

Consumer memory, inflation expectations and the interpretation of shocks*

Daniel Tobias Heim[†] Jonas Strauch[‡] Gabriel Züllig[§]

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Abstract

We study the role of consumers' memories of business cycles when they interpret new macroeconomic data. Individuals who recall co-moving inflation and unemployment from experience are more apt to adjust their inflation expectations in line with supply shocks. We illustrate this behavior during the first wave of the Covid-19 pandemic, which bears elements of both demand- and supply-side shocks, with opposing pressures on inflation. Those cohorts who have experienced more supply shocks increase their inflation expectations more, even conditional on the personal financial situation or differences in consumption baskets. They also devote less attention to demand-side channels and are more likely to have heard news about restricted supply. The shock memory pattern is confirmed in 40 years of survey data. Furthermore, previous supply shock exposure increases the attention to central bank news and the real effects of monetary policy.

JEL classification: D83, D84, E31, E32, E71

Keywords: experience, attention, narrative, Covid-19, business cycles, behavioral macroeconomics, panel data

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[†]E-mail: danielheim97@googlemail.com

[‡]E-Mail: jonas.strauch@googlemail.com

[§]University of Oxford and Danmarks Nationalbank, E-mail: gabriel.zullig@economics.ox.ac.uk

1 Introduction

How does inflation evolve during recessions? An economist’s answer will be: ‘It depends, of course, most prominently on the nature of the shock that causes the recession.’ Laypeople will give widely different answers. In this paper, we argue that their answers depend crucially on inflation developments experienced during *past* business cycles. Individuals with a vivid memory of how unemployment and inflation co-moved positively expect inflation to increase more in light of a negative supply-side shock than consumers for whom business cycle downturns always coincided with decreasing inflation. Arguing that consumers devote more attention to mechanisms they experienced to be important for past inflation and business cycles, our results are an application of “associated memory”—a concept from psychology (Kahana, 2012) brought to the attention of economists by Bordalo et al. (2020)—to inflation expectations. While Malmendier and Nagel (2016) have shown that past inflation *levels* play a role for current expectations, we emphasize the relationship between *changes* of inflation (and its drivers) during past business cycles and *revisions* of inflation expectations that cannot be explained by learning from experience alone.

We study individual revisions of expected inflation in the rotating panel of the Michigan Survey of Consumers (MSC) between 1981 and 2021. Individuals are asked about their inflation expectations twice with a gap of 6 months, allowing us to calculate individual revisions and estimate how they correlate with the shocks that have happened during the six months in between.

For each person at the time of the interview, we construct statistics we refer to as “shock memory”, which summarize the degree of co-movement between inflation and unemployment during the person’s previous lifetime. The prototypical measure is the slope of the reduced-form Phillips curve in the time series the person has experienced based on her age, downweighting information in the distant past using the decreasing-gain learning function calibrated as in Malmendier and Nagel (2016). However, all results are robust to specifications that overemphasize periods of recessions and equalize the weights given to historical data points. The final, most complex measure for memory is the historical decomposition of inflation into demand, supply, and monetary policy shock components in a structural VAR of more than 100 years of data. The shocks are identified with sign restrictions à la Fry and Pagan (2011). If the supply-shock component correlates strongly with the aggregate inflation rate over a person’s lifetime, we define this person’s memory to be shaped by supply shocks.

The revisions of expected inflation are then regressed on the three structural shocks from the VAR. Our results indicate that consumers by and large correctly interpret these macroeconomic shocks in terms of the directional effect on inflation. This is true even after controlling for the movements in actual inflation during the first and second interview in the MSC.

The panel setup allows us to exploit the fact that people of different ages have different levels of shock memory over time. Our main finding is that shock memory is a highly significant factor in shaping the responses of inflation expectations to shocks. In particular, people who have experienced many supply shocks in the past increase their inflation expectations substantially more when confronted with a negative supply shock in the present, regardless of the definition of memory. Our estimations do not show a differential response to demand shocks, which drive inflation, unemployment and the nominal policy rate in the same direction.

The third shock of interest revolves around monetary policy decisions. In our estimations, individual inflation expectations fall in response to monetary contractions. Most importantly, however, individuals whose memories are by one standard deviation more determined by supply shocks react at least 25 percent stronger to monetary policy shocks. Our estimates are economically and statistically significant across the different definitions of memory and alternative monetary policy shocks taken from the literature. Using the MSC respondents' rationale for reported attitudes towards purchases of durable goods, we find that the disproportionate response of those with higher supply shock exposure is coming from higher attention to news about monetary policy, rather than purchasing attitudes conditional on the perceived interest rate. Consumers are more aware of central bank decisions when supply shocks used to dominate in the past. We relate this to rationally inattentive consumers in a world where the central bank does not perfectly stabilize inflation in light of supply disturbances.

[Kamdar \(2019\)](#) argues that these are detrimental to consumer welfare in two ways—both in terms of unemployment risk and prices—and thus supply-side signals receive disproportionate attention when information acquisition is costly. If the central bank is not perfectly committed to keeping inflation stable, consumers who experienced supply shocks needed to pay attention to both the evolution of prices and the nominal interest rates to determine the real rate relevant for their consumption decisions. As a consequence, they are more informed about the monetary policy stance and update their inflation expectations more strongly if it is changed. The rationale is similar in [Maćkowiak and Wiederholt \(2015\)](#): When the central bank fights inflation aggressively, less attention is being given to aggregate conditions.

We introduce and illustrate the role of shock memory during the unprecedented events around the surge of Covid-19 in the spring of 2020. The Covid shock is an ideal case study, first and foremost, because it contains both demand and supply components. Lockdowns in China and Europe along with travel restrictions led to supply-chain disruptions which can manifest in higher prices, as is shown by [Meier and Pinto \(2020\)](#). Equally, decreasing labor supply and perceived shortages at the point of sale can have price-increasing consequences. At the same time, demand-side factors such as high unemployment, low confidence and precautionary motives depress demand. At least in the

early stages of the pandemic, it was not *a priori* clear which effect would eventually dominate.¹

Second, the outbreak of the novel coronavirus in the United States and the stay-at-home orders were the most life-upending pandemic shock in a century, and thus hardly anyone alive could rely on past experiences of pandemics.² Finally, the shock was large and drew much attention within a narrow time period, allowing us to study revisions of repeatedly interviewed individuals around March 2020. [Armantier et al. \(2021\)](#) find that perceived uncertainty of inflation forecasts of households spiked during that time.

We unearth a number of facts from individual revisions of inflation expectations around that time that are in line with consumers relying on their previous experience of inflation fluctuations. First, inflation expectations decreased as Covid-19 arrived, though only for a brief period of time, meaning that the public at large expected demand-depressing effects to dominate.

Second, there are quantitatively large differences in mean inflation revisions between age cohorts. Individuals born after the early 1970s lowered inflation expectations significantly more than individuals in their late 40s or older. Strikingly, this cutoff aligns with the cohorts of individuals who never in their adult lifetime have experienced a recession during which inflation did not decrease significantly. The magnitude of the effect is, depending on the confounding factors we control for, between 1 and 2 percentage points at the mean and thus large relative to the actual level and change of inflation. In particular, the result is robust to controlling for people's outlook of the economy and their personal finances as well as for differences in their perceived inflation rates due to personal shopping experiences, which we account for by approximating consumption baskets for different demographic groups. We find supporting evidence in two alternative datasets.

Third, logistic regressions and nonparametric quantiles show a more nuanced profile: The lowest propensity to increase inflation expectations during Covid-19 and the largest downward-revisions are shown by the people around the age of 40 and the youngest respondents around 20. People above the age of 75 were significantly more likely to increase their inflation expectations. The latter are individuals who have lived through

¹Several empirical and quantitative applications find a non-negligible role of supply-side shocks for the fluctuations in output, inflation, or their expectations during this time ([Baqaee and Farhi, 2021](#), [Bekaert et al., 2020](#), [Meier and Pinto, 2020](#), [Bottone et al., 2021](#)), even though the actual inflation rate fell by 2 percentage points between February and May of 2020. Year-over-year core inflation (excl. food and energy sectors) fell by 1.1 percentage points. [Guerrieri et al. \(2020\)](#) derive conditions under which sectoral supply-side shocks alone can trigger demand shortages that eventually weigh stronger on the aggregate price level. [Balleer et al. \(2020\)](#) find a spike in the dispersion of planned price changes within sectors in the early days of the pandemic.

²The first wave of the Covid-19 pandemic caused around 130.000 deaths. For reference, the entire Spanish flu pandemic of 1918/19 caused an estimated 675.000. Of course, other infectious diseases circulated in the meantime: the 2009 H1N1 flu (estimated 12.000 deaths), the 1968 H3N2 influenza virus (estimated 100.000 deaths) and the 1957/58 H2N2 influenza virus (estimated 116.000 deaths). However, none of these pandemic events were followed by measures as strict as stay-at-home orders or lockdowns. Source: [Center for Disease Control and Prevention](#).

the stagflation period.

Fourth, we use data on which types of news respondents report to have heard recently, thereby relating differences in recall of news to the attention of mechanisms. The same age groups that lower their inflation expectations the most are those who say they have heard about demand-side factors such as consumer confidence, and they have the lowest propensity to support their choices with words that indicate an understanding of supply-side shocks. The opposite is true for consumers who have lived through the 1970s, when inflation was closely linked to bad economic news. All the evidence is consistent with our notion of “shock memory”: If a person has experienced economic fluctuations driven by supply shocks, she is more likely to interpret the events unfolding in 2020 as another inflationary supply shock. In contrast, millennials who by and large have learned that inflation is predominantly demand-driven interpreted the 2020 recession as mostly disinflationary.

Related literature Our paper contributes to the literature on the formation of inflation expectations using survey data and the interpretation of new information about the economy (e.g. [Coibion and Gorodnichenko \(2015\)](#), [Coibion et al. \(2019\)](#), [Roth and Wohlfart \(2020\)](#)) more broadly. A common finding is that new information is noisy or costly to obtain and hence people’s beliefs underreact to new shocks.

Our main finding about the interpretation of supply shocks by those who have experienced them in the past supports results by [Andre et al. \(forthcoming\)](#), who treat individuals with hypothetical shock vignettes and ask them about their subjective forecasts of unemployment and inflation. When asked to make statements about an oil price shock, respondents with memory of the OPEC crisis are more likely to emphasize the cost component of the hypothetical shock. We provide further evidence of such an effect and, by generalizing to several definitions of memory (or “subjective macroeconomic models”) and different contexts in time, support the idea of associative recall by [Bordalo et al. \(2020\)](#) for business cycles.

A number of other behavioral biases of consumers’ inflation expectations have been established. The literature robustly finds across space and time that households overweight information about the *levels* of inflation rates they can remember ([Malmendier and Nagel, 2016](#), [Madeira and Zafar, 2015](#), [Conrad et al., 2021](#)), which is true even for the policy-makers themselves ([Malmendier et al., 2021](#)). We extend the idea of learning from experience to past and current changes of inflation (expectations), which cannot be explained by learning from experience alone.

A second consistent finding is that personally (or locally) experienced price changes contribute excessively to people’s understanding and forecast of inflation ([Kuchler and Zafar, 2019](#), [D’Acunto et al., 2021](#), [Angelico and Giacomo, 2020](#)). We show that not only current and local, but also past and macro experiences matter for human behavior. [Kontny and Yin \(2021\)](#) show that attention is related to action: Having heard news is

positively correlated with the probability of changing ones views. We tie this behavior directly to experienced macroeconomic shocks.

Our results emphasize the expectation channel of monetary policy and also contribute to the literature assessing people’s understanding of monetary policy (Carvalho and Nechio, 2014, Drager et al., 2016, Coibion et al., 2019, 2020b). We provide another rationale for why attention to central bank news or the real effects of monetary policy are time-varying.³ According to all our estimates, individuals born after 1970 will increase their inflation expectations less to a monetary easing today than their parents or grandparents—not because they are younger *per se*, but because they have different narratives about business cycles and a different allocation of attention.

The paper is organized in the following way: Section 2 uses survey data to estimate (heterogeneous) revisions of short-run inflation expectations at the onset of the Covid-19 pandemic. In Section 3 we propose the “shock memory” effect to rationalize how agents interpret shocks and discuss its validity in light of the empirical evidence. We test and discuss the implications for the effectiveness of monetary policy through the expectation channel in Section 4 and summarize our conclusions in Section 5.

2 Heterogeneous revisions of inflation expectations during the first pandemic wave

2.1 Data

Michigan Survey of Consumers (MSC) Our main data source is the Michigan Survey of Consumers (hereinafter: MSC), which 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. At least 500 telephone interviews are held each month and in the latest surveys, between 500 and 700 representative households of the U.S. population participated. In the survey, three areas are addressed: assessment of personal financial situation, opinion over the economy in general, and lastly demographics. The main component of our analysis is based on respondents’ expectations of short-term (12 months) inflation. To retrieve such information, the participants are asked two questions about expected changes in prices over the next year. While question A12 requires a qualitative response, question A12b requires a quantitative statement about the expected change:

A12.) “During the next 12 months, do you think that prices, in general, will go up, or

³For example, Berg et al. (2021) find a stronger consumption response for older individuals. For most—but not all—of the time in our sample, the memory of older consumers is determined more by supply shocks. However, other contributions come to the opposite conclusion. Wong (2019) finds larger monetary policy responses among young people. However, the estimates become insignificant if cohorts are controlled for. It is in line with our results that the consumption response to monetary policy shocks can be cohort-, rather than age-specific (in a non-monotonic fashion).

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?”

We define as the household’s one-year ahead inflation expectation π_{it}^e the numeric answer to question A12b.), taking into account the directional answer of A12.). However, it must be noted that we do not know at what time within the month the interview was conducted.⁴ A key characteristic of the MSC is its rotating sample design: After the first interview, up to half of the participants are re-interviewed six months later. This allows us to define revisions of inflation expectations from January 1981 forward, $\Delta\pi_{it}^e \equiv \pi_{it}^e - \pi_{i,t-6}^e$, which is the main outcome variable we work with. Conveniently, this captures idiosyncratic heterogeneity in the level of inflation expectations (Madeira and Zafar, 2015) and allows us to focus on dynamic updating within a single individual instead. We winsorize individual inflation expectation revisions at the 1st and 99th percentile ($\pm 20\%$). Sampling weights provided by the MSC are used for all descriptive figures and regression results throughout the paper.

Individual inflation experiences Consumers overestimate the importance of price developments in their personal consumption basket when they make inflation forecasts (D’Acunto et al., 2021). To counter this bias, we approximate individual inflation rates for demographic groups allocated by age and income by combining information on the Bureau of Labor Statistics’ Consumer Expenditure (CE) Survey and series on inflation for different items. The CE is a widely used source for expenditure data as it incorporates a sample size of approximately 7,500 households quarterly. For 6 different age groups and 7 splits of household income, we collect data on the average mean expenditure share in 2019. This share shows how much a household spends on average for a particular item in proportion to their total expenditure. We summarize 25 category of goods (“food at home”, “food away from home”, etc.) for which we can link year-over-year growth rates of sub-indices of the CPI.⁵

Aggregate data Finally, we complete our analysis with the help of publicly available time series. Unless explicitly states otherwise, we use year-over-year growth rates of the monthly consumer price index incl. food and energy and the level of the civilian

⁴Therefore, when we compare predicted future inflation to the current actual rate, we lag the actual inflation rate by one month. CPI headline numbers are typically published by the BLS a few weeks into the subsequent month. Therefore, most households surveyed in a month could have access the inflation rates of the previous month, but not of the month during which they answer the survey.

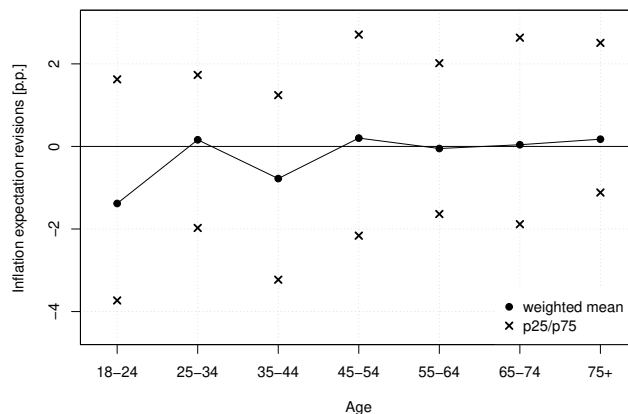
⁵Linking expenditure shares and CPI series closely follows Johannsen (2014) and Lauper and Mangiante (2021) and the series descriptions are contained in Table A1. D’Acunto et al. notice that the frequency of purchase of a category of products matters has slightly higher predictive power than the expenditure weights we use. Data availability constrains us to using the latter.

unemployment rate.⁶

2.2 Results

Figure 1 shows three moments of the distribution of inflation expectation revisions of individuals between their first and second interviews, namely the weighted mean (using the MSC survey weights) and the 25th and 75th percentile. The subsample includes all individuals whose first response was given no later than February of 2020 and whose second interview was conducted between March and July of the same year. We divide individuals i in 7 distinct age groups $g_a(a)$.

Figure 1: Individual inflation expectation revisions



Notes: Differences of inflation expectations between first and second interview ($\pi_{it}^e - \pi_{i,t-6}^e$ for t between March and July 2020. The sample contains 1277 individuals with inflation expectations in both periods (1477 in total). Because π^e is given in integers, the percentiles are adjusted for the relative distance to the closest nominal value. All moments are computed using MSC-provided sampling weights.

Even though the dispersion of both expected inflation and their revisions is large, a recognizable pattern emerges. Cohorts under the age of 25 and those around 40 decrease their inflation expectations on average. People around 50 and the oldest age groups have on average (the most) positive revisions. The pattern is at least as strong at the tails, with a difference between 35-44 and 45-54-year-olds of more than 1% at the 25th and almost 1.5% at the 75th percentile.

The difference might be confounded by a multitude of factors we can control for. We estimate the following regression with the change in inflation expectations as the outcome variable.

$$\Delta\pi_i^e = \alpha + \beta_{g(a)}g(a_i) + \Gamma X_i + u_i \quad (1)$$

⁶The mnemonics CPIAUCSL and UNRATE are retrieved from the Federal Reserve Bank of St. Louis Database. For the construction of shock memories, we will augment the data with historical observations by Ramey and Zubairy (2018) reaching back to 1915 computed. Exact sources and transformations are described in Section 3.1.

$g(a)$ is an indicator function for the age groups shown in Figure 1, omitting the groups of 45-to-55-year-olds. The first column of Table 1 contains the estimates of β , showing that without controlling for any other differences across age groups, generation Z individuals (less than 25 years old in 2020) lowered their inflation expectations by 1.58 percentage points more than the base group. The response of people between 35 and 44 is statistically significantly more negative, too. At the same time, the estimates for older groups tend to be slightly negative but not statistically significant. Columns (2) to (4) iteratively add further control variables to the vector X . The literature has discussed several dimensions along which inflation expectations differ: women, individuals with less education and lower incomes tend to expect higher price increases (D’Acunto et al., 2020, Bryan and Venkatu, 2001, Bruine de Bruin et al., 2010) but also have higher revisions between the first and second interviews (Madeira and Zafar, 2015). We control for these and other demographic factors that might have played a role in the perception of the shock by the first wave of Covid-19. We include dummies for gender, for the 6 levels of education reported in the MSC, for the region of residence, whether or not the household owns a home and stocks.⁷ Because both economic risk during the spring of 2020 and support-measures implemented by authorities strongly varied by pre-crisis income (Ganong et al., 2020), we also control for the income decile before the pandemic, i.e. household income at the time of the first and income growth between the first and second interviews. If anything, controlling for these variables makes the gradient more pronounced, despite the smaller sample size. A second set of control variable concerns the perceived nature and size of the economic and health shock. From the very start of the pandemic, it was clear that older individuals were more vulnerable to the novel coronavirus and the salience of the health risk might go hand in hand with individuals’ perception of magnitude of the recession. At the same time, controlling for the change in the real economic outlook and the personal economic sentiment can catch some of the occupation-specific exposure to the healthcare crisis and partial lockdowns that might correlate with age. Several studies indicate that consumer pessimism is not negatively or even positively correlated with the overestimation of inflation (Ehrmann et al., 2017, Kamdar, 2019, Roth and Wohlfart, 2020), and absorbing both the level and the change in sentiment will allow us to compare consumers with a similar assessment of the economy. Given the answers to the MSC, we control for whether the economy as a whole (a) and the personal financial situation (b) is better or worse than a year ago, whether the economy will experience good/bad times over the coming 12 months (c), as well as the revisions of (b) and (c) between the first and second interviews.⁸ The differences for the youngest and middle-aged cohorts tend to become larger conditional on their assessment

⁷Hanspal et al. (2020) show that stock market exposure had very small effects on spending in the early stages of the pandemic.

⁸(a) and (b) have 3 ordinal answer options (“worse now”, “same” and “better now”) while (c) has 5. The revision variables consider all possible combinations as categorical variables.

Table 1: Inflation expectation revisions during Covid-19 by age group

	(1) Simple	(2) + demogr.	(3) + outlook	(4) Baseline	(5) + future π_{ay}
Age group 18-24	-1.58** (0.67)	-1.88** (0.82)	-2.35*** (0.88)	-2.31*** (0.88)	-2.13*** (0.88)
— 25-34	-0.04 (0.52)	-0.65 (0.61)	-0.80 (0.67)	-0.88 (0.67)	-0.90 (0.67)
— 35-44	-0.98* (0.51)	-1.30** (0.58)	-1.85*** (0.61)	-1.86*** (0.62)	-1.94*** (0.62)
— 55-64	-0.25 (0.49)	-0.52 (0.56)	-0.67 (0.60)	-0.70 (0.60)	-0.74 (0.60)
— 65-74	-0.16 (0.50)	-0.39 (0.59)	-0.81 (0.64)	-0.88 (0.65)	-0.90 (0.65)
— 75+	-0.03 (0.55)	0.25 (0.67)	-0.24 (0.76)	-0.28 (0.77)	-0.34 (0.77)
Demographic contr.	No	Yes	Yes	Yes	Yes
Econ. outlook contr.	No	No	Yes	Yes	Yes
Lagged infl. (age/ income-specific)	No	No	No	Yes	Yes
Future inflation (—)	No	No	No	No	Yes
Observations	1.277	1.004	871	871	871
$H_0 : \beta_a = 0 \forall a$, F(p)	1.80(0.10)	1.92(0.07)	2.39(0.03)	2.32(0.03)	2.28(0.03)
R^2	0.01	0.03	0.07	0.07	0.07

Notes: Dependent variable: Revision of 12-month ahead inflation expectations relative to 6 months ago $\pi_{it}^e - \pi_{i,t-6}^e$ for t between March and July 2020. Main independent variable: Dummies for 6 age groups (base of 45-54-year-old interviewees omitted). Demographic control variables: Gender, education, region, homeownership, stockholdership, household income (10 deciles), income growth rel. to $t-6$ (demographic controls). Economic outlook controls: Economy better, same or worse than year ago; personal finances better, same or worse than year ago; economy experiences good or bad times (with qualifications, all categorical variables), and revisions between first and second interview (all categorical variables). Individual inflation controls: $\pi_{ay,i,t-1}^3$ and $\pi_{ay,i,t-1}^3 - \pi_{ay,i,t-7}^3$, where subscripts ay denote inflation rates for age- and income groups (see Appendix A). Future inflation denotes the ay -specific level and change of 3-months ahead inflation rates for the respective.

Significance levels: *** 1% ** 5%, * 10%.

of the real economy.

When making inflation expectations, households rely on their own (shopping) experiences to grasp the concept of inflation (D’Acunto et al., 2021) and differences in inflation rates across goods and services will thus result in differences in experienced inflation rates. Although the survey question explicitly asks for percent changes of “prices in general”, individual notions of inflation might induce differences in the target the household attempts to forecast and/or differences in the inflation experience the household draws on to predict the future. Column (4) controls for the change of the age- and income-specific inflation rates describes in Section 2.1 between the two interviews, as well as the level of inflation in the three months prior to the interview to control for the fact that household develop inflation expectations in adaption to what they recently experienced in supermarkets (Angelico and Giacomo, 2020). This is our baseline specification. Both

people aged less than 25 as well as those in the group between 35 and 45 lower their inflation expectations significantly more than everyone else. The mean revision of the 45-55-year-olds is the highest, although it is not statistically significantly different from the groups that are older. Notice that a test of whether all age group-specific coefficients are jointly equal to zero is rejected.

In the fifth column, we additionally control for the change in inflation rates *during* the pandemic, i.e. the three months ahead of the second interview. The reason is that it is those inflation rates that really differ across demographic groups: Figure A1 in the appendix shows that inflation rates for representative consumption baskets of the young tend to fall more. Those of the poor old tend to fall the least.⁹ However, estimates are similar when we control for these forward-looking inflation rates.

Multinomial logit regressions Between a fifth and a fourth of respondents did not change their inflation forecasts altogether even as the unemployment rate reached its post-WWII peak. We show that the age gradient is present also at the extensive margin of adjustment. We estimate the following multinomial logistic model for a discrete set of three outcomes:

$$\begin{aligned} \ln \frac{Pr(\Delta\pi_i^e < -1)}{Pr(|\Delta\pi_i^e| \leq 1)} &= \alpha^- + \beta_{g(a)}^- g(a_i) + \Gamma^- X_i + u_i^- \\ \ln \frac{Pr(\Delta\pi_i^e > 1)}{Pr(|\Delta\pi_i^e| \leq 1)} &= \alpha^+ + \beta_{g(a)}^+ g(a_i) + \Gamma^+ X_i + u_i^+ \end{aligned} \quad (2)$$

The base outcome is that the change of expected inflation is no more than 1 percentage point in absolute terms, which is the case for 42% of interviewees with the baseline specification of controls X used in Table 1. In Table 2 we report the average marginal treatment effects implied by the estimated β^- and β^+ for four age groups relative to the slightly larger base group consisting of people aged 45 to 74.

The disproportionate downward-revision of the young is predominantly driven by the group of individuals between 35 and 44. They have a lower propensity to increase expected inflation, rather than a (significantly) higher propensity to decrease. The opposite holds for the oldest cohorts: Relative to the base group, they are only half as likely to decrease their expectations of inflation but significantly more likely to increase it. The age group of the 75-year-olds and older is also statistically significantly more likely to keep their expectations unchanged. This could be in line with learning from

⁹Disproportionately high exposure to food at home (high inflation) and low exposure to gas prices (low/negative inflation) are the prime reasons for this. Of course, consumption baskets relying on weights from 2019 give a potentially distorted picture of inflation experiences during the pandemic. Cavallo (2020) estimates updated weights and concludes that the true disinflation was weaker than measured in the CPI because people relied less on goods with price decreases (transportation) and more on those with relatively high inflation rates (food at home). We refrain from any corrections of the consumption basket at this stage because we do not believe it is going to significantly alter the relative inflation rates across demographic cohorts.

Table 2: Extensive margin of expectation revisions

Multinomial logit of (4)	(a) Pr(Decrease)	(b) Pr(Unchanged)	(c) Pr(Increase)	(c)-(a)
Age group 18-24	0.69 (8.23)	11.63 (7.67)	-12.31* (7.38)	-13.00
— 25-34	-1.34 (5.59)	8.52 (5.18)	-7.18 (5.25)	-8.52
— 35-44	6.40 (4.24)	6.78 (4.51)	-13.18*** (5.80)	-19.58
— 75+	-19.09*** (6.38)	13.87** (5.80)	5.22 (5.14)	24.31
Demographic controls		Yes		
Economic outlook controls		Yes		
Cons. basket controls		Yes		
Frequencies in base group	35%	33%	32%	
Observations		871		
McFadden R^2		0.06		

Notes: Average marginal treatment effects of age group dummies on three mutually exclusive outcomes: inflation expectations decrease/increase more than 1 percentage point or change only within ± 1 percentage point (base outcome). Estimates based on multinomial logit model (Equation (2)) and multiplied by 100 (to be interpreted as percentage point changes relative to base group). Other control variables equal to specification (4) in Table 1. Standard errors are computed using the delta method. Significance levels: *** 1% ** 5%, * 10%.

experience (Malmendier and Nagel, 2016), where older generations are less surprised by new incoming data than less experienced individuals. At the same time, however, millennials and Gen Z's are also more likely to keep expectations unchanged than the older base group. Learning about the (low) level of inflation from experience alone cannot explain the particular probabilities to adjust inflation expectations presented in Table 2.

Quantile regressions Inflation expectation revisions in the spring of 2020 were very heterogeneous both across but also within generations and even cohorts. Our most flexible approach appreciates this by estimating locally linear quantile models of the following form.

$$Q_\tau(\Delta\widetilde{\pi}_i^e) = \beta(\tau)a_i + u_i \quad (3)$$

where $\Delta\widetilde{\pi}_i^e$ is the residualized change of inflation expectations after controlling for the factors in X . The coefficients are found by minimizing the quantile weighted absolute

values of errors.

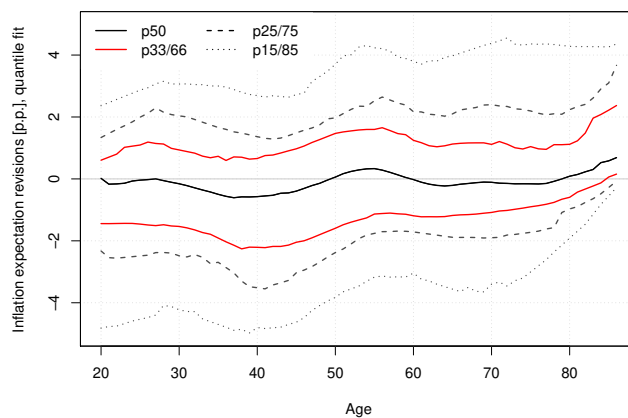
$$\hat{\beta}(\tau) = \underset{\beta(\tau) \in \mathbb{R}}{\operatorname{argmin}} \sum_i w_i(a_i, a_0) \rho_\tau(\Delta \widetilde{\pi}_{it}^e - \beta(\tau)(a_i - a_0)) \quad \text{for } a_0 \in \mathbb{Z} : a_0 \in [18, 90]$$

$$w_i(a_i, a_0) = \phi\left(\frac{a_i - a_0}{h}\right)$$

$$\rho_\tau(u) = u(\tau - 1[u < 0])$$

w_i are kernel weights for different points a_0 on a grid of age levels. ϕ is the normal density and h the kernel bandwidth, which we set to 5 years.¹⁰ ρ_τ is the quantile-weighted absolute loss function (Koenker and Bassett, 1978) and $1[\cdot]$ denotes the indicator function. Figure shows the predicted quantiles $\hat{Q}_\tau = \hat{\beta}(\tau)(a_i - a_0)$ for a range of quantiles. The following two features stand out: First, there is a general upward trend in age further out in the distribution. For the 15th and 95th quantile, the difference between people aged under 25 and over 75 is more than 2 and 1.5 percent, respectively. Second, individuals around age 40 tend to have among the most negative revisions of expectations and people between 50 and 55 among the most positive. This makes the slope between the two age levels particularly steep, and this is true for all quantiles.

Figure 2: Nonparametric quantile regressions



Notes: Fitted values of local linear quantile regressions weighted by age-specific kernels (bandwidth = 5). Dependent variable: Revision of 12-month ahead inflation expectations relative to 6 months ago for t between March and July 2020, residualized for demographic, real economic outlook and age/income-specific basket-weighted inflation.

¹⁰The smoothing parameter is motivated by economic considerations, rather than an optimization of the bias-variance trade-off or particular selection rules (see e.g. Yu and Jones (1998)). Results presented below are robust to different bandwidths.

2.3 Robustness in alternative data sets

We show that the age heterogeneity in inflation expectation revisions is not unique to the MSC by confirming the central result in two more surveys which come with each their particular strengths and weaknesses.

Survey of Consumer Expectations (SCE) The Federal Reserve Bank of New York conducts the Survey of Consumer Expectations, which for our purpose has two distinct advantages relative to the MSC. First, as is shown in Figure 3d, the number of interviews is considerably larger. Second, the respondents are surveyed repeatedly for up to 12 months, which allows to track a single individual’s perceptions over time, but also implies that the stock of unique individuals observed over the first pandemic wave is substantially lower than the number of interviews. Unfortunately, the survey heavily under-samples individuals at the tails of the age distribution. Of the 1,300 answers submitted in March 2020, only 18 are less than 25 and only 76 are at least 75 years of age. These sub-samples are too small to confirm or reject the age-specific pattern in expectation revisions found in Section 2.2 with reasonable statistical certainty. Instead we use the panel of all individuals who answered the survey in February 2020 (time period 0) and at least once more in the 3 months prior or 6 months after and run the following regression:

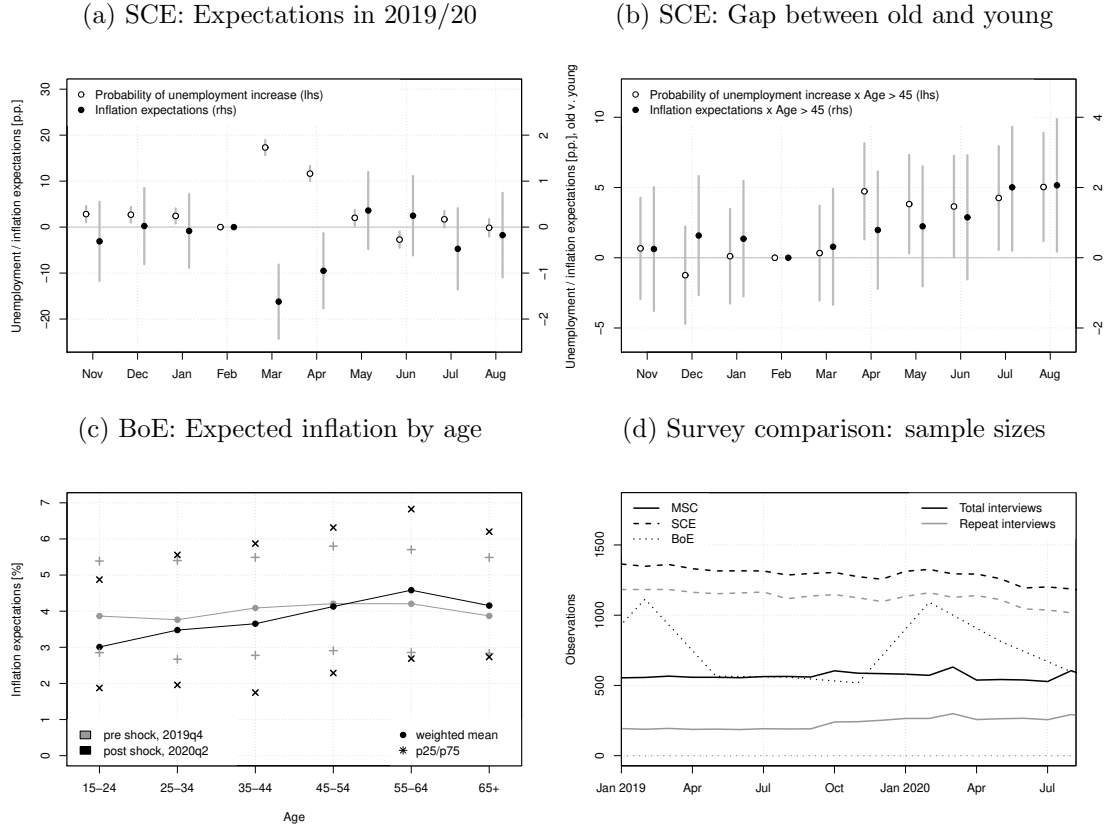
$$\pi_{it}^e = \sum_{\substack{s=t-3 \\ s \neq 0}}^{t+6} \beta_s 1[t = s] + \gamma_i + u_{it} \quad (4)$$

π_{it}^e is the inflation rate expected over the 12 subsequent months.¹¹ We do not have to control for time-invariant covariates since all (observed and unobserved) characteristics are absorbed by the person fixed effect γ_i . Figure 3a shows the vector of estimated β_s ’s, describing the average inflation expectation in month s relative to the pre-shock month of February. The expected disinflation setting in during the month where Covid-19 is declared a global pandemic is estimated to be 1.62 percentage points. In April, the inflation expectations are still 1 percentage point lower relative to February, but the effect quickly subsides and returns to pre-pandemic levels. We re-estimate regression (4) with the subjective probability to an increasing unemployment rate over the subsequent year, which interviewees have to assign at every wave over the 12-month survey period. This likelihood surges by 20 percentage points at the beginning of the pandemic. Taken together, we conclude that for the combined sample of 2,840 individuals, the dominating narrative was that Covid-19 and the lockdowns imposed in March 2020 were a shock to aggregate demand.

At the same time, however, there is considerable heterogeneity of both the inflation

¹¹The questionnaire reads “What do you expect the rate of inflation to be over the next 12 months? Please give your best guess.” A numerical value is given which we winsorize at the 1st (-40%) and 99th percentile (+60%)

Figure 3: Robustness in alternative data sets



Notes: Evidence on the heterogeneity of inflation (and unemployment) expectations with respect to age from two alternative data sources. Panel (a) and (b) take two questions of the Federal Reserve Bank of New York’s Survey of Consumer Expectations, namely the subjective probability of unemployment increasing over the year ahead, and the expected rate of inflation during said period. (a) shows the estimated average developments of answers to both questions at the end of 2019 and first half of 2020 relative to February 2020. (b) plots the estimated difference of revisions for individuals at least 45 years old relative to younger generations. (c) plots the distribution of one-year ahead expected inflation by age group before and after the Covid shock, as measured by the Bank of England/Kantar Inflation Attitudes Survey (BoE). (d) compares the sample sizes of the three surveys. Because the BoE results are published at the quarterly frequency, we divide the number of responses by three to compare to the two monthly publications.

and unemployment response in the Survey of Consumer Expectations, too. Given the data scarcity at the tails, our main objective is to confirm the contrast between younger generations (including millennials) and people aged at least 45 in 2020. We add a respective interaction term to the regression

$$\pi_{it}^e = \sum_{\substack{s=t-3 \\ s \neq 0}}^{t+6} \beta_s 1[t = s] + \sum_{\substack{s=t-3 \\ s \neq 0}}^{t+6} \beta_{s,45+} 1[t = s] \times 1[a_{it} > 45] + \gamma_i + u_{it} \quad (5)$$

and plot the estimates of $\beta_{s,45+}$ in Figure 3b. Given the noise in the data, standard errors are too large to reject the null hypothesis of no difference across groups for most

of the spring. Nevertheless, the estimated differences between individuals under and above 45 increases to 2 percentage points by the summer and becomes statistically significant. These differences are quantitatively meaningful given the overall movements of inflation (expectations) during the period. Additionally, the heterogeneity comes against a backdrop of differences in the real economic outlook. Respondents above 45 have a more pessimistic view on future unemployment throughout the entire period shown. Therefore, their higher inflation expectations are not explained by the perception of a smaller economic shock, but rather of a shock that has more of a supply-side nature where increases in unemployment come with at least some inflationary pressure.

Inflation Attitudes Survey (BoE) Kantar Omnibus conducts face-to-face surveys with adults in the United Kingdom aged 16 years and over on behalf of the Bank of England. Because of its repeated cross-section design (published at the quarterly frequency), we cannot control for individual fixed effects. Figure 3c plots the weighted mean and interquartile range of the *level* of expected inflation over the 12 coming months by age group.¹² Grey markers indicate the distribution during the fourth quarter of 2019, black ones during the second quarter of 2020. Similar to our findings from the MSC, there is a clear distinction in terms of the mean response between individuals below/above age 45/50. The youngest reduce their inflation expectations by almost 1 percentage points over the course of half a year while those with 55 years and more increase them by 0.4. The actual year-over-year CPI inflation rate in the UK decreased by 0.6 percentage points over the respective time period. Again, there are distinct nuances at the tail, with a large mass at the lower end for the young (especially those 35-44 years old) and large increases at the top for the age 55-64 group.

To summarize, we find further evidence of the age heterogeneity in changes of households' expectations of one-year-ahead inflation in a different sample and a different country. Taking its relatively smallest sample size into consideration, we continue to use the MSC because of its rotating panel design and its coverage of a wider age distribution.

3 Memory and the interpretation of shocks

We conjecture that “shock memory” – the (inflationary) nature of shocks an individual has experienced in the past – can explain a significant part of the heterogeneous pattern of inflation revisions observed in 2020. We first describe multiple methods we use to

¹²The second set of questions in the survey starts with “And how much would you expect prices in the shops generally to change over the next twelve months?” with answer options of integer bins from “go down by 5% or more” to “go up by 10% or more”. The age distribution of interviewees is fairly uniform across the categories shown in Figure 3c with the exception of the oldest group which is considerably larger. Notice that the Kantar survey combines the two top age groups in the MSC into one group of 65 years and older. Survey weights ensure that the demographic profile is representative in terms of age, gender, social class, region as well as number of working adults in the household and their labor market status.

measure shock memory, and present them in ascending order of complexity. All methods have in common that they allow the co-movement of economic slack and prices to be time-varying, and thus to be different over the lifetimes of different age cohorts. We contrast them to the slope in inflation expectation revisions. Individuals are more likely to detect the cost-push component of shocks if they have experienced positive co-movement of unemployment and inflation in the past. This is particularly true for a shock as large and unprecedented as Covid-19, but holds more generally as well, as we show in Section 3.3.

3.1 Lifetime co-movement of inflation and unemployment

For the first definition of consumer shock memory, \mathcal{M}^I , we use the typical evolution of inflation during the recessions of a person’s adult lifetime. We follow the NBER’s definition of recessions, which are summarized in Table B1 in the Appendix. The sole focus on recessions acknowledges that times of economic crises are particularly salient in people’s understanding of the economy as attention and demand for more information increase with macroeconomic volatility (Coibion and Gorodnichenko, 2015, Cavallo et al., 2017, Roth et al., forthcoming). Economic narratives can be both a cause and an outcome of business cycle downturns (Shiller, 2017) and as the causes of recessions in the past 100 years have been widely different, so have inflation experiences during these crises and the narratives about them. For 12 out of the 18 recessions preceding Covid-19, the rise in unemployment was accompanied by decreasing inflation rates. Nevertheless, there are large differences over time: During the short post-World War I recession of 1918/19 – which was accompanied but not exclusively caused by the Spanish flu – inflation rates first soared and only strongly decreased after the recession ended. In the 1973-75 recession, higher oil prices pushed up inflation rates by 2 percentage points while the unemployment rate increased by 3.8 percentage points. Similarly, rising oil prices in the summer of 1990 exerted upward-pressure on inflation during the first half of the 1990/91 recession, after which it fell to the pre-recession level. The other most recent economic downturns – the Volcker disinflation period of 1981/82, the burst of the dotcom bubble in 2001 and the Great Recession of 2008/09 – had among the most negative ratios of changes in year-over-year inflation rates and changes in the unemployment rate. We compute this ratio for each recession (see Table B1) and then record, for a household aged a at time t , the mean ratio of all recessions over the adult lifetime weighted by change in the unemployment rate of the respective recession. The results are broadly in line with more rigorously identified supply and demand contributions to each NBER recession by Bekaert et al. (2020).

For the second definition, we account for the fact that memory is fading which leads to the fact that developments in the distant past might be less prominent in their understanding of what a recession entails. The weighting closely follows the decreasing-gain specification

of [Malmendier and Nagel \(2016\)](#), where a person’s learning gain from new information in t is decreasing in age, because an older person has a richer experience of business cycles to draw on. The implied weight a person attributes to an observation $t - s$ periods in the past, can be computed recursively

$$w_{a,t,s} = \begin{cases} \frac{\theta}{a} & \text{if } s = t \\ \left(\frac{a-t+s+1}{a-t+s+\theta}\right) w_{a,t,s+1} & \text{if } s < t. \end{cases}$$

If $\theta > 1$, experiences further in the past are downgraded, and the relative weights are depreciating faster for young people, as is illustrated in [Figure B3a](#). We follow [Malmendier and Nagel](#) by calibrating θ to 3. To compute shock memory \mathcal{M}^{II} , we average the $\frac{\Delta\pi}{\Delta u}$ ratio over a person’s lifetime, weighting not only by the severity of the recession but also with the respective $w_{a,t,s}$ at the time of the end of the recession.

Time-varying Phillips curve Variable memory \mathcal{M}^{III} is defined as the slope of the reduced-form Phillips curve, i.e. the degree to which current year-over-year inflation loads on current unemployment.

$$\pi_t = \alpha + \beta u_t + \xi_t \tag{6}$$

To illustrate the time-variation in β , we have estimated [Equation \(6\)](#) for a 10-year rolling window (see [Figure B1](#) and [Kamdar \(2019\)](#)). The sample data is, as is the case for the following variables, at the quarterly frequency, because it allows us to account for events in memory as far back as 1915.¹³ The long time series are plotted in [Figure B1](#) in the appendix. For most of the sample, the reduced-form estimate is clearly negative, circulating around -0.5. There are notable exceptions, however. Post-WWI, society experienced an adjustment recession to a peacetime economy, the boom of the Roaring Twenties and the Great Depression, during all of which inflation was clearly procyclical. Conversely, the estimated coefficient is positive during the two recessions in the 1970s and in the mid-1990s. It is very close to zero, among others, during the recovery from the Great Recession.

We find age-time-specific estimates of β using weighted-least squares

$$\underset{\alpha, \beta \in \mathbb{R}}{\operatorname{argmin}} \sum_{s=t-a}^{t-1} w_{a,t,s} (\pi_s - \alpha - \beta u_s)^2 \tag{7}$$

$$\mathcal{M}_{at}^{\text{III}} \equiv \hat{\beta} \tag{8}$$

¹³We take quarterly averages of the unemployment rate and the consumer price index of the post-WWII period and augment it with estimates of unemployment and the GDP deflator provided by [Ramey and Zubairy \(2018\)](#). Inflation is defined as the y/y log difference of the quarterly price series because inflation rates are typically reported in deviations from the same period a year ago.

where the weights are computed as above. In words, we use all observations between a person’s birth ($t-a$) and $t-1$ but let more recent data points have more weight in determining the subjective slope of the Phillips curve.¹⁴

Vector autoregression with stochastic volatility and sign restrictions Whether households have experienced inflation to be pro- or countercyclical over the course of their lives depends on the relative strengths of supply shocks they have experienced. In our fourth and final definition of shock memory, we aim to quantify the contribution of supply shocks to fluctuations in inflation. To identify these – alongside monetary policy and other demand shocks – we estimate a vector autoregression of the following form.

$$\Pi(L)Y_t = u_t, \quad E(u_t) = 0, E(u_t u_t') = \Sigma_t \quad (9)$$

Y_t is the vector of endogenous variables featuring the unemployment rate, inflation (q/q), and the short-term nominal interest rate.¹⁵ $\Pi(L)$ are the dynamic coefficients as a function of the lag operator, i.e. $\Pi_1 L + \Pi_2 L^2 + \dots + \Pi_p L^p$ for up to p lags. We use 4 lags for the quarterly model. u_t describes the reduced-form residuals of the regression with a period-specific variance-covariance matrix Σ_t . This heteroskedasticity is important because our sample covers more than 100 years of data. Evidence suggests that time-variation in the structural shocks best describes the swings in macroeconomic volatility (Primiceri, 2005, Sims and Zha, 2006). Implemented by assuming that the variance-covariance matrix can be decomposed into $\Sigma_t = F\Lambda_t F'$, where F is a lower-diagonal matrix with ones on its diagonal, and Λ_t a period specific diagonal matrix with $\text{diag}(\Lambda_t) = (\bar{s}_1 \exp(\lambda_{1t}), \dots, \bar{s}_3 \exp(\lambda_{3t}))$. \bar{s}_i are constant scaling terms and λ_{it} are dynamic processes whose first-order autoregressive coefficient γ we estimate following Jacquier et al. (1994).¹⁶

$$\lambda_{it} = \gamma \lambda_{i,t-1} + \nu_{it}, \quad E(\nu_{it}) = 0, E(\nu_{it} \nu_{it}') = \phi$$

The reduced-form residuals reflect a linear combination of the structural shocks ε_t , which

¹⁴Figure B3b illustrates \mathcal{M}^{III} over time for four distinct age groups, namely a=20, 40, 60 and 80, respectively.

¹⁵We typically use y/y transformations to measure inflation, because this is how it usually is reported in the media and how households think about inflation. In the VAR, this is not required, which is why we use first differences of the quarterly log CPI instead. With respect to the interest rate, FRED mnemonic DTB3 is used post-WWII, to which we link historical 3-month treasury bill rates available in the NBER Macrohistory database and Ramey and Zubairy. It is the series that constrains the starting period to be in 1915, implying that at the start of our sample of inflation expectation revisions (1981), the oldest person has a memory of 66 years.

¹⁶We apply the Bayesian Estimation, Analysis and Regression toolbox and refer the reader to the technical guide on Bayesian VARs with stochastic volatility and random inertia for details of the estimation (Dieppe et al., 2016). More information on the estimation prior are found in Appendix B. See Bekaert et al. (2020) for an application of sign restrictions with heteroskedastic residuals specifically to disentangle supply and demand forces in 2020.

are set identified by means of sign restrictions on the structural impulse response functions Ψ .¹⁷ We disentangle three orthogonal disturbances following the example in [Fry and Pagan \(2011\)](#). Conditional on a cost-push (supply) shock, we require unemployment and inflation to show positive co-movement, and the nominal interest rate controlled by the central bank to go in the same direction. This is opposed to a demand shock, where unemployment and inflation move in opposite ways and the inflation targeting central bank tends to steer the interest rate along with inflation. Finally, the movement of the interest rate distinguishes between monetary policy and other demand shocks. In the former, inflation moves in the opposite direction.¹⁸ The respective restrictions are summarized in [Table 3](#).

Table 3: Identifying assumptions for structural shocks

		Structural shock		
		Demand (ε^D)	Cost-push (ε^S)	Mon. pol. (ε^M)
Effect on	Unemployment	−	+	+*
	Inflation	+	+	−*
	Nom. int. rate	+*	+*	+

Notes: Identifying restrictions for SV-VAR, all required to bind for the first four quarters following the shock. (*) indicates that we do not impose the restriction during the quarter of the shock itself.

Figure [B2](#) in the appendix depicts the time series of the retrieved structural innovations ε_t^D , ε_t^S and ε_t^M , as well as a historical decomposition of inflation developments into its structural sources.¹⁹ The fourth definition of memory is defined as the Pearson correlation coefficient of historical supply shock contributions (denoted π^S) to inflation and

¹⁷More concretely, the algorithm first draws a set of coefficients from the reduced-form model (9), constructs preliminary impulse response functions and multiplies them with the Cholesky factor S of the long-run variance-covariance matrix $\Sigma \equiv \lim_{t \rightarrow \infty} \Sigma_t$, for which it is required that $\gamma < 1$. We then multiply an additionally drawn orthonormal matrix Q and verify if the sign restrictions of [Table 3](#) are satisfied. The eligible set of Q is used to calculate the structural shocks $\varepsilon_t = (SQ)^{-1}u_t$. [Figure B2](#) shows the posterior means of these shocks.

¹⁸[Uhlig \(2005\)](#) finds that this is true even in the absence of a sign restriction on output. This fully disentangles the system. Of course, the sign restrictions of a particular shock are also satisfied if they show the opposite signs of the respective column. Notice that the goal of the estimation is to identify the structural shocks and their contributions to inflation volatility, rather than the shape of the impulse responses as such.

¹⁹Consider that inflation, like any variable in the VAR, can be decomposed into historical contributions by the lagged endogenous variables (deterministic dynamics summarized in d) and the shock components, the latter of which are dissected further. $\Psi_{\pi,j}$ is the j 'th period response of inflation to the structural shocks.

$$\pi_t = d_t + \sum_{j=0}^{t-1} \Psi_{\pi,j} \varepsilon_{t-j} = d_t + \sum_{j=0}^{t-1} \psi_{\pi,j}^D \varepsilon_{t-j}^D + \sum_{j=0}^{t-1} \psi_{\pi,j}^S \varepsilon_{t-j}^S + \sum_{j=0}^{t-1} \psi_{\pi,j}^M \varepsilon_{t-j}^M$$

the observed inflation rate.

$$\hat{\rho}(t, a) = \frac{\sum_{s=1}^t w_{a,t,s}(\pi_s^S - \bar{\pi}^S)(\pi_s - \bar{\pi})}{\sqrt{\sum_{s=1}^t w_{a,t,s}(\pi_s^S - \bar{\pi}^S)^2 \sum_{s=1}^t w_{a,t,s}(\pi_s - \bar{\pi})^2}}, \quad (10)$$

$$\pi_s^S \equiv \sum_{j=0}^{s-1} \psi_{\pi,j}^S \varepsilon_{s-j}^S \quad (11)$$

$$\mathcal{M}_{at}^{\text{IV}} \equiv \hat{\rho}(t, a) \quad (12)$$

$\psi_{\pi,j}^S$ is the effect of a cosh-push shock j periods ago to the current inflation rate. When computing the correlation coefficient, we again apply the adaptive-learning weights to downscale the importance of supply shock contributions in the past. \mathcal{M}^{IV} has the appealing feature that it is bounded by $[-1, 1]$. In a world with only cost-push shocks, all movements of inflation will be determined by supply and the correlation coefficient will be 1 (regardless of how large these shocks are and how the systematic monetary policy response to them is calibrated). According to our shock memory hypothesis, this would imply that agents learn that inflation is mostly supply-driven, i.e. if they observe increasing prices, they will detect it is an adverse supply shock. For the period around the Great Recession, inflation was low overwhelmingly despite, not because of supply shocks. This is in line with evidence of inflationary pressure stemming from the Global Financial Crisis (Gilchrist et al., 2017, Renkin and Züllig, 2021).

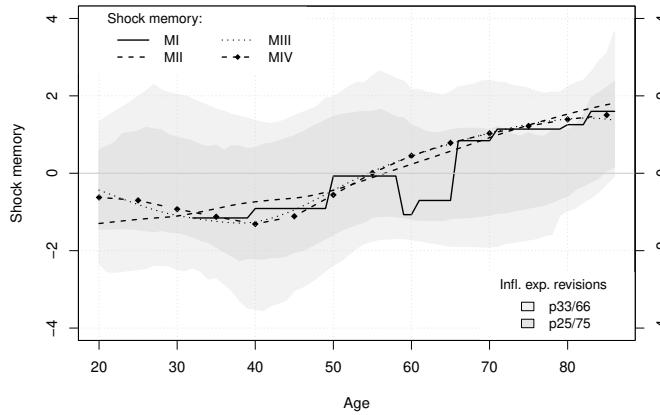
This completes the description of the four shock memory variables we apply to the data.

3.2 Consumers' memory and interpretation of Covid-19

Figure 4 plots the estimated levels of shock memory for individuals at the beginning of 2020. Higher values indicate that during the lifetime of a person with the respective age there was high co-movement of inflation and unemployment, or that inflation was crucially driven by supply rather than demand or monetary policy shocks. For comparability, the measures have been standardized. Superimposed in grey are four of the quantiles of inflation expectation revisions derived in Figure 2.

For 2020, all definitions of shock memory show a clear upward trend, where the people born before the end of the Second World War have the highest values. Not only have these cohorts experienced several recessions during which inflation increased (if only moderately), but the new information from the disinflationary recessions of the 21st century received relatively little weight. The second observation is that for all but the second shock memory definition, millennial around the age of 40, i.e. born after 1980, have the lowest shock memory variables. These individuals grew up during the Great Moderation period where inflation tended to fall in times of economic slack. Before 2020, the Great Recession was the most scarring aggregate economic event in most of their lives. Our VAR model estimates not only that inflation decreased during this time

Figure 4: Shock memory and expectation revisions by age in 2020

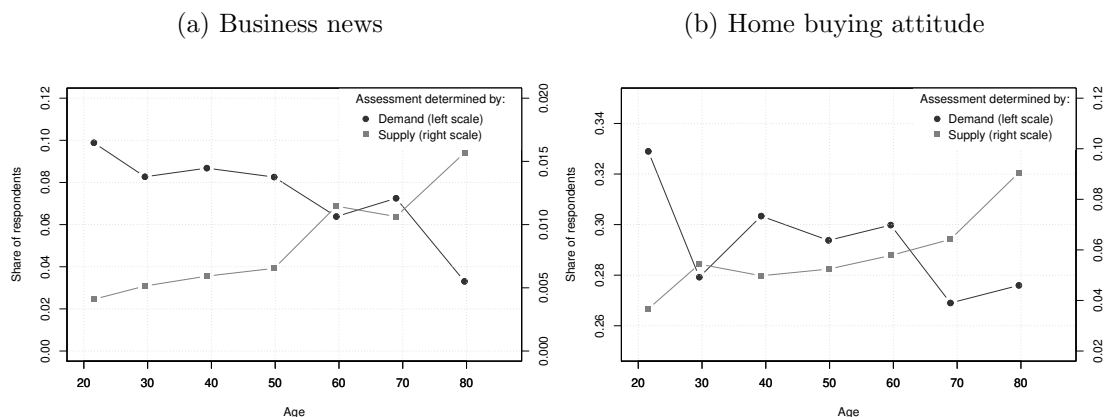


Notes: Lines: Four definitions of shock memories as described in Section 3.1, capturing the degree to which inflation has co-moved with output over a person’s lifetime. \mathcal{M}^I : Inflation during recessions; \mathcal{M}^{II} : ditto, weighted; \mathcal{M}^{III} : slope of reduced-form Phillips curve; \mathcal{M}^{IV} : Correlation of supply shock contribution to inflation and overall inflation. All measures standardized. Grey areas: Smoothed quantiles, see Figure 2.

because of low demand, but that supply factors contributed to increasing inflation. For this generation, inflation is low when demand is low, and it is this generation that shows some of the strongest downward revisions of inflation expectations in the spring of 2020. For consumers born a decade later, who were 25-30 years old in 2020 and came of age during the recovery, inflation barely responded to economic slack, and their inflation expectations also fell less at the onset of the pandemic. Finally, for \mathcal{M}^I , which is the only definition which is not smoothed by gradually down-weighting past events, we see a hump of memory for the people born in the late 1960s. These are the cohorts that did not witness the Volcker disinflation recessions as adults but did experience the 1990/91 crisis with sticky inflation. It is the same hump we observe in the inflation expectation revisions (in grey).

We corroborate this correlation between experienced shocks and inflation expectations with further evidence on associative memory of business cycle narratives. The MSC contains the following question: “During the last few months, have you heard of any favorable or unfavorable changes in business conditions? What did you hear?” The responses are allocated to up to two categories that most often hide whether the assessment was determined by demand or supply mechanisms (e.g. “employment is high/plenty of jobs”). However, we can compute, by age, the share of respondents that provides a narrative which is most clearly associated with either: For demand, this is the category “consumer/auto demand high/low”, regardless of whether or not the news are perceived as favorable. These answers are given by about 7.5% of respondents in 2020. As a proxy for the supply narrative, we compute the share that mentions either “profits (too) high” or “energy crisis/pollution/less natural resources” among all people who have heard un-

Figure 5: Demand vs. supply considerations by age



Notes: Left-hand side panel: Share of people who say that “low/high consumer/auto demand” was the prime or secondary news they have heard about business cycle conditions over the past months. The supply proxy is constructed as the number of individuals with the responses “profits (too) high” or “energy crisis” compared to all individuals with an unfavorable view. Right-hand side panel: Equivalent for home buying attitude, share that mentions “people can (not) afford to buy” and “supply (in)adequate”, respectively. See Appendix B.5 for details on definitions. Age groups are defined as in the remainder of the paper, and connected dots represent the mean for each age group, weighted by MSC sampling weights. We use all survey interviews after March 2020.

favorable news.²⁰ Panel (a) of Figure 5 shows that demand considerations were more salient for the young, most importantly for the youngest cohorts and people around 40. At the same time, they had the lowest propensity to report having heard unfavorable news about “too high profits”, which is our stand-in for a supply-side mechanism.

A second narrative question in the MSC, namely “Do you think now is a good/bad time to buy a house? Why do you say so?” allows to disentangle demand and supply thinking even more clearly. Two of the categories are “People can (not) afford to buy now” and “supply (in)adequate, no shortages now/poor selection”, respectively. Panel (b) shows the respective shares by age group. Individuals around 20 and 40 have the highest likelihood to explicitly state that their home-buying attitudes are driven by demand-side considerations and the lowest for supply-side mechanisms. People over 75 are three times more likely than their grandchildren to say that the supply of housing is what drives their assessment of whether or not it is a good time to buy. The attention that demand and supply factors receive by consumers therefore is increasing with the importance of these factors in driving business cycles in memory (Bordalo et al., 2020). We conclude that for a diverse set of definitions, the degree of co-movement of inflation and unemployment over a person’s lifetime is closely linked to how they interpreted the unprecedented shock they faced in Covid-19.

²⁰ “Profits too high” as a rationale for unfavorable business news can be associated with high producer markups and low consumer welfare. The opposite—low profits combined with a favorable view—is not available in the survey, but the overwhelming majority of respondents had an unfavorable view of the economy in 2020. This answer is chosen considerably less frequently. To increase the sample size, we consider all interviews after March 2020 and not just the second-round ones during the first wave.

It is specific to the 2010s that the (standardized) memory proxies are as closely aligned as they are in Figure 4. Over the full sample, the correlation can be less than 0.5 (see Table B2 and Figure B3b in the Appendix). Therefore, we keep using all four definitions of shock memory as we test if the relationship between previous shocks and reaction to new shocks holds more generally in the Michigan Survey of Consumers.

3.3 Generalization

We now turn to the analysis of how inflation expectations react to shocks more generally. Using the full sample of the MSC (with observations of revisions starting in 1981), we estimate

$$\begin{aligned} \Delta\pi_{it}^e = & \alpha + \beta_D \hat{\varepsilon}_t^D + \beta_{D \times \mathcal{M}}(\hat{\varepsilon}_t^D \times \mathcal{M}_{a(i),t}) \\ & + \beta_S \hat{\varepsilon}_t^S + \beta_{S \times \mathcal{M}}(\hat{\varepsilon}_t^S \times \mathcal{M}_{a(i),t}) \\ & + \beta_M \hat{\varepsilon}_t^M + \beta_{M \times \mathcal{M}}(\hat{\varepsilon}_t^M \times \mathcal{M}_{a(i),t}) + u_{it}, \end{aligned} \quad (13)$$

where $\hat{\varepsilon}^D$, $\hat{\varepsilon}^S$ and $\hat{\varepsilon}^M$ are the posterior means of the structural shocks for demand, supply and monetary policy, respectively, identified by the VAR in Section 3.1. First, we need to re-align the timing and frequency of the shocks to fit the MSC. We divide the (quarterly) shocks by three assuming that it was equally distributed over the quarter and take the sum of the values during the 6 months prior to the second MSC interview. The goal is to assess how inflation expectations react to the macroeconomic shocks that have arrived since the first interview. We are solely interested in explaining the revisions of expectations of a single individual, rather than their levels as Malmendier and Nagel (2016).

Table 4 shows the estimated coefficients for the baseline specification and the four definitions of \mathcal{M} . The linear coefficients imply that consumers interpret all three shocks “correctly”: Inflation expectations increase for inflationary shocks (of increasing demand or decreasing supply) and decrease after contractionary monetary policy. This is remarkable as several analyses using the same or similar survey data have found that households have difficulties interpreting these shocks correctly (Kamdar, 2019, Roth and Wohlfart, 2020, Andre et al., forthcoming). As the interaction variables are standardized, the linear coefficients show the average response of a consumer. With respect to the interaction coefficients themselves, we find a considerable role for the “behavioral” aspect we call shock memory. In response to a cost-push shock, individuals whose shock memory is shaped by such shocks react more.

The interaction coefficients are statistically significantly different from zero with at least 95% confidence. They are also quantitatively meaningful. One standard deviation more exposure to supply-side shocks in the past increases up-ward revisions of inflation by about 20% (and up to 50% in the case of \mathcal{M}^{III} , see column (3)). On the other

Table 4: Shocks and the revisions of inflation expectations

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Demand shocks	0.414*** (0.029)	0.390*** (0.031)	0.385*** (0.029)	0.426*** (0.031)
— × Memory	0.034 (0.028)	0.042 (0.027)	0.010 (0.024)	−0.087** (0.035)
Supply shocks	0.545*** (0.041)	0.552*** (0.041)	0.507*** (0.040)	0.517*** (0.041)
— × Memory	0.107** (0.043)	0.103** (0.047)	0.248*** (0.044)	0.124*** (0.046)
Mon. policy shocks	−0.561*** (0.031)	−0.530*** (0.032)	−0.523*** (0.032)	−0.568*** (0.030)
— × Memory	−0.132*** (0.029)	−0.127*** (0.027)	−0.172*** (0.027)	−0.075** (0.034)
Mean(Memory)	−0.56	−0.64	0.18	0.66
St.dev.(Memory)	0.37	0.29	0.34	0.09
St.dev.(Demand sh.)			1.05	
St.dev.(Supply sh.)			0.71	
St.dev.(MP shocks)			1.12	
Observations	72.867	76.737	76.737	76.737
R^2	0.007	0.007	0.007	0.007
$H_0 : \beta_{-\times\mathcal{M}} = 0$, F(p)	7.25(0.00)	8.11(0.00)	15.79(0.00)	9.83(0.00)

Notes: Estimation results of Equation (13). Dep. var.: Revision of 12-month ahead inflation expectations relative to 6 months ago $\pi_{it}^e - \pi_{i,t-6}^e$ in the Michigan Survey of Consumers (1981-2021). Shocks are retrieved from a quarterly VAR with sign restrictions and then defined as a third of the sum of the (quarterly) shocks in the 6 months preceding the second survey. Memory denotes standardized values of historical co-movement of inflation and unemployment, see Section 3.1 for exact definitions. Significance levels: *** 1% ** 5%, * 10%.

hand, the interaction of memory with conventional demand shocks that push inflation, unemployment and the central bank policy rate in the same direction is not significant in most cases. The most interesting finding, however, is that the individuals with an active memory of supply-side shock revise their inflation expectations substantially more after monetary policy shocks. The magnitudes here are between 13 and 33% for one standard deviation of memory around the mean and are again strongest for column (3), where memory is measured by the slope of the reduced-form Phillips curve. These results survive a battery of robustness tests, which we show in Appendix C. The first one conditions the data set on the 60% of observations during the Great Moderation period, where the variance of all estimated shocks is considerably lower. The interaction terms for columns (1) and (2) which focus only on the history of recessions become insignificant, but for the more sophisticated definitions, the interaction terms for supply and monetary policy shocks have the same sign and are statistically significant. We conclude that the results are not driven by large shocks around the Volcker disinflation period or the

Great Recession of 2008/09. In the second, we show that the results are not driven by differences in experienced levels or variation of inflation rates. Even though these can be significant, they render the estimated interaction terms for memory – if anything – stronger.²¹ The third makes sure that our shock memories do not simply reflect age, which they do in 2020 but not in the whole sample. This would be problematic because new information about inflation weighs disproportionately in learning-from-experience models such as [Malmendier and Nagel \(2016\)](#). The estimated interaction coefficients are virtually unchanged. A fourth addition simply regresses the change in expectation on the change in the actual inflation rate, lagged by one month (to account for publication lag). Not surprisingly, the linear estimand is positive and highly significant, in line with [Armantier et al. \(2016\)](#). Again, this updating is stronger among people whose memory is saturated with large contributions of supply shocks. Fifth, we include the change of actual inflation as a regressor to the baseline specification to show that the revisions that a person makes at the second interview does not solely reflect the change in the actual inflation rate that has happened due to the shocks in the meantime. The relative strength of the shock memory channel is almost unchanged. Finally, we split the sample into college-educated and non-college educated respondents in [Table C6](#). In line with [Armantier et al. \(2015\)](#), who find that the more educated tend to change their inflation expectations more in line with economic theory, the average response to all three shocks is stronger for those with higher education. The role of memory in the interpretation of supply shocks is weaker, while it is stronger when interacted with the monetary policy shock.²²

4 Implications for monetary policy

4.1 Alternative surprises

We devote special attention to the results on monetary policy shocks. Due to the time-variation in the parameters of the monetary policy reaction function ([Primiceri, 2005](#)), one might be concerned that our identified shocks are mis-specified. We address this by employing two alternative series of monetary policy surprises. The first one is one of [Romer and Romer \(2004\)](#) shocks, i.e. the interest rate residualized for its lagged values and the central bank’s own information set as revealed by Greenbook forecasts. We take the monthly series from [Wieland and Yang \(2020\)](#) which is available up to 2007 and combine, for every month, the six past innovations to get an estimate of the cumulated monetary stimulus between the first and the second MSC survey. The results, provided in the upper panel of [Table 5](#), are very similar to the baseline.

²¹[Conrad et al. \(2021\)](#) find that German households who have high levels of experienced inflation respond more strongly to monetary news. [Table C2](#) in the Appendix confirms this result, but our shock memory interaction stays significant and quantitatively stronger.

²²The exception is the fourth definition of memory shown in column (4).

Table 5: Alternative monetary policy surprises

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Romer and Romer shocks (1981-2007):				
Mon. policy shocks	-0.508*** (0.057)	-0.477*** (0.057)	-0.473*** (0.056)	-0.519*** (0.055)
— × Memory	-0.105*** (0.037)	-0.089*** (0.029)	-0.158*** (0.034)	-0.085** (0.034)
Mean(Memory)	-0.47	-0.52	0.28	0.69
St.dev.(Memory)	0.38	0.25	0.35	0.06
St.dev.(MP shocks)			0.61	
Observations	53.017	56.130	56.130	56.130
R^2	0.003	0.003	0.003	0.003
$H_0 : \beta_{-\times\mathcal{M}} = 0$, F(p)	8.04(0.00)	9.63(0.00)	21.94(0.00)	6.07(0.01)
Jarociński and Karadi shocks (1990-2016):				
Mon. policy shocks	-0.428* (0.231)	-0.404* (0.241)	-0.497** (0.240)	-0.351 (0.236)
— × Memory	-0.302 (0.193)	-0.430* (0.236)	-1.014*** (0.220)	-0.644** (0.244)
CBI shocks	1.528*** (0.329)	1.653*** (0.335)	1.248*** (0.329)	1.632*** (0.328)
— × Memory	-0.372 (0.296)	-0.034 (0.342)	-0.930*** (0.318)	-0.965*** (0.337)
Mean(Memory)	-0.58	-0.68	0.20	0.68
St.dev.(Memory)	0.33	0.19	0.27	0.08
St.dev.(MP shocks)			0.12	
St.dev.(CBI shocks)			0.08	
Observations	43.370	45.315	45.315	45.315
R^2	0.005	0.005	0.005	0.005
$H_0 : \beta_{-\times\mathcal{M}} = 0$, F(p)	3.48(0.03)	1.69(0.19)	14.95(0.00)	6.62(0.00)

Notes: Dep. var.: Revision of 12-month ahead inflation expectations relative to 6 months ago $\pi_{it}^e - \pi_{i,t-6}^e$. Monetary policy (MP) shocks are retrieved from [Wieland and Yang \(2020\)](#) for the upper panel and [Jarociński and Karadi \(2020\)](#) for the lower, and in each case values are summed over the 6 months preceding the second survey. For the lower panel, surprises are decomposed into an actual monetary stance (MP) and the central bank information (CBI) components. See Section 3.1 for definitions of Memory. The remaining estimates of Equation (14) are omitted. Significance levels: *** 1% ** 5%, * 10%.

The second robustness check for monetary policy borrows from the high-frequency identification literature, which measures movements of interest rates during narrowly defined time windows around monetary policy announcements and thus purges general interest

rate changes from market expectations.²³ We use the shocks provided by [Jarociński and Karadi \(2020\)](#) who further divide each monetary news event into an actual monetary policy decision and the central bank information component. They find that the two have opposite effects on both output and inflation. Results for the available sample (1990-2016, see lower panel of [Table 5](#)) show that respondents in the MSC revise their inflation expectations down between the first and second round of interviews if the central bank has tightened its policy stance in the meantime. When we use the high-frequency shocks, the coefficients estimated for the shocks’ interaction with memory become relatively even stronger. With respect to the central bank information channel, an interest rate hike increases inflation expectations quite substantially on average. However, for the more sophisticated definitions of memory, the interaction coefficient is firmly negative and highly significant such that the central bank information effect might evaporate for people with sufficient exposure to previous positive co-movement of inflation and unemployment.

4.2 Awareness of monetary surprises and attitude towards purchasing durable goods

Our results strongly indicate that monetary policy is successful at shaping inflation expectations. Contrary to many studies that do not find such evidence, our outcome variable is the change of expectations of a single person, rather than the average level of expected inflation among a changing group of individuals. Nevertheless, even in settings that attempt to hold as many (unobserved) factors constant as possible, the fact that households “correctly” interpret monetary policy shocks is not an established one ([Lamla and Vinogradov, 2019](#), [Coibion et al., 2019](#), [Andre et al., forthcoming](#)), particularly in a low-inflation environment ([Coibion et al., 2020b](#)). Therefore, we provide a more detailed analysis of individuals’ reaction to central bank decisions.

The MSC asks households about their purchases of durables: “Do you think now is a good or a bad time for people to buy major household items?” following up with “Why do you say so?”. The answers to the latter are collected in categories that include, among others, interest rate and credit cost factors, inflation, quality, or economic policy considerations. We define a set of dummies for each respondent in the MSC sample: D^H for whether or not interest rates are perceived as high (e.g. answers with “credit/financing hard to get; tight money” and/or “interest rates will fall later”) and D^L for the opposite (“interest

²³See [Gürkaynak et al. \(2005\)](#) and [Gertler and Karadi \(2015\)](#). [Nakamura and Steinsson \(2018\)](#) have shown that these estimates are subject to the central bank information effect, namely that any central bank communication can simultaneously contain information on news about the actual monetary policy stance as well as on the central bank’s assessment of the economy, referred to as central bank information effect. [Jarociński and Karadi](#) disentangle the two by means of the following sign restrictions. Both shocks are surprise increase of the interest rate. But while actual monetary policy shocks have adverse effects on the stock market (S&P500), the central bank information effect would indicate a positive assessment, convey optimism and boost the stock market. The latter is measured in between a window starting 10 minutes before and ending 20 minutes after each monetary policy announcement.

rates low”). We do so regardless of whether or not the respondent has favorable views about the purchases of major household items. Thereafter, we estimate the following logit model.²⁴

$$\begin{aligned} \ln \frac{Pr(D_{it} = 1)}{1 - Pr(D_{it} = 1)} = & \alpha + \beta_D \hat{\varepsilon}_t^D + \beta_{D \times \mathcal{M}}(\hat{\varepsilon}_t^D \times \mathcal{M}_{a(i),t}) \\ & + \beta_S \hat{\varepsilon}_t^S + \beta_{S \times \mathcal{M}}(\hat{\varepsilon}_t^S \times \mathcal{M}_{a(i),t}) \\ & + \beta_M \hat{\varepsilon}_t^M + \beta_{M \times \mathcal{M}}(\hat{\varepsilon}_t^M \times \mathcal{M}_{a(i),t}) + u_{it} \end{aligned} \quad (14)$$

where D is the above described dummy and the shocks enter in the same way as in Equation (13). The top panel in Table 6 shows the average marginal treatment effect of the monetary policy shock at two distinct values of the standardized memory, namely 0 and 1. All estimated coefficients are highly statistically significant and show that interviewees indeed interpret the monetary policy shocks correctly: At the mean level of memory, a monetary policy tightening increases the probability that respondents perceive interests to be high by between 0.6 and 1.8 percentage points (depending on the definition of memory). At the same time, tightening shocks decrease the likelihood that interest rates are low, even though the magnitudes are slightly lower than for high interest rates. Importantly, the marginal effects of monetary policy shocks on the perceived interest rates is much more sizeable for people whose supply shock memory is one standard deviation higher than the mean. Column (3) shows that those people who have experienced supply shocks react more by a factor of around 3. The difference is larger for shock memory definition \mathcal{M}^{II} and smaller for \mathcal{M}^{IV} .

Finally, we show in the lower panel of Table 6 that these perceived differences of the shock translate—almost one-for-one—into consumption attitudes. To do so, we define the dummy D to be 1 if the time to buy major household items received a positive answer in the MSC. With the exception of column (4), all results point toward the fact that higher interest rates reduce the attractiveness of durable purchases and considerably more so for those with supply shock experience. This result is in itself not surprising (D’Acunto et al., 2016, Coibion et al., 2020a, Andrade et al., 2020). Nevertheless, the relative magnitudes of the estimates, which are rather similar to the first two panels of Table 6, suggest that the differences in attitudes do not stem from differences in consumption behavior conditional on the interest rate. Rather, disagreement between people with different levels of memory is in the level of the perceived interest rate itself. The collection of results presented in this paper are not consistent with simple good/bad heuristics in consumers’ understanding of the economy: While it could be that those who have been exposed to supply shocks are more pessimistic about (high) inflation

²⁴The results hold qualitatively and quantitative when we estimate linear probability models. Each household can give up to two answers such that both the dummies for high and low perceived interest rates can be one at the same time. Therefore, we estimate two separate binary models, rather than a multinomial specification.

Table 6: Marginal effects of monetary policy shocks on awareness

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Interest rates perceived as high				
Monetary policy shocks				
at $\mathcal{M} = 0$	0.91*** (0.13)	0.57*** (0.14)	0.78*** (0.13)	1.80*** (0.12)
at $\mathcal{M} = 1$	3.11*** (0.16)	2.52*** (0.15)	2.26*** (0.13)	2.03** (0.16)
Observations	72.867	76.737	76.737	76.737
McFadden R^2	0.025	0.034	0.022	0.013
Interest rates perceived as low				
Monetary policy shocks				
at $\mathcal{M} = 0$	-0.85*** (0.22)	-0.46** (0.21)	-0.59** (0.22)	-1.04*** (0.21)
at $\mathcal{M} = 1$	-2.40*** (0.29)	-2.60*** (0.28)	-1.92*** (0.26)	-1.39*** (0.30)
Observations	72.867	76.737	76.737	76.737
McFadden R^2	0.013	0.005	0.007	0.005
Good time for durable purchases				
Monetary policy shocks				
at $\mathcal{M} = 0$	-1.06*** (0.22)	-0.44** (0.22)	-1.25*** (0.23)	-1.93*** (0.22)
at $\mathcal{M} = 1$	-3.33*** (0.28)	-3.30*** (0.26)	-2.33*** (0.25)	-0.88*** (0.29)
Observations	70.463	74.243	74.243	74.243
McFadden R^2	0.021	0.023	0.019	0.019

Notes: Average marginal effects of monetary policy shocks on dep. var.: Dummy variables indicating whether interest rates are perceived to be high/low, and whether now is a good time for people to buy durable goods. Estimates based on logistic regression of Equation (14), evaluated at (one standard deviation above) the mean of standardized shock memory of supply exposure, and multiplied by 100 (to be interpreted as percentage point changes). See Section 3.1 for definitions of Memory and Appendix B.5 for the definition of the outcome dummies. Shocks are defined as a third of the sum of the (quarterly) shocks in the 6 months preceding the second survey. The remaining estimates of Equation (14) are omitted.

Significance levels: *** 1% ** 5%, * 10%.

and always increase their forecasts with bad economic news, this would imply that they should also increase them when contractionary monetary policy leads to lower output and higher unemployment. In the data, however, we observe the opposite. Without specifying an exact model of expectation formation, the evidence presented points to costly information acquisition in the spirit of rational inattention (Maćkowiak et al., forthcoming). If a central bank faces a discretionary trade-off between inflation and

output stabilization in light of cost-push shocks, the household will have to pay close attention to both the evolution of interest rates and prices to determine the real interest rate and thus the desired inter-temporal allocation of consumption. If, in contrast, the household knows that inflation is stabilized perfectly at all times, it is less beneficial to devote attention to macroeconomic news. As a ramification, households miss central bank announcements and react less to monetary policy decisions.

In conclusion, our empirical results suggest that the perception of past shocks not only matters for the interpretation of new (supply) shocks, but it also plays a crucial role in the transmission of monetary policy through the expectation channel.

5 Conclusion

We have shown that there is a significant role of what we refer to as shock memory across space and time: When confronted with a new supply shock, individuals who have active memory of positive co-movement of inflation and unemployment in the past tend to increase their inflation expectations by more. Having experienced them in the past, they are (correctly) able to interpret their arrival as inflationary. Of particular interest to policy-makers is that they also decrease their inflation expectations more after a monetary policy tightening, regardless of whether monetary policy innovations are identified using sign restrictions, with a narrative approach or by means of high-frequency identification. This is related to the fact that those with high supply shock exposure in the past pay more attention to monetary policy news and update their perceived interest rate level, inflation expectations and consumption decisions accordingly. Therefore, a central bank that perfectly stabilizes inflation at all times will run the risk of decreasing the power of its monetary policy communication tools in the future.

Shock memory is particularly active during large unprecedented shocks such as the arrival of Covid-19 in the U.S., which bore elements of both demand- and supply-side shocks, with opposing implications for the evolution of prices. We have shown that the inflation expectation response at the individual level is an increasing function of the experienced co-movement of inflation and unemployment over the person's lifetime. It can help explain the pattern of inflation expectations by age. A person with a similar demographic background (other than age), a similar sentiment about the real economy and a similar consumption basket is more than a third less likely to increase her inflation expectations if she is just under 45 years of age, compared to people above. This coincides with the cohorts who came of age after the early 1990s recession, i.e. those who have never experienced a recession during which inflation did not fall substantially. Our results are consistent across four different definitions of shock memory with only moderate correlation.

The conclusions of this paper contribute to understanding the behavioral formation

process of inflation expectations. While [Malmendier and Nagel \(2016\)](#) and others find that past levels of inflation are significant determinants of current inflation expectations, our focus is on how past drivers of inflation affect the current inflation outlook revisions. Households surveyed in the Michigan Survey of Consumers are able to detect demand, cost-push and monetary policy shocks to a degree that is surprising against the backdrop of the existing literature ([Coibion et al., 2019, 2020a](#)), but the notion of memory is still a significant contributor to human behavior. We relate it to associative recall, i.e. the fact that new shocks are interpreted through the lens of individual experiences of macroeconomic co-movement. Therefore, our results are particularly relevant for the cyclical aspects such as the expectation channel of monetary policy. Future research should further investigate the role of the systematic component of the central bank’s reaction function in shaping the role of shock memory.

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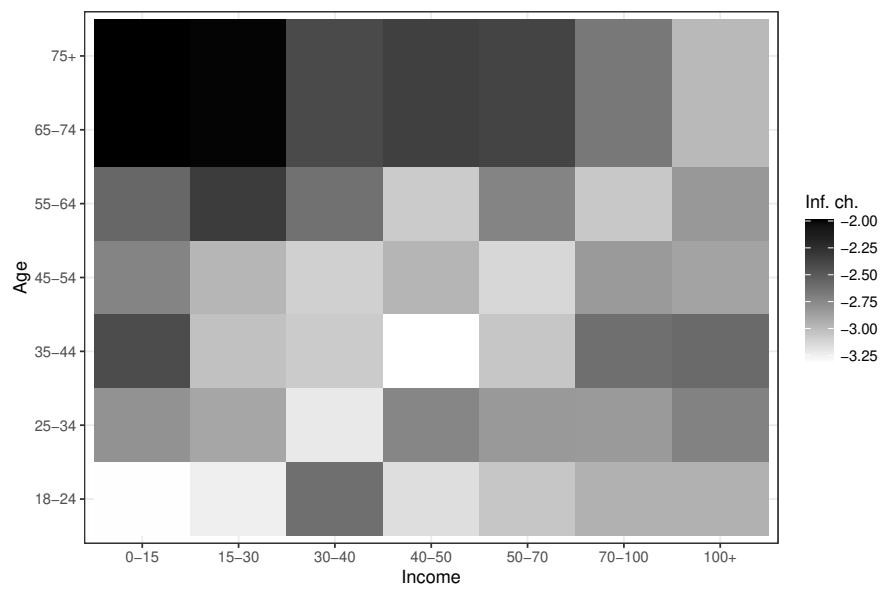
A Estimates of experienced inflation by demographic group

Table A1: Matching of CEX expenditure category and BLS CPI series

CEX expenditure category	BLS CPI series	$\pi_{2020-07}$ $-\pi_{2020-02}$	Avg. share (%)		
			(18-24)	(45-54)	(65+)
Food at home	CUSR0000SAF11	5.19	7.52	9.67	8.99
Food away from home	CUSR0000SEFV	0.77	7.85	6.15	5.53
Alcohol	CUSR0000SAF116	2.45	0.87	0.96	1.00
Owned dwellings	CUSR0000SEHC	-0.66	3.67	10.40	13.43
Rented dwellings	CUSR0000SEHA	-0.90	20.69	12.47	6.12
Other lodging	CUSR0000SEHB	-17.58	1.09	0.97	1.96
Natural gas	CUSR0000SEHF02	-2.83	0.48	0.89	0.98
Electricity	CUSR0000SEHF01	-0.99	2.53	3.51	3.34
Fuel oil & other fuels	CUSR0000SEHE	-25.29	0.08	0.17	0.37
Phone	CUSR0000SAE2	2.52	2.75	3.30	2.52
Water & utilities	CUSR0000SEHG	-0.20	0.84	1.36	1.49
Househ. furnishings & op.	CUSR0000SAH3	2.91	6.02	7.06	8.43
Apparel	CUSR0000SAA	-9.38	3.74	3.54	2.63
Vehicle purchases	CUSR0000SETA	3.97	9.44	6.63	5.95
Gasoline	CUSR0000SETB	-55.15	4.75	4.69	3.20
Other vehicle expenses	CUSR0000SETC/D/E/F	-1.45	6.80	6.84	5.95
Public transportation	CUSR0000SETG	-32.77	1.61	1.22	1.44
Healthcare	CUSR0000SAM	-0.14	4.38	8.00	15.57
Entertainment	CUSR0000SAR	-3.16	4.37	5.20	5.87
Personal care	CUSR0000SAG1	-1.20	1.44	1.47	1.54
Reading	CUSR0000SERG	-0.46	0.13	0.14	0.34
Education	CUSR0000SAE	1.44	7.32	2.18	0.79
Tobacco	CUSR0000SEGA	1.41	0.66	1.26	0.49
Miscellaneous	CUSR0000SEGD	-2.06	1.00	1.95	2.06

Notes: Mnemonics of CPI subcomponents matched to categories in the Consumer Expenditure Survey, for which expenditure shares are published cross-tabulated by age and income.

Figure A1: Age- and income-specific inflation experiences during pandemic



Notes: Difference in the inflation rates between February and July 2020 consumption baskets for age- and income-specific groups, which is the sample used in the micro data of expectation revisions.

B Details on shock memory variables

B.1 Inflation during recessions ($\mathcal{M}^{I,II}$)

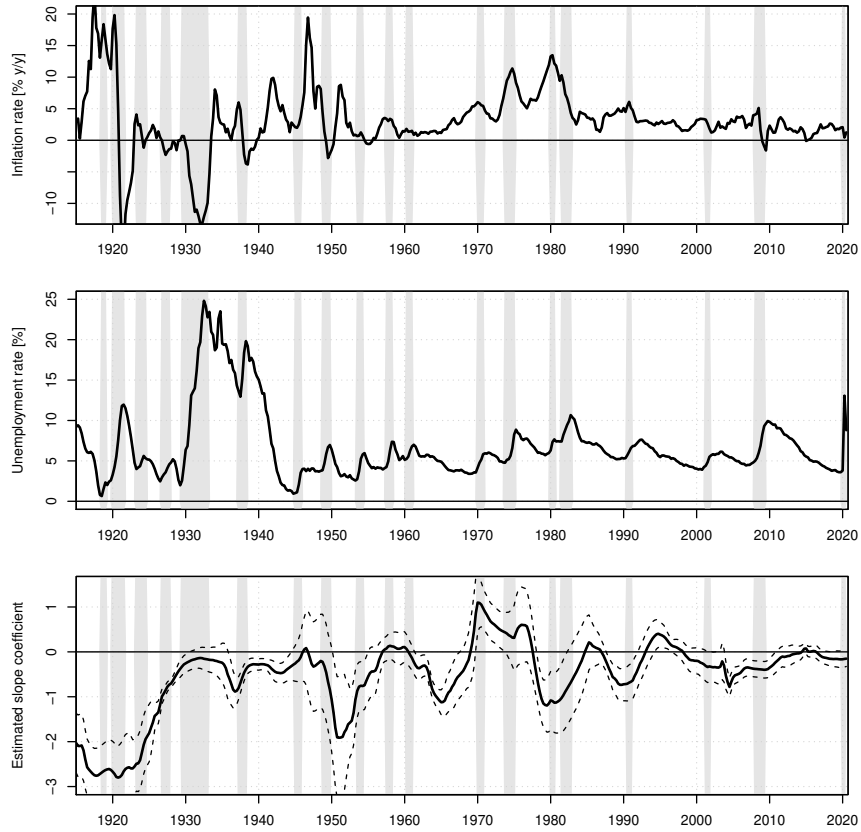
Table B1: Inflation during NBER recessions

Start	End	Narrative explanation	$\Delta\pi$	Δu	$\frac{\Delta\pi}{\Delta u}$	supply contr.	data fr. (m/q)
1918-09	1919-03	war- to peacetime adjustment, Spanish flu	2.91	1.5	1.89	0.74	q
1920-02	1921-07	war- to peacetime adjustment (fiscal tightening), labor union strikes, monetary tightening	-29.40	9.4	-3.13	-0.36	q
1923-06	1924-07	“break” from Roaring 20s	-2.60	0.6	-4.50	1.09	q
1926-11	1927-11	temporary Ford factory conversions	-1.87	2.1	-0.89	-0.50	q
1929-09	1933-03	financial crisis, monetary tightening (gold standard), trade barriers	-9.88	20.8	-0.47	-0.17	q
1937-06	1938-06	fiscal and monetary tightening	-8.46	5.5	-1.54	-1.85	q
1945-03	1945-10	war- to peacetime adjust.	1.26	2.6	0.49	5.00	q
1948-12	1949-10	monetary tightening	-7.33	4.1	-1.79	-0.14	m
1953-08	1954-05	monetary tightening	0.45	3.3	0.14	-0.12	m
1957-09	1958-04	monetary tightening	0.06	3.3	0.02	-1.99	m
1960-05	1961-02	monetary tightening	-0.46	1.7	-0.27	-0.54	m
1970-01	1970-11	fiscal and monetary tightening	-0.28	2.4	-0.12	0.96	m
1973-12	1975-03	oil price shock	2.02	3.8	0.53	1.49	m
1980-02	1980-07	oil price shock, monetary tightening	-0.63	1.5	-0.42	1.29	m
1981-08	1982-11	monetary tightening	-5.85	3.6	-1.63	0.08	m
1990-08	1991-03	oil price shock, monetary tightening	0.00	1.3	0.00	0.63	m
2001-04	2001-11	dot-com bubble	-1.06	1.2	-0.88	0.64	m
2008-01	2009-06	housing bubble, global financial crisis,	-5.26	4.5	-1.17	-2.54	m
2020-03	2020-04	Covid-19 pandemic	-1.95	11.3	-0.17		m

Notes: Recession dates are timed such that they start in the month preceding the peak according to the [NBER business cycle reference dates](#) and end in the month of the trough. Inflation is defined as the log difference with respect to the same period a year earlier, and the change of inflation as the difference at recession end relative to the last period before the start. We use monthly time series for the post-WWII period and quarterly prior. The second last column (“supply contr”) is based on the structural shock contributions to historical inflation shown in Figure B2. Particularly, we divide the supply shock contribution in the last quarter of the recession by the sum of all three contributions. Negative values indicate that supply shocks acted in the opposite direction than inflation went, positive values show that supply shocks contributed to the observed inflation development.

B.2 Time-variation in the Phillips curve (\mathcal{M}^{III})

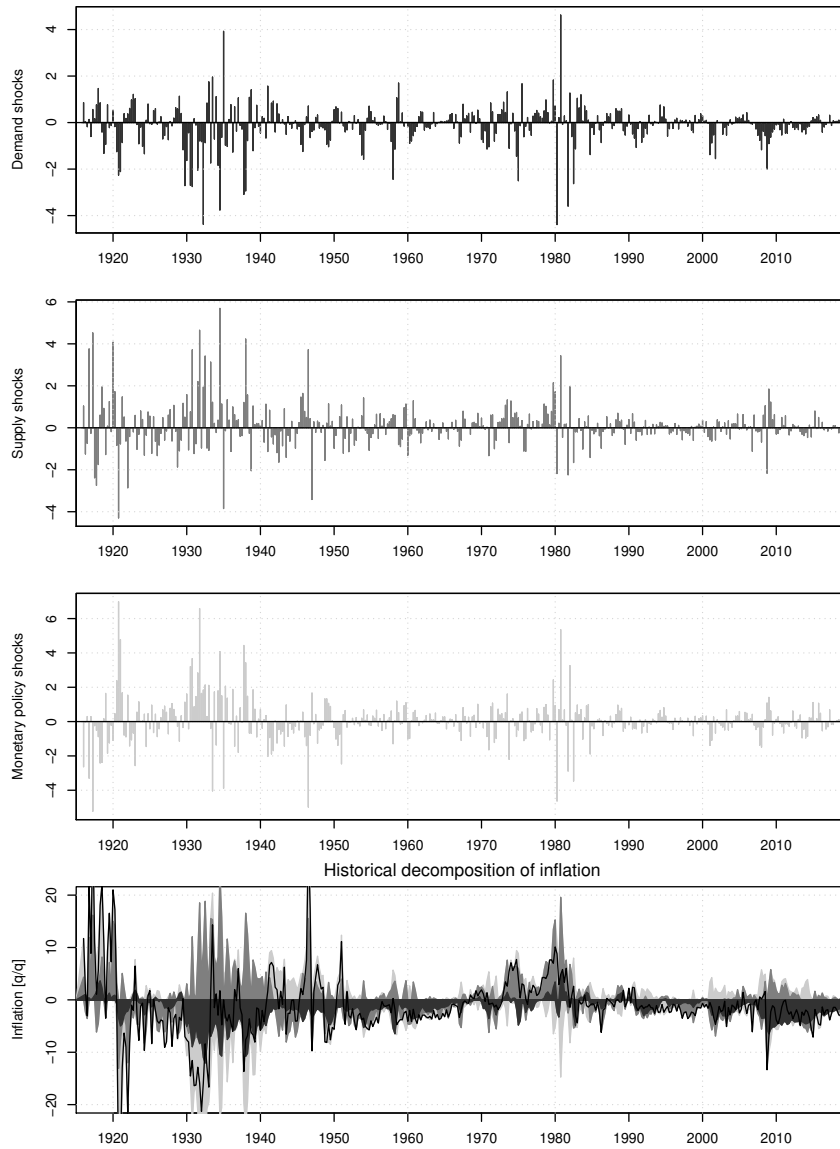
Figure B1: An unstable relationship: π , u and the slope of the Phillips curve



Notes: Time series at quarterly frequency. Sources: FRED mnemonics CPIAUCSL (CPI converted to y/y log differences) and UNRATE for Post-WWII period, [Ramey and Zubairy \(2018\)](#) for 1915-1947. The third panel shows the β 's from 10-year rolling window regressions of $\pi_t = \alpha + \beta u_t + \xi_t$.

B.3 Structural shocks from SV-VAR with sign restrictions (\mathcal{M}^{IV})

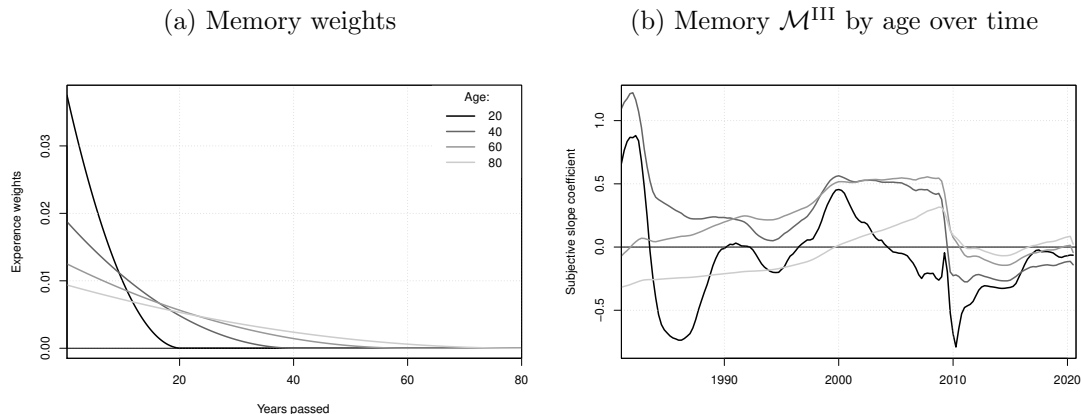
Figure B2: Structural shocks: ε_t^D , ε_t^S and ε_t^M



Notes: Panels 1-3: Posterior means of uncorrelated structural shocks identified from the SV-VAR (Section 3.1). Identification via sign restrictions. Positive demand/supply(/monetary) shocks imply positive(/negative) inflation pressure. Panel 4: Historical decomposition of inflation into structural sources.

B.4 Overview of shock memory

Figure B3: Illustration of shock memory with learning from experience



Notes: Left-hand side panel shows weights assigned to an event as a function of the time passed between the event and the MSC interview. The right-hand side panel shows, for someone of a particular age at the time depicted, the slope of the reduced form Phillips curve, where all historical observations are weighted using the weights on the left-hand side.

Table B2: Correlations of memory variables

	\mathcal{M}^I	\mathcal{M}^{II}	\mathcal{M}^{III}	\mathcal{M}^{IV}
\mathcal{M}^I : Inflation during recessions	1.000			
\mathcal{M}^{II} : ditto, weighted	0.708	1.000		
\mathcal{M}^{III} : Slope of reduced-form Phillips curve	0.541	0.577	1.000	
\mathcal{M}^{IV} : Corr.(supply shock contribution, inflation)	0.463	0.455	0.741	1.000

Notes: See Section 3.1 for definition of shock memory

B.5 Perception and attention in the Michigan Survey

Throughout the paper, we use several measures of perception and attention to demand- and supply-side factors that shape the narrative around economic shocks. This subsection describes the definition of these proxies using [MSC labelling and coding](#).

Business news Two variables displayed in Figure 5(a) indicate whether a person devotes more attention to news about demand- or supply-side factors. With respect to the category codes displayed in Table B3, we proxy demand-side attention with the share of answers motivated with consumer demand regardless of whether the news is perceived to be positive or negative, i.e. $D \equiv (21 + 61)/(\sum_{\text{FAV}} + \sum_{\text{UNFAV}})$. In particular, we do not use the categories mentioning employment and/or purchasing power, because we believe they are not informative enough of the underlying cause. The supply-side proxy

is $S \equiv (75 + 89) / \sum_{\text{UNFAV}}$, which describes the share of all unfavorable assessments that are motivated by either energy crises or the fact that “profits are too high”. These categories best reflect cost-push pressures, be it through marginal cost (in the case of the former) or markups (the latter). Since “too low profits” is not an available reason for favorable news, we use as the denominator only the sum of unfavorable news heard. In 2020, which is the period we use data for to generate Figure 5, the overwhelming majority of respondents have only heard unfavorable news.

Home buying attitudes Similarly, we define attitudes towards the purchases of a home and classify, among all informative answers, the share that mention (un-)favorable conditions because of high/low demand (answers 21, 61 and 62 in Table B4) versus those that emphasize (in-)adequate supply (31 and 71). One could also include references to employment and purchasing power, but since this option is chosen very rarely (and thus does not change the picture), we refrain from doing so and focus on the categories we can clearly allocate to demand or supply only.

Perceived interest rates Table 6 shows regressions with three different dummy outcome variables that are defined based on information on durable purchases, the question and answer categories to which are shown in Table B5. The dummy for good times of durable purchases is equal to 1 if the answer code is 1 and 0 if the respondent is unsure (3) or has a bad attitude toward durable purchases (5). “Don’t know” and missing answers are excluded. The dummy D^H describes whether interest rates are perceived to be high, which includes categories of perceived tight credit or expectations of lower interest rates “later”. Notably, this is defined independently of the answer to the above question on durable purchases, i.e. people can perceive interests to be high and (not) still consider it a good time to buy major items. The opposite dummy D^L is defined for low(er) perceived interest based on the answer codes market in Table B5. Because respondents’ answers are allocated to up to two categories, both dummies can be true at the same time, for example if a person thinks interest rates are high, but credit is easily available.

Table B3: MSC “NEWS” about business conditions

Category label	Favorable	Unfavorable	NA
During the last few months, have you heard of any favorable or unfavorable changes in business conditions? What did you hear?			
Elections, admin, Congress, President	10	50	
More military spending, more ware/tensions	11	51	
Less military spending, few tensions	12	52	
Government programs improved/changed	13	53	
Government programs incr./cont./begun	14	55	
Government programs decr./ended	15	54	
Taxes, changes/reforms, rebates	16	56	
Fiscal policy, budgets, deficits; other ref. to government; government (not) improving bus. cond.	17–19	57–59	
Opening/closing of plants, factories, stores	20	60	
Consumer/auto demand high	21(D)	61(D)	
Purchasing power high/low	22	62	
Employment is high, plenty of jobs; Drop in employment, less overtime	23	63	
Population increase, more people to buy/immigration	24	64	
Low/high debts, higher/lower savings/assets	25	65	
Other ref. to employment and purchasing power	27	67	
Production in-/decreasing, GNP up/down	28	68	
Unemployment has risen, good for economy	29		
Tight money, interest rates high	30	73	
Lower/stable prices, less inflation	31	71	
Higher prices, inflation	32	72	
Easier money, credit easy to get, low interest rates	33		
Profits (too) high/rising	35	75(S)	
Profits low/falling		74	
Stock market, rise/decline in price of stocks	36	76	
Other references to prices/credit	37	77	
Balance of payments, dollar devalue	38	78	
Controls (price or wage)	39	79	
Better/bad race relations, less/more crime	40	80	
Union disputes settled, relations good; Excessive wage demands by unions, labor unrest	41	81	
Times/business is good in the coming year/are bad now and won't change; Bad/good times can't last, due for good times/for a fall; See sign of improvement already/downward trends	42–44	82–84	
Improvements/decline in specific industries; Farm situation good/bad, crops good/drought	45–46	85–86	
Other good/bad factors or (un-)favorable reference; Economy more/less stable, optimism/lack of confidence	47–48	87–88	
Energy crisis, pollution, natural resources	49	89(S)	
Has heard of no changes			0
Change mentioned but nother whether (un-)favorable			97
Total	$\equiv \sum_{\text{FAV}}$	$\equiv \sum_{\text{UNFAV}}$	

Notes: Interviewees' answers are assigned to up to two categories. (D) and (S) indicate that the category was used to determine whether the respondent paid attention to particular demand/supply side factors, respectively.

Table B4: MSC “HOMRN” about home buying attitudes

Generally speaking, do you think now is a good or bad time to buy a house?			
Category label	Good	Bad	NA
	1	5	3,8-9
Why do you say so?			
Interest rates won't get any lower/are low	10,16	50	
Prices are low, stable/too high	11	51	
Good buys available/Seller's market, few sales or discounts	12	52	
Prices are going up/will fall, come down	13	53	
Prices won't get any lower	14		
Lower/higher down payment required	15	55	
Interest rates too high, will go up; will come down later		56,58	
Credit easy to get, easy money; Debt or credit bad; Credit hard to get	17	54,57	
Lower/higher taxes, taxes higher later	19	59	
People can (not) afford to buy now	21(D)	61(D)	
People should save money, uncertain of future		62(D)	
Buying makes for good times/contributes to inflation and makes bad times	23	63	
Energy crisis, shortage of fuels		65	
Other references to employment and purchasing power	27		
Supply (in-)adequate, not shortages now/few houses on market	31(S)	71(S)	
Quality is good/poor, better, may get worse/may improve; New models have improvements, new features/poor designs; Good selection	32-34	72-73	
Seasonal references only	41	81	
Difficult to get rid of present house		82	
If you need it this is a good time	42		
Low sales won't last, will pick up soon	43		
Renting is (un-)favorable because high/low rents or shortages	44	84	
Owning/renting is always a good idea, renting a bad/good idea	45	85	
Capital ap-/depreciation, buying a good/bad investment; Better return on alternative investments	46	83,86	
Variable mortgage rate	48	88	
Policy, reference to government	49	89	
Other	47	87	
No mention			0
Total	$\equiv \sum_{\text{GOOD}}$	$\equiv \sum_{\text{BAD}}$	

Notes: Interviewees' reasons are assigned to up to two categories. (D) and (S) indicate that the category was used to determine whether the respondent paid attention to particular demand/supply side factors, respectively.

Table B5: MSC “DURRN” about durables buying attitudes

Generally speaking, do you think now is a good time or a bad time for people to buy major household items?			
Category label	Good	Bad	NA
	1	5	3,8-9
Why do you say so?			
Interest rates won't get any lower/are low	10,16(L)	50(L)	
Prices are lower, reasonably stable, won't get any lower/too high, going up	11,14	51	
Good buys available, sales, discounts / Seller's market, few sales or discounts	12	52	
Prices are going up, future uncertainty	13		
Prices will fall later, will come down		53	
Lower/larger down payment required	15	55	
Credit easy to get, easy money	17(L)		
Interest rates are going up, credit tighter	18(H)		
Credit hard to get, tight money; Debt or credit is bad		54,57(H)	
Interest rates high, going up		56(H)	
Interest rates will fall later		58(H)	
Low/high taxes	19	59	
People can (not) afford to buy now, have money to spend	21	61	
People should save money		62	
Buying makes for good times/contributes to inflation and makes bad times	23	63	
Energy crisis, shortages of fuels		65	
Supply (in-)adequate, not shortages now/poor selection; Quality is good, may get worse/poor; New models have improvements; Good selection/unattractive styling	31-34	71-73	
Seasonal references only	41	81	
International references		82	
If you need it this is a good time	42		
Low sales won't last, will pick up soon	43		
Policy, reference to government	49	89	
Other	47	87	
No mention			0
Total	$\equiv \sum_{\text{GOOD}}$	$\equiv \sum_{\text{BAD}}$	

Notes: Interviewees' reasons are assigned to up to two categories. (H) and (L) indicate that the category was used to determine whether the respondent perceived interest rates to be high and low, respectively.

C Robustness and further results

Table C1: Robustness I

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Demand shocks	0.386*** (0.052)	0.357*** (0.052)	0.373*** (0.052)	0.380*** (0.056)
— × Memory	-0.044 (0.053)	0.042 (0.055)	-0.060 (0.054)	0.070 (0.045)
Supply shocks	0.306*** (0.066)	0.324*** (0.066)	0.342*** (0.066)	0.344*** (0.068)
— × Memory	0.101 (0.065)	0.072 (0.065)	0.317*** (0.071)	0.129** (0.060)
Monetary policy shocks	-0.440*** (0.062)	-0.426*** (0.062)	-0.443*** (0.062)	-0.455*** (0.065)
— × Memory	0.040 (0.063)	-0.035 (0.067)	-0.104* (0.062)	-0.124** (0.057)
Mean(Memory)	-0.54	-0.61	0.20	0.70
St.dev.(Memory)	0.35	0.13	0.26	0.06
St.dev.(Demand shocks)			0.72	
St.dev.(Supply shocks)			0.51	
St.dev.(Mon. policy shocks)			0.67	
Observations	42.826	45.575	45.575	45.575
R^2	0.002	0.002	0.002	0.002
$H_0 : \beta_{-\times\mathcal{M}} = 0$, F(p)	1.68(0.17)	0.99(0.39)	6.78(0.00)	2.53(0.06)

Notes: Repetition of Table 4 for the Great Moderation subsample (1984-2006). See Section 3.1 for definitions of Memory.

Significance levels: *** 1% ** 5%, * 10%.

Table C2: Robustness II

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Full sample (1981-2021):				
Demand shocks	0.417*** (0.031)	0.375*** (0.033)	0.378*** (0.034)	0.434*** (0.033)
— × Memory	0.015 (0.032)	0.032 (0.038)	0.023 (0.027)	−0.059 (0.039)
— × Lifetime average infl.	−0.058 (0.040)	−0.099** (0.042)	−0.085* (0.043)	−0.049 (0.040)
— × Lifetime infl. volatility	0.085** (0.033)	0.099*** (0.035)	0.119*** (0.033)	0.081** (0.035)
Supply shocks	0.524*** (0.042)	0.508*** (0.042)	0.487*** (0.042)	0.531*** (0.042)
— × Memory	0.200*** (0.047)	0.351*** (0.059)	0.255*** (0.045)	0.062 (0.049)
— × Lifetime average infl.	0.061 (0.072)	−0.017 (0.073)	−0.008 (0.073)	0.078 (0.074)
— × Lifetime infl. volatility	−0.265*** (0.064)	−0.326*** (0.065)	−0.165*** (0.063)	−0.202*** (0.066)
Monetary policy shocks	−0.539*** (0.031)	−0.481*** (0.033)	−0.485*** (0.033)	−0.537*** (0.031)
— × Memory	−0.165*** (0.036)	−0.285*** (0.043)	−0.206*** (0.031)	−0.093** (0.037)
— × Lifetime average infl.	0.014 (0.049)	0.141*** (0.053)	0.118** (0.052)	0.034 (0.049)
— × Lifetime infl. volatility	0.064 (0.041)	0.096** (0.042)	−0.046 (0.041)	−0.025 (0.042)
St.dev.(Average infl.)			1.38	
St.dev.(Infl. volatility)			3.92	
Observations	72.867	76.737	76.737	76.737
R^2	0.007	0.008	0.007	0.007
$H_0 : \beta_{-\times Mem} = 0, F(p)$	8.96(0.00)	17.61(0.00)	17.04(0.00)	9.03(0.00)

Notes: Extension of Table 4 by the mean and variance of inflation over respondent's lifetime (both weighted by [Malmendier and Nagel \(2016\)](#) learning weights). See Section 3.1 for definitions of Memory. Significance levels: *** 1% ** 5%, * 10%.

Table C3: Robustness III

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Full sample (1981-2021):				
Demand shocks \times Memory	0.024 (0.029)	0.041 (0.027)	0.002 (0.026)	-0.143*** (0.039)
Supply shocks \times Memory	0.143*** (0.046)	0.129*** (0.048)	0.276*** (0.047)	0.116** (0.048)
MP shocks — \times Memory	-0.130*** (0.031)	-0.141*** (0.027)	-0.153*** (0.029)	-0.035 (0.036)
Demand shocks \times Age grp.			Yes	
Supply shocks \times Age group			Yes	
MP shocks \times Age group			Yes	
Observations	72.867	76.737	76.737	76.737
R^2	0.008	0.008	0.008	0.008
$H_0 : \beta_{- \times \mathcal{M}} = 0, F(p)$	6.55(0.00)	9.36(0.00)	13.28(0.00)	9.17(0.00)

Notes: Robustness to Table 4. We additionally interact each shock with a categorical age group variable, each of which comprises 10 years. According to [Malmendier and Nagel \(2016\)](#), young individuals' inflation forecasts are less anchored by experience and thus *per se* more responsive to shocks. Few of those (omitted) interaction coefficients are significant. See Section 3.1 for definitions of Memory. Significance levels: *** 1% ** 5%, * 10%.

Table C4: Robustness IV

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Full sample (1981-2021):				
$\pi_{t-1} - \pi_{t-7}$	0.301*** (0.016)	0.283*** (0.017)	0.272*** (0.017)	0.299*** (0.016)
— \times Memory	0.100*** (0.016)	0.087*** (0.014)	0.100*** (0.013)	0.093*** (0.019)
Observations	72.867	76.737	76.737	76.737
R^2	0.006	0.006	0.006	0.005

Notes: Regress the dependent variable ($\pi_{it}^e - \pi_{i,t-6}^e$) on change of the actual inflation rate in between the two surveys ($\pi_{i,t-1} - \pi_{i,t-7}$). Regressor is lagged by one month due to publication lag of actual inflation series and because it is unknown at what time during the month each survey was conducted. See Section 3.1 for definitions of Memory. Significance levels: *** 1% ** 5%, * 10%.

Table C5: Robustness V

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Full sample (1981-2021):				
$\pi_{t-1} - \pi_{t-7}$	0.094*** (0.027)	0.082*** (0.028)	0.096*** (0.027)	0.089*** (0.027)
Demand shocks	0.324*** (0.039)	0.313*** (0.040)	0.297*** (0.040)	0.341*** (0.039)
— × Memory	0.023 (0.028)	0.026 (0.027)	0.001 (0.024)	−0.090*** (0.035)
Supply shocks	0.446*** (0.050)	0.465*** (0.050)	0.404*** (0.050)	0.421*** (0.050)
— × Memory	0.122*** (0.044)	0.128*** (0.047)	0.264*** (0.044)	0.140*** (0.046)
Monetary policy shocks	−0.435*** (0.048)	−0.424*** (0.048)	−0.394*** (0.048)	−0.445*** (0.048)
— × Memory	−0.124*** (0.030)	−0.122*** (0.027)	−0.170*** (0.027)	−0.074** (0.034)
Observations	72.867	76.737	76.737	76.737
R^2	0.007	0.007	0.007	0.007
$H_0 : \beta_{-\times Mem} = 0, F(p)$	6.58(0.00)	7.19(0.00)	16.16(0.00)	9.63(0.00)

Notes: Robustness to Table 4. We additionally include the change in the actual inflation rate between the first and second interviews to show that expectation revisions do not simply reflect the change in actual inflation the shocks have caused. The additional regressor is lagged by one month due to publication lag of actual inflation series and because it is unknown at what time during the month each survey was conducted. See Section 3.1 for definitions of Memory.

Significance levels: *** 1% ** 5%, * 10%.

Table C6: Robustness VI

	(1) Memory \mathcal{M}^I (Infl. during recessions)	(2) Memory \mathcal{M}^{II} (—, weighted)	(3) Memory \mathcal{M}^{III} (Red. form PC slope)	(4) Memory \mathcal{M}^{IV} (Corr. o. supply+infl.)
Not college-educated (1981-2021):				
Demand shocks	0.363*** (0.044)	0.368*** (0.048)	0.364*** (0.046)	0.366*** (0.042)
— × Memory	0.022 (0.041)	-0.023 (0.039)	-0.025 (0.034)	-0.023 (0.050)
Supply shocks	0.487*** (0.062)	0.499*** (0.062)	0.465*** (0.062)	0.495*** (0.062)
— × Memory	0.133** (0.066)	0.164** (0.069)	0.264*** (0.066)	0.095*** (0.072)
Monetary policy shocks	-0.498*** (0.049)	-0.490*** (0.051)	-0.491*** (0.049)	-0.504*** (0.046)
— × Memory	-0.110** (0.046)	-0.090** (0.041)	-0.120*** (0.039)	-0.087 (0.053)
Observations	40.155	43.288	43.288	43.288
R^2	0.005	0.004	0.005	0.004
College-educated (1981-2021):				
Demand shocks	0.501*** (0.036)	0.462*** (0.038)	0.433*** (0.041)	0.574*** (0.040)
— × Memory	0.047 (0.035)	0.154*** (0.036)	0.053 (0.033)	-0.260*** (0.047)
Supply shocks	0.576*** (0.050)	0.556*** (0.051)	0.524*** (0.049)	0.497*** (0.050)
— × Memory	0.081 (0.053)	0.010 (0.060)	0.234*** (0.054)	0.173*** (0.053)
Monetary policy shocks	-0.633*** (0.037)	-0.592*** (0.037)	-0.550*** (0.038)	-0.653*** (0.037)
— × Memory	-0.167*** (0.036)	-0.197*** (0.034)	-0.240*** (0.034)	-0.028 (0.040)
Observations	32.529	33.254	33.254	33.254
R^2	0.013	0.013	0.013	0.013

Notes: Robustness to Table 4, splitting the sample into (not) college-educated respondents. See Section 3.1 for definitions of Memory.

Significance levels: *** 1% ** 5%, * 10%.