumer Expectations from the Federal Reserve Bank of New York are re-questioned every month for 12 consecutive months

hypotheses. The section closes with the contribution of this thesis to the existing literature. Subsequently, section 3 describes the used data sources and introduces the sample data-set. It explains in detail the Michigan Survey of Consumers with its cross-sectional and panel-data design as well as other applied data sources. Furthermore, it offers a first descriptive overview of the responses. In section 4, the econometric methodology including descriptive regression analysis, panel data regression (baseline regression) and chi-square coefficients tests is presented. Subsequently, section 5 lists the result of the baseline regression and other related econometric values. To explain the attained baseline regression results, two hypotheses are introduced and empirically tested in section 6. After each hypothesis, a short critical discussion is put forward. Section 7 summarises and discusses the implications of our results in a broader context and comments on further research topics. Lastly, we provide a brief outlook.

2 Related Work

Our thesis is related to the strand of literature on the determinants of households' inflation expectations. Given its importance and its influence on the real economy, inflation expectations are becoming an increasingly studied field of research. For decades, academics have analysed the nature of inflation expectations from a theoretical as well as from an empirical point of view. For a better understanding, this chapter is in large part chronologically structured. First, with a short journey through time, the concept of rational expectations and the relevance of inflation expectations for policymakers is introduced. Subsequently, with the *sticky-information model* and the *rational inattention model*, two alternatives to rational expectations are presented. After that, the major empirical studies on demographic heterogeneity are categorized into four stylized facts. Next, as the focus of this thesis is the formation of inflation expectations in crises, a listing of empirical studies that were concentrated on crises, especially the Corona Crisis, is put forward. The section is closed with the gap in research in which this thesis is placed.

2.1 A journey through time: *Rational Expectation Theory*

In his pioneering *General Theory* in macroeconomics, Keynes (1936) first mentioned the importance of expectations and how beneficial they are to explain booms and busts in an economy. They are a central part of his school of thought which advocated accommodative monetary policy when private demand was insufficient and public programs were needed to stimulate demand. Consequently, over the years, many economists incorporated expectations into their macroeconomic models. At the same time, academics realised that the formation process of expectations should not be neglected and, hence, undertook first attempts to model this formation process. A prominent attempt was done by Muth in 1961 who bridged prevailing macroeconomic models with an agent-centric view and essentially introduced the concept of rationality. However, the proposal of Muth was not met with great excitement (Coibion et al., 2018) and academics devoted more attention to adaptive expectations, another concept that describes expectations as based on lagged experience. Building on this concept, until the late 60s, Keynesian models suggested that public programs could forever be an available tool for policymakers to achieve higher output and lower unemployment at the cost of higher inflation. However, with the *stagflation* period in the US during the early 70s, which was characterised by low economic growth, high inflation and high unemployment, a rethinking of macroeconomic models emerged. The rethinking was centred around the "decisive appearance in macroeconomics" (Evans and Honkapohja, 2012 p.8) of rational expectations in the papers of Lucas (1972) and Sargent et al. (1973). Their work marked the beginning of the *rational expectation revolution* (Coibion et al., 2018) and after some years, equilibrium models characterized by agents with rational expectations largely replaced Keynesian models. The new models assumed that people look into the future and try to predict the future as accurately as they can. Some examples of the rational expectation assumptions are the efficient market hypothesis or the permanent income theory of consumption. In order to understand the focus of this thesis and the rest of this chapter, the next section sketches the *Rational Expectation Theory*.

2.1.1 Rational expectation theory

Although other alternatives to *Rational Expectation Theory* have been argued for (namely adaptive expectations), the model of rational expectations has been the most assertive concept and is described as the workhorse model for more novel approaches (Coibion et al., 2018). Agents are modelled as if they have an economic model in mind whenever they face economic decisions. Therefore, rational expectation economists placed econometricians and agents on equal terms. This implies that people understand how the economy works and how government policies alter macroeconomic variables such as the price level and the level of unemployment. The model describes the fact that individuals are forward-looking and only incorporate the most recent and relevant information when forming expectations. All agents are endowed with the same information sets and process them in the same way. For agents, it implies quick and error-free reactions of all kind of prices and all kind of agent behaviour to every kind of new information. From a more technical point of view, rational expectations imply efficient forecasting in the sense that forecast errors are not predictable. Any possible forecast error, that is the difference in the actual price level in $t+1$ and the expected price level in t for $t+1$, does not allow to differ among individuals. The equal terms for econometricians and agents in turn postulated that the forecasts of the agents within the model were no worse than those of the econometricians who had the model. Therefore, the theory does not offer disagreement among consumers. Besides this important drawback, Lucas (1976) argued that individuals do not act all the time in the same way but change their behavioural pattern when policy changes. Therefore, any macroeconomic model should be derived from microeconomic foundations to essentially understand aggregate relationships. The next section describes such foundations in more detail.

2.1.2 Microeconomic foundations

In essence, micro foundation here refers to take a thorough look at individuals, firms and monetary policy and how the different players make decisions. Modelling such economic decision is as abstract as it is complex and requires a set of assumptions. For households, the standard and most important channel through which inflation expectations are intended to influence household economic decisions is the *Euler equation* on consumption. In order to derive the *Euler equation*, first, one must consider the *Life-Cycle Hypothesis* developed by Modigliani and Brumberg (1954) and Modigliani and Ando (1963). In very general words, the idea of the hypothesis is that households do not only consider their current income when making consumption and savings decisions but also take all of their future life periods into account. Galí (2008) derives the Euler Equation for the *Classical Monetary Model*.[1] The model assumes perfect competition in goods and labour markets, flexible prices and wages, no capital accumulation, no fiscal sector, and a closed economy. According to the *Life-Cycle-Hypothesis*, households maximize the sum of their discounted utilities subject to their personal budget constraint among all periods. Solving the underlying maximization problem under various assumptions (e.g. constant relative risk aversion utility function) leads to the *Euler Equation*. Galí (2008) log-linearizes[2] the Euler equation in order to describe the relationship between household's consumption, household's inflation expectations and the nominal interest rate:

$$c_t = E_t\{c_{t+1}\} - \frac{1}{\sigma}(i_t - E_t\{\pi_{t+1}\} - \rho) \quad (2.1)$$

[1] We refer to Galí (2008) for the entire model, exact derivations and further modifications of the *Classical Monetary Model*. In addition, his work provides an overview of further models which are relevant for central banks.

[2] Log-linearizing means to take logs in a first step and use a Taylor approximation around a steady-state as a second step.

Where c_t is the log of consumption in period t respectively the consumption growth, i_t corresponds to the nominal interest rate[3], and $\pi_{t+1} = p_{t+1} - p_t$ is the rate of inflation between t and $t+1$. Consequently, the term $E_t\{\pi_{t+1}\}$ refers to the inflation expectations for the following period. σ represents the degree of relative risk aversion. Lastly, ρ is the household's discount rate.

In the log-linearized Euler equation from above, the importance of inflation expectations is directly visible as the consumption growth c_t depends positively on inflation expectations $E_t\{\pi_{t+1}\}$. Furthermore, the *Classical Monetary Model* draws on the Fisher Equation:

$$i_t = E_t\{\pi_{t+1}\} + r_t \tag{2.2}$$

Thus, given a real interest rate r_t that is determined exclusively by real factors, the nominal interest rate i_t adjusts to the exact same extent as the inflation expectations change. In order to incorporate the Fisher Equation into the consumption growth path, we have to rearrange it first:

$$r_t = i_t - E_t\{\pi_{t+1}\} \tag{2.3}$$

As we insert the relationship described by the Fisher equation into the log-linearized Euler equation, the implications of inflation expectations for the monetary policy become apparent. Inflation expectations as well as nominal interest rates do directly influence the real interest rate. The real interest rate, in turn, is negatively correlated with the consumption growth:

$$c_t = E_t\{c_{t+1}\} - \frac{1}{\sigma}(r_t - \rho) \tag{2.4}$$

Thus, ceteris paribus increasing inflation expectations have the same effect on the real interest rate as a one for one decreasing nominal interest rates. Accordingly, monetary policymakers can for instance countermeasure inflation expectations in order to influence consumption respectively on aggregate the Gross Domestic Product (hereinafter: GDP). Much like argued in the introduction, in a low nominal rate environment, inflation expectation is a valuable asset as it is the only way to increase consumption of households (Krugman et al., 1998).

[3]Notice that $i_t = -logQ$ holds. In other words, i_t is formed as the log of the gross yield of the one-period bond.

Central banks use macroeconomics models which incorporate inflation expectations as "pinned down" (Galí, 2008, p. 21) in the *Classical Monetary Model*. In the light of the Euler Equations and the *Rational Expectation Theory*, it is of major importance to analyse to what extent micro-data in form of surveys is consistent with *rational expectations*. In order to answer this, it is crucial to understand how inflation expectations can be measured in the first place.

2.2 Inflation Expectations: Measurement and Usefulness

In themselves, inflation expectations are not directly observable like prices in the supermarket but several methods exist for deriving them from available data sources. The two most prominent ones are extracting the expectations from financial market instruments (e.g. *Treasury Inflation Protection Securities*) or deriving them from surveys. Although there is an ongoing debate on which method is more useful, Ang et al. (2007) found that survey expectations on 12-months ahead inflation outperform alternative inflation forecasts. Consistent results are reported by Thomas (1999), Croushore and Stark (2001) and Mehra (2002). Surveys either capture the responses of professional forecasters or of households. For professional forecasters, there exists extensive literature (see Croushore et al. (1998) for a survey) but for the intention of this paper, we focus mainly on related work around household surveys. The results of professional surveys are mentioned but their meaningfulness will only superficially touched upon. One of the main points of criticisms on household surveys is that their truth content is flawed as the respondents might answer carelessly. However, an experiment by Armantier et al. (2015) countered the allegation by showing that households have the right incentives when answering the survey and therefore answer to the best of their knowledge and belief. The design of household surveys is quite similar by asking a large number of respondents standardized questions regarding their expectation for the future. Most of the surveys have the intention to accurately mimic the general public to facilitate external validity. The most important interpretation of external validity is whether the respondents in the survey are able to forecast future inflation. It has been found that there is a significant co-integration between inflation expectations and actual inflation (Mehra, 2002), which demonstrates the relevance for policymakers.

However, one large drawback of consumer surveys needs to be taken into consideration. It has been found that the wording of the questions in surveys cannot be neglected (Bruine de Bruin et al., 2010). Some surveys, such as the Michigan Survey of Consumers, intentionally use a simplified language to accommodate the subjects missing technical knowledge. Instead of asking for the *rate of inflation*, it asks for the direction of *prices in general*. While it may seem understandable to use such language, there is reason to believe that it may be counter-productive. Bruine de Bruin et al. (2010) show that asking about the *rate of inflation* yields lower results compared to questioning *prices in general*. The meaning behind these two terms is the same but the respondents may form different associations. *Prices in general* could be associated more with products from the supermarket purchased on a daily basis and less with intangible goods. As a result, the respondents of the Michigan Survey could be biased towards their own *perceived* inflation rate and do not respond to the overall inflation rate of the economy. Consistent studies are presented by Bruine De Bruin et al. (2011). Policymakers are informed about such drawbacks that come with the information content of consumers expected inflation. Nevertheless, the formation of inflation expectations tells a much bigger story than one might think at first glance. The presented importance of consumer surveys together with the mathematical appeal of the rational expectations raise the logical step to test for rationality in micro-data.

The correspondence between consumer surveys and rationality has been tested in various studies and, hence, there exists a broad literature strand on testing the null hypothesis of rational expectation with microeconomic evidence from consumer surveys. The introduction of large-scale household surveys facilitated research significantly. The most influential empirical study on the rationality of inflation expectations was conducted by Mankiw et al. (2003). Besides analysing the Michigan Survey of Consumers for the general public, they analysed the Livingston Survey as well as the Survey of Professional Forecasters. In contradiction to the *Rational Expectation Theory*, the authors found evidence of auto-correlation by regressing year *t*'s forecast error on the realized error over year *t-1*. This indicates that last year's forecast error incorporates information that is not being exploited in the formation of this year's forecast. For instance, they found that some macroeconomic information (e.g. level of unemployment, T-bill, or inflation rate) is not fully incorporated into agent's inflation forecast. Other evidence that contradicts the null of rational expectations for households comes from Branch (2004).

Mankiw et al. (2003) also found that inflation expectations vary between professional forecasters and households; that is, the respondents do not necessarily all share the same expectations. Disagreement was measured as the interquartile range and the existence of quite long tails in the density function. It was found to be greater among consumers than among professional forecasters. In precise, while consumer expected inflation in 2003 to rise between 0% and 5%, professionals expected it to rise between 1.5% to 3%. Moreover, the magnitude of the disagreement varied tremendously over time and among consumers it appeared to rise during recessions. Again, this stands in stark contrast to the *Rational Expectation Theory* as the theory offers no theoretical grounds for disagreement. If consumers do not form their inflation expectations rationally but disagree substantially, it is inevitable to get to the bottom of the disagreement.

Spurred on by these results, Souleles (2004) focused on the disagreement for consumer inflation expectation. Similar to Mankiw et al. (2003), by employing household-level data from the Michigan Survey of Consumers, he found that expectations appear to have been biased, at least ex-post, as forecast errors did not average out between 1978 and 1996. The bias was found to be related to the inflation regime and the business cycle. Furthermore, the forecast errors were strongly correlated with consumer's demographic characteristics, suggesting a systematic heterogeneity. Essentially, this heterogeneity suggests an important role for "time-varying, group-level shocks" - aggregated shocks to the economy do not hit all consumers equally (Souleles, 2004, p.65). Further empirical evidence is offered by Madeira and Zafar (2015) and Puri and Robinson (2007). Taken together, these results build the framework for the following sections. The presence of disagreement among consumers and its correlation with demographic characteristics are one cornerstone to understand how inflation expectations are formed if not rationally. More novel theoretical explanations as alternatives to the *Rational Expectation Theory* were brought forward to address disagreement. The next section introduces the two most prominent theoretical explanations that depart from *rationality*.

2.3 Alternatives to *Rational Expectation Theory*: Informational Rigidities

The two major theoretical explanations that emerged out of the *Rational Expectation Theory* are the *Sticky-Information Theory* and the *Rational Inattention Theory*. Although different in their line of argument and model design, they both call forth informational rigidities as the reason why agents do not form their expectations rationally. In other words, agents face certain limitations on information processing in the context of forecasting inflation and information is not as flexible and fast-responding as asserted. It is beyond the scope of this thesis to disentangle extensively the two different explanations. However, to understand the listed empirical studies, the two theoretical explanations are sketched out in the next section.

2.3.1 Sticky-information model

The *Sticky-Information model* is a theoretical explanation that deviates substantially from the *Rational Expectation Theory* and was developed by Mankiw and Reis (2002). The key difference is that information is no longer universal across all consumers but due to its sticky characteristic, individuals are endowed with different information sets at a different point in time. Any information about macroeconomic conditions diffuses slowly through the decision-makers. The rate of diffusion, ultimately, depends on either the costs of acquiring information or the costs of re-optimization. Given the costs, every single individual decides whether to update their information set, and hence their inflation expectation, or not. As a result, only a fraction of the whole population updates their expectations in accordance with new information and the remaining part of the population continues to act in accordance with their pre-existing plans based on old information. Therefore, the *Sticky-Information Theory* is, at least partly, able to explain the systematic heterogeneity across demographic characteristics of consumers outlined in the previous section 2.2: With the staggering updating of the population, the theory essentially generates heterogeneity that is endogenous to the model.

Mankiw et al. (2003) argue that the *Sticky-information Theory* is the only theory that is able to explain the disagreement in the Michigan Survey of Consumers. By estimating a vector auto-regression on US monthly data, and assuming that each period, a fraction λ of the population obtains new information about the state of the economy, their model results corresponded very well to the actual data. For the Michigan Survey of Consumers, a value of 0.08 for λ was calculated which means that households update their expectation on average every 12.5 months. However, the dispersion was substantially higher on average in the survey data than predicted by the model. The authors noted that this is most likely explained by idiosyncratic heterogeneity in the population because individuals have different sources where they retrieve their information, in their sophistication in making forecasts, or even in their commitment to truthful reporting in a survey. Although their results give important insights into the formation of inflation expectations of households, the authors stress out that a better understanding of bounded rationality with micro-foundations is needed.

2.3.2 Rational Inattention model

One may see the *Rational Inattention Model* as an example of a model that incorporates bounded rationality. It also argues that consumers do not form inflation expectations rationally because information rigidities are present (Sims, 2003). In plain, it explains why consumers do not incorporate the information that lies in front of them "for free" (Sims, p.3). In this context, free information is e.g. information published in books, newspapers, and scientific articles or knowledge through social interactions. In the model, agents can only observe the current state imperfectly and must then form a belief about the inflation based on what variables they observe. The observed variables are either noisy signals (together with some error) or valuable information. Individuals have only a limited amount of attention and therefore need to decide to which signals they optimally allocate their attention to. This stands in contrast to rational expectations as it assumes that people fully and quickly process all available information. According to the rational inattention model, individuals optimally *budget* their attention.

Therefore, the model explains heterogeneity across individuals in inflation expectations due to the fact that they incorporate or economize information in different ways. Even if all individuals have the same objective function and constraints, they may process signals differently. Especially nowadays, in uncertain environments, the processing of weighting the costs and benefits of paying attention to a specific volatile variable is difficult (Mackowiak & Wiederholt, 2009).

2.4 Present and Past: How personal experiences drive heterogeneity

Both the *Sticky-Information Model* and the *Rational Inattention Model* criticise rational expectations and offer an explanation for heterogeneity in inflation expectation across households. The first generates it as staggered updating leads to heterogeneous information sets. The latter generates it as capacity constraints, objective functions and information processing errors are heterogeneous. Therefore, both offer an interesting starting point to analyse the formation process of household inflation expectation in greater detail. So far, we refrained from stating the demographic heterogeneity specifically. Now, with the two theoretical explanations in the back of one's mind, this section lists studies that found inflation expectations to differ across demographic subgroups. In summary, the studies show that:

1. Women tend to have higher inflation expectations

2. Low-income tend to have higher inflation expectations

3. Financial literate consumers tend to have lower inflation expectations

4. There is no persistent relationship between age and inflation expectation

The empirical findings are arranged to either find their explanation in present local (shopping) experience or find their explanation in past (lifetime) experience. The first one argues more from a standpoint of everyday decision making of the individual. The latter one is a more holistic view of the individual as it incorporates the economic environment and the past experience of the individual. However, both have in common to emphasize the importance of *perceived* inflation. We introduced the term earlier where we pointed to a large drawback of consumer surveys that respondents may answer based on their (different) perception of inflation. Different to actual inflation which is measured by the consumer price index, the *perceived* inflation is what consumers think the rate of inflation has been last year (Bruine de Bruin et al., 2010; Jonung, 1981).

2.4.1 Local Experience: Shopping experience

1. Women tend to have higher inflation expectations

One of the first differences discovered was the heterogeneity in inflation expectations between women and men. According to the literature, women tend to expect higher inflation than men. The most influential study on this behalf was done by Bryan and Venkatu (2001). Together with the Ohio State University, they conducted a monthly telephone survey of a representative sample of approximately 500 Ohioans. The style of the questionnaire was chosen to closely mimic the Michigan Survey of Consumers but it was also extended to ask respondents about the current inflation perception. For the whole data set, they found a substantial overestimation of inflation expectation. More precise, they found that the respondents overestimated inflation (as compared to the Consumer Price Index) by more than two percentage points between August 1998 and December 2000. Spurred by these results, they analysed the Michigan Survey of Consumers and found an overestimation of more than one percentage point between 1990 and 1999. Further, they noticed a large disagreement in inflation expectations across demographic groups. This is consistent with Mankiw et al. (2003) and Souleles (2004). Building on these results, in a follow-up study, Bryan and Venkatu (2002) focused on the surprising fact that even after controlling for income, age and education, there remains a substantial gender gap in inflation expectations of more than two percentage points. Again, this observation was not unique in their telephone survey as they found the gap also in the Michigan Survey of Consumers (ranging from 1.9 for a low income married female to 0.3 for a single female). They believed that the explanation of this observation is key to the apparent *irrationality* of inflation expectation. To shed more light on this, in a related set of experiments they analysed whether women and men *perceive* price changes for the same commodity as different. Interestingly, they found that women perceived grocery and apparel goods as rising between 1.3 and 2.2 percentage points higher than men. In the same vein, men saw gasoline prices as rising 3.6 percentage points more than women. This indicated that shopping behaviour cannot be ignored. Their results are consistent in a broader sense with Jonung (1981) who already found that women had a higher *perceived* past inflation rate than men in 1977 because women purchased a larger share of food and food price inflation in 1977 was higher than the general inflation rate. Grocery shopping as well as refuelling the car are local shopping experiences that drive both perceived inflation and inflation expectations. Thus, we will draw on these results later when we formulate the hypothesis in section 6.2. More recent consistent evidence for the gender differences is provided by Meyer and Venkatu (2011), Bruine De Bruin et al. (2011), Ehrmann et al. (2017) and D'Acunto et al. (2020).

2. Low-income tend to have higher inflation expectations

Bryan and Venkatu (2001) found in the same study from above that lower-income groups tend to have higher inflation expectations than other demographic groups. For example, respondents in the lowest income quintile expect inflation to be twice as high as respondents in the highest income quintile. As a robustness test, they controlled for inter-dependencies between certain demographic qualities (e.g. people with less education tend to be people with less income) but the results persisted. To explain the disagreement in inflation expectations, they tested to what extent the cost of different consumption basket was the driver. The argumentation is that the CPI is an expenditure-weighted price index that might be weighted towards the spending habits of higher-income people. However, even after re-weighting the CPI on the basis of population demographics, the results remained unchanged. This led them to conclude that the difference in inflation expectations roots in the fact that demographic groups *perceive* inflation differently. However, they were unable to answer the question of *why* this is the case.

A possible *because* is offered by a remarkable study by Johannsen (2014). He constructed household-specific inflation rates and found a substantial and persistent difference across income. He proxied low-income households with low-expenditure households and found that the dispersion for them is significantly higher. Also, these households have more heterogeneous expenditure weights on food and energy. Interestingly, he also studied demographic groups formed on age but neither found a persistent difference in the dispersion of experienced inflation nor of expected inflation. Therefore, his work offers a vague explanation as to why consumers in similar cohorts might disagree about expected inflation. He shows that this empirical result is consistent with a model of imperfect information in which households' own rates of inflation serve as signals about the aggregate inflation rate of the macroeconomy.

3. Financial literate tend to have lower inflation expectation

Although the result from Bryan and Venkatu (2001, 2002) were seminal, the specifics behind the heterogeneity remained unclear. If different consumer groups really had a different *perception* about future inflation, then an overarching factor may help to explain it. In one following study, Bruine de Bruin et al. (2010) took the earlier results from Bryan and Venkatu (2001, 2002) and Souleles (2004) and found that a measure of financial literacy is associated with heterogeneity in inflation expectations. The degree of financial literacy is substantially correlated with the forecast of inflation expectation. The more *educated* a consumer is, the higher is its focus on different types of information and, hence, the more correct are his or her forecasts. Their survey evidence suggested that the information set of each individual is a crucial factor in their expectation formation process. Based on this study, Burke and Manz (2014) conducted experiments and presented new evidence that identified a link between a measure of economic literacy and the accuracy of individual inflation forecasts. They found that economically literate subjects make better forecasts by choosing more relevant information and utilising it more. Their measure of economic literacy was associated with gender, race and educational attainment. After controlling for economic literacy, the contribution of demographic factors becomes less important but persisted.

The fact that gender, income and literacy have a meaningful impact on the formation of inflation expectations is of great interest. Besides their persistent pattern in household surveys, an experiment conducted by Armantier (2016) sheds more light from a different angle. In a laboratory setting, the respondents received either information about last years average food price inflation or today's average forecast of professionals. Because the respondents had to report their inflation expectation before and after they receive the information, the experimental design closely mimics panel data. Their results showed that respondents revised their inflation expectations when they received information on the forecast of professionals as well as information on changes in food prices. The magnitude was found to be higher when uncertainty in their baseline inflation expectation was greater. The experiment used the so-called *perception gap* as a measurement of respondents' ex-ante informedness. This gap was found to be quite significantly, indicating a general overestimation. Consistent with other research, female, lower-income, and less-educated respondents as well as those with less financial literacy - generally have larger *perception gaps*.

4. There is no persistent relationship between age and inflation expectation

From an empirical point of view, the relationship between age and inflation expectation is not as crystal clear and persistent as gender, education and income. In fact, empirical studies found conflicting results. Therefore, for one thing, we provide empirical evidence that is more related to local experiences such as shopping behaviour, and for another thing, list personal lifetime experiences in the next section to further expand on this.

For local experiences, the available literature is rather sparse. Again, the study by Bryan and Venkatu (2001) provides evidence that age has a significant impact on inflation expectation. Younger individuals (18 to 25 years) reported higher expectations than their middle-aged counterparts. With almost 60 basis points higher than the reference group (white male aged 46–55) and 110 higher than the age group above 65, the difference is substantial. The authors argue that the difference may be explained by a different perception of inflation. On this note, Amble and Stewart (1994) for instance found that the differences in the expected rate of inflation across demographic groups based on age are due to persistently different expenditures. Conflicting evidence is offered by Blanchflower and MacCoille (2009) who found that inflation expectations rise with age and by Diamond et al. (2019). In the latter study, Diamond et al. (2019) combined a panel data set of consumers' purchase histories, a data set on the consumers' demographics and lastly a survey that captures consumers' expectation about prices and inflation. Their results reveal that older individuals pay the highest price for goods in the common basket and households' inflation rate generally rises with age. The authors explained the source of variation in inflation rate across age by pointing to differences in the amounts consumed of different goods in this common basket. In more understandable words, this means that old people face high inflation rates because they consume relative more items that are characterized as high inflation rate items compared to the young age groups. They further showed that the positive correlation between age and inflation expectation can be (at least partly) explained by shared historical inflation experiences. This possible explanation offers a good bridge for the literature strand on past experience and economic environment.

2.4.2 Past Experience and Economic Environment

As the studies from above on age were conducted at different points in time, it is useful to consider the economic environment of the respondents. Motivated by this idea, Cavallo et al. (2017) surveyed households simultaneously in the US and in Argentina. At that time, the US experienced a decade of very low-interest rates and inflation while Argentina had high inflation rates. According to the *Rational Inattention Model*, individuals in a high inflation context should have strong priors about inflation because the financial cost of misperceiving inflation is high (Sims, 2003). This is consistent with Akerlof et al. (1996) who noted that workers only inform themselves about the inflation rate when it is too costly to ignore. By comparing how individuals incorporated information statistics and historical prices (as a proxy for the type of information that individuals obtain from personal shopping experiences), Cavallo et al. (2017) was able to analyse the relevance of personal shopping experience. For example, the respondents assigned a weight of just 15 per cent to their prior expectations in the US when provided with information about professional statistics or specific supermarket prices. Compared to roughly 50 per cent in Argentina, this is a substantial gap. Also, they found evidence that individuals do use their own memories about past supermarket prices when inflation expectations are formed. Indeed, if personal memories about historic prices cannot be neglected, the relationship between age and inflation expectations needs to incorporate the past experience of individuals.

Memories of respondents may be partly inaccurate and thus induce large errors in expectations. However, memories may be an important driver of inflation expectations and are essentially what remains of the experienced past of an individual. Out of this argument, a literature strand has evolved around *personal lifetime experience* that puts more importance on each individual's past and tries to find past experiences that may determine nowadays behavior. The earliest study that looked at *personal lifetime experience* was conducted by Jonung in 1981 for Swedish individuals. Besides finding a significant linear relationship between perceived and expected inflation in January 1978 with a cross-sectional correlation coefficient of about 0.5, he found that perceived and expected inflation are comparably affected by socioeconomic factors. However, age was found to be the only socioeconomic variable that differentially affected inflation expectations and perceptions. When controlled for the perceived rate of inflation, the expected rate of inflation declines in age. As a result, (Jonung, 1981) concluded that the lifetime experience of respondents significantly influences inflation expectations.

In the Swedish sample at hand, older respondents tend to expect substantially lower inflation rates than younger respondents because the experience of younger respondents is overshadowed by the high inflation rates of the 1970s.

With a similar focus but with a more sophisticated approach, Malmendier and Nagel (2016) conducted by far the most influential empirical study on personal experience and inflation expectation. They used 57 years of micro-data in inflation expectation from the Michigan Survey of Consumers. They build upon a learning model developed by Orphanides and Williams (2005) in which agents form their expectations limited to their most recent experience. Different in their extended model is that the magnitude of the effect of experience decreases in age. Or in other words, agents are more strongly influenced by inflation realization experienced during their lives than by other historical data. Following this, younger agents "react more strongly to an inflation surprise" (Malmendier and Nagel, 2016, p.55) as they have a shorter data series in their lifetime to draw from. According to them, the disagreement across age groups is very well explained by differences in their lifetime experience. Consisting evidence is offered by Madeira and Zafar (2015) who also found statistical evidence for the role of lifetime experience. Although, they found the effect to be smaller in magnitude, they give evidence for substantial demographic heterogeneity. According to them, individuals differ in how much weight they give to "life realizations" (Madeira and Zafar, 2015, p.2) and how fast they update their information. More precisely, women and less educated agents are slower to update their expectations, hence, they focus less to recent inflation events. In a related study on the role of personal experience, Kuchler and Zafar (2019) found that personal experiences of house prices and unemployment greatly influence the expectations of national US house prices expectations about the national unemployment rate. Other experience effects are documented in Greenwood and Nagel (2009), Kaustia and Knupfer (2008), and Malmendier and Tate (2005).

2.5 Inflation Expectations during crises

Before we touch upon literature that focused on inflation expectations in crises and eventually during the Corona Crisis, we do a brief wrap-up of what has been documented so far. We started with a short journey through time and introduced the idea of rational expectations. Then, the *Sticky-*

Information Model and the *Rational Inattention Model* were presented as consumer surveys were found to be inconsistent with rational expectations. Lastly, a broad set of empirical studies on demographic heterogeneity were listed.

Understanding the impact of an economic crisis on inflation expectation is deeply linked to how individuals form and update their inflation beliefs in sound economic times. We showed that this field of study is relatively well-researched. However, even though the studies had samples stretched over many decades and therefore implicitly incorporate the interpretation of crises, none of the studies explicitly did so. Is the found heterogeneity even more visible or does it vanish after all? Such question and many more remain unanswered. The next section is meant to present empirical evidence and possible indications on how consumers form their inflation expectations during and after crises.

2.5.1 Empirical studies on economic crises

After a macroeconomic shock, both the *Sticky-Information Model* and the *Rational Inattention Model* offer a theoretical framework in which the mean forecast across agents of inflation expectations will be smaller in magnitude in comparison to the actual response of the macroeconomic variable. According to the *Sticky-Information Model*, this is explained by the fact that some consumers will be unaware that the shock occurred and will, as a consequence, not change their forecast. In the *Rational Inattention Model*, even if the consumer receives the signal of changing prices, they will only gradually adjust their expectations because uncertainty regarding noise or true information remains. Only a few studies have studies how inflation expectations behave in times of crisis. An increase in inflation expectation during the 2007-2009 Great Recession was documented by Galati et al. (2011). However, the author concentrated their study on professional forecasters and other data and not on consumers.

The most noteworthy study that dealt with the formation of inflation expectations during crises for consumers, in general, was conducted by Kamdar (2019). Based on the fact that during a financial crisis, the general public expects unemployment to rise, he found that consumers who believe unemployment will rise also expect higher inflation on average. Therefore, a financial crisis is expected to lead to higher inflation. However, for the past 40 years, the US economy has been characterized by a negative correlation between inflation and unemployment rates. In fact, the only period in which a positive correlation existed was the stagflation period of the late 1970s. His result indicates that, despite macroeconomic theory and US experience suggesting inflation is pro-cyclical, consumers believe inflation will be higher when unemployment rises. He argued that consumer sentiment (that is whether the consumer is *optimistic* or *pessimistic*) is the single most important driver of the responses. From a model-based explanation, anticipating inflation to be anti-cyclical, is consistent with consumers anticipating a crisis with a negative supply shock. Therefore, he argues, consumers form their expectations according to the *Rational Inattention Model* because the costs of *interpreting* the shock correctly are substantially high. A negative supply shock is particularly harmful to consumers both inflation and unemployment rise. To avoid such thinking costs, they believe that supply shocks were the dominant driver of the business cycle. They do understand that demand shock matter for the business cycle but know that supply shocks can be acutely painful. Most interestingly is the fact that the relationship between unemployment and inflation is correctly understood by professional forecasters. These results stand in contrast to consumer surveys but are in line with US experience and standard macro-models. Another empirical study that also looked at the effects of crises was conducted by Ehrmann et al. (2017). The authors found that during recessions, consumers have a significant "additional upward in inflation expectations" (Ehrmann et al., 2017, p. 247). Without analysing this in specific, they point to an underprediction of the fall in the inflation rate. In that context, a study by Coibion and Gorodnichenko (2013) found that consumer inflation expectations are highly responsive to changes in the oil price. It was found that recessions are mostly characterized by an increase in gasoline prices.

Do consumers interpret every crisis as a negative supply shock and hence expect higher inflation? If that is indeed the case, we are still missing the crucial part of how different types of consumers (different demographic groups) react to a crisis. The next section is primarily about empirical studies conducted at the onset of the Corona Crisis.

2.5.2 Corona Crisis: An empirical overview

One of the first meaningful studies was done by Binder (2020) who conducted an online survey using Amazon Mechanical Turk. On March 5 and 6 2020, she surveyed US consumers and found general attention and concern about the coronavirus. For example, her results show that 28% had cancelled or postponed travel and about 40% had purchased food and supplies in response to the crisis. The majority of the variation seemed idiosyncratic, or not explained by basic demographic characteristics. Regarding inflation expectation, she found a substantial and immediate increase. She indicated that consumer sentiment, or more concretely an increase in pessimism, was the main driver of the spike in inflation expectations in the months after the pandemic outbreak. This is consistent with Kamdar's (2019) finding from above in which sentiments is argued to be the single driver of expectations, especially in crises. Although Blinders (2000) results offer a good starting point in understanding how the pandemic affects inflation expectations, there are a couple of drawbacks. Firstly, the study was conducted when the effects of COVID-19 has not yet spread widely in the US as many workplaces and schools remained to be open. Therefore, her data may only capture the immediate effects and not the full effects. Secondly, her sample size is rather small and does not offer a panel data feature when compared to large-scale surveys such as the Michigan Survey of Consumers. The persistence of the effects on beliefs and expectations are much easier detected with panel surveys.

A couple of weeks later, Meyer et al. (2021) found by analysing the Michigan Survey of Consumers that households expected inflation to increase. According to the authors, this may be explained by how sensitive households are to particular price changes in the economy. Grocery prices increased substantially and, therefore, household's spike in inflation expectation may be explained by an overreaction to these prices. This is consistent with Binder (2020) who found that most concerned by the coronavirus are those most vulnerable to spikes in food prices. The authors pointed to the enormous impact the pandemic has had on retail prices and consumer spending patterns and argue that households may be responding to salient relative price changes instead of aggregate inflation when surveyed about *prices in general* or *prices overall in the economy*.

Another empirical study was conducted by Armantier et al. (2020). By analysing the Survey of Consumer Expectations, which is conducted on specific dates at a monthly frequency, they were able to explore how inflation expectations responded after specific events. Consistent with the results of Binder (2020) and Meyer et al. (2021), short-run inflation expectations were found to increase sustainable. For example, the respondents expected inflation to increase by between 42 and 66 basis points. Across demographic groups, a heterogeneity in inflation expectation was found *before* the pandemic. Consistent with the listed literature, they found gender, income and age are significantly correlated with inflation expectations. For example, consistent with the learning model by Malmendier and Nagel (2016), they found that older respondents assigned a higher probability to high inflation and a lower probability to deflation. However, except for education, the pandemic neither exacerbated nor reduced any of the heterogeneity identified along socio-demographic dimensions. Nevertheless, this does not mean that there exists no impact of crises on the heterogeneity of inflation expectations. Their used methodology neither capture the impact of crises explicitly nor does it account for very small sized age groups.

In summary, these three studies show that inflation expectation for the general public has substantially increased at the onset of the Corona Crisis. What the driver behind this increase remains unknown. Also, why demographic subgroups responded differently and the relatedness of the Corona Crisis to other crises concerning inflation expectations remain unanswered.

2.6 Inflation Expectations: Gap in research

The structure we chose for this chapter resembles how this work fills a gap in the existing research. First, we listed a battery of studies that prove individuals do not form their expectation rationally and that demographic differences exist. Secondly, we showed that the existing literature on inflation expectation in a crisis is rather sparse. Most recent empirical studies showed that consumers expected short-term inflation to increase at the onset of the pandemic, but a thorough explanation taking the heterogeneity into consideration is missing. Therefore, the panel feature of the Michigan Survey of Consumers allows us to study how different demographic groups revised their expectation. Especially, we are the first ones that take a close look at the people in the tails of the age distribution (youngest and oldest age groups, or margin age groups) as these two subgroups are sufficiently large in our sample to draw more general conclusions. Therefore, our work fills this gap. We analyse the effect of the recent Corona Crisis on the change in inflation expectation given the heterogeneity of the respondents, namely age. Comparing obtained results to earlier crises (namely Global Financial Crisis and Dot-Com Crisis) helps us to formulate hypotheses that can potentially explain our results. To our knowledge, we are the first ones that take the existing novel explanations (such as effect through experience) and link them to the interpretation of a global shock to the economy.

3 Data and Descriptive Analysis

As outlined at the end of the last chapter, we strive to close a gap in the existing literature on inflation expectations during crises. A necessity is utilising relevant and appropriate data. The following chapter is meant to give the reader an overview of the incorporated data. We used both publicly available microdata and macrodata in our analysis. This chapter is structured as follows. First, our central source of data, the Michigan Survey of Consumers, is introduced. Then, to put consumer expectations into a better perspective, with Federal Reserve Economic Data, the Consumer Expenditure Survey, and the Survey of Professional Forecasters, three additional data sources are consulted. Afterwards, a descriptive analysis of the Michigan Survey responses is outlined. The chapter closes with depicting the used crises subset for the regressions following.

3.1 Michigan Consumer Survey

The Michigan Survey of Consumers[1] (hereinafter: MSC) is conducted by the Survey Research Center at the University of Michigan since 1953. In its early years, respondents were asked three times a year, then quarterly and since January 1978 monthly. In the latest surveys, between 1500 to 2000 representative households of the US population are asked questions on their sentiment in form of telephone interviews within one quarter. The interview questions range from personal to more sophisticated ones in which respondents are asked about their thoughts about the US economy. Hence, it contains information on a broad set of factors that influence consumers' inflation expectations. As outlined in section 2.3, the MSC is not the only available consumer survey. Nevertheless, there are three characteristics as to why the MSC is the most appropriate survey for our intentions. First, its long history offers a unique possibility to track changes over a long period of time. Other surveys with a similar design and coverage start much later, e.g. the Survey of Consumer Expectations from the Federal Reserve Bank of New

[1] Retrieved from https://data.sca.isr.umich.edu/

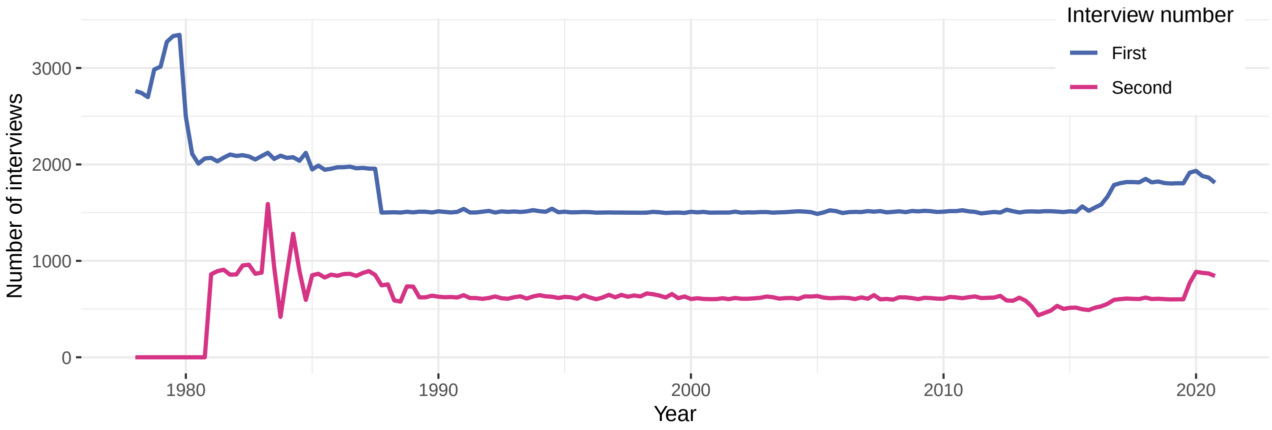

Fig. 3.1: Numbers of interviews by quarters (1978-2020)

York started in 2013. As a consequence, we manage to incorporate diverse macroeconomic periods including different crises into our analysis. Secondly, by incorporating questions on macroeconomic variables, such as inflation expectations and unemployment, hypotheses testing is facilitated. Lastly, the MSC features a rotating sample design which helps to incorporate idiosyncratic heterogeneity and to capture the dynamic updating of each agent's inflation expectations. Therefore, it allows us to isolate the effects of crises. In precise, after a first interview, around half of the respondents are re-interviewed six months later. Figure 3.1 exhibits the number of observations per quarter in the MSC vs. how many of the interviews are part of the rotating panel. Approximately 45 per cent of prior respondents are re-interviewed in every round, while the remaining 55 per cent are new households.

3.1.1 Data preparation

The three mentioned characteristics of the MSC combined offer a unique opportunity to answer our research question. To obtain descriptive results, run regressions and test hypotheses, we conducted some initial steps to transform the raw data into an analysable format. As a first step, we exported all available variables for the entire survey period from January 1978 to February 2021.[2] For our intentions, we excluded a set of variables and consequently focused on a subset. We refer to the appendix for a summary of the used variables and additional information. In the second step, we recoded the subset of variables. The MSC contains questions that require either an ordinal, a nominal or numerical response. For ordinal responses, we recoded the responses as follows.

[2] The retrieved data is numerically coded. The published codebook and questionnaire were relied on to process the data.

1. Go up/ will be better of / higher
3. Stay the same / same /about the same
5. Go down / will be worse off / lower
8. DK
9. NA

were replaced with 1, 0, -1, NA, NA. Some ordinal questions offered more response possibilities. In a consistent manner, we recoded here as follows.

1. Good times
2. Good with qualifications
3. Pro-con
4. Bad with qualifications
5. Bad times
8. DK
9. NA

were replaced with 2, 1, 0, -1, -2, NA, NA. Nominal questions were recoded in an identical manner and numerical questions were not recoded. Moreover, it was not distinguished between "DK (don't know)" as an answer or a missing answer (NA). Indeed, both were treated as missing answer.

3.1.2 Key demographics

We follow the demographic groups discussed in chapter 2.4 and illustrate key statistics of the MSC variables related to age, income, gender, and the educational background for the entire dataset.

Age
The average age of a respondent over the entire period is 47.5 years. The left panel of 3.2 illustrates an increasingly older sample of the MSC until the peak was reached in 2013 at 56 years. Thereafter, the average age of the respondents has drastically decreased and is slightly increasing again in recent years. Furthermore, we constructed age groups with an interval of five years with the exception of

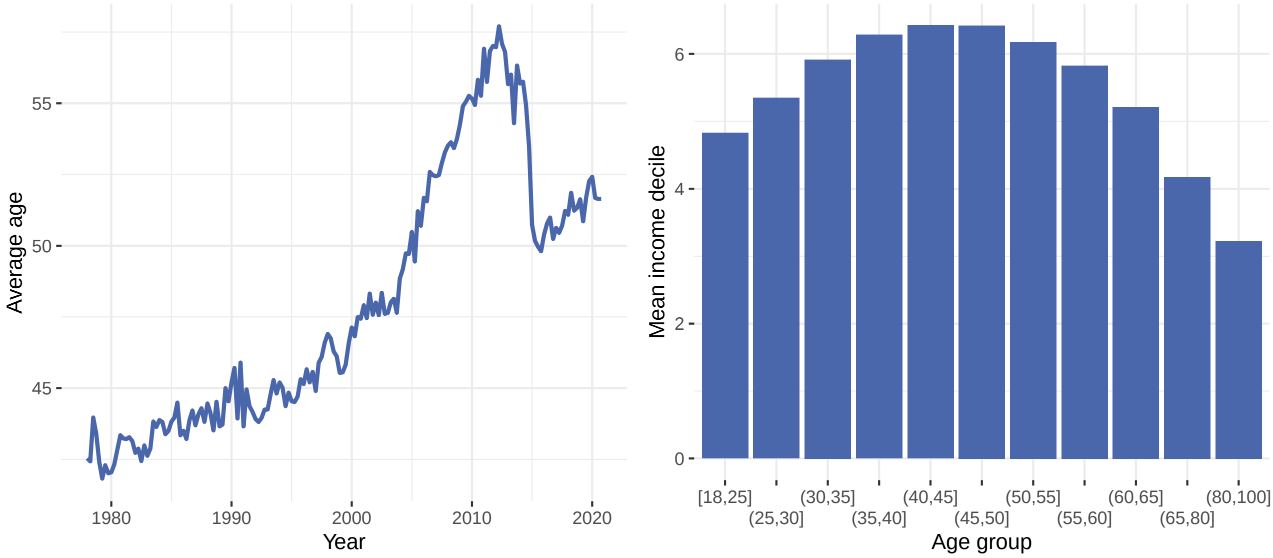

Fig. 3.2: Data-set split by age as well as age groups and income (1978 - 2020)

the youngest and the oldest age group. For these two groups, the interval is seven and twenty years respectively to attain decently sized groups. The x-axis of the right-hand side of figure 3.2 depicts the resulting age groups. As a relatively low average age in the 20th century (and a constant number of participants, compare figure 3.1) suggests, there may not be a sufficient amount of observations for old age groups for our intentions. We will take that into consideration for our future analyses.

Income

The right-hand side of figure 3.2 shows the mean income decile across age groups. Consumers in their 40s have the highest income with an average in the 6th income decile. Indeed, this is the only point where we found the MSC to be inconclusive. The survey question we refer to reads as follows:
"Now, thinking about your total income from all sources (including your job), how much did you receive in the previous year?"
However, the remainder of the income questions always directly address the family or household income and the "INCOME" item is described as "TOTAL HOUSEHOLD INCOME - CURRENT DOLLARS" in the available codebook. Consequently, the income variable is not a pure individualistic characteristic. This complicates the interpretation of the income, but we will nevertheless refer to it later in the paper.

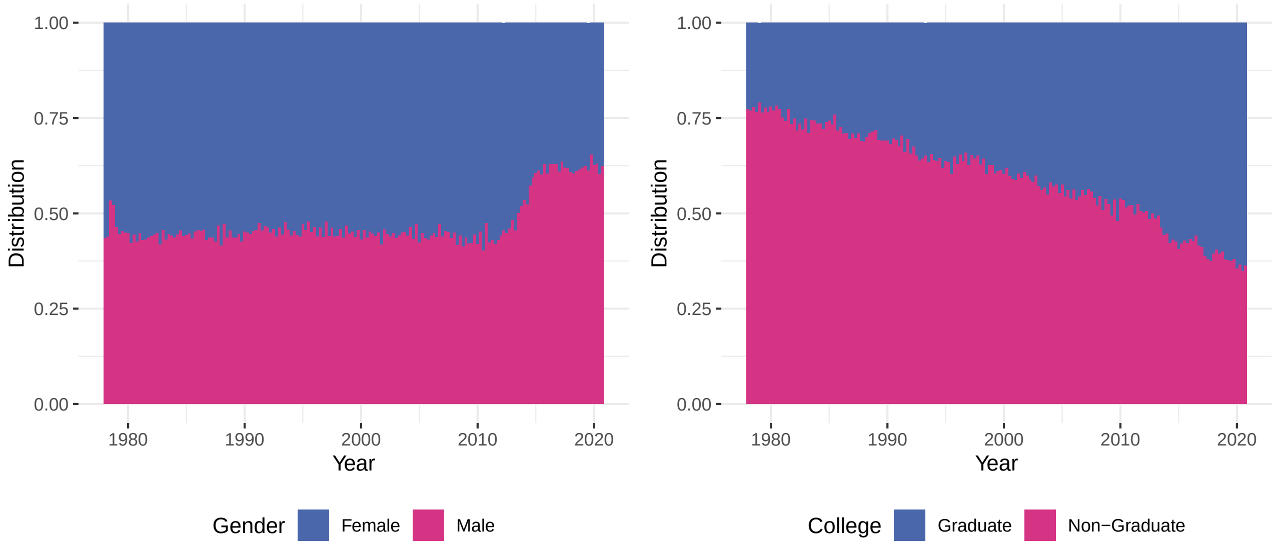

Fig. 3.3: Dataset split by gender and college graduation from (1978 - 2020)

Furthermore, the MSC dataset includes variables that indicate the top income and bottom income households denoted as YTL10 and YTL90. For the intention to enable a more holistic picture and account for missing information, we construct for the whole period income deciles. We determine the time-resistant corresponding income deciles every year anew. A higher decile level corresponds to a higher income. As figure 3.2 clearly indicates, there is a positive correlation between household income and age until the age of 50. After that, the average income decile drops faster and faster which is in line with the average retirement age between 60 and 65 years (Munnell, 2015).

Gender

Around 52% of the full dataset are male, 47% are female and the remaining part does not provide information on their sex. Figure 3.3 illustrates the distribution of respondents between men and women over time. For most of the time since the survey started, the gender ratio was relatively balanced but since 2014, male constitute the majority. In 2020 over 62% of all respondents are male. We address this circumstance by controlling for gender in our main analyses.

Education

As we are particularly interested to distinguish between individuals that are financial literate and those who are not, we look at the education variables in the MSC. While the variables EHSGRD and ECLGRD offer information if a respondent graduated from high school or respectively college, the question

ECGRADE indicate additional information with regards to the duration of education. The variable EDUC consolidates all this information into one item. Bruine de Bruin et al. (2010) extensively tests the financial literacy of individuals using 16 questions. For our intentions, it is sufficient to focus on the criteria if an individual holds a college degree or not since this indicates financial literacy (Lusardi and Mitchell, 2011). We consider the distribution between respondents with and without a college degree (compare left-hand side figure 3.3). The share of individuals that do not report any information on this question is negligibly small and thus excluded from the graph. The most striking development is the increasing proportion of college graduates, resulting that in the most recent survey years six out of ten respondents hold a college degree. This is consistent with the increasing educational attainment in the US driven by a sharp rise in college enrollment and by enhancements among colleges and universities in graduating students (Rampell, 2013). As such, the MSC seems to represent the development in the US population quite well regarding education. As emphasised before, a higher share of college graduates is related to a higher share of financially literate respondents. Once more, we account for this fact by incorporating control variables in our main analyses.

3.2 Federal Reserve Economic Data

The Federal Reserve Economic Data[3] (hereinafter: FRED) is used as the source for macroeconomic data. The database exists since 1946 and contains a large set of macroeconomic US indicators. To complement inflation expectations extracted from the MSC, we retrieved the following two variables.

- CPIAUCSL: *Headline Consumer Price Index* is an aggregate of prices paid by urban consumers for a typical basket of goods and services.

- CPILFESL: *Core Consumer Price Index* is an aggregate of prices paid by urban consumers for a typical basket of goods and services, excluding food and energy.

[3]Federal Reserve Economic Data *(FRED)* a database provided and maintained by the research division of the Federal Reserve Bank of St. Louis. Retrieved from: https://fred.stlouisfed.org/

The two variables are reported at a monthly frequency as the absolute price for a representative basket. With equation 3.1, we computed the year-on-year inflation rates of CPIAUCSL and CPILFESL:

$$\begin{aligned} g12P_t &= \frac{CPIAUCSL_t - CPIAUCSL_{t-12}}{CPIAUCSL_{t-12}} \\ g12CP_t &= \frac{CPILFESL_t - CPILFESL_{t-12}}{CPILFESL_{t-12}} \end{aligned} \tag{3.1}$$

The first growth rate $g12P_t$ is denoted as headline inflation and the latter $g12CP_t$ one as core inflation. The subscript t refers to the observation month. Both inflation rates are plotted in figure 3.4. Two characteristics stand out. First, both have decreased tremendously since 1980 and average around the two per cent line since the last 1990s. To understand this pattern, one must look back to the summer of 1979. During one of the highest postwar inflation rates in the US at around 11 per cent, Paul Volcker was named chairman of the Board of Governors of the Federal Reserve Board. In October 1979, he called a surprise meeting and set a dramatically tighter course of monetary policy by raising interest rates, e.g. in April 1980 they spiked to 17.6 per cent (Goodfriend & King, 2005). Within three years, he reduced the inflation rate to four per cent. With the continuing efforts of Alan Greenspan, in the subsequent years, inflation rates narrowed further down to two per cent. In that sense, Volcker's era established the Great Moderation, a long period of economic stability (Powell, 2020). Ever since, especially under Ben Bernanke's leadership, the Federal Reserve adopted continuous actions to retain inflation within a corridor (Shapiro, 2019). Secondly, core inflation shows a less volatile pattern as it excludes food and energy which both are characterised by volatile prices. For example, around the year 2014, the price of oil decreased sharply which caused the illustrated downturn of headline inflation in the figure.

In addition to headline and core inflation, we further consider category-specific inflation rates. In this respect, FRED reports time-series data for Consumer Price Index (CPI) subcategories. For consistency purposes, we calculated the year-on-year growth rates exactly as described in equation 3.1. These inflation rates are a central ingredient for the first hypothesis and are extensively elaborated in section 6.1. With the computed inflation rates over time, the last step of the preparation of the FRED data is to build revision variables to match the panel aspect of the MSC. The revision variables are computed as the six-month change of the year-on-year inflation rate for our two main inflation rates as well as for

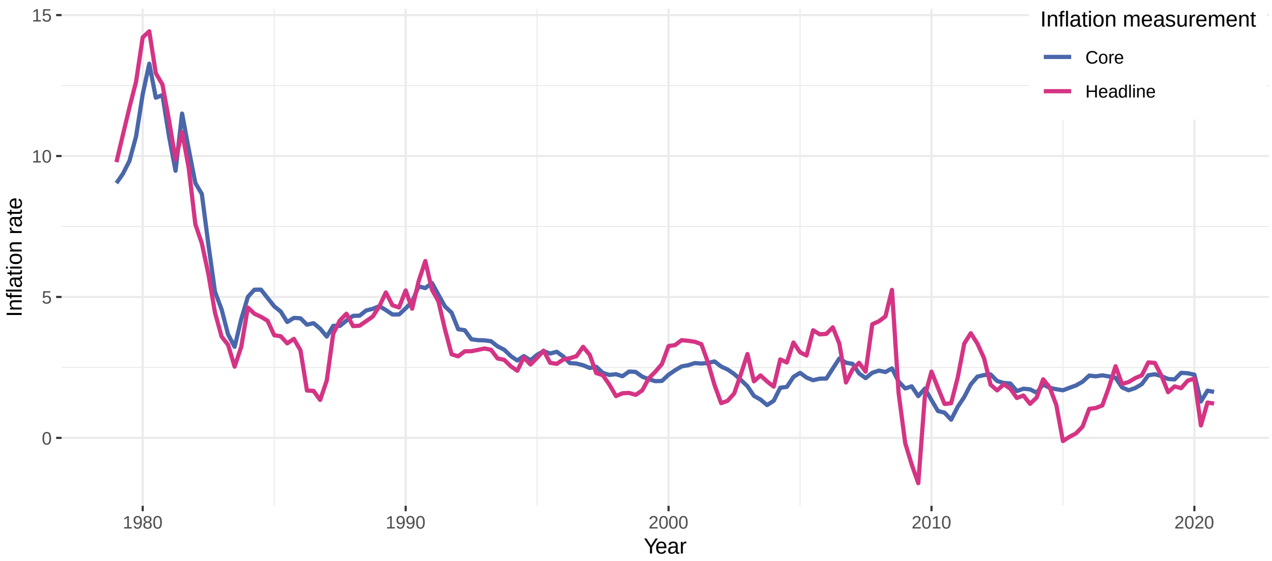

Fig. 3.4: Headline vs. core inflation (1978 - 2020)

the category-specific inflation rates. The following example represents the corresponding computation for the headline inflation:

$$dg12P_t = g12P_t - g12P_{t-6} \tag{3.2}$$

Besides inflation rates, we retrieved real GDP which is reported on a quarterly basis as well as the monthly unemployment rate.[4] The real GDP serves as an inflation adjusted measure of US economic output as it is the market value of all in the US produced services and goods (Investopedia, 2021). Analogous to the inflation rates, we calculate the year-on-year economic growth. The unemployment rate is published once a month by the US Bureau of Labor Statistics (hereinafter: BLS) and depicts the number of unemployed as a proportion of the labour force. For the unemployment rate, we calculate not only the one-year growth rates but also the monthly, quarterly and annual differences.

3.3 Consumer Expenditure Survey

Besides the MSC, another micro-data source we consult is the Consumer Expenditure Survey[5] of the BLS (hereinafter: CE). The CE is a widely used source for expenditure data as it incorporates a sample size of approximately 7,500 households quarterly. The CE is representative of the US population and

[4]The corresponding variables are named GDPC1 and UNRATE by FRED.
[5]Retrieved from: https://www.bls.gov/cex/tables.htm

is a rotating panel as households are re-interviewed after three months. The CE tables report the aggregation on expenditure and income of different demographic and geographic groups from 1989 forward. Therefore, we retrieved the latest available aggregate expenditure table and transformed it into an analysable format. We refrain from pulling the data for the entire observation period of the CE but refer to the last available year solely. As of April 1st 2021, the most recently available calendar year was 2019. For our intentions, the table containing income and expense information split by the age of the reference person is sufficient. In detail, the table splits the data set into two dimensions. On the one hand, there are the different items that refer to the annual aggregate expenditures, personal information, income information, and key statistics. On the other hand, the data-set is split among different age groups. The age groups cover an interval of 10 years. An exception is made for the margin age groups, i.e. the under-25s are grouped into the youngest age group and the over-75s into the oldest age group. 2019 alone contains over 130 thousand consumer units that are almost equally split among all age groups. As we do not use one of the included variables explicitly, we refrain from diving into further detail on the CE data set at this point and explain in more detail in section 6.1.

3.4 Survey of Professional Forecasters

The Survey of Professional Forecasters[6](hereinafter: SPF) is a quarterly survey of macroeconomic variables issued by the Federal Reserve Bank of Philadelphia. The survey started in 1968 and the number of participants varies, but recent surveys have approximately 35-40. Participants in the survey are drawn primarily from business and are arguably the most sophisticated macroeconomic forecasters available (Ang et al., 2007). For our intentions, we only retrieved the forecasted next year inflation of the professionals.

Figure 3.5 illustrates that the SPF closely follows core inflation (albeit the one-year forward-looking lag). This comes at no surprise as the survey respondents devote a lot of time and other resources to forecast inflation as correctly as possible. Furthermore, the SPF seems to expect the fall of inflation less extreme during recessions. For instance, during the Dot-Com Crisis and the Global Financial Crisis (hereinafter: GFC), core inflation dropped slightly more. Since 2000, inflation forecasted by the SPF is

[6]Retrieved from: https://www.philadelphiafed.org/surveys-and-data/data-files

Fig. 3.5: SPF inflation vs. actual inflation (1981 - 2020)

around 2% which is again consistent with the average inflation target of the Federal Reserve (Powell, 2020).

3.5 Descriptive

In this section we describe key features of the MSC that we utilize for our analysis and report some preliminary evidence on consumers' inflation expectations.

3.5.1 Descriptive: Inflation Expectation

The main component of our analysis is based on respondents' expectations of short-term (12 months) inflation. The participants are asked two questions about expected changes in prices over the next year. While question A12 asks for a qualitative response, question A12b asks for a quantitative statement about the expected change.

A12.) "During the next 12 months, do you think that prices, in general, will go up, or go down, or stay where they are now?"
1. Go up 3. Stay the same 5. Go down 8. Don't know.

A12b.) "By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?"

Besides the two questions on short-term price expectations, the respondents are also asked regarding their long-term expectations. They are asked question 13 and 13b respectively.

A13.) "What about the outlook for prices over the next 5 to 10 years? Do you think prices will be higher, about the same, or lower, 5 to 10 years from now?"
1. Go up 3. Stay the same 5. Go down 8. Don't know.

A13b.) "By about what percent per year do you expect prices to go (up/down) on the average, during the next 5 to 10 years?"

The survey controls for unrealistic answers with the help of comprehension questions. For instance, participants who reported extreme inflation expectations over five per cent or below minus five per cent are encouraged to rethink their answer.[7] The answer to question A12b is the short-term inflation expectation represented by the variable *pi_p4* in this paper.

As figure 3.6 shows, there are only very few respondents that expect a negative inflation rate within one year after the survey. The diagram suggests that the possibility of falling prices, or *deflation*, is rather unapparent for consumers. In the short run, a large share of consumers does not expect prices to change. The other shares expect prices to increase at a rate between 0% and 10%. There is substantial mass at values that represent multiples of 5%. Recent research (e.g., see Binder (2017b)) argues that this rounding can be an indication of uncertainty in expectation. Long-run inflation expectations are less gathered at 0% and, hence, consumers expect prices to not remain the same in the next 5 to 10 years. Most of the responses are clustered at 3% and, once more, at multiples of 5%. The density

[7] The respondents are asked the follow-up question: "Let me make sure I have that correct. You said that you expect prices to go up during the next 12 months by [x percent]. Is that correct?"

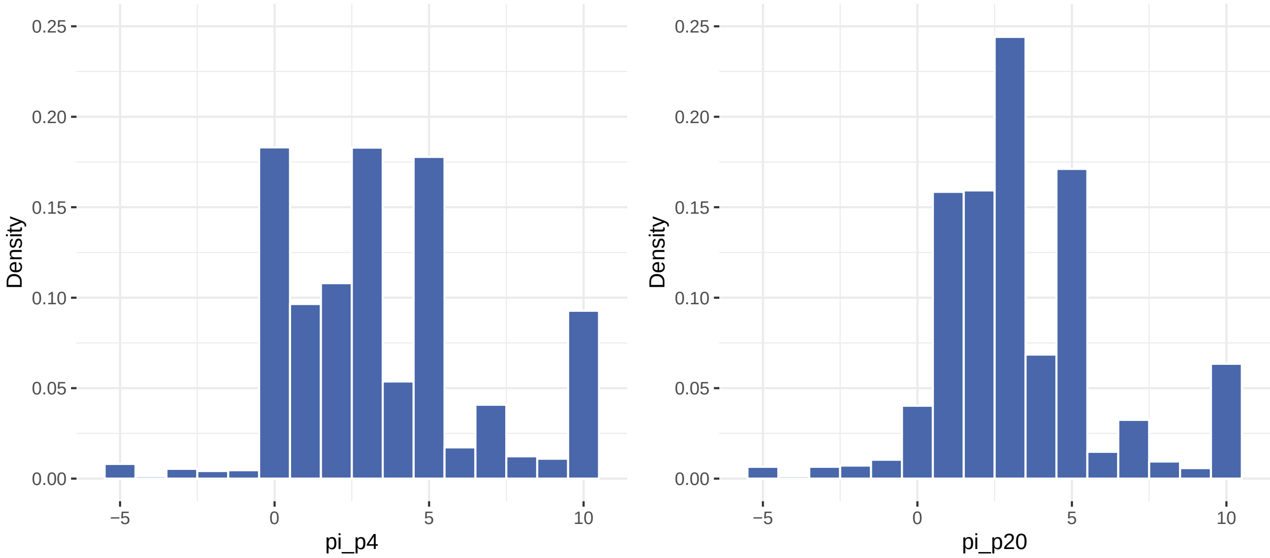

Fig. 3.6: Inflation expectations (1978-2020)

plot for the long-run price expectations looks more bell-shaped. For the subsequent analysis in the following chapters, we only concentrate on the short-run inflation expectation. As they appear to be more volatile and less anchored compared to the long-run ones, they serve better our research question. This is consistent with the *Euler Equation*, which incorporates the one-year ahead inflation expectations (compare equations 2.1 and 2.4).

Figure 3.7 plots the time series of mean inflation 12-months ahead expectations in the US for the MSC vs. the SPF expectation and actual headline inflation rate since 1979.[8] As already explained previously, the SPF follows the actual inflation rate very well. However, consumer expectations from the MSC show a different pattern over time. Since the beginning of our data set, consumer inflation expectations are higher than SPF expectations and actual inflation. We reported this overestimation of consumer expectations in the last chapter (see Mankiw et al. (2003) and Souleles (2004)). Although all time series decreased sharply during the GFC in 2007, the overestimation of the MSC continues to increase substantially. This is consistent with the findings of Coibion et al. (2020) and Ehrmann et al. (2017). For example, household expectations have averaged around 3.5% since the early 2000s while those of professionals averaged around 2%. Besides this peculiarity, another general characteristic is that consumer expectations seem to be more volatile than both SPF inflation expectations and actual inflation. In summary, figure 3.7 offers a rationale to analyse the formation of consumer inflation

[8] We plotted the inflation expectations at time t with actual inflation twelve months later to align the two time series.

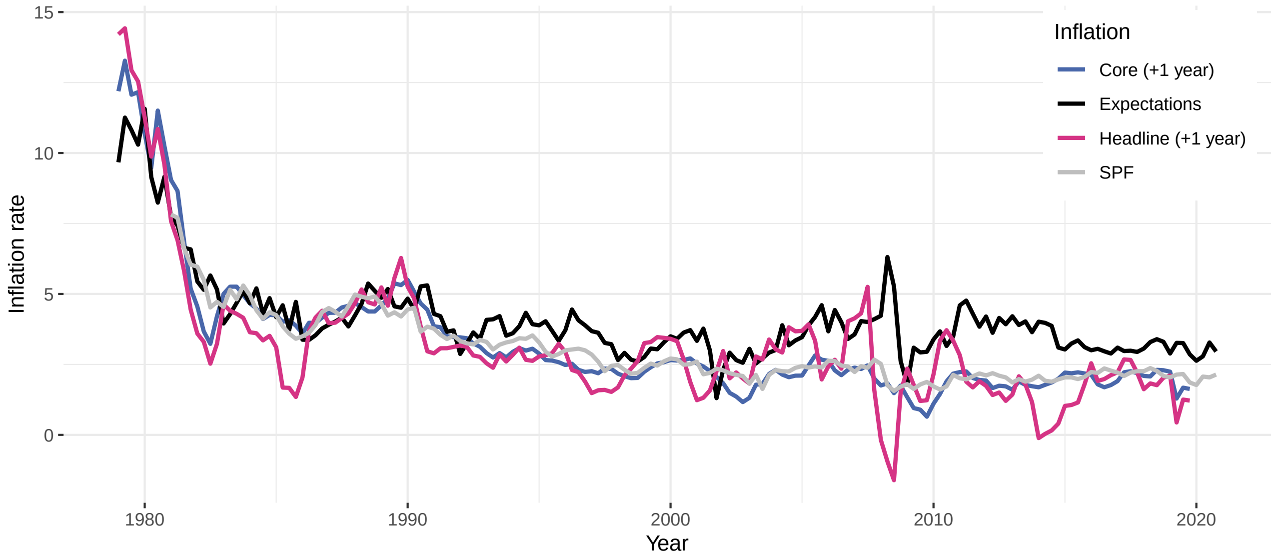

Fig. 3.7: Actual vs. expected short-run inflation (1978 - 2020)

expectations in great detail. Although it is beyond the scope of this work to examine the overestimation since the GFC in detail, this observation guides us to answer our research question.

3.5.2 Inflation Expectation across demographic groups

In the following section, we created demographic subgroups of the MSC and plot their inflation expectations over time. By investigating how they expect inflation over time, we are able to obtain a better understanding of the formation of inflation expectation in crises. In chapter 2.4, we listed empirical studies that found four stylized patterns on gender, college degree, income and age. Following this, the intention of the plots is first to examine if we treated the raw data correctly, and secondly, to check for deviations in the observed patterns. To better illustrate lower-frequency variation, we plot the data as four-quarter moving averages.

The left panel of figure 3.8 is in line with Bryan and Venkatu (2001) and Bryan and Venkatu (2002) who examined the MSC over 20 years ago. Consistent with their results, women tend to have higher inflation expectations than men while both group means follow the same pattern over time. Interestingly, the gender gap almost disappeared shortly before and especially during the GFC, but has remained constant ever since, including the recent Corona Crisis. More recent evidence on the gender gap is offered by D'Acunto et al. (2020).

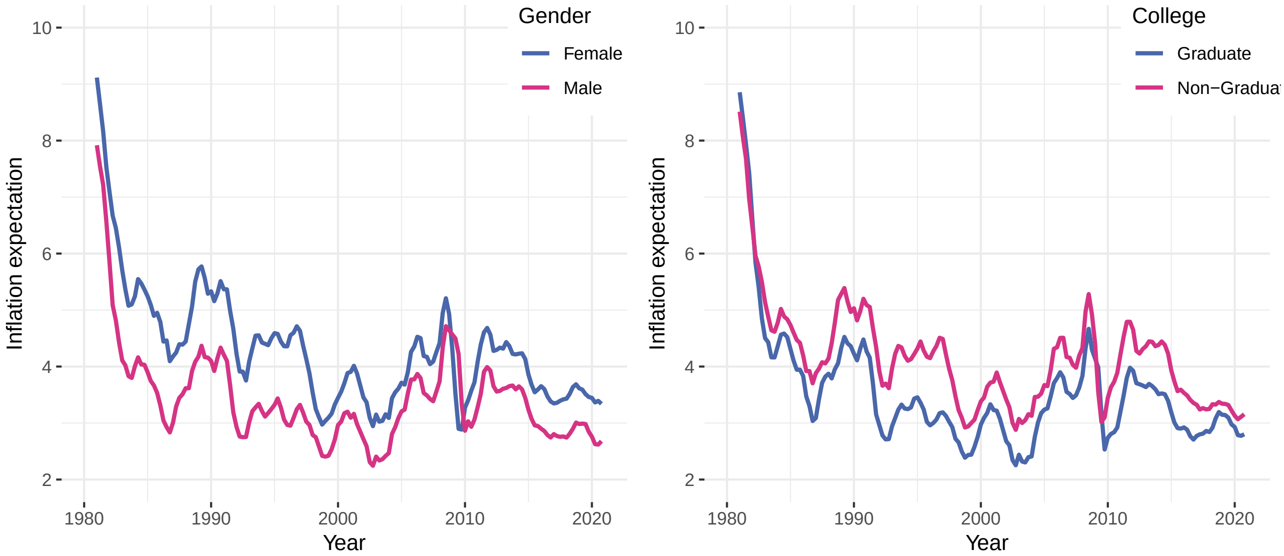

Fig. 3.8: Inflation expectations split by gender and education (1980 -2020)

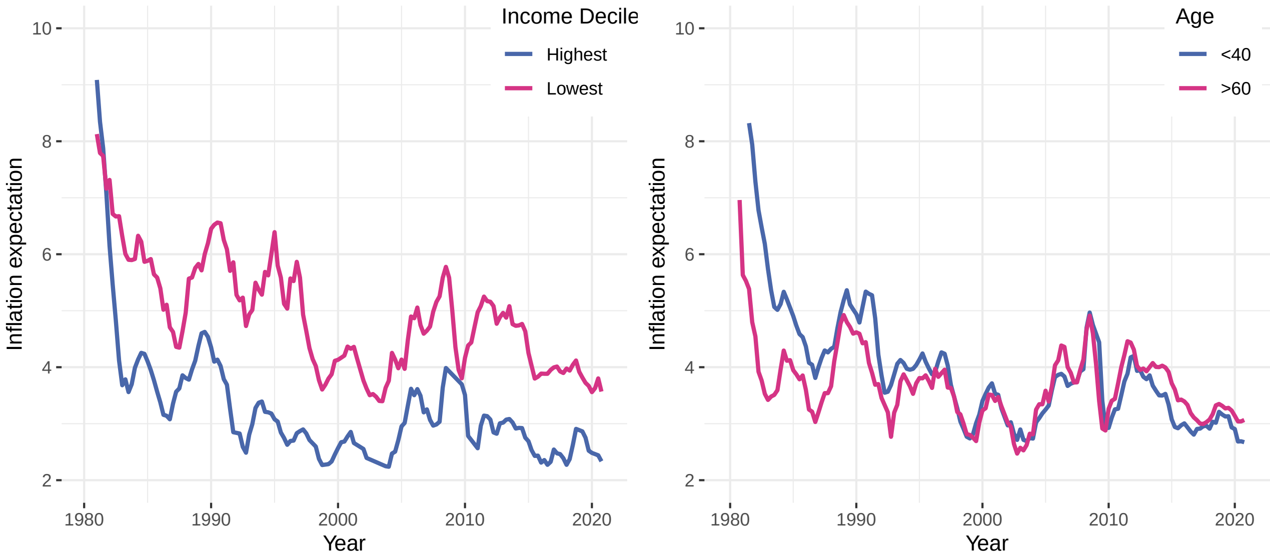

Fig. 3.9: Inflation expectations split by income and age (1980 -2020)

The right panel of figure 3.8 illustrates that non-graduate report higher inflation expectations on average. This is consistent with Bruine de Bruin et al. (2010) who found that financial literate and college-degree holders have lower inflation expectations.

Moreover, Bryan and Venkatu (2001) and Johannsen (2014) proposed that low-income households tend to have higher inflation expectations. In order to illustrate that circumstance, we make use of the income deciles as introduced in section 3.1.2. Accordingly, the left-hand side of figure 3.9 compares the average inflation expectation of individuals within the lowest income decile with the corresponding mean of the highest income decile over time. Since the mid-80s, there is a gap of around two to four per cent between individuals in the highest income decile and the one in the lowest income decile. The right-hand side of 3.9 depicts how individuals below 40 and above 60 expect inflation on average. Again, consistent with the literature in chapter 2, the pattern seems to be less persistent over time. Until 2000, younger individuals reported substantially higher numbers compared to the elderly. However, since the year 2000, the pattern has changed and in recent years, the elderly reported higher inflation expectations.

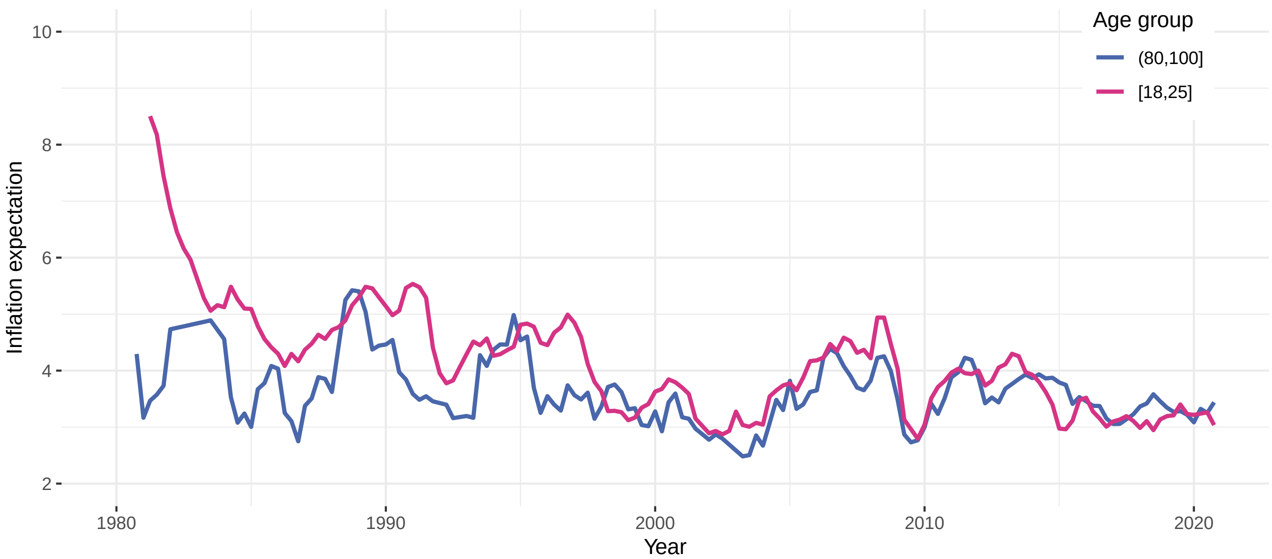

Fig. 3.10: Inflation expectations split by margin age groups (1980 -2020)

Additionally, figure 3.10 depicts time series of mean inflation expectations for the two margin age groups. It must be noted that until the the year 2000, the elder groups were smaller in size. The patterns of the two age groups are comparable since around 2000 as the two margin age groups are decently sized since then. Between the years 2000 and 2014, the younger group shows higher inflation expectations compared to the elder group. Since 2014, the younger group reports lower inflation expectation. Interestingly, to the end of the time series, at the onset of the Corona Crisis, the margin age groups move in opposite directions.

3.6 Crises subset

The previous section displayed how different demographic subgroups expect inflation over time. At the first glimpse, our time series plots seem to be consistent with the empirical studies introduced in chapter 2. However, we aim to analyse to what extent these patterns hold during economic crises. Especially, the fact that different age groups seem to respond differently depending on the time, is crucial. To evaluate inflation expectations during crises, we created a crisis subset out of the MSC. Compared to the whole MSC dataset, it differs along two dimensions. First, we solely take responses since the year 2000 into consideration. Among others, the main motivation behind this shortening of the dataset lays in the necessity of having sufficiently large age groups for each crises.[9] With the Dot-Com Crisis, the GFC and the Corona Crisis, we also cover sufficient many economic crises for our intentions. Secondly, we further limit our dataset to individuals who responded twice[10]. The main reason for this is that our ultimate analysis requires individuals to have participated in the survey twice within a six-month period. Furthermore, if we look at point forecasts for our descriptive regression analysis, we look at second answers only. In this light, different studies (Ehrmann et al., 2017; Madeira & Zafar, 2015) highlighted the higher representativeness of results derived by second answers solely.

Figure 3.11 illustrates the monthly expected short-term inflation since 2000 for the subset built as described above. We solely illustrate the aggregate of reported inflation expectations at the second interview, however, we cannot see any difference in the course and characteristics compared to the previous graphs. Furthermore, compared to the previous figures 3.5 and 3.7, we do not include a lag of one year but show the time series of headline inflation, core inflation, SPF and mean inflation expectations obtained in the MSC in figure 3.11. Thus, we can evaluate how inflation expectations

[9]For example, the early 1980s recession or the early 1990s recession only included 20-30 observations in the age groups above 80

[10]As outlined in 3.1 only around 40-50 per cent are questioned a second time

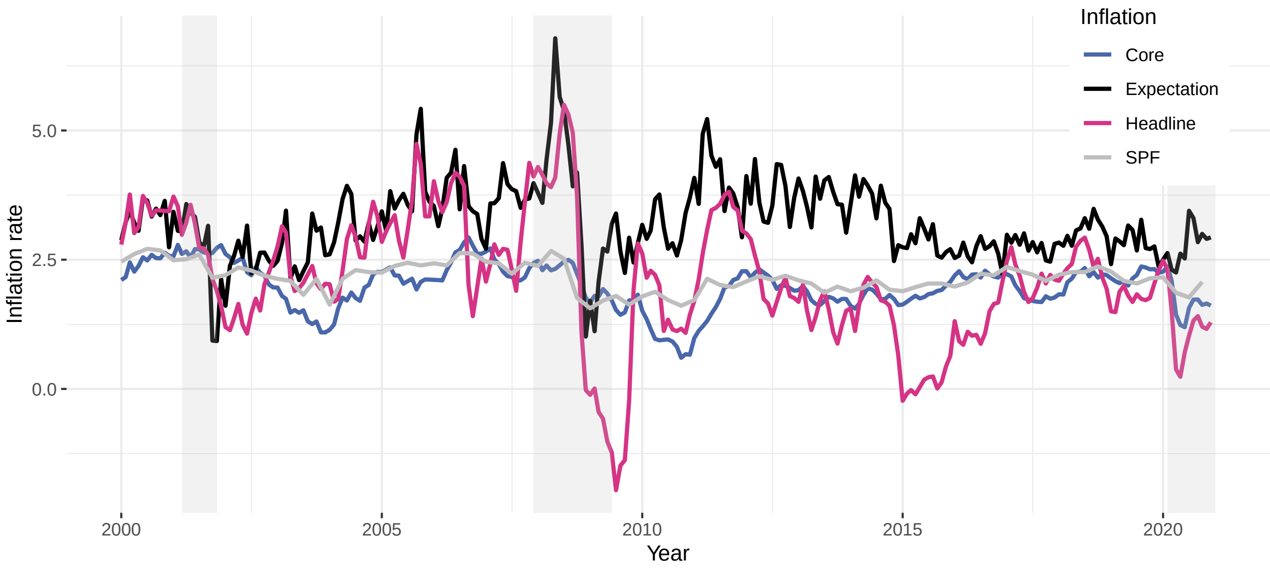

Fig. 3.11: Actual vs expected inflation (2000 - 2020)

are connected with actual inflation rates at the time when the survey is conducted. The last difference compared to the previous figures is the more volatile course of the different measurements as the time series are plotted at monthly frequency (except the SPF). Furthermore, the areas shaded in grey mark recession times[11]. A number of observations are noteworthy. Household inflation expectations seem to have increased at the onset of the Corona Crisis, rather than decreased like those of professional forecasters. This is not unique to the Corona Crisis, as the same pattern can be observed for the other two recession areas shaded in grey. The responses of professional forecasters during recessions are in line with an economy driven by demand shocks and a Phillips curve: they lower their inflation expectation when they see a worsening of the economy. In contrast, the responses of household depict the opposite pattern: they raise their inflation expectations when they see a worsening of the economy. In that sense, they behave as if the Phillips curve is upward sloping. Evidence for the Survey of Consumer Expectations from Armantier et al. (2020) is consistent with this pattern.

In the next step, we utilise the rotating panel characteristics of the MSC and complete our panel data crises subset. The crises subset consists as of now only of second answers. Thus, in detail, we identify the corresponding first interview based on the variables DATEPR and IDPREV respectively the date and the ID of the previous interview. Subsequently, we allocate all answers reported during the first interview to the second interview. In order to distinguish which interview we are dealing with, we

[11] According to Business Cycle Dating retrieved from https://www.nber.org/research/business-cycle-dating

assign the suffix $.l1$ to all answers given during the first interview. Consequently, the variable has no suffix if it was the second interview or if the individual did not undertake the survey twice. As emphasized before, we limit our approach to respondents that participated twice and thus eliminate all other observations. To make full use of the rotating panel characteristic, we built revision variables indicated by the suffix $.rev$. Revision variables are simply the difference between the second and the first answer. Following this, the variables *pi_p4.rev* and *pi_p20.rev* are constructed to depict the revised inflation expectations. Revision variables allow to catch the effect of the crises on consumers in a more isolated way. However, this approach requires setting the threshold for a crisis correctly. As a consequence, we seek to identify the key start dates of the crisis within our subsample.

We consider the key date as the time when the shock takes a strong impact on households on aggregate. First, we followed the *Business Cycle Dating*[12] of the *National Bureau of Economic Research* (compare figure 3.11 grey shaded areas) to determine the approximate crises start dates. Secondly, we paid attention to specific incidents that potentially delayed the shock effect on households. In specific, for the Corona Crisis, we follow the date when COVID-19 was characterised as a global pandemic by the Wealth Health Organization on the 11th of March 2020[13] and, therefore, we choose March 2020 as the pandemic start month. For the GFC we identified the collapse of Lehman Brothers on September 15, 2008, as key date (Reuters, 2008). We included a small lag of one month compared to the *Business Cycle Dating* for the Dot-Com Crisis to reflect the impact of the crisis on the course of the inflation variables (compare figure 3.11). In summary, we determined the following three crises start months respectively key dates.

- Dot-Com Crisis: April 2001
- Global Financial Crisis: September 2008
- Corona Crisis: March 2020

[12]Retrieved from: https://www.nber.org/research/business-cycle-dating
[13]Retrieved from https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020

Tab. 3.1: Summary table of crisis subset

	2000-2020		DOT		GFC		C19	
Subset period	Jan 2000 - Dec 2020		Apr 2001 - Sept 2001		Sept 2008 - Feb 2009		Mar 2020 - Aug 2020	
Observations	43,419		983		993		1,556	
	Obs.	(%)	Obs.	(%)	Obs.	(%)	Obs.	(%)
Male	23,579	54.31%	490	49.85%	485	48.84%	1,063	68.32%
College	24,080	55.46%	440	44.76%	518	52.17%	1,061	68.19%
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Age	52.98	54	47.83	46	53.60	53	54.27	57
Income (USD)	87,930	67,500	66,135	50,000	85,478	67,500	124,492	100,000
pi_p4	3.20	3	3.19	3	2.48	3	2.74	3
pi_p4.rev	-0.20	0	-0.25	0	-3.67	-2	-0.05	0

In the following, we look at all second interviews within the first six months from the start of the crisis. Therefore, we manage to catch the effect of the crises on inflation expectations since the first interview took place before the onset of the crisis respectively the identified key date. The first part of table 3.1 reports the months of consideration and the total observations for each crisis subset. Note that we also indicate all numbers for the entire sample ranging from 2000 to 2020. Although all crisis subsets include six observation months, the number of observations is more than 50% higher for the Corona Crisis subset because of an increased number of survey participants (compare figure 3.1).

Furthermore, table 3.1 shows key figures for the whole period and the three included crisis subsets. The observed patterns of a growing share of male and college graduate respondents (compare figure 3.3) are reflected in the subsets resulting in nearly 70% male respectively college graduate respondents for the Corona Crisis subset. The same observation holds for the average age among the subsets (compare left panel of 3.2). In general, the mean and the median lie close to each other which suggests a balanced sample. The only exception is the Corona Crisis subset where the age median is nearly three years above the median which indicates a slight overrepresentation of the old population. The average annual income is about USD 87,930 for the entire period. The corresponding median is USD 67,500. Consequently, the distribution of the family income is right-skewed for the sample.[14] Overall, keeping the demographic developments since 2000 in mind, the subsets compare very well with each other and represent the US population appropriately.

[14] In general, this pattern can be observed for the US population as e.g. data from the US Census Bureau suggests. Retrieved from: https://www.census.gov/topics/income-poverty/income.html

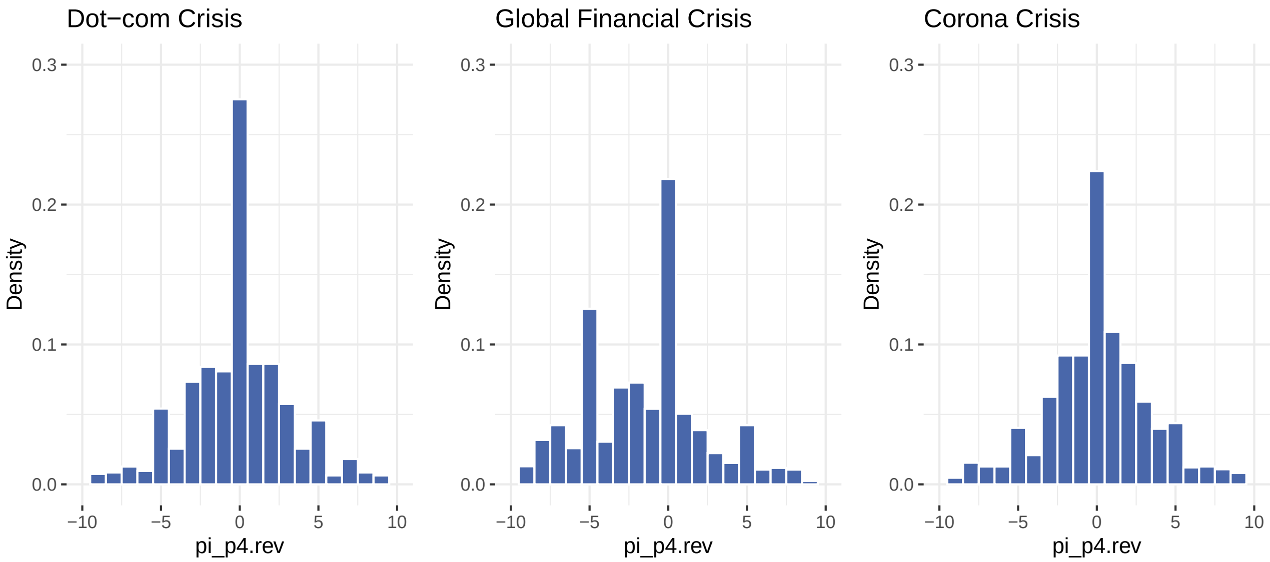

Fig. 3.12: Revised short-term inflation expectations

The second last row of table 3.1 indicates key statistics with regards to the one-year inflation expectations pi_p4. Even though all subperiods show a median of 3, the mean ranges from 2.74 to 3.20. We extensively discussed the development of the inflation expectations over time in the previous chapter. More interesting for our purposes is the last line of the table including information on the revised inflation expectations $pi\_p4.rev$. As stated before, the constructed revision variables on inflation expectations indicate how the same individual answered six months prior to the beginning of the crisis. In this way, we obviate a possible selection bias and can therefore analyse how consumers interpret the crises from an economic point of view. The slight downward trend of inflation rates in the 2000s (compare figure 3.7) is also reflected in the mean of the revision variable for the whole period 2000-2020. The three crisis draw a different picture. The Dot-Com Crisis sub-period does not deviate from the overall sample. While inflation expectations fall on average by over 3.5 per cent as a reaction to the GFC. A mean close to zero and a median of zero indicate no adaption on aggregate of inflation expectations as a response to the Corona Crisis. Figure 3.12 further illustrates this revision.

The three panels in figure 3.12 underline that the majority of consumers do not revise their inflation expectations during a crisis. Most responses are accumulated at the 0% mark for each recession. Especially for the Dot-Com Crisis is this apparent. The GFC seems to lead consumers to downgrade their inflation expectations as there is a substantial mass at the 5% mark and only a smaller share revised their expectations up. As the majority did not change their inflation expectations, the distribution

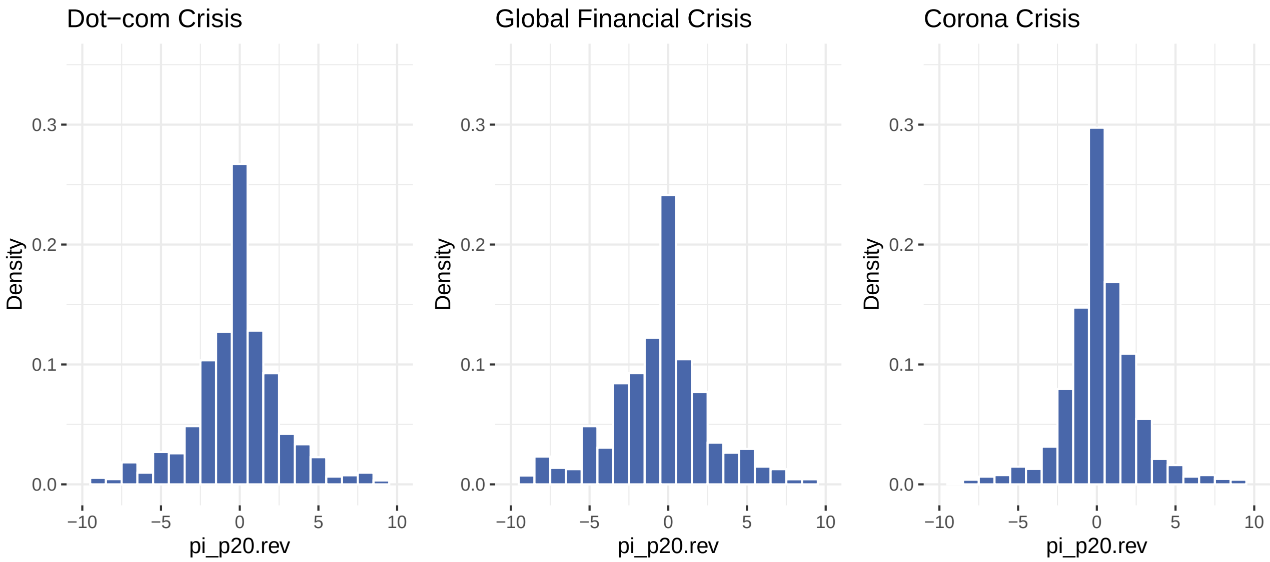

Fig. 3.13: Revised long-term inflation expectations

appears left skewed and the mean is smaller than the median (compare table 3.1). The density plot for the Corona Crisis looks different. While a quarter of all consumers in the crisis subset expect the change of inflation to be 0%, similar shares of consumers either revised their inflation expectations upwards or downwards. At first sight, the Corona Crisis appears similar to the Dot-Com Crisis and both very different compared to the GFC. To analyse if this observation only holds for short-term expectation, we draw on the revised long-term inflation expectations in figure 3.13.

The three density diagrams show how consumers revised their long-term inflation expectations. The density of responses at the 0% mark slightly increased, indicating that long-term expectations are revised to a smaller extent. Especially, for the Corona Crisis a share of 30% does not revise their expectation. Moreover, similar to the inflation expectations plotted in 3.6, the density diagrams are more bell-shaped which indicates that long-term inflation expectations are well-anchored (Bernanke, 2004; Powell, 2020). The muted impact of the GFC and the Corona Crisis on long-term inflation expectation has been also discussed by Armantier et al. (2020). Figure 3.13 underlines the statement made before that long-term inflation expectations do not offer a complementary picture. Therefore, we focus from now on solely on short-term inflation expectations.

4 Methodology and Econometric Framework

In chapter 2, we presented theoretical and empirical work on the heterogeneity in inflation expectation across demographic groups. In the previous chapter 3.5, we depicted the first indications for this heterogeneity. We showed substantial and persistent deviation that arise due to different levels of income, gender, educational background and age. To analyse these heterogeneities in more detail, and especially during crises, this chapter outlines the used methodology. The structure in this chapter is as follows. First, we seek statistical evidence for the observed heterogeneity among individuals. Our initial intention is to validate whether the presented stylized demographic heterogeneities persist in our crises subset. Hereby, we build a model that describes inflation expectations pi_p4. It is a linear regression model that incorporates both individual variables and general macroeconomic measurements from the described data sources (see chapter 3.5) as independent variables. The obtained results help to answer our first two subquestions and furthermore serve as a bridge to our baseline regression in the next chapter.

We limit this chapter to the most necessary principles and theories when elucidating the procedure and the findings. Deliberately, we refrain from describing the theoretical foundations of our regression in advance and report definitions and theories at the appropriate point. Thus, the focus is intentionally on the results and on the structure as well as on the model choice. In this context, we will particularly underline results relevant to our intention and comment on other statistics or findings if they show abnormal patterns and thus indicate bias in our model.

4.1 Descriptive Regression Analysis

In the initial regression analysis, we validate to what extent the demographic factors gender, income, education and age are statistically significant in our crises subset and, more specifically, during the three crises individually. To achieve this, we draw on the theory and empirical studies outlined in chapter 2 as well as on our descriptive observations in chapter 3.5. The employed econometric methodology is a multiple linear regression model as we do focus on the second answers only.[1] The linear model estimates the effects of distinct independent variables on a dependent variable. The assigned independent variables are either categorical (men vs. women and college vs. non-college) or numerical (income and age). Therefore, we use both dummies and numerical treatment to estimate the dependent variable. The dependent variable throughout the descriptive regression analysis is the short-run inflation expectation labelled as pi_p4_i. By choosing a multiple linear regression model, potential problems and inferences, e.g. multicollinearity and omitted variable bias, could arise (Wooldridge, 2018). In the further course, we describe how we control and overcome potential interference. Consequently, the general regression model is specified as follows.

$$pi\_p4_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + u_i \tag{4.1}$$

where Z_i is an example for a specific characteristic that is constant over time and X_i is an example for a numerical explanatory variable and u_i refers to the error term. The following paragraphs evaluates the selection of the independent variables X_i and Z_i. β_1 and β_2 are the corresponding coefficients and β_0 represents the constant or intercept of the linear model or, in other words, it is the expected value of pi_p4_i if all other variables equal 0. Note that we omitted time subscripts for simplicity.

4.1.1 Simple linear regression model

In our descriptive chapter, we illustrated with time series plots that inflation expectations and actual inflation follow each other closely. For many decades, this close co-movement persisted but since 2010 consumer expectations increasingly depart from actual inflation. Nevertheless, in our first regression

[1] For instance, including the first answers requires a multivariate regression model.

model, we include actual inflation as an independent variable. It is included in a way that matches the month of the survey. Concretely, this means when explaining inflation pi_p4_i for January 2020, we are including the past 12-month headline inflation into the model. This corresponds e.g. to the growth of CPIAUCSL between January 2019 to January 2020 (see equation 3.1). Incorporating actual inflation is a good starting point for the inclusion of further independent variables (see e.g. Armantier, 2016; Madeira and Zafar, 2015). Furthermore, inter alia figure 3.7 shows that during a crisis the expected inflation follows the movement of actual inflation rates. With core inflation and headline inflation, we introduced in section 3.2 two measures of actual inflation. Including both variables simultaneously as explanatory variables may lead our model to suffer from multicollinearity. Hence, the following simple linear regressions for all observations since 2000 are conducted to decide which of the two variables has higher explanatory power.

$$\begin{aligned} pi\_p4_i &= \beta_0 + \beta_1 g12P_i + u_i \\ pi\_p4_i &= \beta_0 + \beta_1 g12CP_i + u_i \end{aligned} \tag{4.2}$$

In general, we use Stargazer (Hlavac, 2018) to illustrate our regression results. Table 4.1 shows the regression results for the models specified in equation 4.2. The columns indicate the different models we ran in the corresponding step. So here we include information about the dependent variable and the model's period. The rows indicate the coefficients of the different independent variables. The very left column indicates the variable that the coefficient refers to. Generally speaking, a coefficient describes how a certain explanatory or independent variable impacts the dependent one (Wooldridge, 2018). One has to distinguish between coefficients that change the slope of the regression as for example $g12P$ or $g12CP$ and the intercept. The intercept is denoted as $Constant$ in the Stargazer output and as β_0 in our models. We report Ordinary Least Squared (hereinafter: OLS) estimators. Under the assumptions of linearity of parameters, random sampling, no perfect collinearity, zero conditional mean of the error term, and homoskedasticity, the OLS-coefficients are the best linear unbiased estimators. We refer to Wooldridge (2018) or Stock and Watson (2015) for more detailed explanations. To test hypotheses, such as the significance of a coefficient, one can compare the critical value with the value of the t-statistic. The t-statistic is subject to the assumption of normal distribution in large samples and is calculated as follows:

$$t = \frac{estimated\ value - hypothesized\ value}{standard\ error\ of\ the\ estimator} \tag{4.3}$$

Instead of reporting the t-statistic, we use p-values to determine the significance level of the model coefficients. The p-value is the probability that indicates the smallest significance level at which the hypothesis is rejected. Thus, a smaller p-value indicates a higher significance of the coefficient (Stock & Watson, 2015; Wooldridge, 2018). The asterisks indicate the approximate p-value of the respective coefficient as stated further in the note. If there is no asterisk, the p-value is greater than or equal to 10% and we do not find a sufficient impact of the independent variable on the dependent variable. Furthermore, standard errors are reported in parentheses below the coefficient. Standard errors describe the average deviation from the mean and thus give an approximate estimate of how accurate the coefficient is (Wooldridge, 2018). At the bottom of the table, there is also further information, e.g. the number of observations or the R^2-value about the regression model that can be adjusted as required. R^2, as a measure of fit, explains what share of the sample variance of the dependent variable pi_p4_i is explained by the independent variable or the respective actual inflation rate (Wooldridge, 2018). In the following course of this paper, we will refrain from detailed explanations of how Stargazer tables are interpreted and mainly focus on the economic implications of the shown models.

Tab. 4.1: Simple Linear Regression Output

	Dependent variable:							
	pi_p4							
	2000-2020		DOT		GFC		C19	
g12P	0.327		0.663		0.585		0.304	
	(0.014)		(0.384)		(0.091)		(0.231)	
g12CP		0.117		−1.407		4.246		−0.012
		(0.039)		(2.490)		(0.670)		(0.360)
Constant	2.506	2.970	1.195	6.915	1.519	−5.970	2.467	2.756
	(0.036)	(0.080)	(1.164)	(6.593)	(0.236)	(1.345)	(0.234)	(0.572)
Observations	43,419	43,419	983	983	993	993	1,556	1,556
R^2	0.012	0.0002	0.003	0.0003	0.040	0.039	0.001	0.00000
Note:						$p<0.1$;	$p<0.05$;	$p<0.01$

The output table 4.1 shows that both inflation measurements are significantly positively correlated with inflation expectations for the period 2000 to 2020. More precise, an increase of the year-on-year headline inflation rate by 1% leads to around 0.33% higher inflation expectations in aggregate while a corresponding rise by 1% of the core inflation leads to around 0.12%. The intercept of both models is rather similar. Without any explanatory year-on-year inflation, the average expected 12-month inflation rate is between 2.5% and 3%. Comparing column (1) with column (2), it is apparent that the model using headline inflation has a higher measure of fit for 43,419 observations between 2000 and 2020. The subsequent columns show the regression results for the three crises in our subset.

The direction and the significance of headline inflation remain similar for the Dot-Com Crisis and the GFC. During the GFC, the coefficient is higher by 0.2. Also, core inflation is highly significant during the GFC. Note that the Constant for the corresponding model is also quite high, resulting in a absolute high coefficient for $g12CP$. The Corona Crisis shows a different picture, as both headline inflation and core inflation are not significant although the direction of the first one remains unchanged. In itself, this is an interesting finding which already constitutes the uniqueness of the Corona Crisis compared to other crises. It will be further elaborated on in section 6.1. By not including any other independent variable besides an actual inflation measure, the R^2-value in both models appear relatively low. Nevertheless, with its relatively higher explanatory power, we decide to incorporate headline inflation into all further models.

4.1.2 Multiple linear regression model

In our multiple linear regression model, we first include three demographic variables. This enables us to statistically estimate if the presented demographic heterogeneity also occurs in our crises subset. For gender and education, we used dummy variables which allow us to incorporate binary information into regression models (Wooldridge, 2018). For gender, we used a single dummy independent variable to represent the gender impact on inflation expectation. The built dummy variable $male$ takes on the value 1 if the respondent is male and consequently the value 0 if the respondent is female. A dummy variable is also used to control if the respondent holds a college degree. Following the notation from before, the coefficient $college$ is activated when the respondent has successfully completed college. Further, we included age as an independent variable. As we only look at the 21st century in our regression, we expect that with increasing age, inflation expectations increase as well (compare figure 3.9). The resulting regression model is:

$$pi\_p4_i = \beta_0 + \beta_1 g12P_i + \beta_2 male_i + \beta_3 college_i + \beta_4 age_i + u_i \tag{4.4}$$

Table 4.2 includes all mentioned demographic explanatory variables and follows the same logic as table 4.1 to report the regression results. Column (1) shows that all three demographic characteristics are statistically significant at the 1% level for the whole crisis subset. Female, non-college and older respondents report higher inflation expectations. Holding other predictors constant, a female respondent has around 0.58% higher inflation expectations. However, if she holds a college degree, her inflation expectations are lowered by around 0.41%. This effect is neutralized if she is ceteris paribus 40 years older. Even after including the three independent variables, the coefficient $g12P$ remains significantly positive albeit smaller in magnitude. The detected heterogeneities are consistent with the literature (see chapter 2). Moreover, the R^2-value increased largely.

Tab. 4.2: Multiple linear regression output

	Dependent variable:			
	pi_p4			
	2000-2020	DOT	GFC	C19
age	0.010***	0.004	−0.002	0.012*
	(0.001)	(0.009)	(0.012)	(0.006)
male	−0.577***	−0.994***	−1.441***	−0.575**
	(0.035)	(0.266)	(0.364)	(0.239)
college	−0.413***	−0.361	−0.220	−0.596**
	(0.035)	(0.269)	(0.368)	(0.239)
g12P	0.311***	0.702*	0.598***	0.298
	(0.014)	(0.382)	(0.090)	(0.231)
Constant	2.551***	1.525	2.417***	2.630***
	(0.075)	(1.252)	(0.747)	(0.478)
Observations	43,419	983	993	1,556
R^2	0.023	0.019	0.056	0.011
Note:		*p<0.1; **p<0.05; ***p<0.01		

During the individual crises in our subset, the demographic coefficients are less clear and a more indistinct picture emerges. The only demographic factor that remains statistically significant throughout the three periods is gender. During all crises, women expect higher inflation on average. Education is significant at the 5% level only during the Corona Crisis (consistent with Armantier et al. (2020)). A possible explanation could be that college graduates may be more informed about the expectation of professional forecasters (Armantier et al., 2015; Bruine de Bruin et al., 2010). The headline inflation rate remains significant during the Dot-Com Crisis and the GFC but not during the pandemic (as already reported in the last regression). Only during the Corona Crisis, the variable age has a positive impact on inflation expectations at a 10% significance level. Although similar in size to the whole crisis subset, such a difference is not reported during the two other crises.

Table 4.2 presents crucial findings that help to get to the bottom of our research question. While the interpretation of both $college$ and $education$ as binary independent variables is quite straightforward, the interpretation of the variable age as an integer is rather difficult. To alleviate this, we split the variable into the listed age groups from section 3.2. As we aim to stress a potential heterogeneity across age groups, we refrain from incorporating a single dummy for every age group, but create a reference group (Hardy, 1993). The reference group is not explicitly listed but is instead integrated into the slope. It is important to select an age group as a reference group that neither is very old nor very young in order to catch potential heterogeneities appropriately. Thus, we resort to simple key statistics to make the decision. With exception of the Dot-Com Crisis, all age means lie in between the interval $(50, 55]$, which consequently serves as reference group. Following this, the variable age in equation 4.4 is replaced by a set of age group dummies. The variable $agegroup_i^h$ describes the corresponding age group h of individual i.

$$pi\_p4_i = \beta_0 + \beta_1 g12P_i + \beta_2 male_i + \beta_3 college_i + \beta_h agegroup_i^h + u_i \tag{4.5}$$

So far, we did not include household income as an independent variable in our model. For the following regressions, we include it to complement our line of thinking. Besides gender, education and age, it is the last demographic characteristic that was reported in the previous chapters (see 2 and 3.1). By including the variable, we need to check if the model suffers from multicollinearity since there could be an observed correlation between age and household income (compare figure 3.2). A simple test for multicollinearity is to check the correlation between age and household income for the whole sample, the below 50 years old, and the above 50 years old. The correlation is found to be -0.044, 0.158, and -0.186 respectively which means that we can establish neither perfect nor imperfect multicollinearity. In the following, we include $income$ as our fourth independent demographic regressor in our model.

More specifically, we include the log-transformed household income $ln.inc$.[2] Therefore, the model is extended to the one below.

$$pi\_p4_i = \beta_0 + \beta_1 g12P_i + \beta_2 male_i + \beta_3 college_i + \beta_h agegroup_i^h + ln.inc_i + u_i \tag{4.6}$$

In the following, we will not only comment on the regression result of a model that includes income but also compare it with the model described in equation 4.5. This allows us to present the effect of the household income on inflation expectations more isolated which is preferable in our eyes since the household income is potentially influenced by other household members and thus not purely individualistic. Furthermore, the interpretation of the intercept becomes more challenging when including the income variable. Table 4.3 reports results for models 4.5 and 4.6 for the entire period and the crises.

Including *income* has an indirect and a direct impact on the model. The indirect impact is through the change in the coefficients of the other predictors and the direct one is on the model per se. Indirectly, the significance of the model does not change when including *income*. Merely the magnitude of the significance of the three independent variables $male$, $college$, and $g12p$ is in some cases marginally lower in the model 4.6 when looking at the crisis periods. Directly, the impact is stronger. For the whole crises subset, as well as for the three individual crises periods, the household income is negatively correlated with the reported inflation expectations on a significance level of at most 5%. In detail, an increase in household income by e.g. 10% lowers inflation expectations by approximately 0.04 to 0.07 percentage. As all three coefficients during the crises are larger in size compared to the whole crisis subset, inflation expectations are more sensitive to income during crises. Ultimately, we improve the explanatory power of our model by the inclusion of $ln.inc$ as we can explain a higher share of the variation of the dependent variable by the independent variable, indicated by a higher R^2-value for all periods of consideration.

Furthermore, by including small stepped age groups, it becomes apparent that higher inflation expectations are associated with older individuals for the period 2000 to 2020. While the younger age groups

[2] Taking the natural logarithm of a dependent variable allows to treat extreme values of the predictor and enables a more straightforward interpretation (Knoke & Burke, 1980)

Tab. 4.3: Multiple linear regression output - incorporating age groups and income

	Dependent variable:							
	pi_p4							
	2000-2020		DOT		GFC		C19	
	4.5	4.6	4.5	4.6	4.5	4.6	4.5	4.6
agegroup[18,25]	−0.253	−0.414	−0.742	−1.164	0.099	0.410	−0.574	−1.023
	(0.093)	(0.094)	(0.684)	(0.726)	(1.117)	(1.199)	(0.594)	(0.603)
agegroup(25,30]	−0.537	−0.666	−0.884	−1.003	−0.196	−0.154	−0.117	−0.456
	(0.094)	(0.094)	(0.669)	(0.685)	(1.064)	(1.078)	(0.609)	(0.614)
agegroup(30,35]	−0.398	−0.460	−0.617	−0.709	−0.024	0.045	−0.662	−0.970
	(0.087)	(0.087)	(0.592)	(0.608)	(0.947)	(0.958)	(0.590)	(0.597)
agegroup(35,40]	−0.309	−0.314	0.506	0.547	−0.512	−0.407	−0.725	−0.849
	(0.082)	(0.083)	(0.563)	(0.579)	(0.884)	(0.893)	(0.547)	(0.550)
agegroup(40,45]	−0.223	−0.224	0.516	0.425	−0.961	−0.730	−0.230	−0.301
	(0.080)	(0.080)	(0.556)	(0.573)	(0.772)	(0.778)	(0.591)	(0.593)
agegroup(45,50]	−0.110	−0.102	−0.486	−0.470	−0.527	−0.364	−0.260	−0.379
	(0.077)	(0.078)	(0.562)	(0.578)	(0.763)	(0.768)	(0.606)	(0.610)
agegroup(55,60]	−0.065	−0.083	−0.106	−0.157	−0.292	−0.338	−0.442	−0.441
	(0.076)	(0.076)	(0.635)	(0.649)	(0.796)	(0.806)	(0.517)	(0.521)
agegroup(60,65]	−0.011	−0.061	0.306	0.304	−0.543	−0.628	0.266	0.011
	(0.076)	(0.077)	(0.782)	(0.840)	(0.773)	(0.784)	(0.505)	(0.511)
agegroup(65,70]	0.103	0.017	0.024	−0.100	0.622	0.530	−0.363	−0.721
	(0.079)	(0.080)	(0.689)	(0.725)	(0.829)	(0.844)	(0.512)	(0.521)
agegroup(70,75]	0.137	−0.002	−0.569	−1.217	−0.661	−0.805	−0.442	−0.688
	(0.086)	(0.088)	(0.787)	(0.828)	(0.940)	(0.954)	(0.535)	(0.542)
agegroup(75,80]	0.124	−0.052	−0.658	−1.149	0.615	0.176	−0.287	−0.396
	(0.098)	(0.101)	(0.805)	(0.889)	(1.087)	(1.146)	(0.592)	(0.606)
agegroup(80,100]	0.061	−0.109	−0.014	−0.030	−1.713	−2.240	1.478	1.248
	(0.101)	(0.104)	(0.913)	(0.986)	(0.990)	(1.037)	(0.684)	(0.709)
male	−0.580	−0.478	−0.982	−1.008	−1.398	−1.238	−0.582	−0.417
	(0.035)	(0.036)	(0.267)	(0.278)	(0.367)	(0.378)	(0.240)	(0.246)
college	−0.403	−0.178	−0.459	−0.267	−0.187	0.209	−0.616	−0.329
	(0.036)	(0.039)	(0.274)	(0.293)	(0.378)	(0.413)	(0.241)	(0.254)
g12P	0.312	0.298	0.696	0.767	0.599	0.610	0.328	0.357
	(0.014)	(0.015)	(0.386)	(0.398)	(0.090)	(0.092)	(0.232)	(0.233)
ln.inc		−0.407		−0.428		−0.681		−0.653
		(0.024)		(0.196)		(0.260)		(0.149)
Constant	3.180	7.591	1.931	6.368	2.630	9.798	3.495	10.841
	(0.069)	(0.268)	(1.216)	(2.442)	(0.646)	(2.864)	(0.512)	(1.724)
Observations	43,419	42,104	983	926	993	963	1,556	1,526
R^2	0.024	0.031	0.032	0.043	0.064	0.072	0.019	0.033

Note: $p<0.1$; $p<0.05$; $p<0.01$

show negative coefficients, the older age groups show positive coefficients. The relationship is not linear. For example, the coefficient for the age group (18,25) is smaller in magnitude compared to the age group (26,35) who are divided into three further age groups. The reference group of (50,55) has to be kept in mind when comparing the coefficients. To statistically verify that the age group coefficients are different from each other, we conduct Pearsons's (1900) Chi-Square Test of Independence. If dealing with categorical variables, this test is the appropriate one (Wooldridge, 2018). Accordingly, we test the hypotheses:

$$H_0\text{: The two variables are independent vs.}$$
$$H_1\text{: A relationship between the two variables exist}$$

In more practical terms, we can test whether the youngest group $[18, 25]$ reports significantly different inflation expectations compared to the oldest age group $(80, 100]$. As in the assessment of the significance of a coefficient, the p-value is determined. The underlying distribution is the Chi-Square test statistic. If the p-value is small enough, we fail to reject the H_0 hypotheses on a certain significance level and accordingly find evidence that the two coefficients are independent or in our case two age build their inflation expectations differently in a statistically significant way. Furthermore, this methods allows to detect possible age group differences that are not obvious at first glance, as the coefficient is not significantly different from zero. Therefore, it is particularly evident that the respondents up to 35 years reported significantly lower inflation expectations than the part of the respondents over 40 years. In particular, the age group $(25, 30]$ has lower short-term inflation expectations on aggregate for the whole observation period since 2000.

Table 4.3 indicates that the heterogeneity between different age groups vanishes in the Dot-Com Crisis subset and to a large extent in the GFC. Merely the oldest respondents fall out of line and remain to report significantly lower 12-month ahead inflation expectations during the GFC than the other age groups. These results stand in stark contrast to the observations during the Corona Crisis. During the pandemic, old individuals estimate the inflation to be significantly higher than the rest. In addition, the wedge between old individuals and young individuals is larger since the age group $[18, 25]$ report substantially low inflation expectations. Considering the p-value of the Chi-square statistic, the separation of the elderly individuals is higher during the Corona Crisis than during the GFC since the highest p-value for the corresponding age group is around 6.5% for the Corona subset and just below 15% for the GFC subset.

4.2 Rotating Panel

In the next step, we use a method that incorporates idiosyncratic heterogeneity and dynamic updating of each agent's inflation expectations. In detail, we consider the revised inflation expectations instead of absolute expectations to isolate the effect of a crisis on inflation expectations. Therefore, we attain statistically more robust results and account for the fact that the indicated differences we see for the Dot-Com Crisis, GFC, and Corona Crisis subsets were already present before the crisis started. First, we shortly introduce the panel regression method itself.

In chapter 3.1, we stated that the MSC is the most useful survey available that meets our intentions. We argued that with its panel data feature, we are able to analyse the effects of crises on inflation expectation from a different perspective and in greater detail. As such, the following methodology mainly builds on the rotating panel of the MSC. To understand why conducting a panel data regression is useful, it is inevitable to elaborate on the advantages of it in a more general fashion.

Panel data methods are used when dealing with samples that contain both a time-series and a cross-sectional aspect. Therefore, the same multi-dimensional data is followed over time (Wooldridge, 2018). There are several advantages. The most important one is the ability to allow for unobserved heterogeneity across individuals and address dependencies across data observations (Baltagi, 2005; Hsiao, 2007). Thus, panel data manages to model both the common and the individual behaviour. In addition, panel data provides more degrees of freedom, greater variation, and less co-linearity (Park, 2011). Hence, econometric estimation becomes more efficient (Hsiao, 2007). Panel data also mitigate the causes of endogeneity that arise due to correlation between the error terms and regressors (Baltagi, 2005). An example is omitted variable bias, which occurs when a model omits relevant variables that end up in the error term. Thereafter, the model attributes the effects of the omitted variables to the included variables (Hsiao, 2007). In summary, the panel aspects offers not only a great opportunity to detect the dynamics of inflation expectations during crises but although provides several estimation advantages. As we pointed out in chapter 3.6, we eliminated all individuals that were not interviewed twice, i.e. the panel is balanced (Wooldridge, 2010).

As the analysis is based on the reported individuals' inflation expectation, the population regression model is specified as follows:

$$pi\_p4_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_i + u_{it} \tag{4.7}$$

where the Z_i are individual-specific characteristics that are constant over time and X_{it} is an explanatory variable as for example the actual headline inflation rate. In the following, we sketch shortly how the first difference regression model is derived. For detailed theoretical explanations, we refer to Stock and Watson (2015) or Wooldridge (2018).

When considering the present data-set, there are only $T = 2$ time periods. In detail, the expectations at $t = 1st, 2nd$ are relevant. As stated in chapter 3.1, the suffix $.l1$ indicates the first interview answers and no suffix refers to the second interview. Consequently, we have for $t = 1st$ and $t = 2nd$ respectively:

$$\begin{aligned} pi\_p4.l1_i &= \beta_0 + \beta_1 X.l1_i + \beta_2 Z_i + u_{i.l1} \\ pi\_p4_i &= \beta_0 + \beta_1 X_i + \beta_2 Z_i + u_i \end{aligned} \tag{4.8}$$

Taking the difference of the inflation expectation before and after a crisis eliminates the individual specific characteristics:

$$pi\_p4_i - pi\_p4.l1_i = pi\_p4.rev_i = \beta_1(X_i - X.l1_i) + u_i - u.l1_i \tag{4.9}$$

As there are only two time periods, the estimators of a fixed-effects panel data regression is numerically equivalent to a first difference estimation as sketched by equation 4.9. Furthermore, the regression model stated in equation 4.9 yields an estimate for β_1 that profits from the elimination of $\beta_2 Z_i$ from the model. So the estimator is robust to a potential bias that arises because of the individual characteristics and consequently does not suffer from an omitted variable bias.

4.3 Baseline Regression

In its design, the model specified by equation 4.9 is similar to Armantier (2016), Cavallo et al. (2017), Kuchler and Zafar (2019), and Madeira and Zafar (2015) who also incorporated changes in recent actual inflation. To meet the underlying data-set of this paper, the following analysis is based on the six-month change of the one-year inflation expectation $pi\_p4.rev$[3] and the six-month change of the year-on-year headline inflation at the time of the survey denoted as $g12P$. The baseline first difference regression is as follows:

$$pi\_p4.rev_i = \beta_1(g12P_i - g12P.l1_i) + u_i - u.l1_i = \beta_1 \Delta g12P_i + \Delta u_i \qquad (4.10)$$

The similarities with the simple linear regression model are apparent. In the previous chapter, we outlined the advantages of a first difference regression and how individual characteristics are eliminated with this. However, we want to consider the possibility that individuals do not only form their inflation expectations differently but also, react to shocks in a different manner. In that sense, demographic attributes may play a role in how an individual reacts to a shock. This train of thought was already shortly elaborated on the end of chapter 2. As a consequence, our model incorporates all characteristic that we discussed extensively in the previous chapters and econometric in chapter 4.1. Subsequently, we include fixed effects for different age groups, the gender and the information if the respondent holds a college degree. Furthermore, we add the logarithmic household income to the regression model in order to control for financial differences. Ultimately, we run the following regression for our crises sub samples:

$$pi\_p4.rev_i = \beta_1 \Delta g12P_i + \beta_2 male_i + \beta_3 college_i + \beta_h agegroup_i^h + ln.inc_i + \Delta u_i \qquad (4.11)$$

As mentioned above, we will resort to running two models per period to better discuss the impact of the household income. Methodologically, we supplement the regression model with the already introduced chi-squared hypothesis tests and further key statistics. In the following chapter we present the results in detail.

[3]We refer to section 3.11 for the derivation of the revision variables.

5 Results of Baseline Regression

This chapter presents the results of our baseline regression. While the results of the descriptive regression analysis in chapter 4.1 give evidence for a general heterogeneity across different demographic groups, the results of the baseline regression thoroughly answer our research question and clarify how individuals interpret economic shocks with regards to inflation expectations. At the end of this chapter, we report conducted robustness checks of our model that emphasize the statistical validity of the model.

5.1 Results

Table 5.1 reports the regression results of our baseline regression (compare equation 4.11). For the intention to make full use of the model at hand, we perform chi-squared for independence tests across all age groups. Again, we refer to the appendix for tables including corresponding p-values.

Before commenting on the effect on the different $agegroup$ variables, we point to more general findings that concern all crises. The first general finding we observe is that the explanatory power of our baseline regression model remains as high as in our descriptive regression. This is depicted with approximately equal R^2-values for each crisis. Given that there are less significant predictors, this is remarkable. Secondly, the variables $male$ and $college$ are almost exclusively no longer significant. Therefore, we can not confirm an interpretation heterogeneity across individuals with different educational background nor an existing gender gap with regards to revised inflation expectations on a 5% significance level. Thirdly, except for the Dot-Com Crisis, the variable $\Delta g12P$ which captures the six-month change in headline inflation is significant. Interestingly, the direction of the coefficients are of opposite sign for the GFC and the Corona Crisis. On average, a decrease of 1% of the year-on-year headline inflation

Tab. 5.1: Baseline regression output

	Dependent variable:					
	pi_p4.rev					
	DOT		GFC		C19	
agegroup[18,25]	−0.657	−0.078	0.275	0.900	−1.460	−1.721
	(0.823)	(0.878)	(1.393)	(1.494)	(0.654)	(0.668)
agegroup(25,30]	−1.081	−0.809	−0.584	−0.527	−0.125	−0.301
	(0.804)	(0.827)	(1.328)	(1.344)	(0.671)	(0.681)
agegroup(30,35]	0.285	0.515	0.660	0.761	−0.698	−0.874
	(0.712)	(0.735)	(1.182)	(1.194)	(0.650)	(0.662)
agegroup(35,40]	0.784	0.921	−0.635	−0.391	−0.840	−0.889
	(0.678)	(0.700)	(1.103)	(1.113)	(0.602)	(0.610)
agegroup(40,45]	0.907	1.054	−0.840	−0.646	−0.468	−0.486
	(0.667)	(0.690)	(0.963)	(0.970)	(0.651)	(0.658)
agegroup(45,50]	−0.822	−0.709	−0.597	−0.431	−0.954	−1.039
	(0.676)	(0.698)	(0.952)	(0.958)	(0.667)	(0.677)
agegroup(55,60]	−0.630	−0.482	−0.028	0.034	−0.171	−0.156
	(0.763)	(0.783)	(0.994)	(1.004)	(0.570)	(0.578)
agegroup(60,65]	−0.153	0.255	−0.038	0.093	−0.329	−0.443
	(0.941)	(1.015)	(0.965)	(0.978)	(0.556)	(0.567)
agegroup(65,70]	0.469	0.965	0.827	0.614	−0.194	−0.414
	(0.830)	(0.877)	(1.035)	(1.051)	(0.563)	(0.577)
agegroup(70,75]	−0.317	−0.051	0.093	0.223	−0.810	−0.953
	(0.948)	(1.001)	(1.173)	(1.189)	(0.589)	(0.601)
agegroup(75,80]	0.111	0.139	0.556	0.614	−0.959	−0.965
	(0.970)	(1.075)	(1.357)	(1.428)	(0.652)	(0.672)
agegroup(80,100]	1.477	2.072	0.463	0.714	1.103	1.113
	(1.099)	(1.192)	(1.235)	(1.292)	(0.753)	(0.786)
male	0.057	−0.133	−0.793	−0.727	0.191	0.275
	(0.321)	(0.336)	(0.458)	(0.471)	(0.264)	(0.273)
college	−0.343	−0.586	0.274	0.332	−0.350	−0.206
	(0.330)	(0.355)	(0.472)	(0.514)	(0.266)	(0.282)
$\Delta g12P$	0.188	0.224	0.719	0.705	−0.427	−0.415
	(0.427)	(0.444)	(0.088)	(0.089)	(0.231)	(0.234)
ln.inc		0.304		−0.232		−0.382
		(0.237)		(0.324)		(0.165)
Constant	−0.086	−3.321	−1.218	1.114	0.010	4.342
	(0.594)	(2.621)	(0.831)	(3.580)	(0.562)	(1.913)
Observations	983	926	993	963	1,556	1,526
R^2	0.021	0.024	0.070	0.068	0.014	0.018
Note:				$p<0.1$;	$p<0.05$;	$p<0.01$

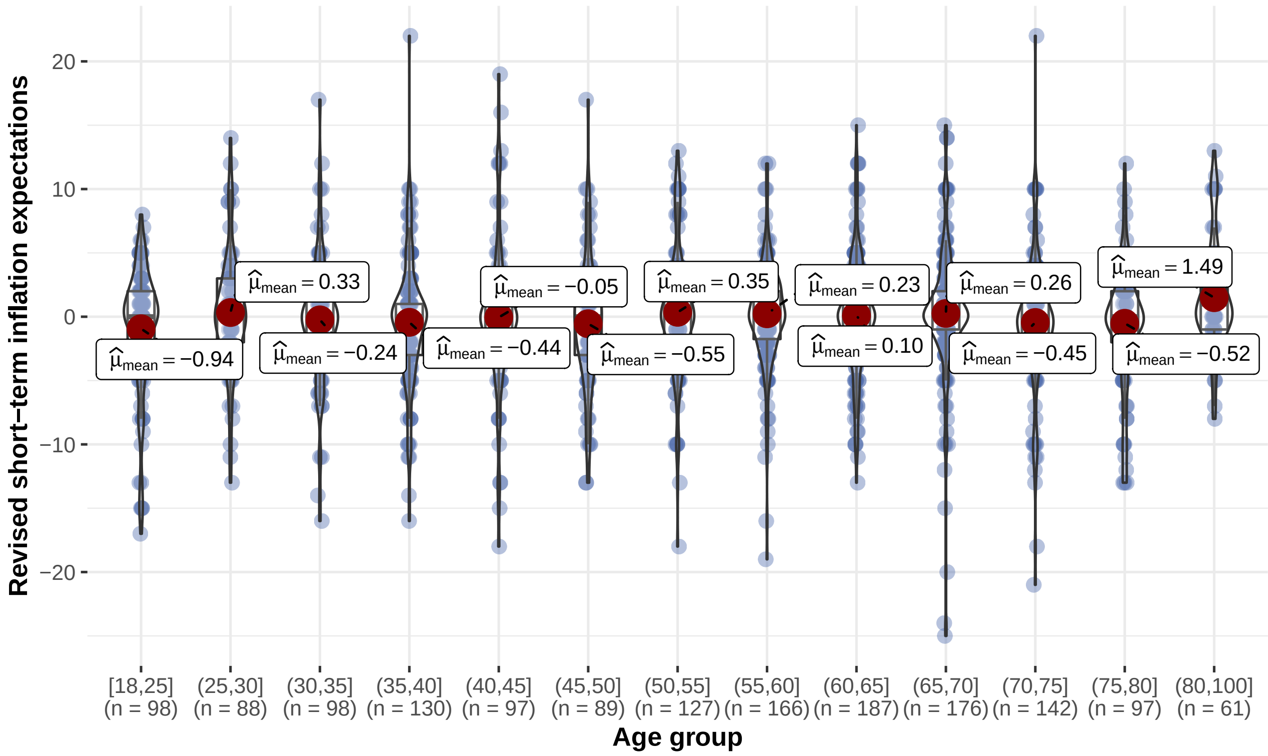

Fig. 5.1: Mean of the revised inflation expectation (Corona Crisis)

leads to a downward revision of inflation expectations by 0.7% and an increase of the variable by 0.4% during the Corona Crisis. Lastly, only during the Corona Crisis the variable $ln.inc$ is significant. With a coefficient of -0.382 significant at the 5% level, individuals with lower income revised their inflation expectations stronger. The asymmetrical movement for headline inflation and income has already been highlighted by other studies (Armantier et al., 2020). However, other authors have not yet stressed the effects on age groups.

By looking at the twelve age groups, we see a unique characteristic for the Corona Crisis. The coefficient for the youngest $agegroup[18, 25]$ is highly significant. With a coefficient of -1.46 when excluding income and -1.72 when including income respectively, the age group stands in stark contrast to the reference group $agegroup(50, 55]$. Such a deviation is not observed in another crisis for any other age group in the underlying sample. In addition, the wedge between the coefficients of the youngest and the oldest age group is striking. Figure 5.1 plots inter alia the mean of the revised inflation expectations and, thus, illustrates the wedge between the age groups during the Corona Crisis.

The figure illustrates that the youngest age group revised their inflation expectations downwards by almost 1% on average at the onset of the Corona Crisis. In contrast, the oldest age group revised their inflation expectations upwards by 1.5% on average. The wedge between these two age groups results in almost 2.5 percentage points. In addition, the other age groups in between barely revised their inflation expectations. The averages lie between -0.55 and 0.35. With 98 and 61 observations, the two age groups are relatively smaller compared to the other ones but sufficiently large for robust results. We confirm the heterogeneity in revision across age groups by conducting hypothesis tests for independence. Indeed, the p-value indicates that the 18 to 25-year-old respondents are significantly different to most of the age groups. We prove the at least 80-year-old individuals to be independent of most other age group variables on a 5% level with a few exceptions including the reference group. All in all, table 5.1, figure 5.1 and the p-values indicate a high dispersion of inflation expectations across the margin age groups. We compared the results for the Corona Crisis to results for the two other crises to emphasize the uniqueness of it. Indeed, we could not find such a dispersion with any of the above listed methods for the GFC subsample. The chi-squared tests show no p-value below 22.5% which indicates a low probability for independence among age groups. Strengthening our argumentation, figure 5.2 underlines that the range of the averages of the age groups for the GFC is considerably smaller. The absolute difference is 1.76 percentage points. Moreover, the extreme wedge between the two age groups at the margin does not exist.

Besides finding no analogousness for the GFC, we also did not find any for the Dot-Com Crisis. Although the coefficients in column (1) and (2) in table 5.1 already indicate no significance on a 5% level, we resort to the method of hypothesis testing to uncover potential discrepancies masked by the choice of reference group. In fact, we can see independence between a couple of age groups (e.g. age group $[45, 50]$ stands out). However, we do not observe an explicit pattern or a huge gap in between the means of the corresponding groups (compare figure 5.3). Indeed, we observe the maximal spread of about 2.5 percentage points for two age groups that are characterized by a very low number of observations. As described in section 3.6, we excluded other crises due to too small age groups. Therefore, this findings is very vulnerable. Excluding age groups with below 30 observations leads to a maximum spread of merely 2%.

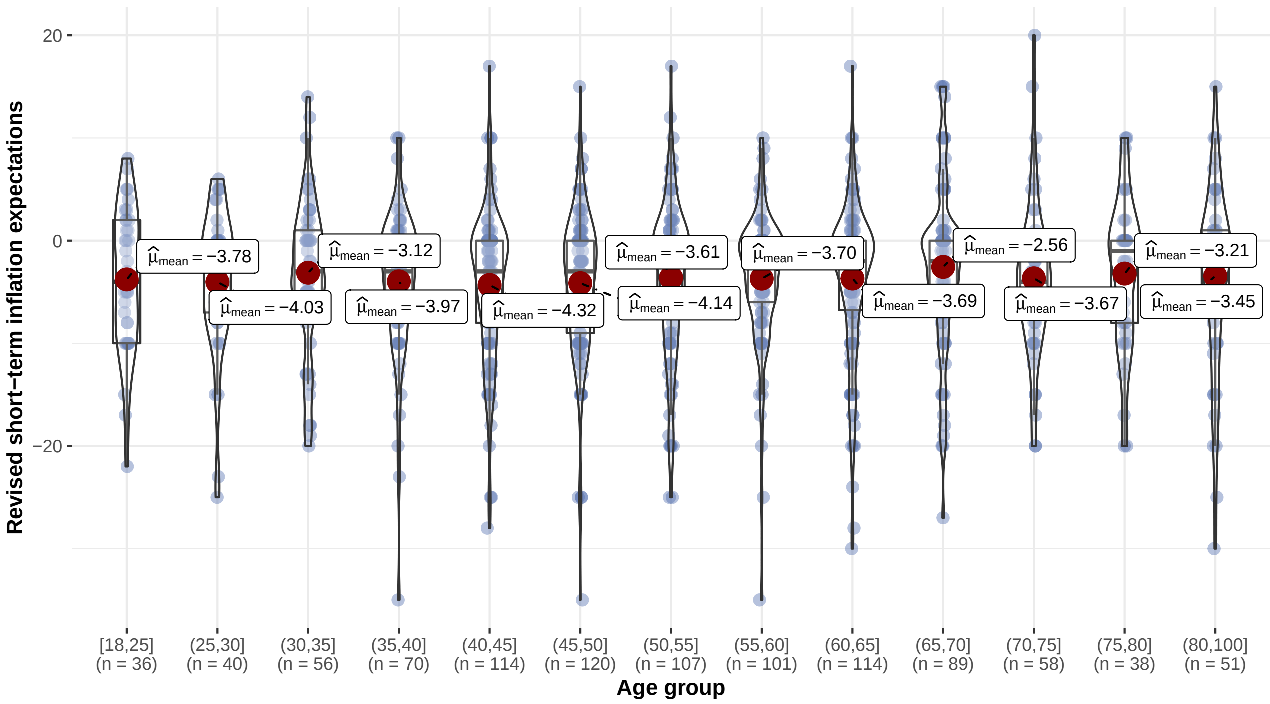

Fig. 5.2: Mean of the revised inflation expectation (GFC)

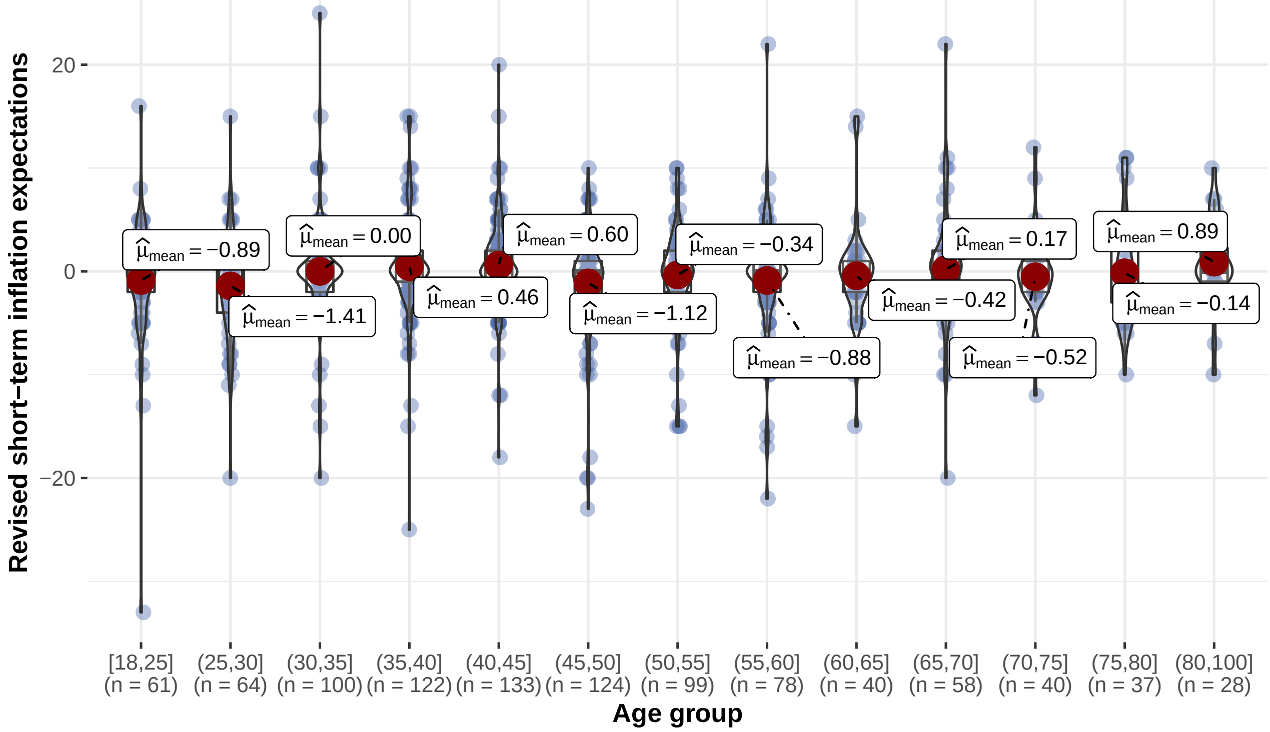

Fig. 5.3: Mean of the revised inflation expectation (Dot-Com Crisis)

All in all, our approach to incorporate revised inflation expectations which compare expectations pre and post the start respectively key date of a crisis combined with existing inflation expectation theory exposes a generational discrepancy for the Corona Crisis subsample. Older respondents above 80 years adapted their inflation expectations positively while the very young lowered their inflation expectations. The comparison with other major crises in the 2000s underlines this abnormality. The GFC in particular shows a great consistency across all age groups. Furthermore, we also observe a more negative adjustment with increasing income exclusively for the recent Corona Crisis.

5.2 Robustness checks

Before discussing the implications of our findings and the reason for the observed heterogeneity in the interpretation of the Corona Crisis, we outline that the present results are not due to our model specifications. Thus, this section sketches how we tested the validity of our model's assumptions.

First, we validate that the underlying model is linear in its parameters. Thus, there are no limitations between the independent variable and its predictors (Wooldridge, 2018). As the survey itself cancels out invalid answers, we refrain from trimming (Wooldridge, 2010) further observations in the first step and resort to winsorizing the underlying dependent variables (Barnett & Lewis, 1984). As we do so, we reach the same conclusions while some coefficients are less significant. Nevertheless, they do not disappear and the direction is always as in the standard model. Independent variables do not require to be winsorized as we have to assume that e.g. a high reported household income corresponds to reality. As a second, step we follow inter alia Armantier et al. (2020), Coibion et al. (2018), and Ehrmann et al. (2017) and exclude observations with inflation expectations below -10% or above +30%. This rule does not change our presented results and conclusions as it only affects below 0.5% in the whole crises sample and for example 0.6% for the Corona Crisis subset. We reach the same conclusions if we apply alternative trimming rules.

As we already stated in subsection 4.1, we tested if the family income is correlated with the respondents' age. We performed the same tests for all other independent factors by building an extensive correlation matrix and found no indications for perfect or imperfect collinearity.

We double check if the mean of the residuals is equal to zero to control for misspecification of the model (Wooldridge, 2018). The omitted variable bias is circumvented by looking at revision variables instead of simple one-year ahead inflation expectations. Nevertheless, we potentially have to account for changed circumstance, e.g. sudden deterioration of the family's financial situation. Consequently, we included various MSC variables into our regression and run the resulting regressions. In detail, we incorporated the PAGO.rev, PEXP.rev, INEX.rev, RINC.rev, BAGO.rev, BUS12.rev, UNEMP.rev and RATEX.rev separately to the baseline regression.[1] As the suffix indicates, we calculated the revision as described in section 3.6. With the exception of INEX.rev, all variables are categorical and where thus included as dummy variables. Indeed, most of the variables offer explanatory power and where highly significant but did not change any conclusions about other coefficients except of the intercept. Or in other words, the added variables are not correlated with already incorporated predictors and solely change the constant (Berry et al., 1985).

The underlying analysis assumes that the variance of the error term is homoskedastic respectively unrelated to the predictors and constant (Stock & Watson, 2015). Thus, we include robust standard errors in our models and re-run them accordingly. We do not find any evidence for heteroskedasticity. Performing the White test (1980) leads to the same conclusion.

[1]We refer to the appendix for the specific questions.

6 Hypotheses and Discussion

The previous chapter highlighted the generational gap that we exclusively identified for the Corona Crisis. In this chapter, we seek to explain the found heterogeneity across age groups at the onset of the Corona Crisis compared to other crises. Thus, we formulate two hypotheses that both address the role of personal experiences. The first hypothesis concerns the rather present local experiences in form of expenditure patterns. The second hypothesis concerns the past lifetime experiences in form of experienced unemployment. Both hypotheses are well justified by the broad strand of literature on the formation of inflation expectation in chapter 2. The structure of the following two hypotheses section is similar. We begin with a short introduction that lays the foundation of the followed methodology. Then, the obtained variable for each hypothesis is added as an independent regressor to our baseline model of section 4.10. Each hypothesis is closed with a discussion.

6.1 Hypothesis I: Personal local experience

Our first hypothesis tests whether the personal local experiences of age groups explain the found different interpretation of the Corona Crisis. Empirical research shows that respondents are strongly biased by their consumption pattern when asked about the general inflation outlook of the economy (Armantier, 2016). We discussed in chapter 2 a set of empirical studies that argue personal shopping experiences are strongly linked to inflation expectation through a difference in *perceived* inflation. As the margin age groups are substantially far from each other with almost half a decade in between them, an unequal shopping behaviour is easily justifiable. If both groups show a significant difference in their consumption pattern, they might experience other price changes. Consequently, they do not base their inflation expectations on the published overall inflation rate but instead on the observed price changes of the goods they consume. Consistent with this argument is the finding of Diamond et al. (2019) who found that the majority of the respondents in their survey claimed to base their judgement on inflation expectations to the prices of items that they purchase daily. Our hypothesis builds on the empirical work of Hobijn and Lagakos (2005) who constructed household-specific inflation rates using survey data from the CE. The authors found that cost of living generally are highest for older individuals and suggest that this can be attributed to medical care, which constitutes a larger expenditure share for older people. Besides Hobijn and Lagakos (2005), another approach was conducted by McGranahan and Paulson (2005). By also relying on the CE and on item- or category specific inflation rates by the BLS, they calculated inflation measures for 13 different demographic groups from 1981 to 2004. Again, they found that the eldest age group is also the one that shows the largest deviation of group-specific inflation from the general one. On average, their cumulative inflation is five per cent higher than the actual inflation. One of the most recent empirical studies of constructing household-specific inflation rates was conducted by Johannsen (2014) (see chapter 2) who found that low educated consumers have more heterogeneous expenditure weights on food and energy. Besides these empirical studies, another motivation for this hypothesis roots in an explanation on the BLS website[1] that hypothetical individual's inflation experience may differ from the published inflation number. The construction of individual's experienced inflation based on relative importance (i.e. consumption weights) and relative price changes alleviate this concern. Following this line of thinking, we propose our first hypothesis.

H1: The heterogeneity across age groups exists due to distinct expenditure patterns which shape inflation expectations.

With this hypothesis, we essentially propose that the representative consumption basket can vary significantly across age groups and we account for the possibility that the age groups might have the rate of inflation computed from their age-specific consumption basket in mind when forecasting the rate of inflation. To test this hypothesis, we draw on the available data from the BLS. The CE (introduced in chapter 3.3) offers a wide range of expenditure information as well as data on household socio-economic characteristics. Besides publishing the survey itself, they provide their data in a table format. We will use the published tables to construct age-specific inflation rates. Merged with the MSC, the change in age-specific inflation rates will be added as an explanatory variable to our regression.

[1]Retrieved from https://www.bls.gov/cpi/factsheets/averages-and-individual-experiences-differ.htm from 2016

6.1.1 Methodology

Following this, our methodology is as follows:

1. Create a matrix of budget shares defined over expenditure categories across age groups

2. Create a matrix of category-specific inflation rates by disaggregating the CPI

3. Calculate age group specific inflation rates

4. Build on OLS-Regression with age group specific inflation rates as explanatory variable

Step 1: Create a matrix of budget shares defined over expenditure categories across age groups
To create the budget share matrix ($w_{k,j}$), we retrieved data from the table which report the average mean expenditure, that is how much a consumer spends on average for a particular item, and the aggregate expenditure share, that is the portions of aggregate expenditures (as percentages) allotted to distinct expenditure groups.[2]. The BLS organises expenditure into 14 broad categories which are broken out further (see appendix - it gives a thorough overview of how the BLS classifies items). Out of the 14 expenditures types, we combined Food and Alcoholic Beverages, Reading and Education, and lastly grouped Personal care products and services with Tobacco products and smoking supplies, Miscellaneous, Cash contributions and Personal insurance and pensions. We combined them to follow the classification from FRED. Table 6.1 shows the expenditure pattern as of 2019 for eight age groups. By far the largest share of the expenditure is devoted to housing followed by transportation and food and beverages. Figure 6.1 below depicts the expenditure shares for the youngest and for the oldest age groups.

[2]The data was retrieved from US Bureau of Labor Statistics (see https://www.bls.gov/cex/) for 2019 A cross-check was done for 2008 as a base year and no significant difference was found (see appendix)

Tab. 6.1: Decomposition of age-specific inflation basket (2019)

Category / Age	Under 25	25 to 34	25 to 34	35 to 44	45 to 54	55 to 64	65 to 75	Above 75
Food and Beverages	15.70%	13.80%	13.70%	13.90%	13.30%	14.10%	14.40%	13.60%
Housing	32.40%	35.90%	33.00%	30.90%	30.50%	34.80%	34.00%	36.20%
Apparel	3.60%	3.30%	3.30%	3.10%	2.60%	2.60%	2.70%	2.40%
Transportation	21.10%	18.00%	18.30%	17.30%	16.40%	14.90%	15.70%	13.70%
Medical Care	3.80%	5.50%	6.40%	6.90%	8.60%	13.60%	12.30%	15.80%
Recreation	3.50%	4.20%	4.90%	5.00%	5.70%	4.70%	4.90%	4.50%
Education and communication	7.60%	2.10%	1.60%	3.50%	2.60%	0.70%	0.80%	0.50%
Other goods and services	12.20%	17.20%	18.80%	19.40%	20.20%	14.50%	15.20%	13.30%

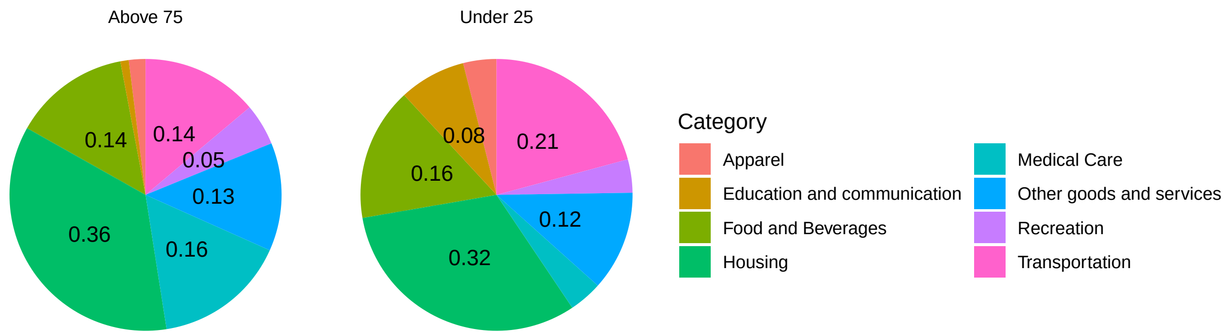

Fig. 6.1: Decomposition of age-specific inflation rates

Although both age groups seem to spend a relatively equal amount on housing and food and beverages (roughly 50 per cent) as well as on Other Goods and Services, there are substantial differences in the other categories. First, the youngest age group spends relatively more money on Transportation and Education. Secondly, the oldest age group spends relatively more on Medical Care. These differences are not surprising: People educate themselves at early ages and are more reliant on medical care once older. These observations might explain the different *perceived* inflation as prices of these categories may have developed differently. In order to answer this, we look at the development for these categories in the next step.

Step 2: Create a matrix of category-specific inflation rates by disaggregating the CPI

FRED reports annual basket prices for the eight categories from above as sub-indexes of the Consumer Price Index. Following the same argumentation as in chapter 3.2, we calculated the year-on-year growth rates. Equation 6.1 from below shows the computation for the one-year inflation rate of Food and Beverages (CPIFABSL):

$$g12P_{CPIFABSL,t} = \frac{CPIFABSL_t - CPIFABSL_{t-12}}{CPIFABSL_{t-12}} \tag{6.1}$$

The other seven category-specific inflation rates were calculated in the same fashion. The plots from below depicts how the category-specific inflation rates behaved around the GFC and the Corona Crisis. Each time series is plotted over 18 months to illustrate possible fundamental movements.

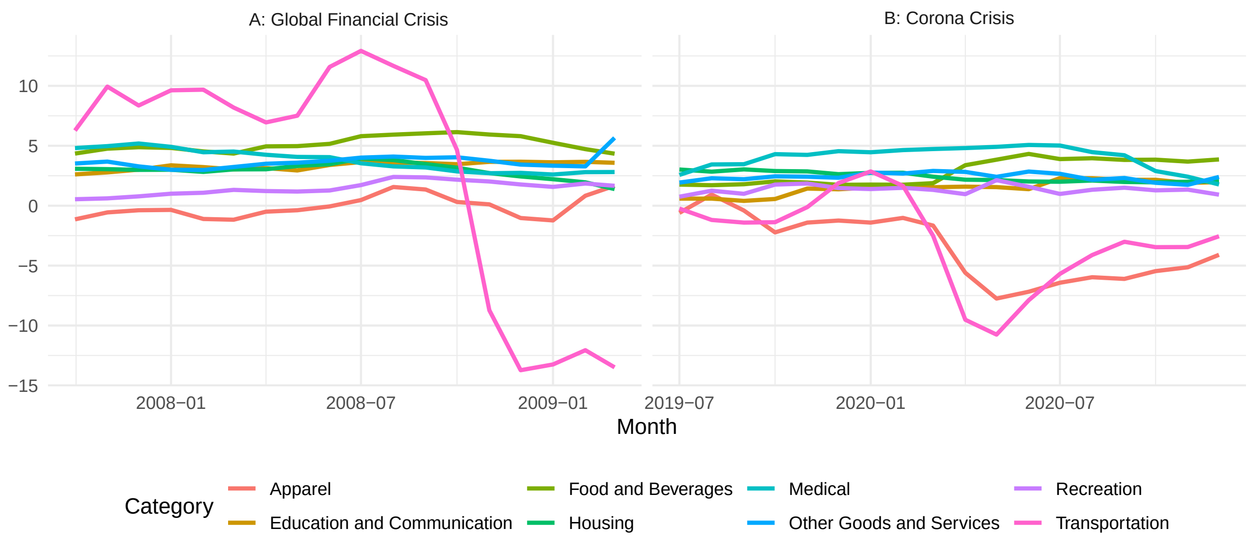

Fig. 6.2: Category-specific inflation rates during the Global Financial Crisis and the Corona Crisis

Two features stand out in figure 6.2. First, Transportation shows a very volatile pattern. Without going into specifics, this is largely driven by an increase or a decrease respectively in the price of oil. Looking at the many components of Transportation, we find that gas prices contribute a total share of 20 per cent alone. Secondly, the other categories are found to be less volatile and average around three per cent. Before the GFC, the inflation rates were a bit higher but besides Transportation show a continuous time path without large movements. At the onset of the GFC in August 2007, prices for Transportation increased slightly which was most likely to be caused by the increase in oil price. The months following, the price of oil declined tremendously. For the Corona Crisis, the category-specific inflation rates behaved differently. Due to a large drop in the oil price, prices for Transportation decreased significantly.

Interestingly, also Apparel seems to be affected adversely. Moreover, Food and Beverages increased, albeit with a smaller magnitude.

Step 3: Calculate age group specific inflation rates

To create age group specific inflation rates, we merge our results from the previous two steps. Mathematically, we multiply our expenditure share across age reference group matrix with the computed category-specific inflation rates matrix. Therefore, the age group specific inflation rate is calculated as:

$$\pi_{k,t} = \sum_{j=1}^{n} \omega_{k,j} \quad \frac{P_{j,t} - P_{j,t-12}}{P_{j,t-12}} \tag{6.2}$$

where k is an index over the age groups and j an index over the expenditure categories. There are $n = 8$ categories in total. $P_{j,t}$ and $P_{j,b}$ are the values of the price index of expenditure category j in period t and in the base period respectively. Lastly, $w_{k,j}$ is the budget share of the expenditure category j for the age group k in the base period.

We did the computation for the period around the GFC and for the period around the Corona Crisis. Figure 6.3 depicts the result.

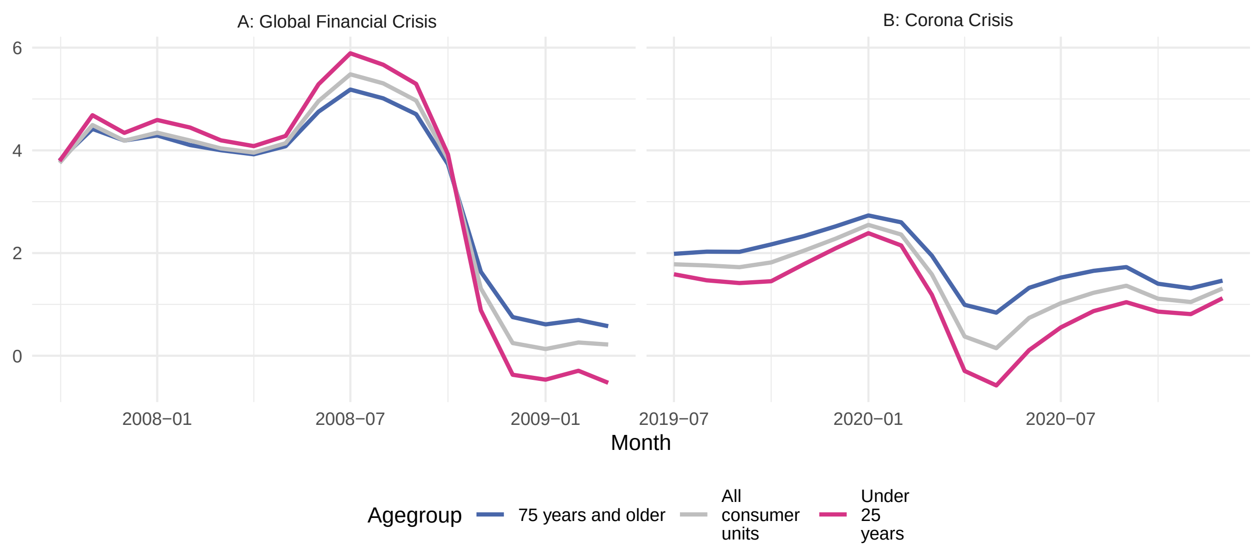

Fig. 6.3: Age-specific inflation rates during the Global Financial Crisis and the Corona Crisis

The figure shows surprising results. While the youngest age group had the highest age-specific inflation rate before the GFC, afterwards it had the lowest one. In the Corona Crisis, the oldest age group has the highest age-specific inflation rate. For all consumers, the line is in the middle. In the Corona Crisis, across all age groups, the inflation rates decreased substantially by around 150 basis points each. The first glimpse indicates that indeed the different expenditure pattern may cause the age groups to *perceive* and, therefore, *expect* inflation differently. However, before jumping to conclusions, in the next step we run an OLS regression.

Step 4: Build on OLS-Regression with age group specific inflation rates as explanatory variable
In the last step of testing the hypothesis, we merged the age-specific inflation rates with our crisis subset extracted from the MSC. We matched the different respondents in accordance to their age group. For our model (compare equation 4.11), this means that instead of incorporating the actual headline year-on-year inflation rate, we include the age-specific year-on-year inflation rate at the time of the second interview. A marginal difference is that FRED reports slightly different age groups than we used in our first results. While we included individuals aged 25 in the youngest age group (18-25), FRED excluded them from their youngest age group. Therefore, they did not experience the same $\Delta g12Page$.

$$pi\_p4.rev_i = \beta_1 \Delta g12Page_i + \beta_2 male_i + \beta_3 college_i + \beta_h agegroup_i^h + ln.inc_i + \Delta u_i \tag{6.3}$$

6.1.2 Results

Table 6.2 shows the OLS regression results. Consistent with the methodology in the previous chapter, we used the age group aged between 50-55 as our reference group. Different to table 5.1 from the previous regression, the coefficient $\Delta g12Page$ is now added as an explanatory variable. Overall, there are a few things to note about the results. First, during the GFC, individuals strongly based their inflation expectation on their age-specific inflation rate. With a coefficient of 0.757 significant at the 1% level, the relationship is quite robust. Compared to our earlier regression, the effect turns out to be stronger. We also see a slight improvement in R^2 e.g. from 7% (see 5.1) to 7.2% for the GFC without $ln.inc$. Secondly, the coefficient $\Delta g12Page$ in column (3) and (4) is higher compared to our baseline regression results for the Corona Crisis, indicating that consumers do base their inflation expectations

Tab. 6.2: Hypothesis I regression output[3]

	Dependent variable:			
	pi_p4.rev			
	GFC		C19	
agegroup[18,25]	0.741	1.304	-1.579^{**}	-1.842^{***}
	(1.394)	(1.493)	(0.658)	(0.673)
$\Delta g12Page$	0.770^{***}	0.757^{***}	-0.450^{**}	-0.450^{**}
	(0.093)	(0.094)	(0.217)	(0.219)
ln.inc		-0.235		-0.383^{**}
		(0.324)		(0.165)
Constant	-1.186	1.188	-0.030	4.292^{**}
	(0.829)	(3.575)	(0.559)	(1.911)
Observations	993	963	1,556	1,526
R^2	0.072	0.071	0.015	0.019
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

on their age-specific inflation rates. However, the large difference between the youngest and the oldest age group is found to persist. A critical examination of the chi-squared p-values confirms this. Still, even with including age-specific inflation rates, the youngest age group interprets the Corona Crisis with revising their inflation expectation negatively and the oldest-age group positively. Conclusive, we were able to explain more variation of $pi\_p4.rev$ but still age specific effects remain to persist.

6.1.3 Discussion

Although we had to reject our first hypothesis, a few things need to be mentioned. First, it may be useful to look not only at the different consumption set but also at a different shopping behaviour. To take shopping behaviour into consideration as well, it is necessary to undertake an even more granular approach. Our analysis focused on eight categories with their respective inflation rates. However, if one analyses the shopping behaviour on an item-level, further insights can be drawn. Following this motivation, a recent study by D'Acunto et al. (2019) takes a closer look at the item price changes to which consumers are exposed in their daily lives. By observing individual consumption baskets, the prices individuals pay for each good over time and their inflation expectation, they are able to

[3] Only significant dummy coefficients on a 5% are reported. We refer to the appendix for the entire regression output.

emphasize the role of expenditure patterns.[4] They document that consumers who grocery shop less frequently observe on average higher price changes in their consumption basket than consumers that shop more often. If individuals shop often, the observed prices in the supermarket are probably the same for most shopping trips. Once in a while, these individuals will observe a price change. The share of shopping trips in which these individuals observe price changes would thus be relatively low. Instead, if individuals shop infrequently, they are likely to observe price changes more often. The share of shopping trips in which infrequent shoppers observe price changes should thus be higher than the share for frequent shoppers. Although lacking sufficient data, it is quite conceivable that older people may do grocery shopping less frequently compared to younger people.

Secondly, due to its unprecedented character, the Corona Crisis had a unique heterogeneous effect on prices of certain goods. Within days, some sectors were shut down (e.g. travel) which led to a market breakdown or a dramatic fall in prices. Other sectors experienced a price surge that was never seen before (e.g. medical devices). In a sense, the shock turned any equilibrium of supply and demand upside-down (Armantier et al., 2020). In such a unique environment, expenditure patterns are forced to change. Especially, for the youngest and the oldest age group, a different expenditure pattern may be justified. As shown in figure 6.1, the old age group spends relatively more money on medical healthcare. This category has experienced a surge in prices (Binder, 2020). In comparison, the youngest group spends more on Travel. With travel restrictions, they were unable to do so. Given that the BLS only publishes the 2019 expenditure tables, we were not able to take a revised spending pattern into consideration. In an interesting attempt to alleviate this problem, Cavallo (2020) updated the official basket weights and thereby calculated a Corona inflation rate. In March 2020, when the pandemic hit the US, both headline inflation and Corona inflation decreased significantly. However, the Corona index only decreased half as strong (e.g. in April -0.09% vs. -0.69%) indicating that a revised spending pattern indeed has explanatory power. Furthermore, in a St. Louis FED blog report, McCracken (2021) offers a very vivid example for revised spending pattern with Food at Home. On the aggregate level, this category had a weight of 7.6 % when the official CPI-based inflation across 2020 was calculated. However, with the social restrictions in place, the true value should be around 4 percentage points higher.

[4] The authors used the *Nielsen Consumer Panel* with more than 90,000 households and survey data from *Chicago Booth Expectations and Attitudes Survey* which both are not publicly available.

6.2 Hypothesis II: Personal lifetime experience

Given that age-specific inflation rates could not explain the divergence across the two margin age groups, we formulated a second hypothesis. In the related work chapter, we referred to a growing strand of literature that focuses on the past experience of an individual (compare section 2.4.2). Pioneers on this are Malmendier and Nagel (2016) with their adjusted learning model. The learning model states that "individuals overweight inflation experienced during their lifetimes" (Malmendier and Nagel, 2016, p. 1). Following Malmendier and Nagel (2016), a similar approach was conducted for German consumers by Goldfayn-Frank and Wohlfart (2020) who show that East Germans expect higher inflation, most likely due to higher experienced inflation rates after the German re-unification. Furthermore, the learning model has already been adapted to explain the expected development of house prices or gas prices (Binder & Makridis, 2020; Kuchler & Zafar, 2019; Severen & Van Benthem, 2019). Albeit its high explanatory power in financially stable times, the current selection of learning models does not examine the consequences of shocks on inflation expectations specifically. However, Malmendier and Nagel (2016) have already shown that the Great Depression had a long-lasting impact on stock market participation. Similarly, the oil crisis and the recession thereafter have been dramatic and memorable for many individuals but the literature does not focus on such incidents specifically. In the years 1973 and 1974, the price of imported crude oil quadrupled and the traditional explanation for this rise is a negative shock to the supply of oil (Hamilton, 2003). Both mentioned shocks were undeniably very memorable and at the same time very different in their nature as prices moved in opposite directions. Accordingly, we formulate our second hypothesis.

H2: The heterogeneity across age groups exists due to experienced past crises which shape the interpretation of future crises.

Thus, we add another important facet to the learning model, namely experienced shocks. We follow the general idea of Malmendier and Nagel (2016) and overweight experienced crises in comparison to those crises that did not happen during the lifetime of the individuals. In addition, we apply a unique approach to control for the fact that not all crises have impacted the economy to the same extent. Our approach relies on the Business Cycle Dating published by the National Bureau of Economic Research and macroeconomic variables provided by FRED (compare chapter 3.1).

6.2.1 Methodology

In detail, we structure our approach as follows:

1. Identify relevant shocks
2. Create a vector of shock-specific weights based on macroeconomic figures
3. Construct a vector that depicts the average six-month change of the year-on-year inflation rate during the shock periods
4. Determine personal experience rule and accordingly form dummy vector
5. Calculate shock-specific variable based on previous steps
6. Run OLS-Regression with shock-specific inflation rates as an explanatory variable

Step 1: Identify relevant shocks

Section 3.6 introduced the three crises that were in our special interest. We increase our scope to all crises since 1950 in order to cover most of the crises during the lifetime of the old individuals. Again, we follow the Business Cycle Dates[5] to identify crises periods. According to the National Bureau of Economic Research, we denote the start month of a crisis as $peak$ and the end month as $trough$. As the Corona Crisis is still ongoing and unprecedented in its nature, we exclude it from the experience sample. Consequently, the sample consists of ten recession periods ranging from six months (early 1980s recession) up to 18 months (GFC) and an average duration of 11.1 months.

[5]Retrieved from: https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions

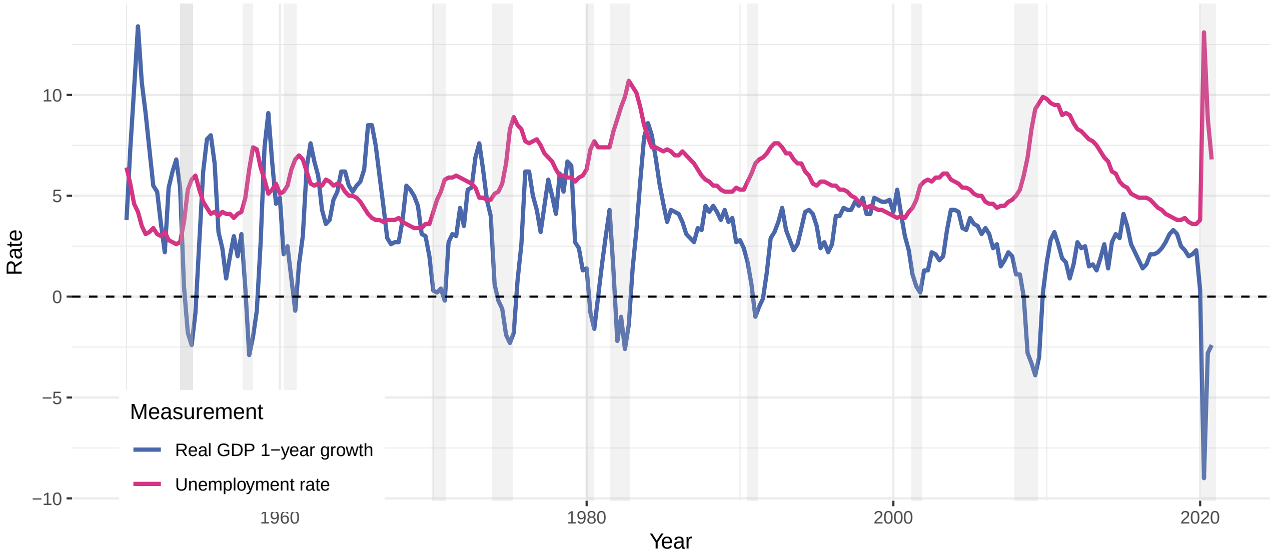

Fig. 6.4: Unemployment rate and one-year real GDP growth rate since 1950

Step 2: Create a vector of shock-specific weights based on macroeconomic figures

After we have specified the crisis periods, we turn to the challenge of classifying crises according to their severity. Severity can be proxied by the magnitude of declining economic activity and rising unemployment (McCallum, 1988). Consequently, real GDP and the unemployment rate fall into our focus. Figure 6.4 illustrates the development of both variables. We observe that one-year real GDP growth rate falls during recession times (shaded areas) below the zero threshold and quickly recovers to values slightly above zero. The unemployment rate, on the other hand, rises during a recession and usually peaks around the time of the $trough$. Subsequently, the unemployment rate takes a long time to recover.

Generally, we observe a permanent increase in unemployment in all past recession periods, while real GDP appears more volatile (compare figure 6.4). Moreover, the higher available frequency on FRED of the unemployment rate enables a more accurate approach. Ultimately we determine the weight for crisis k. As a consequence, we rely on the unemployment rate to determine the shock-specific weight w_k even though the GDP is considered as "the single best measure of aggregate economic activity".[6]

$$w_k = \frac{UNRATE_{trough} - UNRATE_{peak}}{UNRATE_{peak}} \tag{6.4}$$

[6] https://www.nber.org/research/business-cycle-dating

Tab. 6.3: Input variables hypothesis II

$peak$	$trough$	Duration	w_k	$dg12Pshock_k$
Jul 1953	May 1954	10	1.27	0.08%
Aug 1957	Apr 1958	8	0.80	-0.11%
Apr 1960	Feb 1961	10	0.33	-0.01%
Dec 1969	Nov 1970	11	0.69	0.05%
Nov 1973	Mar 1975	16	0.79	1.73%
Jan 1980	Jul 1980	6	0.24	1.73%
Jul 1981	Nov 1982	16	0.50	-1.72%
Jul 1990	Mar 1991	8	0.24	0.57%
Mar 2001	Nov 2001	8	0.28	-0.64%
Dec 2007	Jun 2009	18	0.56	-1.11%

Thus, we consider the growth rate of the unemployment rate as shock weight. We find factors ranging from 0.24 to up to 1.27 (compare table 6.3).

Step 3: Construct a vector that depicts the average six-month change of the year-on-year inflation rate during the shock periods

We follow the thought to incorporate six month changes of the actual inflation rate into our baseline regression in order to explain the impact of a crisis. However, we refrain from identifying one key date or month and consider instead the simple moving average of all months that lie in the time frame from $peak$ until $trough$ month. Therefore, the variable $\Delta g12Pshock$ is calculated as follows:

$$\Delta g12Pshock_k = \frac{\sum_{t=peak}^{trough} g12P_t - g12P_{t-6}}{through - peak - 1} \tag{6.5}$$

As a result, we attain a vector of revision variables that describe the direction and the average development of the headline inflation rate of each crisis. The simplified interpretation is that negative factors represent a demand shock and positive factors a supply shock (Mankiw & Taylor, 2017). Consequently, the factor for the 1973 oil crisis is positive and indicates increased prices, while the GFC is characterised by a fall in prices on average $dg12Pshock_GFC = -1.11\%$. Table 6.3 contains a full list of all derived revision factors and information gathered in steps 1 to 2.

Step 4: Determine personal experience rule and accordingly form dummy vector

As we follow Malmendier and Nagel (2016) and overweight experienced shocks, we implement a strict rule to determine which crises contribute to an individual's experience. Every crisis during which an individual was at the $trough$ date at least 18 years old counts as an *experienced* crisis. All crises which do not fulfil this threshold do not count into the experienced shocks. The only exception is made for all individuals who were 17 or younger during the GFC, to whom we assign the same factor as to all those who were already exactly 18 at that time. For computation simplification, we only incorporate years. Accordingly, the rule to determine the individual's crisis weight $p_i(k)$ is set as follows:

$$p_i(k) = \begin{cases} 1, & \text{if } trough_{year,k} - cohort_i \geq 18 \\ 0, & \text{otherwise} \end{cases} \tag{6.6}$$

where $trough_{year,k}$ is the end year of a recession k and $cohort_i$ is the birth year of individual i.

Step 5: Calculate shock-specific variable based on previous steps

Subsequently, we attain the shock-specific crisis variable $\Delta g12Pshock_i$. Step 2 to 4 described the main ingredients for this. As the first crisis in the consideration period started 1953 and the last crisis of interest 2007, the variable is calculated as follows:

$$\Delta g12Pshock_i = \frac{\sum_{i=1953}^{2007} \sum_{k=1953}^{2007} p_i(k) \quad w_k \quad \Delta g12Pshock_k}{\sum_{i=1953}^{2007} \sum_{k=1953}^{2007} p_i(k) \quad w_k} \tag{6.7}$$

Accordingly, we match a consumer that was born in 1936 (or earlier) and experienced all crises in our sample the weighted average inflation revision rate of all crises. This value is approximately 0.055%. By contrast, we allocate to an individual who has only experienced the GFC a shock variable amount to around -1.110%.

Step 6: Run OLS-Regression with shock-specific inflation rates as an explanatory variable

Subsequently, we include the individual shock variable into our regression model. Even though we rejected the elaborated hypothesis in the previous section, we build on a model incorporating both, an age-specific revision variable that represents present experience as it provides higher explanatory model to the model (compare section 6.1.3). Furthermore, we include the shock-specific revision variable that accounts for past experience.

$$pi\_p4.rev_i = \beta_1 \Delta g12Page_i + \beta_2 male + \beta_3 college + \beta_h agegroup_i^h + ln.inc_i + \beta 4 \Delta g12Pshock_i + \Delta u_i \tag{6.8}$$

6.2.2 Results

Tab. 6.4: Hypothesis II regression output[7]

	Dependent variable:					
	pi_p4.rev					
	All outputs below refer to the Corona Crisis period					
	Baseline		Hypothesis I		Hypothesis II	
agegroup[18,25]	-1.460^{**}	-1.721^{**}	-1.579^{**}	-1.842^{***}	-1.085	-1.312^{*}
	(0.654)	(0.668)	(0.658)	(0.673)	(0.776)	(0.787)
college	-0.350	-0.206	-0.348	-0.204	-0.348	-0.200
	(0.266)	(0.282)	(0.266)	(0.282)	(0.266)	(0.282)
ln.inc		-0.382^{**}		-0.383^{**}		-0.393^{**}
		(0.165)		(0.165)		(0.165)
$\Delta g12P$	-0.427^{*}	-0.415^{*}				
	(0.231)	(0.234)				
$\Delta g12Page$			-0.450^{**}	-0.450^{**}	-0.449^{**}	-0.448^{**}
			(0.217)	(0.219)	(0.217)	(0.219)
$\Delta g12Pshock$					1.100	1.199
					(0.914)	(0.922)
Constant	0.010	4.342^{**}	-0.030	4.292^{**}	0.698	5.206^{**}
	(0.562)	(1.913)	(0.559)	(1.911)	(0.824)	(2.036)
Observations	1,556	1,526	1,556	1,526	1,556	1,526
R^2	0.014	0.018	0.015	0.019	0.016	0.020
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

As the constructed shock variable is only valid for the most recent Corona crisis, we refrain from running the model for previous crises and include instead a comparison of already discussed models, namely regression models 4.11 and 6.3. This facilitates the discussion of the impact of past experience. Accordingly, regression output table 6.4 reports the results.

We make three main observations. First, the newly implemented shock-specific revision variable does not have a significant impact on the revised short-term inflation expectations. Secondly, all other variables excluding the age groups have not significantly changed to the model developed in hypothesis 2. Thirdly, the heterogeneous pattern of the age groups partly vanishes. In that sense, we find only

[7] Only significant dummy coefficients on a 5% are reported. We refer to the appendix for the entire regression output.

little evidence that the age group (18,25) react differently to the reference group. The difference of the reference group and the oldest age group even disappears. Considering the p-values of the chi-square hypothesis tests for independence underline this new finding. Indeed, the corresponding p-value for the margin age group is 0.215 now and we clearly reject independence between the two factors. This is a tremendous difference to the baseline regression and the regression performed in the course of hypothesis 1. Here we failed to reject the null hypothesis on a 1% significance level. Consequently, the two margin age groups were independent from each other. In general, we do not find as much independence as in previous models when incorporating experienced crises. Remarkably, we prove a certain independence for age groups that are not too far apart in terms of age. In conclusion, we shed light on age-specific effects in the revision of inflation expectations during uncertain time by incorporating lifetime experiences in our model. This suggests that consumers extrapolate from their own experience when forming inflation expectations which is consistent to Kuchler and Zafar (2019). In the next section, our results and this extrapolation will be discussed thoroughly.

6.2.3 Discussion

We consider crises as part of personal lifetime experience if the individual was sufficient old enough at any point of a past crisis. So, if an individual finds himself in sound economic times but then a severe crisis leads to market turmoil, unemployment and financial uncertainty, this incidence may not be forgotten for the rest of his life. This argumentation follows the learning model research (Kuchler & Zafar, 2019; Malmendier & Nagel, 2016) that shows that the severeness of past experiences substantially impacts inflation expectations in the later life. On this, further research by Binder and Makridis (2020) found that the oil crises of the 1970s still influence how consumers, who lived through these episodes, interpret gas prices as signals about the overall direction of the economy. We follow this idea by including the facet in our model, and manage to explain observed age group differences. Therefore, we at least partially confirm our developed second hypothesis. The more intuitive reason for this lies in a closer look at the experienced crises. On the one hand, according to our assumption, everybody that was born after 1973 only experienced a crisis in which the average inflation rate changed negatively (compare table 6.3). Consequently, the younger age group associates shocks with negative revisions. On the other hand, most of the crises until 1980 were characterized by increasing inflation rates. Thus, individuals that were at least 48 year old in 2020 do form their expectations slightly differently. Ultimately, the significant independence of some age groups indicates that we do potentially miss to catch the personal weight of the crises. The reason for this is that we do observe this pattern now only for groups that are not too far apart in terms of age. We do prove the long-lasting impression of experienced shocks on inflation expectations by looking at the interpretation of the Corona Crisis. Other authors do emphasize the long-lasting effects of the Corona Crisis itself. Kozlowski et al. (2020) formulate a theoretical model that incorporates consumers' belief dynamics. In that sense, consumers update their shock expectations if they experienced an extreme, negative shock to the economy during their lifetime. The authors describe this as "scarring effect" (Kozlowski et al., 2020, p.2). Malmendier and Shen (2021) take up this idea and investigate it by building on the synaptic tagging hypothesis which suggests strong evidence that personal experience changes the way we think about the world. Neuropsychological synaptic tagging or emotional tagging (Dolan, 2002) deviates from saving memories rationally since incisive personal experiences are rewired in such way that they do have a higher impact on for example expected inflation than past macroeconomic conditions. Indeed, Malmendier and Shen (2021) find that dynamics in the consumption behaviour are not solely due to present labor-market adjustments, but there is also an indelible memory of crises that disrupted the labor-market in the past. In a similar fashion, Federal Open Market Committees are influenced by past experiences even though they have the required expertise and the adequate information (Malmendier et al., 2021). In this light, our approach and especially our findings appear fundamental when considering future crisis as we do account for labor-market adjustments by incorporating the unemployment rate. To put this in perspective, individuals who experienced the Corona Crisis will always remember how the unemployment rate peaked in April 2020 around 15% which corresponded to an increase of over 300% within one month. Figure 6.4 also impressively illustrates this fact and shows that the GDP fall by nine per cent in the second quarter of 2020 compared to the previous year. The underlying scarring effect is indisputable.

7 Conclusion

7.1 Summary of results

7.1.1 Descriptive regression results

The presented demographic patterns in section 3.5.1 were validated by performing an OLS regression. Thus, we are able to confirm three main findings.

First, we show that both headline inflation and core inflation at the time of the interview are significantly positively related to inflation expectations. Over the whole sample period, headline inflation has a higher explanatory power. Secondly, we show that substantial heterogeneity across demographic subgroups in our crisis subset exists. The variables male, college and age are significant regressors in our descriptive regression. Thirdly, after splitting the age variable into a broad set of staggered age groups, we show heterogeneity in responses across age. During the whole crisis subset, all groups below 45 years report lower inflation expectations. During the Corona Crisis, the youngest age group reports negative inflation expectation and the oldest age group positive ones. The difference between the two adds up to around 230 basis points.

The three results from above answer our first two sub-questions by showing which demographic characteristics have explanatory power to describe the formation of inflation expectations and whether there exists general heterogeneity in responses.

7.1.2 Baseline regression results

We make use of the rotating panel characteristic of the MSC and built revision variables to answer our third sub-question. Thereby, we isolate the effects of crises on inflation expectation while allowing individuals-specific interpretation. Our results comprise of two findings.

First, there is no significant heterogeneity for the two categorical variables *male* and *college* with respect to revised inflation expectations. For example, women do not revise their inflation expectation to a larger extent than men and, therefore, both genders interpret crises similar. Secondly, the youngest age group adapts their inflation expectations negatively compared to the selected reference group while the oldest age group revise their inflation expectations in the opposite direction (albeit not significant) during the Corona Crisis. Employing additional hypotheses test that the independence of the two margin age groups is significant and underlines a huge difference to all other crises. Indeed, we do not find heterogeneity among all age groups for the GFC and the Dot-Com Crisis does not show an obvious pattern.

With the results of the first difference regression, we answered the first part of our research question. While gender and college had no significant explanatory power during the three crises, different age groups revise their inflation expectation differently in the Corona Crisis. The youngest age group lowers inflation expectations 172 basis points more than the reference group at a significant level of five per cent. Furthermore, the two margin age groups react significantly different to most of the other age groups. To explain this observed heterogeneity and to complement our answer to the research question, we tested two hypotheses on the role of personal experience.

7.1.3 Hypotheses results

The past and present personal experience has not been extensively incorporated in the model so far. So, we computed the change of age-specific inflation rates. Adding this variable as an independent variable to our first-difference regression model does not remove the found significance of the youngest age group. In fact, the age group (18,25) reports an even more negative coefficient which is significant at the 5% level. Similar to the change in the headline inflation rate, during the Corona Crisis, there is a negative relationship between age group specific inflation rate and inflation expectation. Therefore, the first hypothesis is rejected as the significance remains.

Incorporating past experience with regard to shocks in form of a shock-specific inflation rate sheds some light on the reason for the heterogeneity among age groups. Indeed, we eliminate most of the significant differences among age groups. In addition, the observed pattern of the outstanding margin age groups nearly completely disappears. The shock factor itself does have a positive but not significant impact on inflation expectations. With the testing of both hypotheses, we answer our last two subquestions and complement the answer to the overall research question. Indeed, the concept of personal experience can (at least partly) explain potential heterogeneity in interpretation.

7.2 Implications and Further Research

The results in this paper open new avenues of research and policy-making. This chapter is meant to wrap up our findings. We elaborate on the implications of substantial heterogeneity across individuals, especially across different age groups, in inflation expectations. The implications are divided into implications for policy-makers and into implications for academia as suggestions for further research.

7.2.1 Implications for policy-makers

There are several implications for central banks which all build on the same principle which is that consumer surveys have information content that should not be ignored. In a nutshell, consumer surveys comprise the presence of substantial heterogeneity in inflation expectations across consumers. Further, this heterogeneity has a significant impact on the interpretation of macroeconomic shocks. Not only shocks may be interpreted differently, also many economic decisions on the household level are affected. This gives central bankers and policymakers sufficient reasoning to rethink their macroeconomic models, especially how inflation expectations enter these models. We introduced the Euler equation (2.1) at the beginning of this thesis. It shows that policymakers can stimulate current demand through consumption by raising consumer inflation expectations. If the Euler equation continues to incorporate rational expectations and all individuals are treated identically, this may have adverse implications for policymakers. If all individuals are assumed to expect inflation as the young age groups during the Corona Crisis (that is to have lower inflation expectation), consumption and, hence, aggregate demand decreases. In contrast, if macroeconomic models assume that expectations are similar to the ones from the older generations, the real interest rate decreases and consumption increases. Both assumptions require distinct policy measures. Therefore, the implication for central banks is to incorporate the detected heterogeneity into their policies. If they are unsuccessful in doing so, the causality between inflation expectation and consumption may begin to falter. Eventually, this may have potential consequences on the effectiveness of monetary policy and may prevent central banks from achieving their objectives of stable prices and maximum employment.

A possible implementation to counter the consequences of this implication concerns their voice to the general public (Coibion et al., 2020). In most advanced economies, central banks' communication channel only target financial markets and not consumers. A revised communication strategy could be e.g. a layered one that treats consumer and financial markets differently. To even go one step further, it may be wise to treat consumer subgroups differently. New communication strategies could be implemented along two dimensions. The first dimension concerns the type of information provided. Recent evidence suggests that when households are supplied with appropriate and explicit information about inflation, they adjust their beliefs accordingly and revise their inflation expectation very strongly (Armantier, 2016). This strong correlation indicates that there is scope for revised communication strategies for central bankers and, hence, use inflation expectations as a more direct policy tool. By varying the content of the information provided, they have a more direct impact on the formation of expectations. The second dimension concerns the use of information channel. The information treatments could be targeted through social media or targeted ad campaigns (Binder, 2017a). Especially targeting consumers who are in the right tail of the distribution, i.e., those who have a particularly strong upward bias may be adequate. Hereby, policymakers take the heterogeneity across age into consideration. In summary, simple but yet powerful and decisive words as a whatever it takes[1] broke the first grounds in a new era of monetary policy and moved financial markets in dramatic ways. Other research shows that e.g. policy announcements about future VAT increases in Germany moved inflation

[1]Mario Draghi's speech at the Global Investment Conference in London in 2012

expectations and stimulated consumption (D'Acunto et al., 2015). This implicates policymakers can intentionally provide information to consumers and influence whether expectations are to rise or to fall. Depending on their intention, they can emphasize other numerical values (e.g. recent inflation rates) if they want to steer inflation in another direction.

7.2.2 Further Research

In our examination of inflation expectations during economic crises, our findings have a noteworthy implication for academia. With the found heterogeneity in inflation expectation during crises across age groups, we show evidence and emphasize that the broad literature on information expectation is far from complete. How different consumers interpret an economic crisis and how this interpretation can be explained by individual characteristics is still a long way to go. The learning model by Malmendier and Nagel (2016) laid the groundwork to view individuals in all their facets, that is to include its past experiences. Our second hypothesis shows that the heterogeneity across age groups in crises can partially be explained by studying the individuals' experienced past. Unemployment is only one of many possible angles to look at but it offers a great starting point. Even though we were able to construct a categorical variable that shows how consumers interpret a crisis, there is still room for improvements and further advancements. To what extent e.g. parents pass their experiences in crises on to their children remains missing in our specifications. Future research could incorporate the experiences during a crisis (e.g. personal unemployment or loss in income) into the learning model and enhance our findings. Moreover, by relying on big data methods, researchers could receive better data on lifetime experiences. Thereby, questions i.e. "Where was the individual during the crisis and how was its family affected?" can be answered.

The formation process of consumers' inflation expectation can only be fully understood when working with micro-evidence. The MSC, as a large scale consumer survey, was sufficient and adequate for our intentions but given its drawbacks, other data should be drawn upon as well. Therefore, we advise researchers to analyse whether our findings hold in the Survey of Consumer Expectations. With monthly re-questioning, the survey has a larger panel data dimension and therefore a higher number of observations for each crisis period. Besides consumer surveys, we believe that experiments in a laboratory setting entail great information content. In such an environment, an economic crisis or a fall in prices can be simulated and subsequently the decision-making of individuals can be analysed more isolated. A sophisticated combination of consumer surveys and experiments are a further step to answer decisive questions.

7.3 Outlook

The outlook we want to draw is two-folded. On the one side, we point towards the recent increases in inflation in the US and how our surveys may have forecasted this. On the other side, to meet the argumentation and the results of the second hypothesis, we point towards the potential long-lasting impact of the Corona Crisis on individuals.

First and foremost, consumers in the MSC expected inflation to increase to 3.2% over the next 12 months at the onset of the Corona Crisis. This stood in stark contrast to how prices actually have behaved in that time as there was a large drop in inflation down to 0.3%. However, from that time onward, core and headline inflation increase and were reported at around 2.6% in March 2021 (FRED, 2021). The question arises on which grounds the respondents of the MSC reported a rise in expected inflation for next year during the Corona Crisis. Announced policy actions in the US potentially explain this observation. For example, Democrats in January 2021 proposed a $ 1.9 trillion pandemic relief program coupled with additional government spending in form of infrastructure programs (Reuters, 2021). To what extent these programs will be financed by taxes or by extra borrowing remains open. In any case, it will lead to further pressures on inflation. Simultaneously, the prices of commodities are starting to pick up (The Economist, 2021). Moreover, once a sufficient amount of the population received the vaccine, there will be an additional wave of inflation as their spending are likely to exceed the production. There are some voices warning that the economy might overheat. In a recent post, Lawrence Summers[2] argues that the fiscal stimulus leads to either precipitating higher inflation or leads the FED to raise interest rates and thereby pushing the economy toward recession. Statements on such scenarios add fuel to the media fire and might bear some truthfulness. In any scenario, there is a risk that consumer's inflation expectations become self-fulfilling.

[2]Former US Treasury Secretary under the Obama administration

Secondly, the potential long-term effects of the Corona Crisis on young individuals may be severe. Besides experiencing the GFC, followed by the Great Recession, they again find themselves in a financially unstable environment. Much like older individuals, who are argued to be "stuck in the 70s" (Binder & Makridis, 2020) or young individuals in Japan who have "grown up without ever having experienced inflation" (Diamond et al., 2019, p.2), the youngest age group may form their inflation expectation in the future based on their memories of the GFC and Corona Crisis. This means that the two crises have strong predictive power for future decisions. "These individuals will tend to act as if a crisis were really likely to happen again, because that is what they have seen in their lives. And they will adjust their behaviour and their decisions accordingly." (Malmendier, 2020). How this adjustment takes place in the real economy on an individual level remains to be seen.

Both sides of our outlook conflate into a common scenery to round of the presented metaphor from the introduction. Besides the continuous use of unconventional monetary policy tools, the Corona Crisis coupled with large government spending has led the tiger to awake. It may be the first time since the young individuals hear the roar of the tiger in the midst of the otherwise peaceful-sounding jungle. Scared by its presence, they expect it to have a severe impact on the equilibrium of their habitat. In contrast to this, older individuals have not forgotten how to live with the tiger among them.

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Appendices

.1 Michigan Survey of Consumers

We provide here the list of variables from the Michigan Surveys of Consumers that we used in the course of this paper. The order is according to the available codebook respectively questionnaire. The survey data can be found at: https://data.sca.isr.umich.edu/. For further explanations of the questions we refer to the questionnaire (https://data.sca.isr.umich.edu/fetchdoc.php?docid=24776). In addition to the variables listed here, we have screened all the available ones.

Variable	**Question**
CASEID	Case Identification Number
YYYYMM	Survey Year & Month
YYYYQ	Survey Year & Quarter
YYYY	Survey Year
ID	Interview ID
IDPREV	Previous ID
DATEPR	Previous Date
PAGO	"We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better or worse off financially than you were a year ago?"
PEXP	"Now looking ahead –do you think that a year from now you (and your family living there) will be better off financially, worse off, or just about the same as now?
INEX	"During the next 12 months, do you expect your (family) income to be higher or lower than during the past year?" And "By about what percent do you expect your (family) income to increase during the next 12 months?"
RINC	"During the next year or two – do you expect that your (family) income will go up more than prices will go up, about the same, or less than prices will go up?"
BAGO	"Would you say that at the present time business conditions are better or worse than they were a year ago?
BUS12	"Now turning to business conditions in the country as a whole – do you think that during the next 12 months we'll have good times financially, or bad times, or what?"

UNEMP	"How about people out of work during the coming 12 months – do you think that there will be more unemployment than now, about the same, or less?"
RATEX	"No one can say for sure, but what do you think will happen to interest rates for borrowing money during the next 12 months–will they go up, stay the same, or go down?"
PX1Q1	"During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?"
PX1Q2	"By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?"
PX1	"During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?" And "By what percent do you expect prices to go up, on the average, during the next 12 months?
PX5Q1	"What about the outlook for prices over the next 5 to 10 years? Do you think prices will be higher, about the same, or lower, 5 to 10 years from now?"
PX5Q2	"By about what percent per year do you expect prices to go (up/down) on the average, during the next 5 to 10 years?"
PX5	"What about the outlook for prices over the next 5 to 10 years? Do you think prices will be higher, about the same, or lower, 5 to 10 years from now?" And "By what percent per year do you expect prices to go up, on the average, during the next 5 to 10 years?"
INCOME	"Now, thinking about your total income from all sources (including your job), how much did you receive in the previous year?"
YTL10	Income Percentiles (Bottom 10 Percent)
YTL90	Income Percentiles (Top 10 Percent)
YTL50	Income Percentiles (Above/below Median)
YTL5	Income Percentiles (Quintiles)
YTL4	Income Percentiles (Quartiles)
YTL3	Income Percentiles (Terciles)
AGE	Age of Respondent
BIRTHM	"What is the month and year of your birth?"–MONTH
BIRTHY	"What is the month and year of your birth?"–YEAR

REGION	Region of Residence
SEX	Sex of Respondent
EDUC	Education of Respondent
ECLGRD	"Do you have a college degree?"
EHSGRD	"Did you get a high school graduation diploma or pass a high school equivalency test?"
ECGRADE	"What is the highest grade of school or year of college you completed?"

Tab. .1: MSC variables

.2 Hypothesis Testing

In the course of our regression analyses we performed hypothesis testing in order to test the independence of age groups. In the following, we list all corresponding chi-squared based p-values for performed models including $ln.inc$. We do refrain from showing models without the incorporation of $ln.inc$ because we did not find any significant differences. The left top cell indicates the period, the sections the corresponding model.

.2.1 Descriptive Regression Analysis

2000 - 2020	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
(25,30]	0.0209	/									
(30,35]	0.6544	0.0461	/								
(35,40]	0.3192	0.0004	0.1168	/							
(40,45]	0.0012	0.0000	0.0090	0.2920	/						
(45,50]	0.0513	0.0000	0.0001	0.0119	0.1375	/					
(55,60]	0.0005	0.0000	0.0000	0.0053	0.0804	0.8066	/				
(60,65]	0.0002	0.0000	0.0000	0.0024	0.0438	0.5962	0.7698	/			
(65,70]	0.0000	0.0000	0.0000	0.0001	0.0040	0.1427	0.2094	0.3322	/		
(70,75]	0.0001	0.0000	0.0000	0.0008	0.0149	0.2606	0.3548	0.5057	0.8285	/	
(75,80]	0.0015	0.0000	0.0002	0.0129	0.0971	0.6189	0.7536	0.9287	0.5025	0.6486	/
(80,100]	0.0091	0.0000	0.0018	0.0602	0.2856	0.9511	0.8064	0.6450	0.2358	0.3400	0.6388

Tab. .2: p-values Descriptive Regression Analysis (2000 - 2020)

DOT	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										
(25,30]	0.8374	/									
(30,35]	0.5253	0.6651	/								
(35,40]	0.0144	0.0184	0.0294	/							
(40,45]	0.0211	0.0272	0.0450	0.8214	/						
(45,50]	0.3191	0.4162	0.6768	0.0625	0.0947	/					
(55,60]	0.1778	0.2362	0.3885	0.2550	0.3377	0.6113	/				
(60,65]	0.1105	0.1431	0.2249	0.7663	0.8810	0.3426	0.5929	/			
(65,70]	0.1932	0.2510	0.3980	0.3556	0.4491	0.5962	0.9390	0.6624	/		
(70,75]	0.9524	0.8068	0.5338	0.0280	0.0383	0.3506	0.2092	0.1283	0.2185	/	
(75,80]	0.9875	0.8762	0.6178	0.0506	0.0670	0.4332	0.2738	0.1678	0.2768	0.9471	/
(80,100]	0.2726	0.3406	0.4848	0.5503	0.6344	0.6473	0.8976	0.7681	0.9467	0.2816	0.3309

Tab. .3: p-values Descriptive Regression Analysis (DOT)

GFC	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										
(25,30]	0.6890	/									
(30,35]	0.7822	0.8686	/								
(35,40]	0.5217	0.8253	0.6629	/							
(40,45]	0.3365	0.5887	0.4124	0.7130	/						
(45,50]	0.5113	0.8427	0.6629	0.9604	0.6254	/					
(55,60]	0.5357	0.8653	0.6919	0.9385	0.6196	0.9731	/				
(60,65]	0.3832	0.6573	0.4780	0.8030	0.8943	0.7273	0.7141	/			
(65,70]	0.9223	0.5388	0.6272	0.3181	0.1294	0.2752	0.3070	0.1611	/		
(70,75]	0.3521	0.5867	0.4363	0.7021	0.9368	0.6358	0.6255	0.8500	0.1737	/	
(75,80]	0.8724	0.8078	0.9174	0.6317	0.4266	0.6326	0.6546	0.4768	0.7614	0.4303	/
(80,100]	0.0527	0.0988	0.0498	0.1008	0.1424	0.0650	0.0671	0.1137	0.0088	0.2098	0.0638

Tab. .4: p-values Descriptive Regression Analysis (GFC)

C19	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										
(25,30]	0.3794	/									
(30,35]	0.9330	0.4235	/								
(35,40]	0.7691	0.5158	0.8365	/							
(40,45]	0.2551	0.8096	0.2871	0.3489	/						
(45,50]	0.3206	0.9072	0.3588	0.4353	0.9027	/					
(55,60]	0.3069	0.9793	0.3480	0.4267	0.8018	0.9147	/				
(60,65]	0.0610	0.4095	0.0737	0.0861	0.5697	0.4902	0.3366	/			
(65,70]	0.5883	0.6423	0.6536	0.8025	0.4498	0.5507	0.5606	0.1143	/		
(70,75]	0.5664	0.6968	0.6262	0.7630	0.5028	0.6035	0.6246	0.1547	0.9468	/	

(75,80]	0.3243	0.9258	0.3657	0.4474	0.8818	0.9801	0.9367	0.4658	0.5629	0.6186	/
(80,100]	0.0020	0.0223	0.0025	0.0027	0.0353	0.0298	0.0133	0.0644	0.0034	0.0052	0.0265

Tab. .5: p-values Descriptive Regression Analysis (C19)

.2.2 Baseline Regression

DOT	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										
(25,30]	0.4397	/									
(30,35]	0.4934	0.1071	/								
(35,40]	0.2370	0.0294	0.5599	/							
(40,45]	0.1745	0.0173	0.4311	0.8387	/						
(45,50]	0.4539	0.8998	0.0780	0.0135	0.0065	/					
(55,60]	0.6547	0.7052	0.1979	0.0605	0.0367	0.7604	/				
(60,65]	0.7645	0.3246	0.7973	0.5007	0.4158	0.3287	0.4802	/			
(65,70]	0.2915	0.0622	0.6058	0.9589	0.9156	0.0477	0.1124	0.5255	/		
(70,75]	0.9803	0.4741	0.5666	0.3165	0.2493	0.4970	0.6731	0.8002	0.3550	/	
(75,80]	0.8512	0.4015	0.7241	0.4558	0.3785	0.4184	0.5709	0.9271	0.4790	0.8790	/
(80,100]	0.0857	0.0198	0.1861	0.3245	0.3792	0.0170	0.0337	0.1844	0.3832	0.1119	0.1652

Tab. .6: p-values Baseline Regression (DOT)

GFC	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										
(25,30]	0.4159	/									
(30,35]	0.9327	0.3892	/								
(35,40]	0.4164	0.9245	0.3726	/							
(40,45]	0.2956	0.9288	0.2326	0.8162	/						
(45,50]	0.3644	0.9423	0.3076	0.9706	0.8186	/					
(55,60]	0.5646	0.6782	0.5454	0.7055	0.4906	0.6325	/				
(60,65]	0.5862	0.6419	0.5717	0.6609	0.4415	0.5788	0.9524	/			
(65,70]	0.8519	0.4098	0.9060	0.3897	0.2235	0.3054	0.5830	0.6123	/		
(70,75]	0.6771	0.6159	0.6923	0.6360	0.4609	0.5735	0.8744	0.9115	0.7486	/	
(75,80]	0.8746	0.4989	0.9251	0.5073	0.3753	0.4576	0.6852	0.7114	0.9995	0.8008	/
(80,100]	0.9131	0.4308	0.9741	0.4270	0.2890	0.3660	0.5994	0.6246	0.9397	0.7302	0.9506

Tab. .7: p-values Baseline Regression (GFC)

C19	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										

(25,30]	0.0470	/									
(30,35]	0.2244	0.4206	/								
(35,40]	0.2046	0.3806	0.9825	/							
(40,45]	0.0790	0.7959	0.5774	0.5350	/						
(45,50]	0.3421	0.3129	0.8173	0.8215	0.4372	/					
(55,60]	0.0131	0.8224	0.2505	0.1982	0.5947	0.1672	/				
(60,65]	0.0367	0.8216	0.4781	0.4224	0.9434	0.3420	0.5831	/			
(65,70]	0.0342	0.8581	0.4537	0.4008	0.9076	0.3259	0.6290	0.9560	/		
(70,75]	0.2348	0.3233	0.9019	0.9127	0.4662	0.8964	0.1549	0.3487	0.3299	/	
(75,80]	0.2839	0.3569	0.8970	0.9075	0.4977	0.9188	0.2023	0.3981	0.3777	0.9851	/
(80,100]	0.0005	0.0872	0.0144	0.0099	0.0499	0.0095	0.0931	0.0358	0.0402	0.0071	0.0114

Tab. .8: p-values Baseline Regression (C19)

.2.3 Hypothesis I

GFC	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										
(25,30]	0.3269	/									
(30,35]	0.8070	0.3780	/								
(35,40]	0.3224	0.9182	0.3647	/							
(40,45]	0.2127	0.9263	0.2213	0.8052	/						
(45,50]	0.2400	0.9962	0.2572	0.8878	0.9007	/					
(55,60]	0.3702	0.7833	0.4314	0.8417	0.6157	0.6975	/				
(60,65]	0.3840	0.7482	0.4514	0.7991	0.5659	0.6456	0.9546	/			
(65,70]	0.6075	0.5004	0.7568	0.5013	0.3076	0.3571	0.5954	0.6234	/		
(70,75]	0.4518	0.7403	0.5453	0.7883	0.5995	0.6658	0.9176	0.9541	0.7200	/	
(75,80]	0.5897	0.6610	0.7128	0.6956	0.5435	0.5957	0.7967	0.8245	0.8940	0.8745	/
(80,100]	0.6113	0.5884	0.7485	0.6121	0.4469	0.4979	0.7103	0.7379	0.9512	0.8019	0.9446

Tab. .9: p-values Hypothesis I (GFC)

C19	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										
(25,30]	0.0397	/									
(30,35]	0.1975	0.4219	/								
(35,40]	0.1755	0.3871	0.9904	/							
(40,45]	0.0659	0.8059	0.5700	0.5338	/						
(45,50]	0.2738	0.3520	0.8776	0.8784	0.4777	/					
(55,60]	0.0071	0.7104	0.1956	0.1505	0.5030	0.1492	/				
(60,65]	0.0202	0.9526	0.3824	0.3307	0.8210	0.3049	0.5941	/			

(65,70]	0.0179	0.9993	0.3531	0.3046	0.7757	0.2832	0.6531	0.9409	/		
(70,75]	0.1478	0.4332	0.9392	0.9234	0.5916	0.8095	0.1739	0.3739	0.3447	/	
(75,80]	0.1671	0.5054	0.9022	0.8863	0.6644	0.7854	0.2537	0.4703	0.4382	0.9536	/
(80,100]	0.0002	0.0548	0.0079	0.0052	0.0304	0.0061	0.0724	0.0273	0.0319	0.0056	0.0111

Tab. .10: p-values Hypothesis I (C19)

.2.4 Hypothesis II

C19	[18,25]	(25,30]	(30,35]	(35,40]	(40,45]	(45,50]	(55,60]	(60,65]	(65,70]	(70,75]	(75,80]
[18,25]	/										
(25,30]	0.0395	/									
(30,35]	0.1965	0.4221	/								
(35,40]	0.2773	0.2749	0.7937	/							
(40,45]	0.1207	0.6227	0.7647	0.5518	/						
(45,50]	0.7838	0.1439	0.4218	0.4980	0.2509	/					
(55,60]	0.0875	0.7603	0.6328	0.3994	0.8404	0.1143	/				
(60,65]	0.8078	0.2723	0.5591	0.6275	0.3839	0.9644	0.1917	/			
(65,70]	0.9824	0.2595	0.4924	0.5378	0.3457	0.8282	0.1867	0.6700	/		
(70,75]	0.7033	0.1290	0.2784	0.2885	0.1679	0.4466	0.0635	0.1958	0.3495	/	
(75,80]	0.7393	0.1467	0.3060	0.3222	0.1932	0.4986	0.0836	0.2810	0.4601	0.9323	/
(80,100]	0.2150	0.8795	0.5648	0.4383	0.6496	0.1686	0.6783	0.0639	0.0272	0.0047	0.0101

Tab. .11: p-values Hypothesis II (C19)

.3 Hypothesis

.3.1 Hypothesis I

Expenditure types	Detailed expenditures
Food	Food at home Food away from home
Alcoholic beverages	Alcoholic beverages at home Alcoholic beverages away from home
Housing	Shelter Utilities, fuel, and public services Household operations

	Housekeeping supplies Household furnishings and equipment
Apparel and services	Men and boys Women and girls Children under 2 Footwear Other apparel products and services
Transportation	Vehicle purchases (net outlay) Gasoline, other fuels, and motor oils Electric vehicle charging Other vehicle expenses Public and other transportation
Healthcare	Health insurance Medical services Drugs Medical supplies
Entertainment	Fees and admission Audio and visual equipment and services Pets, toys, hobbies, and playground equipment Other entertainment supplies, equipment and services
Personal care products and services	Personal care products Personal care services
Reading	Newspapers, magazines, newsletters, books, encyclopedia and other sets of reference books, and digital book readers
Education	Tuition, student loans, test preparation and tutoring services, and school supplies
Tobacco products and smoking supplies	Cigarettes, other tobacco products, smoking accessories, and marijuana
Miscellaneous	Miscellaneous fees, lotteries, ad pari-mutuel losses, and miscellaneous personal services
Cash contributions	Cash contributions
Personal insurance and pensions	Life and other personal insurance Pensions and social security

Tab. .12: Detailed expenditure types

Category / Age	Under 25	25 to 34	25 to 34	35 to 44	45 to 54	55 to 64	65 to 75	Above 75
Food and Beverages	17.00%	14.00%	14.00%	13.00%	13.00%	13.00%	14.00%	13.00%
Housing	34.00%	36.00%	35.00%	32.00%	32.00%	35.00%	33.00%	38.00%
Apparel	5.00%	4.00%	4.00%	4.00%	3.00%	3.00%	3.00%	2.00%
Transportation	19.00%	18.00%	17.00%	17.00%	17.00%	15.00%	16.00%	14.00%
Medical Care	2.00%	4.00%	4.00%	5.00%	7.00%	12.00%	12.00%	14.00%
Recreation	5.00%	6.00%	6.00%	5.00%	6.00%	5.00%	6.00%	4.00%
Education and communication	6.00%	2.00%	2.00%	3.00%	2.00%	1.00%	1.00%	1.00%
Other goods and services	12.00%	17.00%	18.00%	20.00%	21.00%	15.00%	15.00%	14.00%

Tab. .13: Decomposition of age-specific inflation basket (2008)

	Dependent variable:			
	pi_p4.rev			
	GFC		C19	
agegroup[18,25]	0.741	1.304	−1.579	−1.842
	(1.394)	(1.493)	(0.658)	(0.673)
agegroup(25,30]	−0.473	−0.414	−0.194	−0.373
	(1.326)	(1.342)	(0.673)	(0.683)
agegroup(30,35]	0.806	0.903	−0.765	−0.944
	(1.181)	(1.193)	(0.652)	(0.664)
agegroup(35,40]	−0.510	−0.268	−0.902	−0.952
	(1.102)	(1.112)	(0.604)	(0.611)
agegroup(40,45]	−0.729	−0.537	−0.529	−0.548
	(0.962)	(0.969)	(0.653)	(0.660)
agegroup(45,50]	−0.585	−0.421	−0.967	−1.054
	(0.951)	(0.956)	(0.667)	(0.676)
agegroup(55,60]	−0.106	−0.043	−0.145	−0.132
	(0.992)	(1.003)	(0.569)	(0.578)
agegroup(60,65]	−0.118	0.013	−0.294	−0.410
	(0.964)	(0.976)	(0.555)	(0.566)
agegroup(65,70]	0.733	0.518	−0.149	−0.372
	(1.034)	(1.050)	(0.562)	(0.576)
agegroup(70,75]	−0.046	0.080	−0.750	−0.895
	(1.171)	(1.187)	(0.589)	(0.601)
agegroup(75,80]	0.248	0.325	−0.849	−0.857
	(1.355)	(1.426)	(0.651)	(0.671)
agegroup(80,100]	0.170	0.437	1.219	1.228
	(1.234)	(1.291)	(0.752)	(0.786)
male	−0.817	−0.747	0.190	0.274
	(0.458)	(0.471)	(0.264)	(0.273)
college	0.291	0.351	−0.348	−0.204
	(0.471)	(0.514)	(0.266)	(0.282)
$\Delta g12Page$	0.770	0.757	−0.450	−0.450
	(0.093)	(0.094)	(0.217)	(0.219)
ln.inc		−0.235		−0.383
		(0.324)		(0.165)
Constant	−1.186	1.188	−0.030	4.292
	(0.829)	(3.575)	(0.559)	(1.911)
Observations	993	963	1,556	1,526
R^2	0.072	0.071	0.015	0.019
Note:		p<0.1;	p<0.05;	p<0.01

Tab. .14: Hypothesis I full regression output

.3.2 Hypothesis II

	Dependent variable:					
	pi_p4.rev					
	(1)	(2)	(3)	(4)	(5)	(6)
agegroup[18,25]	−1.460	−1.721	−1.579	−1.842	−1.085	−1.312
	(0.654)	(0.668)	(0.658)	(0.673)	(0.776)	(0.787)
agegroup(25,30]	−0.125	−0.301	−0.194	−0.373	0.300	0.159
	(0.671)	(0.681)	(0.673)	(0.683)	(0.788)	(0.796)
agegroup(30,35]	−0.698	−0.874	−0.765	−0.944	−0.271	−0.412
	(0.650)	(0.662)	(0.652)	(0.664)	(0.770)	(0.780)
agegroup(35,40]	−0.840	−0.889	−0.902	−0.952	−0.563	−0.585
	(0.602)	(0.610)	(0.604)	(0.611)	(0.666)	(0.673)
agegroup(40,45]	−0.468	−0.486	−0.529	−0.548	−0.207	−0.200
	(0.651)	(0.658)	(0.653)	(0.660)	(0.706)	(0.712)
agegroup(45,50]	−0.954	−1.039	−0.967	−1.054	−0.990	−1.082
	(0.667)	(0.677)	(0.667)	(0.676)	(0.667)	(0.677)
agegroup(55,60]	−0.171	−0.156	−0.145	−0.132	−0.083	−0.067
	(0.570)	(0.578)	(0.569)	(0.578)	(0.571)	(0.580)
agegroup(60,65]	−0.329	−0.443	−0.294	−0.410	−0.880	−1.047
	(0.556)	(0.567)	(0.555)	(0.566)	(0.738)	(0.749)
agegroup(65,70]	−0.194	−0.414	−0.149	−0.372	−0.980	−1.284
	(0.563)	(0.577)	(0.562)	(0.576)	(0.891)	(0.908)
agegroup(70,75]	−0.810	−0.953	−0.750	−0.895	−1.578	−1.801
	(0.589)	(0.601)	(0.589)	(0.601)	(0.906)	(0.921)
agegroup(75,80]	−0.959	−0.965	−0.849	−0.857	−1.658	−1.746
	(0.652)	(0.672)	(0.651)	(0.671)	(0.936)	(0.958)
agegroup(80,100]	1.103	1.113	1.219	1.228	0.434	0.365
	(0.753)	(0.786)	(0.752)	(0.786)	(0.996)	(1.029)
male	0.191	0.275	0.190	0.274	0.191	0.279
	(0.264)	(0.273)	(0.264)	(0.273)	(0.264)	(0.273)
college	−0.350	−0.206	−0.348	−0.204	−0.348	−0.200
	(0.266)	(0.282)	(0.266)	(0.282)	(0.266)	(0.282)
ln.inc		−0.382		−0.383		−0.393
		(0.165)		(0.165)		(0.165)
$\Delta g12P$	−0.427	−0.415				
	(0.231)	(0.234)				
$\Delta g12Page$			−0.450	−0.450	−0.449	−0.448
			(0.217)	(0.219)	(0.217)	(0.219)
$\Delta g12Pshock$					1.100	1.199
					(0.914)	(0.922)
Constant	0.010	4.342	−0.030	4.292	0.698	5.206
	(0.562)	(1.913)	(0.559)	(1.911)	(0.824)	(2.036)
Observations	1,556	1,526	1,556	1,526	1,556	1,526
R^2	0.014	0.018	0.015	0.019	0.016	0.020
Note:				$p<0.1$;	$p<0.05$;	$p<0.01$

Tab. .15: Hypothesis II full regression output