DEPARTMENT
OF ECONOMICS

Essays on the Dynamics of Inflation Expectations

Sebastian Rast

Thesis submitted for assessment with a view to
obtaining the degree of Doctor of Economics
of the European University Institute

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European University Institute
Department of Economics

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I confirm that chapter 2 was jointly co-authored with Evi Pappa and Alejandro Vicondoa and I contributed 33% of the work.
I confirm that chapter 3 was jointly co-authored with Jonas Fisher and Leonardo Melosi and I contributed 33% of the work.

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12/04/2022

Abstract

This thesis investigates the dynamics of inflation expectations with a particular focus on survey data. It aims to further the understanding of what drives inflation expectations and what are the implications of changes in inflation expectations for economic choices.

The first chapter examines to what extent monetary policy moves household inflation expectations. More specifically, I study the effect of different types of monetary policy announcements on household inflation expectations based on micro data from a survey of German households. As unique feature, interviews of the survey were conducted both shortly before and after monetary policy events. This timing provides a natural experiment to identify the immediate effects of policy announcements on household inflation expectations. In contrast to most existing studies, the availability of the survey over a period of 15 years also allows me to exploit the time-series dimension to estimate how policy announcements affect household inflation expectations over the medium-term. I find that policy rate announcements lead to quick and significant adjustments in household inflation expectations with the effect peaking after half a year. Announcements about forward guidance and quantitative easing, on the other hand, have only small and delayed effects. My results suggest that monetary policy announcements can influence household expectations but further improvements in communication seem to be necessary to reach the general public more effectively. In particular, in an environment where policy rates are constrained by the effective lower bound, it may be very hard for central banks to influence household expectations.

In the second chapter, joint with Evi Pappa and Alejandro Vicondoa, we focus on expectations about inflation in the medium to long run and study the implications of changes in these expectations for households' economic choices. We identify in a SVAR shocks that best explain future movements in different measures of underlying inflation at a five-year horizon and label them as news augmented shocks to underlying inflation. Independently of the measure used, such shocks raise the nominal rate and inflation persistently, while they induce mild and short-lived increases in economic activity. The extracted inflation shocks have differential distributional effects. They increase significantly and persistently the consumption of mortgagors and homeowners. Differently from the traditional monetary policy disturbances, news augmented shocks to underlying inflation induce a positive wealth effect for mortgagors and homeowners, driven by a reduction in the real mortgage payments and a persistent increase in real house prices that they induce.

The third chapter, joint with Jonas Fisher and Leonardo Melosi, is also about long-run inflation expectations but in this case the focus is on professional forecasters. We use panel data from the U.S. Survey of Professional Forecasters to estimate a model of individual forecaster behavior in an environment where inflation follows a trend-cycle time series process. Our model allows us to estimate the sensitivity of forecasters' long-run expectations to incoming inflation and news about future inflation, and measure the coordination of beliefs about future inflation. We use our model of individual forecasters to study *average* long-run inflation expectations. Short term changes in inflation have small effects on average expectations; the sensitivity to news is over twice as large, but is still relatively small. These findings provide a partial explanation for why the anchoring and subsequent de-anchoring of average inflation expectations over 1991 to 2020 were such long-lasting episodes. Our model suggests coordination of beliefs also played a role, slowing down but not preventing the pull on average expectations from inflation running persistently below target. We apply our model to the case of a U.S. central banker setting policy in September 2021. Our results suggest the high inflation readings of mid-2021 would have to be followed by overshooting of the Fed's target generally at the high end of the Fed's Summary of Economic Projections to re-anchor long term expectations at their pre-Great Recession level.

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Contents

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Central Bank Communication with the General Public: Survey Evidence from Germany

Abstract This chapter studies the effect of different types of monetary policy announcements on household inflation expectations based on micro data from a survey of German households. As unique feature, interviews of the survey were conducted both shortly before and after monetary policy events. This timing provides a natural experiment to identify the immediate effects of policy announcements on household inflation expectations. In contrast to most existing studies, the availability of the survey over a period of 15 years also allows me to exploit the time-series dimension to estimate how policy announcements affect household inflation expectations over the medium-term. I find that policy rate announcements lead to quick and significant adjustments in household inflation expectations with the effect peaking after half a year. Announcements about forward guidance and quantitative easing, on the other hand, have only small and delayed effects. My results suggest that monetary policy announcements can influence household expectations but further improvements in communication seem to be necessary to reach the general public more effectively. In particular, in an environment where policy rates are constrained by the effective lower bound, it may be very hard for central banks to influence household expectations.

1.1 Introduction

Managing inflation expectations is generally considered to be paramount for successful monetary policy. Nonetheless, the evidence on how well central banks can steer inflation expectations is mixed. A large literature has shown that expectations of financial markets respond strongly to monetary policy (see e.g. Andrade and Ferroni (2021), Del Negro et al. (2015) and Swanson (2021)). Instead, household and firm expectations seem to respond much less to monetary policy (Coibion et al. (2020b)). While the literature on financial markets is primarily using time series methods, the literature on household and firm expectations has relied more on microeconometric approaches. This paper provides novel evidence on the effectiveness of monetary policy on household inflation expectations. It distinguishes between different types of monetary policy announcements and exploits both microeconometric and time series methods to estimate the short- and medium-term effects of policy announcements on household inflation expectations. I find that announcements about conventional policy rate changes are (most) effective, whereas announcements about unconventional measures have only small and delayed effects.

Understanding the effects of monetary policy on household expectations is particularly relevant in current times. First, interest rates have been low for several years and in many advanced economies central banks have been frequently constrained by the lower bound on nominal interest rates. In such an environment, managing public expectations is crucial and optimal monetary policy prescribes that central banks should promise lower future interest rates to raise inflation expectations (Woodford (2003)). Second, several policymakers and some scholars have recently advocated that central banks need to reach out to the broader public more.[1] For effective and targeted central bank communication, understanding how inflation expectations are formed and to what extent monetary policy influences them is important.

In this paper, I study the effect of different types of monetary policy announcements by the European Central Bank (ECB) on household inflation expectations in Germany over the period from 2004 to 2019. I use micro data on household expectations from a survey conducted by the Gesellschaft für Konsumforschung (GfK). In order to identify the unexpected component of monetary policy announcements, I apply the methodology developed by Altavilla et al. (2019). Policy surprises are based on high-frequency interest rate changes around monetary policy events and are decomposed into Target, Timing, Forward Guidance and Quantitative Easing (QE) surprises. Target announcements

[1] See for example the speech by ECB president Lagarde (2020): "There is one issue, however, on which I can be decisive today: we must explain much better to the general public what we are doing and why, and we must talk to people that we do not normally reach." In terms of scholars see for example the 2020 Jackson Hole presentation by Yuriy Gorodnichenko (Candia et al. (2020)) or Haldane and McMahon (2018).

refer to changes in the short-term policy rate. Timing and Forward Guidance announcements provide guidance about the (expected) future path of policy rates over the next few months and next few years, respectively. Lastly, QE announcements primarily affect the interest rates at the long end of the yield curve. Altavilla et al. (2019) show that these announcements correspond to asset purchases such as the ECB's Asset Purchase Programme (APP) initiated in mid-2014.[2]

This distinction between different types of monetary policy announcements is largely unexplored in the literature on household inflation expectations. In the context of household expectations, the distinction is relevant for several reasons. First, unconventional monetary policy, such as QE, is a relatively new and complex tool for households to understand.[3] Therefore, it is interesting to investigate how responsive households' expectations are to these new and fairly sophisticated tools. Second, households might care more about the current interest rates than guidance about (expected) changes in the future path of these rates (see McKay et al. (2016) or Gabaix (2020) for theoretical formulations of this idea), and hence also here it is of high importance to shed light on different effects.

To identify the effect of monetary policy announcements on household expectations I follow two approaches. First, I use the timing of interview dates within the month which, together with the timing of policy announcements, provides a natural experiment framework. The interviews in the GfK survey are always conducted in two independent waves and in many cases the ECB Governing Council meetings take place at the end of the first wave and before the start of the second wave. This unique feature allows me to estimate the immediate effect of policy announcements by comparing responses of households from the waves before and after Governing Council meetings of the ECB. In contrast, most of the existing literature on household or firm expectations relies on monthly or quarterly data that makes identification more difficult. Moreover, I exploit the rich information on demographic characteristics entailed in the GfK dataset to study potentially heterogeneous effects. Second, I aggregate the cross-sectional survey data at the monthly level and use local projections to estimate the dynamic effects of policy announcements over a 12-month horizon. These medium-term effects might be different from the short-term effects due to informational rigidities.

My main finding is that Target announcements significantly affect household inflation expectations. A 25 basis point positive Target surprise reduces the probability that people expect an increase in inflation by around 2.7 percentage points. Timing, Forward Guidance and QE instead have no significant effect in the short run. This result highlights that the type of policy announcement matters for the reaction of household inflation expectations. These different effects depending on the type of policy announcement

[2] QE announcements target interest rates at long maturities since the average maturity of the QE program by the ECB is around 8 years.

[3] See D'Acunto et al. (2021a) on the role of cognitive abilities in the transmission of economic policies.

are also confirmed when looking at different subgroups of households. Households who are likely to pay more attention to inflation based on demographic characteristics such as income, education, age or their financial situation respond to Target announcements. However, they also do not respond significantly to the other type of announcements. Moreover, households who are well-informed about inflation in the sense that their inflation expectations are reasonable or their inflation expectations are ex-post accurate also only respond significantly to Target announcements.

When I estimate the dynamic effects on household inflation expectations over a 12-month horizon, I find that the effect of Target rate announcements increases over the medium term with a maximum effect reached after 4-6 months. Timing and QE announcements also affect inflation expectations negatively but only after around 8 and 3 months, respectively. The effects of Forward Guidance announcements remain quantitatively small and mostly insignificant for the entire forecast horizon. While these dynamic results point to some delayed effects of unconventional policies on household inflation expectations the effects are smaller and conventional interest rate changes seem to be most effective overall.

In order to provide an additional validation to how I interpret my results, I analyse the relationship of policy announcements and public interest in the ECB and its policies. More specifically, I use the search interest based on Google trends data as a proxy for public interest and the likely degree of media coverage. While Target and QE announcements are associated with an increase in public interest with respect to the ECB and its monetary policy, other announcements such as forward guidance do not have the same effect. This could explain why households react less to the latter type of announcements.

When I apply the different types of policy announcements on inflation expectations by financial markets and professional forecasters the picture is different. In contrast to households, financial market expectations react strongly to unconventional tools such as forward guidance. The response of professional forecasters is qualitatively more similar to households but their response is overall more immediate and significant compared to households. This suggests that unconventional tools are powerful because they affect financial markets and thereby also influence household choices through borrowing and saving rates, but household inflation expectations themselves do not (yet) seem to be an important transmission channel of unconventional monetary policy.

Finally, I test the predictions of standard macroeconomic models according to which higher inflation expectations stimulate current household spending. I investigate the validity of this prediction looking at how expectations including spending attitudes of each individual household responds to its inflation expectations in my data set. I find that inflation expectations are negatively related with various other household expectations, suggesting that households relate higher inflation expectations to worse economic outcomes. This reduced-form relationship also appears when estimating the effect of different types of monetary policy announcements on proxies of consumer spending attitudes. Positive Target surprises that reduce household inflation expectations have a positive effect on consumer spending attitudes. This positive effect goes in the opposite direction than one would expect from theoretical macroeconomic models with a representative agent where the intertemporal Euler equation intuition is at the core. Instead, it suggests that other channels such as income and wealth effects might be more important. This last result highlights that an additional challenge for effective central bank communication beyond reaching the broader public and influencing its expectations is to influence in the desired direction.

My results show that households adjust their expectations more to some policy announcement and less to others. These findings suggest that monetary policy communications are heard by households but further improvements in communication is needed to influence their expectations with newer and more sophisticated tools of modern monetary policy. This is all the more important in a low interest rate environment in which the effective lower bound is recurrently constraining the manoeuvring of the conventional policy rate.

Related Literature This paper contributes to two strands of the literature. First, there is a growing literature studying the effects of monetary policy measures and communication strategies on the broader public. Most of the currently existing literature finds that neither households' nor firms' expectations respond much to monetary policy as reviewed by Coibion et al. (2020b). In particular, Lamla and Vinogradov (2019) run surveys shortly before and after each FOMC press conference between 2015 and 2018 to estimate the effect of announcements on consumers' inflation perceptions and expectations. They find that announcements have no significant effect on inflation perceptions and expectations, but they make people more likely to receive news about the central bank announcements. However, Lamla and Vinogradov (2019) use an announcement dummy which does not distinguish between different types of measures announced at the same time and also does not measure the size and direction of the unexpected component in the monetary policy announcement as I do in this paper. Fiore et al. (2021) follow a similar approach for US FOMC meetings between 2013 and 2019 but use high-frequency monetary policy surprises more similar to this paper. They find that Fed announcements affect household expectations about interest rates of saving accounts but other expectations are not really influenced. D'Acunto et al. (2021b) analyze the effect of an unexpected value-added tax increase on German consumers and compare it with the more complex policy measure of the forward guidance announcement by the ECB in July 2013. They show that while the former has a significant effect on household consumption via influencing household inflation expectations, the latter announcement has no significant effect. Brouwer and de Haan (2021) study the impact of communication about monetary policy instruments on inflation expectations and trust in the ECB based on a randomized control trial among Dutch households. They show that providing households not only with information about the ECB's goal but also about the policy instruments leads to inflation expectations being closer aligned with the ECB's target. Their findings also suggest that the information treatment effect varies depending on the type of monetary policy instrument with information about (conventional) interest rate policies having stronger treatment effects than information about more unconventional instruments. Coibion et al. (2020a) use a randomized control trial to study how information about current and future interest rates affect households' expectations. They find that information about current and next year's interest rates move inflation expectations but providing also information beyond one or two years in the future has no additional effect.

To the best of my knowledge, my paper is the first one to use household level inflation expectations data and to distinguish between different types of monetary policy tools covering both conventional and unconventional policy times. This long sample has the advantage that it allows me not only to study the immediate announcement effects but also the dynamic effects over the medium term.

One closely related paper to my analysis is Lewis et al. (2019). They study the response of consumer confidence in the US to different types of monetary policy announcements between 2008 and 2017. Using daily data, they find that in contrast to most of the existing literature households respond very quickly to some news. In particular, they show that surprises to the federal funds rate lead to quick adjustments of consumer confidence but forward guidance and asset purchase surprises yield no significant effect. While this paper also distinguishes different types of monetary policy announcements, my focus on inflation expectations as variable of interest and the identification approach is different.

Additionally, my paper is related to Enders et al. (2019) and Bottone and Rosolia (2019), who study the response of firm expectations to monetary policy in an event study approach similar to this paper. Apart from studying expectations of firms, their papers are different in the sense that they do not distinguish between different types of monetary policy announcements and they only focus on the immediate policy effects.

The second strand of literature deals with the effectiveness of unconventional monetary policies and to which extent they can help to circumvent the constraint of the zero/effective lower bound on the short-term nominal interest rate. Swanson (2021) argues for the US that unconventional policies such as forward guidance and QE have been effective substitutes for conventional monetary policy. Similarly, Debortoli et al. (2020) find that the zero lower bound in the US between 2009 and 2015 was irrelevant likely because of the use of unconventional monetary policies during that time. In contrast, Campbell et al. (2019) show that the Fed has a limited ability to influence expectations especially at longer horizons and highlight the role of imperfect communication. The main focus of this literature has been on financial markets and professional forecasters or the macro effects in general.[4] In contrast, my paper focuses on one specific part of the transmission channel: the role of the general public and household inflation expectations.

Outline The rest of this paper is organized as follows. Section 2 describes the household survey data and the construction of monetary policy surprises. In Section 3, I present the identification approach and the main results on the effects of different types of monetary policy announcements on household inflation expectations. Section 4 discusses the role of media coverage and public interest as potential transmission channels and contrasts the findings for households with those of financial markets and professional forecasters. Section 5 provides some evidence on the relationship of household inflation expectations with other household expectations and the effects of policy announcements on consumer spending attitudes. Section 6 concludes.

1.2 Data and descriptive evidence

1.2.1 Household survey data

Most of the analysis is based on household survey data by the Gesellschaft für Konsumforschung (GfK). As part of a harmonized EU consumer survey program, the GfK interviews repeated cross-sections of around 2000 consumers in Germany at the beginning of every month. The survey is conducted via face-to-face interviews that take place in two independent waves of around 1000 consumers each. The first wave starts on a Friday and goes for one week and the second wave starts on the following Friday. This timing is important and will be exploited in the empirical approach described in Section 3. The GfK asks consumers both qualitative and quantitative questions on expected inflation over the next twelve months. The questions on inflation expectations used in this paper are:

> How do you think consumer prices will develop over the next 12 months, in comparison to the last 12 months? They will...
>
> 1. Increase more rapidly
> 2. Increase by approximately the same rate
> 3. Increase less strongly

[4]See also Inoue and Rossi (ming), Del Negro et al. (2015) Altavilla et al. (2019) and Campbell et al. (2012)

4. Stay about the same
5. Fall
6. Don't know

By how much percent do you think will consumer prices in the next 12 months increase (if 1, 2 or 3) / decrease (if 5)?

Answer options: enter number or don't know

In addition, the survey contains other questions about perceived current personal and economic conditions and expected future conditions. Finally, the GfK survey collects rich information on demographic characteristics (see summary statistics in the Appendix, Table A.1). The questions on quantitative inflation expectations are only available starting in January 2004 and in May 2019 there was a structural change in the way the consumer data is collected. Therefore, I use the sample from January 2004 until April 2019. section A.1 provides more details on the survey.

Figure 3.1 shows the distribution of qualitative inflation expectations which are the main focus of this paper. It highlights that there is substantial variation both over time and across individuals. More than 80% of households expect inflation to be either around zero or to be positive with most households expecting either around zero or approximately constant inflation.

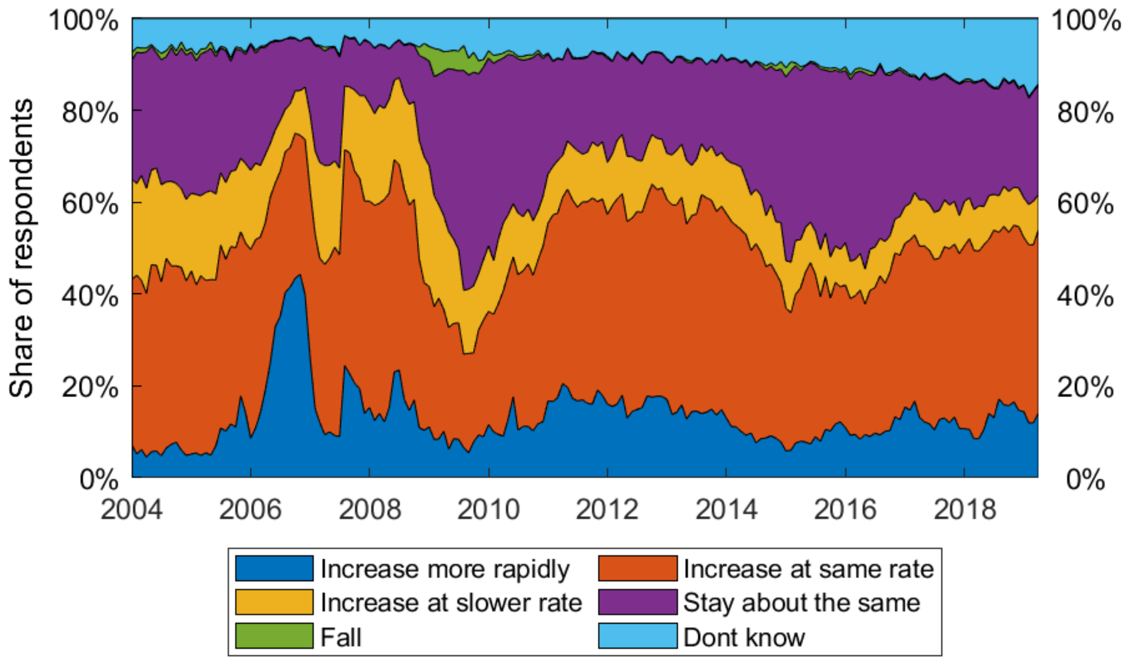


Figure 1.1 Distribution of qualitative inflation expectations over time

For some of my analysis I construct an aggregate measure of qualitative inflation expectations following Arioli et al. (2017). They propose a balanced statistic which is computed as the difference between the relative frequencies of responses falling in different categories. More specifically, the balanced statistic is defined as

$$P[1]+0.5P[2]-0.5P[4]-P[5] \tag{1.1}$$

where P[i] is the frequency of response with P[1]: increase more rapidly, P[2]: increase approximately at the same rate, P[4]: stay about the same and P[5]: fall. This balanced statistic can take values between -100 and 100. A value of 100 would imply that everybody expects higher inflation and a value of -100 that everybody expects deflation.

Besides the micro data for German consumers, I also use more aggregated data from the harmonized EU consumer survey program. This allows me to compare the results for Germany with the euro area as a whole.[5]

Properties of inflation expectations By definition, qualitative inflation expectations do not provide a point forecast for the level of inflation but they can still be a useful measure to capture households' expectations about future inflation dynamics. In fact, in the following I am describing some properties and argue why qualitative inflation expectations are the focus of this paper and preferable towards quantitative inflation expectations in the given survey. First, there is some co-movement between the dynamics of headline inflation and qualitative inflation expectations as measured by the balanced statistic. Similar to the US evidence presented by Cavallo et al. (2017) and Coibion and Gorodnichenko (2015b) among others, this co-movement is mainly driven by non-core items such as food and energy prices to which consumers are more regularly exposed (see the cross-correlations in Figure A.3). Second, qualitative inflation expectations capture meaningful variation in future realized core inflation which is more relevant for consumers durable consumption. Since I am also interested in studying potential effects of higher inflation expectations on durable consumption this is a relevant property. Figure 1.2 illustrates this point and plots inflation expectations from one year before as measured by the balanced statistic together with current HICP core inflation. For most of the sample period the dynamics of the two series are very similar (see also Figure A.3 for the cross-correlations at different horizons).

[5] Link to EU consumer survey: https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en. The underlying micro data for all European countries is confidential and the European Commission only publishes some aggregated time series data.

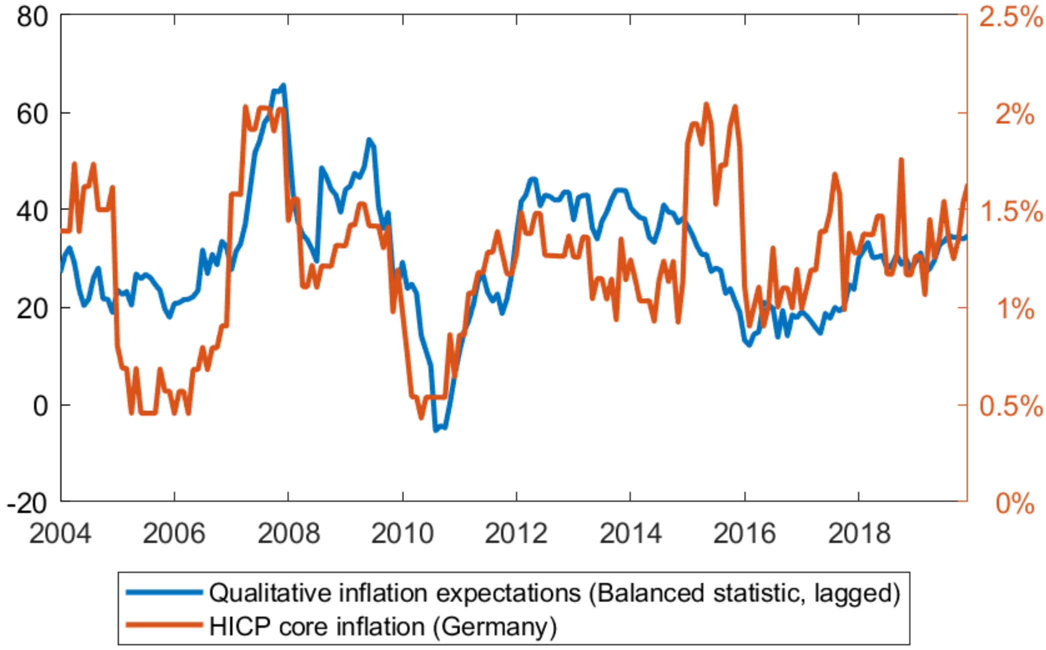


Figure 1.2 Inflation expectations and actual realized inflation

Notes: HICP core inflation (rhs) is inflation excluding food and energy and is calculated as year on year growth rate. Inflation expectations are lagged by one year and calculated as balanced statistics following Arioli et al. (2017).

While average quantitative inflation expectations also exhibit some co-movement with inflation their predictive power for future realized inflation is very limited and much smaller than for qualitative inflation expectations (see the cross-correlations in Figure A.4). In addition, it has been well documented in the literature that the average level of quantitative inflation expectations by households is much higher than actual inflation and many households provide extreme point forecasts. This is also the case in the given survey where the average level of expected inflation over my sample period is 4.6% while the actual realized level of inflation was only 1.6% (see also Figure A.1 in the Appendix). Based on these properties, I focus on qualitative inflation expectations in this paper. I will discuss the findings for quantitative inflation expectations and the comparison with qualitative expectations more detailed in section A.6.

1.2.2 Monetary policy surprises

I use monetary policy surprises based on the high-frequency identification approach introduced first by Kuttner (2001). Policy surprises are captured by high-frequency interest rate changes in a narrow window around the announcement on the day of ECB Governing Council meetings. The narrow window ensures that surprises measure the unanticipated component of ECB policy announcements since during this narrow window asset prices respond to monetary policy but there is no reverse causality from asset prices to monetary policy.[6]

For most of my analysis, I build on the Euro Area Monetary Policy Event-Study Database (EA-MPD) compiled by Altavilla et al. (2019).[7] This database provides data on changes of various interest rates around ECB Governing Council meetings. More specifically, the events of interest are the press release and the press conference that follow each Governing Council meeting. The press release is just a short statement on the policy decisions taken. Until March 2016 this only contained decisions on policy rates and since March 2016 also decisions on unconventional measures have been included. The press conference starts with the ECB President reading a prepared Introductory Statement on the rationale behind the decisions followed by a question-and-answer session with journalists. Therefore, for each ECB Governing Council meeting there are three event windows: the press release window, the press conference window and the monetary event window which contains both press release and press conference. The changes in interest rates are based on high-frequency tick-data and defined as follows for the three windows:

1. The press release window captures the change in the median quote from the window 13:25-13:35 before the press release to the median quote in the window 14:00-14:10 after it.
2. The press conference window captures the change in the median quote from the window 14:15-14:25 before the press conference to the median quote in the window 15:40-15:50 after it.
3. The monetary event window captures the change around both events, i.e. the change in the median quote from the window 13:25-13:35 before the press release to the median quote in the window 15:40-15:50 after the press conference.

The database contains interest rate changes for each window spanning the full term structure from 1 week to 20 years maturity.

In order to identify different types of policy announcements, I rely on the decomposition of policy surprises by Altavilla et al. (2019).[8] Their approach builds on a large literature of high-frequency

[6] I follow this high-frequency identification approach based on asset prices as it is very widely used to identify monetary policy shocks in the presence of the lower bound on the short-term nominal interest rate (see for example Rossi (2020) for an overview of identification approaches). Additionally and more importantly for the question of this paper it allows me to disentangle different types of announcements in one consistent framework.

[7] https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx

[8] Since their series of surprises end in September 2018, I extend their analysis to obtain a series of surprises for my sample period until April 2019. Over the common sample period until September 2018 the original series of surprises and my estimated series of surprises have a correlation of more than 0.99.

identification of monetary policy announcements, in particular Gürkaynak et al. (2005) and Swanson (2021). In the following, I describe their approach more detailed. For each of the two windows (press release and press conference), they estimate latent factors from changes in yields of risk-free rates at different maturities, spanning 1 month to 10 years.[9]

$$X^j = F^j \Lambda^j + \epsilon^j \qquad \text{with j=\{press release, press conference\}} \tag{1.2}$$

where X is a matrix of yield changes, F are unobserved factors, Λ the loadings matrix and ϵ white noise residuals. They test for the number of statistically significant factors in each of the two factor models. For the press release window they estimate a single significant factor which they label Target as it primarily loads on the short end of the yield curve. This factor is primarily about changes in the current policy target rate (see factor loadings in Appendix B, Figure A.1). For the press conference window they estimate two significant factors for the period before QE (until December 2013) and three factors for the full sample. This suggests that there is a third factor that is only active from 2014 onwards.

The three factors in the press conference window are only unique up to an orthonormal transformation and do not have an economic interpretation.[10] To allow for an economic interpretation, the orthogonal factors are identified by imposing restrictions on the rotation matrix similar to Gürkaynak et al. (2005) and Swanson (2021): (i) the second and third factor do not load on the 1-month OIS and (ii) the third factor has the smallest variance in the pre-crisis period. Then, they label the first factor that loads on the 1-month OIS as Timing that captures near-term expected policy actions. The second factor that is also active for the full sample is labelled Forward Guidance (FG) as it has the strongest effects on the medium-term horizon of the yield curve. Finally, the third factor is labelled QE and is shown to load only on longer-term yields with the effect being greater the longer the maturity. This is consistent with the assets purchased by the ECB which had an average maturity of about eight years. All the factor loadings and the series of Target, Timing, Forward Guidance and QE surprises are plotted in Appendix B (see Figure A.1 and Figure A.2). The four factors are normalized to have a one unit effect on 1-month, 6-month, 2-year and 10-year OIS, respectively.

Note that the last factor (QE) is only active from 2014 onwards but the series of surprises shown in Figure A.2 also exhibits some larger surprises in the years between the Great Recession and 2014. These

[9]When available they use overnight-index-swap (OIS) interest rates to proxy the risk-free rate curve. Before August 2011 OIS data on maturities longer than 2 years is not available and they use yields on German sovereign yields instead.

[10]To see that F and Λ are not uniquely identified, take orthonormal matrix U satisfying UU'=I. Then, $\tilde{F} \equiv FU$ and $\tilde{\Lambda} \equiv U'\Lambda$ and $\tilde{F}\tilde{\Lambda} = F\Lambda$. Unique identification requires putting restrictions on U. See Appendix F of Altavilla et al. (2019) for more details on identification and factor rotation.

are likely related to other monetary policy announcements that moved primarily long-term interest rates for example around the sovereign debt crisis. These types of announcements are different from the asset purchase announcements from 2014 and not the focus of this paper.[11]

In some analysis, I use two alternative monetary policy surprise measures. On the one hand, I directly use the change of the 1-year OIS interest rates from the monetary event window of the EA-MPD as this maturity has been commonly used in the literature as (summary) policy indicator for monetary policy including the effective lower bound period (see for example Gertler and Karadi (2015)). On the other hand, I use the monetary policy surprises by Kerssenfischer (2019) who follows a similar approach as Jarociński and Karadi (2020). He uses 2-year Bund futures and then disentangles the information component from the policy component using a VAR model with sign-restrictions on interest rate and stock prices.

1.2.3 Other data

There are three other types of data that I use in the rest of this paper. First, this is data on macroeconomic variables such as HICP, Industrial Production, short-term and long-term interest rates and credit spreads. This data is downloaded from the ECB Statistical Data Warehouse and the OECD library and the credit spreads from the paper by Gilchrist and Mojon (2018). Second, I use daily data on German inflation-linked bonds downloaded from Bloomberg. Third, I obtained inflation forecasts from a Bloomberg survey of professional forecasters that is conducted monthly.

1.3 Identification approach and main results

I use two empirical approaches to estimate the effects of monetary policy announcements on household expectations. First, I exploit the survey design together with the timing of monetary policy announcements to identify the short-term effects of monetary policy announcements. Second, I use a local projections approach to estimate the dynamic effects of policy announcements over the medium term.

1.3.1 Event study approach

In the following, I describe how I exploit the timing of the ECB Governing Councils and the survey timing design for identification. As shortly mentioned in section 2.1, the GfK interviews take place at the beginning of every month in two independent waves of around 1000 consumers each. The first

[11] In the robustness analysis I check that controlling explicitly for these surprises before 2014 does not meaningfully affect my results.

survey wave starts on a Friday and goes for a week when the second survey wave starts for a week (see Figure 1.3 for illustration). Interviews are face-to-face and relatively evenly distributed during the whole week.

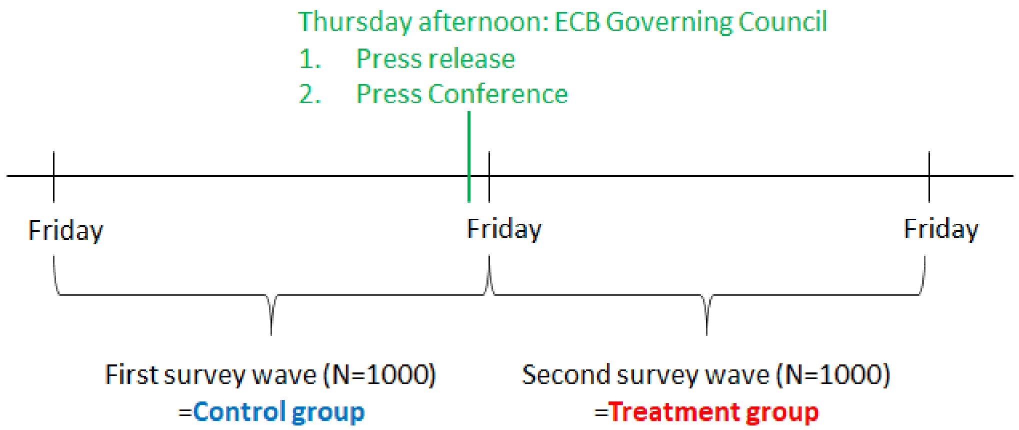


Figure 1.3 Survey timeline

Until 2014 the ECB Governing Council meeting usually took place at the beginning of every month. From 2015 the ECB Governing Council met only every six weeks. The press release and press conference is usually on Thursday afternoon. Due to this timing of events there is a considerable amount of ECB Governing Council meetings that take place exactly between the two survey waves such that I observe some households that answer the survey right before the ECB policy announcements and some households that answer the survey directly afterwards. This provides a natural experiment to identify the immediate effects of policy announcements. More specifically, for the period January 2004 until April 2019 around 65% of ECB Governing Council meetings take place between the two survey waves (see the blue bars in Figure A.2 for the ECB Governing councils that are included).[12]

To identify the effects of different types of policy announcements, I estimate the following regression model:

$$Y_{i,t} = \alpha + \beta_1 D_{i,t} Target_t + \beta_2 D_{i,t} Timing_t + \beta_3 D_{i,t} FG_t + \beta_4 D_{i,t} QE_t + \gamma X_{i,t} + u_{i,t} \qquad (1.3)$$

where $Y_{i,t}$ refers to inflation expectation over the next twelve months of consumer i at month t. $D_{i,t}$ is a dummy variable equal to one if respondent i in month t is in the second survey wave and zero if it is in the first wave. $Target_t$, $Timing_t$, FG_t and QE_t are equal to the different policy announcement surprises described in the previous section. $X_{i,t}$ includes month fixed effects, a dummy for consumer i

[12]Due to the change from a monthly to six weeks schedule in 2015 the number of meetings covered after 2015 is much lower than before 2015.

belonging to wave 1 or 2 and various household controls such as age, household income, occupation, education, gender, city size, state, marital status, housing status, household size (see also Table A.1 for an overview and summary statistics). Additionally, I include the average value of expectations in the previous 4 survey waves as control variable. I use robust standard errors that are clustered at the monthly level. As baseline I use qualitative inflation expectations as depicted in Figure 3.1. This means that the dependent variable is an ordered categorical variable and estimating a linear model is likely to yield biased estimates. Therefore, I estimate the model as ordered logit model.

Table 1.1 shows the results of the ordered logit model based on Equation 1.3. For reasons of simplicity the table only focuses on one outcome category. More specifically, the table shows the average marginal effect on the probability that households expect prices to increase more rapidly, i.e. inflation to go up. The marginal effects for the other outcome categories are reported in Table A.1. The effects are scaled to a shock corresponding to a 25 basis point increase in the respective reference rate.[13] This implies the coefficients show by how much percent households are more/less likely to expect inflation to go up if there is an announcement that increases the corresponding reference rate by 25 basis points.

Table 1.1 Main results for effect of different types of policy announcements

	(1)	(2)	(3)	(4)
Target	-0.022*	-0.026**	-0.027***	
	(0.012)	(0.013)	(0.010)	
Timing	0.000	-0.003	0.002	
	(0.016)	(0.015)	(0.016)	
FG	-0.009	-0.010	-0.008	
	(0.007)	(0.008)	(0.007)	
QE	-0.009	-0.004	-0.017	
	(0.014)	(0.015)	(0.015)	
1Y OIS				-0.009
				(0.009)
N	203.778	203.778	203.778	203.778
Month FE	Yes	Yes	Yes	Yes
Wave dummy	No	Yes	Yes	Yes
HH controls	No	Yes	Yes	Yes
Past expectations	No	No	Yes	Yes
Sample	2004-2019	2004-2019	2004-2019	2004-2019

Notes: Results based on ordered logit model. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points on probability that prices increase more rapidly (=inflation goes up). Standard errors clustered at the monthly level are in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

[13] As mentioned in the previous section, the reference rates are the 1-month, 6-month, 2-year and 10-year OIS rate for the Target, Timing, FG and QE announcements, respectively.

In columns (1)-(3), I successively add the different types of control variables. Column (1) only includes month fixed effects as control variables. Column (2) also includes a wave dummy and household controls. Generally, the differences in coefficients between the first two columns are small. Moreover, the coefficient on the wave dummy is not statistically different from zero. This is important as it confirms that the two waves are quite similar and comparable. Column (3) includes all control variables including average expectations during the past 4 survey waves. This is my baseline specification. I find that a 25 basis points Target surprise makes it 2.7% less likely that households expect inflation to go up. The effect of Timing, FG and QE are imprecisely estimated and especially for Timing and FG the magnitude is very small. In column (4), I show the response when using the high-frequency change in the 1-year OIS which is commonly used as a summary indicator of monetary policy. The insignificant response highlights that it is important to consider the multi-dimensionality of monetary policy announcements.

The scaling of surprises can be done in various ways and to some extent this is arbitrary. In the description above and also in the rest of the paper I use a scaling of 25 basis points change in the reference rate. I follow this approach because 25 basis points is a conventional size considered in the literature and makes the comparison with alternative monetary policy surprises easier. However, note that for the given surprises and sample period surprises of this size basically do not not exist. The standard deviation of Target, Timing, FG and QE surprises are 1.9, 2.3, 3.4 and 1.9 basis points, respectively. The average surprises are of the order of 1 basis point in absolute terms and the largest surprises are usually between 10 and 15 basis points in absolute terms. Therefore, I would argue that households being 2.7% less likely to expect higher inflation as shown in the table above for the Target surprise is a rather small effect in economic terms.

While the baseline results show that only Target announcements lead to a significant effect on household expectations, it might be that certain household groups react more to monetary policy announcements including also forward looking communication. In the following, I will analyse this for (i) demographic characteristics and (ii) how well households are informed about inflation.

Table 1.2 shows that the evidence from Table 1.1 is supported by looking at different demographic groups who are likely to be more responsive to monetary policy announcements. These are in column (2) households in the top quartile of the net income distribution, in column (3) households with a high school degree or more, in column (4) middle-aged households who are typically the ones who get a mortgage or who need to save for retirement and in column (5) households who say that they can save a bit or a lot. The last household group can be considered as a proxy for households with little financial constraints. For all these four groups the response of inflation expectations to Target surprises is significant. The magnitude of coefficients is larger but the difference to the baseline is not in all cases statistically significant. For the other types of policy announcements, the effects are again very imprecisely estimated with the signs of the coefficients often changing across the four columns. There is only a significant effect of QE surprises in the case of high-income households, hence suggesting that overall the conclusion from the baseline analysis also holds for different household subgroups.

Table 1.2 Results for different demographic characteristics

	(1) Baseline	(2) High income	(3) Higher education	(4) Age (30-60)	(5) Saver
Target	-0.027***	-0.046**	-0.031***	-0.048***	-0.030***
	(0.010)	(0.018)	(0.009)	(0.010)	(0.009)
Timing	0.002	-0.020	0.000	0.003	-0.009
	(0.016)	(0.028)	(0.020)	(0.017)	(0.018)
FG	-0.008	-0.015	0.001	-0.006	0.005
	(0.007)	(0.014)	(0.009)	(0.009)	(0.009)
QE	-0.018	-0.100**	-0.017	-0.041	0.003
	(0.015)	(0.043)	(0.024)	(0.030)	(0.020)
N	203.778	42.020	122.340	108.549	112.268

Notes: Results based on ordered logit model. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points on probability that prices increase more rapidly (=inflation goes up). High income refers to households in the top 25% of the monthly net income distribution, higher education to households with high school or higher degree, saver to households who save a bit or a lot. Standard errors clustered at the monthly level are in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 1.3 shows the results for households who are better informed about inflation and should therefore be more likely to pay attention and adjust their expectations. I use the answers to the quantitative questions on inflation expectations and perceptions. In column (2), these are households who expect inflation to be between 0 and 3 percent in line with the range of realized inflation in the period between 2004 and 2019. In column (3) and (4), I show the responses for households who are better forecasters of ex-post realized inflation. Finally, column (5) reports the response of households who provide consistent answers to the questions on quantitative and qualitative inflation expectations. These households are likely to understand the survey questions well. Again for all four household groups there is a significant effect of Target surprises on inflation expectations but for the other three types of announcements there is generally no consistent evidence for significant effects.

Overall, these results suggests that qualitative inflation expectations respond to Target surprises but for the other types of announcement the evidence points to households not responding to them in line with a large degree of inattention/unresponsiveness to monetary policy that is highlighted in the previous literature. Moreover, this result also holds when looking at various subgroups of households

Table 1.3 Results for "informed" households

	(1) Baseline	(2) Reasonable	(3) Top 10% accurate	(4) 1pp accurate band	(5) Consistent
Target	-0.027***	-0.058***	-0.032***	-0.020***	-0.043***
	(0.010)	(0.014)	(0.010)	(0.007)	(0.008)
Timing	0.002	-0.036**	0.022	-0.005	0.018
	(0.016)	(0.016)	(0.032)	(0.019)	(0.025)
FG	-0.008	0.018	0.013	-0.002	-0.017
	(0.007)	(0.013)	(0.024)	(0.017)	(0.013)
QE	-0.017	0.044	0.018	0.008	-0.094*
	(0.015)	(0.043)	(0.069)	(0.039)	(0.051)
N	203.778	37.064	31.860	41.585	100.023

Notes: Results based on ordered logit model. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points on probability that prices increase more rapidly (=inflation goes up). Reasonable refers to households that expect inflation between 0 and 3 percent, top 10% accurate refers to the households that are among the 10% households that were most accurate in terms of one year ahead realized inflation, 1 percentage point accurate band refers to households that have inflation expectations that are within a 1 percentage point band of actual one year ahead realized inflation. Consistent refers to households who give quantitative inflation expectations that are consistent with their qualitative inflation expectations. Standard errors clustered at the monthly level are in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

that are likely to be more attentive to inflation and monetary policy.

Robustness and extensions I perform several robustness checks and extensions for which most of the results can be found in section A.3. The results are robust to using other model specifications than an ordered logit model. In particular, the effects are similar when using (i) a logit model where the dependent variable is a dummy variable that is one if households expect prices to increase more rapidly and zero otherwise or (ii) a linear regression model (see Table A.2). Besides, Table A.3 highlights that the policy announcements have no significant effect on the proportion of households answering "Don't know" which would be problematic for the use of the ordered logit model.

In Table A.4, I analyse the role of perceptions about past inflation which are likely correlated with inflation expectations. In order to make sure that my results are not driven by an effect on inflation perceptions, I control for inflation perceptions in Equation 1.3 and show that the effects of monetary policy announcements on inflation expectations are similar to the baseline in that case. Moreover, the different type of policy announcements do not significantly affect the perception of households about past inflation.

In my baseline analysis I follow Altavilla et al. (2019) and assume that the third factor (QE) is only active from 2014. However, Figure A.2 shows that there are also larger surprises in this factor before 2014. In Table A.5, I show that controlling for these surprises does not really affect the coefficients of the other types of monetary policy announcements and the pre 2014 surprises itself have no significant effect on household inflation expectations.

When looking at the role of large surprises I find that dropping the three largest Target surprises yields effects that are similar to the baseline results presented before (see Table A.6). Table A.7 shows that results are also robust to excluding the Great Recession period between March 2008 and June 2009.

The literature has emphasized that high-frequency identified monetary policy surprises are often predictable by current economic conditions and correlated with central banks' private macroeconomic forecasts (see Ramey (2016) and Miranda-Agrippino and Ricco (2021)). In order to address these issues I follow Miranda-Agrippino and Ricco (2021) and orthogonalize the monetary policy surprises with respect to (i) current economic conditions and (ii) the central banks' private macroeconomic forecasts. First, I take the residuals from a regression of the surprises on a set of macro-financial factors extracted from a broad collection of real-time monthly variables.[14] Second, I take the residuals from a regression of the surprises on the ECB's one-year ahead GDP and inflation forecasts and forecast revisions. This second regression should control for the signalling channel as described in Melosi (2016) where there is some information asymmetry between private agents and the central bank and therefore central bank announcements also have some effect via signalling the central bank's view about the macroeconomic development.

Column (1) and (2) in Table 1.4 show the results for the two orthogonalized monetary policy surprises and results are very similar to the baseline. Moreover, in column (3) I show that results are robust to using the monetary policy surprises orthogonalized with respect to 3 lags and leads of each of the surprises to control for potential serial and cross-correlation of the surprises.[15] As a further robustness check, I consider two alternative monetary policy surprises. First, I do not use a factor model as Altavilla et al. (2019) but simply take the 1-year OIS change for the press release window and the press conference window. The press release window is just a short statement about policy actions taken by the Governing Council and until 2014 this just included interest rate changes. The press conference is more about communication and explains the underlying reasons for the policy decisions and also provides a further outlook. Second, I take the monetary policy surprise series by Kerssenfischer (2019) who decomposes monetary policy news into a policy and an information component similar to Jarociński and Karadi (2020). Results are shown in Column (4) and (5) of Table 1.4 and in both cases the surprises that are about policy actions yield a stronger response compared to the surprises that are more about communication and providing information about potential future actions. One potential

[14] I use the Euro Area Real-Time Database which has been constructed by Giannone et al. (2012) and can be found here: https://sdw.ecb.europa.eu/browseExplanation.do?node=9689716.

[15] According to the Akaike information criteria, 3 is the optimal number of lags.

Table 1.4 Results for alternative monetary policy surprises

	(1)	(2)	(3)	(4)	(5)
Target	-0.024**	-0.028**	-0.031**		
	(0.009)	(0.011)	(0.016)		
Timing	0.004	0.002	0.007		
	(0.017)	(0.016)	(0.021)		
FG	-0.009	-0.007	-0.011		
	(0.008)	(0.008)	(0.012)		
QE	-0.019	-0.013	-0.017		
	(0.015)	(0.017)	(0.016)		
1Y OIS (release)				-0.033**	
				(0.013)	
1Y OIS (conference)				-0.005	
				(0.009)	
Policy					-0.016**
					(0.008)
Info					0.009
					(0.013)
N	203.778	203.778	203.778	203.778	201.946

Notes: Results based on ordered logit model. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points on probability that prices increase more rapidly (=inflation goes up). Column (1) shows the responses using monetary policy surprises orthogonalized with respect to current economic conditions. Column (2) shows the responses using monetary policy surprises orthogonalized with respect to the ECB's macroeconomic forecasts and forecast revisions. Column(3) shows the responses using the monetary policy surprises orthogonalized with respect to three lags and leads of the surprises to control for serial and cross-correlation. Column (4) shows the response to the change of the 1-year OIS during press release and press conference, respectively. Column (5) shows the response to policy and information shock series by Kerssenfischer (2019) which go only until December 2018. Standard errors clustered at the monthly level are in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

reason for this could be that (current) policy actions are covered more by media and therefore reach households more easily.

1.3.2 Local projections approach

The previous section has focused on the immediate response of household expectations to policy announcements. The literature on information rigidities (see for example Coibion and Gorodnichenko (2015a)) highlights that households often need some time to process new information or do not pay attention all the time and therefore only react with some time lag to news. Therefore, in this section I estimate the medium-term dynamic effects of policy announcements on inflation expectations. Since the survey consists of repeated cross-sections of consumers it is not possible to directly follow individual respondents over time. I aggregate household expectations at monthly frequency and then estimate the dynamic effects of policy announcements by local projections building on Jordà (2005).[16] Alternatively, I construct a pseudo panel as introduced by Deaton (1985). The results for the pseudo panel approach are presented in section A.5 and lead to qualitatively similar conclusions.

I estimate the following specification for $0 \leq h \leq 12$ months:

$$y_{t+h} = \beta_h^{Ta} Target_t + \beta_h^{Ti} Timing_t + \beta_h^{FG} FG_t + \beta_h^{QE} QE_t + \gamma_h X_t + u_{t+h} \tag{1.4}$$

where y_t are inflation expectations in month t and $Target_t$, $Timing_t$, FG_t and QE_t correspond to the policy surprises in month t. X_t includes three lags of the policy surprises and two lags of y_t, the short-term interest rate, the long-term interest rate, the HICP index, the industrial production index and a credit spread.[17] Inflation expectations are aggregated at the monthly frequency to a balanced statistic as described in section 1.2 (see time series in Figure 1.2). The contemporaneous values of the control variables are not included such that I implicitly allow for contemporaneous (within the month) effects of announcements on all control variables. 68% and 90% confidence bands are computed using Newey-West standard errors to control for heteroscedasticity and serial correlation.

Figure 1.4 shows the response of qualitative inflation expectations to the different types of monetary policy announcements. The response of the macro variables and interest rates are shown in the Appendix (see subsection A.4.1). The responses are scaled such that respective reference rates - 1-month, 6-month, 2-year and 10-year OIS, respectively - increase by 25 basis points on impact. The units are changes in the balanced statistic. A positive Target surprise significantly reduces household inflation expectations on impact and with a peak effect of around -30 reached after around 5 months. While a 25 basis point surprise is very large this effect implies even for smaller scaled surprises that Target announcements have an economically meaningful and sizeable effect. For the other types of announcements there is no significant effect on impact. Positive Timing surprises slightly increase expectations during the first months but then lead to a reduction of inflation expectations as measured by the balanced statistic by around 10 after 6-8 months. For FG surprises the effects are generally small and mostly insignificant. Positive QE surprises decrease inflation expectations but the effect is only significant after a few months with a maximum effect of slightly more than -10.

In subsection A.4.2, I provide several robustness checks including alternative lag lengths, controlling for surprises in the QE factor before 2014 and the role of potential cross-correlation of policy surprises.

[16] This approach also allows me to exploit the full sample of Governing Council meetings since 2004 and to compare the responses to the euro area as a whole and professional forecasters for which the empirical approach described in the previous section is not feasible due to the data frequency.

[17] The number of lags is set based on the Akaike information criteria. Results are robust to using alternative lag specifications.

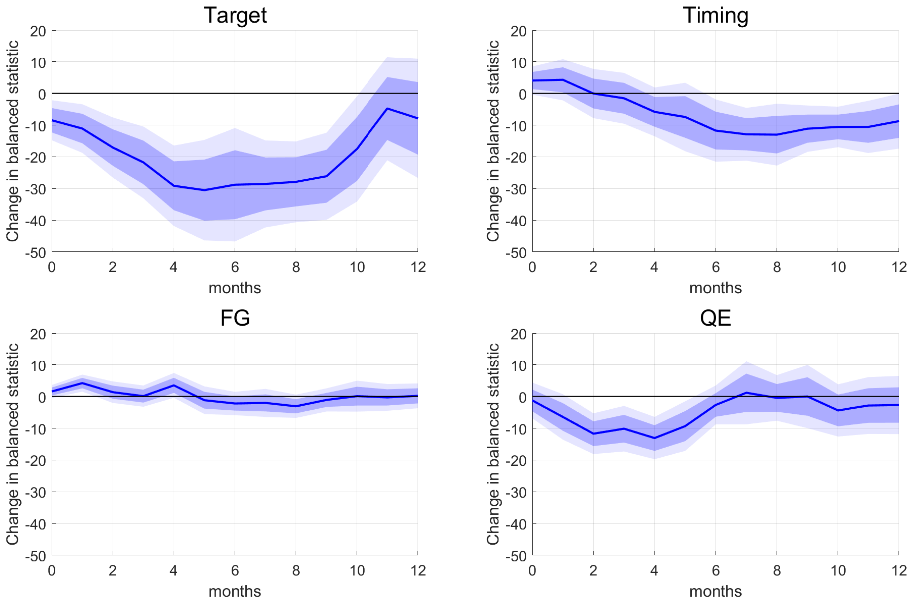


Figure 1.4 Response of qualitative inflation expectations (balanced statistic)

Notes: Estimates based on local projections of qualitative inflation expectations (balanced statistic) on monetary policy surprises and control variables as in Equation 2.4. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the respective reference rate by 25 basis points.

Overall, the above evidence is broadly in line with the results from the event study approach in the previous section. While Target announcements lead to a significant and sizeable reduction in inflation expectations, the other announcements have no or only smaller delayed effects. Besides, the results for Germany are qualitatively similar to the euro area as a whole (see Figure A.6 in the Appendix). Comparing these results to the existing literature on monetary policy and household inflation expectations might look contradictory. However, most existing studies focus on quantitative inflation expectations. In section A.6, I provide some results and discussion about quantitative inflation expectations.

1.4 Discussion

In this section I provide further analysis to explain and put the previous results into context. First, I analyse the role of media as potential transmission channel. Second, I compare the response of households to financial markets and professional forecasters.

1.4.1 The role of media as transmission channel

The literature on household expectations often uses designed experiments in which researchers provide participants with specific pieces of information and then estimate the effect of this information. In contrast, in this framework I do not control or know the news or signals that households receive. It is likely that almost no household follows the ECB's press conference or directly obtains information from the ECB via their website. Instead, it is more likely that information on ECB monetary policies reaches households via "classical" media or social media such as Twitter and they react to this information. Therefore, media coverage might play an important role in explaining the previous results. If some type of policy announcements lead to more/different media coverage than others that could explain the differences across types of announcement presented in the previous section. Even though a detailed analysis is beyond the scope of this paper, I am using Google trends data to establish to what extent different policies reach people. Google trends data measures the search interest for certain topics/keywords and can reflect the general public interest in a topic, how much people pay attention and if people search for information on a topic. Therefore, I would argue it is related to media coverage and can be considered as a proxy for the media transmission channel.

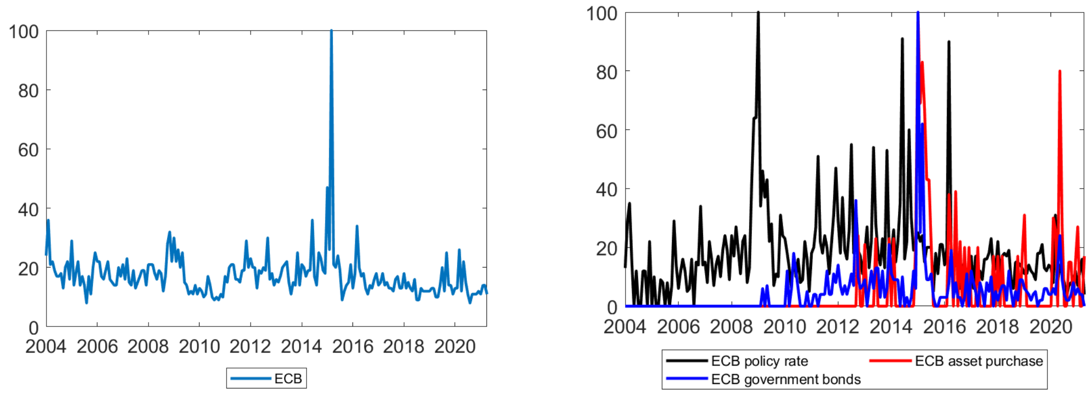


Figure 1.5 Search interest for different keywords on Google Search in Germany

Notes: The four keywords used in German are "EZB", "EZB Leitzins", "EZB Anleihenkauf" and "EZB Staatsanleihen", respectively. Series show how frequently a given search term is entered into Google's search engine relative to the site's total search volume over a given period of time. Series are scaled such that 100 indicates the point with the maximum search interest over time. Monthly data from January 2004 until April 2021.

Figure 1.5 shows the search interest for different keywords related to the ECB and its policies in Germany over time since 2004. The largest search interest for the keyword ECB is in the beginning of 2015 when the ECB announced the asset purchase programme (APP). Looking at the figure on the right side the spikes in the keywords "ECB asset purchase" and "ECB government bonds" also relate to events about asset purchases such as the introduction of APP and the announcement of the pandemic purchase programme in March 2020. For the term "ECB policy rate" there are also other events that generate high search interest such as late 2008 and early 2009 when the ECB changed the key interest rates several times or June 2014 when the ECB first lowered the deposit facility rate below zero and in March 2016 when the rate on main refinancing operations was lowered to zero.

Table 1.5 Effect of policy announcements on Google search interest

	(1) ECB	(2) ECB policy rate	(3) ECB	(4) ECB asset purchase	(5) ECB government bonds
Target	0.646***	2.621***	-0.685	-5.634	-4.925
	(0.232)	(0.944)	(2.121)	(4.243)	(3.431)
Timing	0.298	1.007*	0.949	-8.519	0.634
	(0.200)	(0.587)	(2.817)	(5.654)	(3.897)
FG	0.119	-0.056	1.852	4.824	-1.275
	(0.133)	(0.321)	(2.307)	(4.682)	(3.534)
QE	2.687**	0.972	2.906**	7.496**	6.324*
	(1.178)	(0.826)	(1.328)	(3.210)	(3.680)
Sample	2004-2019	2004-2019	2014-2019	2014-2019	2014-2019

Notes: Results based on regression of Google search interest on **absolute** value of announcement surprises. The keywords used in German and for Google in Germany are "EZB", "EZB Leitzins", "EZB Anleihenkauf" and "EZB Staatsanleihen", respectively. The sample period goes from January 2004 until April 2019. Robust standard errors in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.010$.

In order to measure the effects of different types of policy announcements on search interest I regress the different series of search interest on the absolute values of the monetary policy surprises.[18] Table 1.5 shows the results. Column (1) indicates that Target and QE announcements are significantly related with increases in the search interest for the keyword ECB. Larger surprises in absolute terms lead to higher search interest and public interest. For Timing and FG announcements the effects are smaller and not statistically significant. Looking at the other keywords this result is broadly confirmed. For the keyword "ECB policy rate" Timing announcements are also weakly related with Google search interest but the magnitude is smaller than for Target announcements. Columns (3)-(5) indicate that for the last years since 2014 QE announcements are the only announcements that are significantly related with Google search interest. Overall, this indicates that announcements about changes in the policy rate and asset purchases might be more likely to reach the public and generate more public interest compared to Timing and especially FG announcements. This can contribute to explaining the differential response of households' inflation expectations to the different type of policy announcements.

[18]Using the absolute value allows me to take into account the size of monetary policy surprises but I abstract for simplicity from potential differences depending on the direction of policy change.

1.4.2 Financial markets and professional forecasters as benchmark

This section compares the response of household inflation expectations with the response of inflation expectations by financial markets and professional forecasters. Especially professional forecasters who are well informed economic agents can be regarded as natural benchmark for comparison to consumers.

In order to measure the response of inflation expectations by financial markets, I use German inflation linked bonds at 1-4 years maturity (see time series of inflation linked bonds in Figure A.11). I estimate the effects of policy announcements based on an event study framework.[19] More specifically, I regress one-day changes from the day before the Governing Council meeting to the end of the day of the Governing Council meeting on the different types of monetary policy surprises. Table 1.6 shows the results for 25 basis points policy surprises. Positive Target and QE announcements lead to a reduction in inflation expectations while Timing and FG announcements increase inflation expectations. In particular, for FG announcements the effects are highly significant which is different from the household responses. The magnitude of the effects is fairly similar across type of announcements which is also in contrast with the responses of household inflation expectations. These results are qualitatively similar to Andrade and Ferroni (2021) who distinguish between a target and path factor and find that especially the path factor has strong positive effects on market-based inflation expectations. The positive response to FG and Timing announcements is in line with the signalling/information channel of monetary policy that has been documented in the literature (see Melosi (2016) and Nakamura and Steinsson (2018)).

Table 1.6 The response of financial markets: German inflation linked bonds

	1Y	2Y	3Y	4Y
Target	-0.24*	-0.25*	-0.10	-0.08
	(0.13)	(0.13)	(0.19)	(0.17)
Timing	0.20**	0.03	0.10	0.04
	(0.10)	(0.06)	(0.08)	(0.06)
FG	0.19**	0.20***	0.20***	0.21***
	(0.08)	(0.05)	(0.06)	(0.05)
QE	-0.13**	-0.08*	-0.12**	-0.12**
	(0.05)	(0.04)	(0.05)	(0.06)
N	132	137	137	136

Notes: Regression of one-day changes in German inflation linked bonds on the four different surprise series (included simultaneously). Responses are scaled to a shock that increases the respective reference rate by 25 basis points. Due to data availability sample starts only at the Governing Council in May 2006. Robust standard errors are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

[19] In Figure A.12 I also show the dynamic effects over the next 120 days using local projections.

In order to measure the response of inflation expectations by professional forecasters, I use survey data from a monthly Bloomberg survey that asks professional forecasters about their inflation expectations several quarters ahead. Consistent with the horizon of household expectations I focus on one-year ahead inflation expectations and I use the same local projections framework as defined in Equation 2.4. Figure 1.6 plots the impulse response functions for inflation expectations in Germany. Given that the data for Germany is only available from February 2008, I also show the response for the euro area where the data is available from October 2005 (see Appendix Figure A.7). Qualitatively, the responses show some similarities with those by households. This is not completely surprising given that the series of inflation expectations by households and professional forecasters have a correlation of 0.76 (see also Figure A.5 for the time series). The similarity is true in particular for Target and QE announcements. For Target surprises the effect is stronger on impact compared to the more delayed response by households. A 25 basis points Target surprise leads to a reduction in inflation expectations by up to 0.5 percentage points.

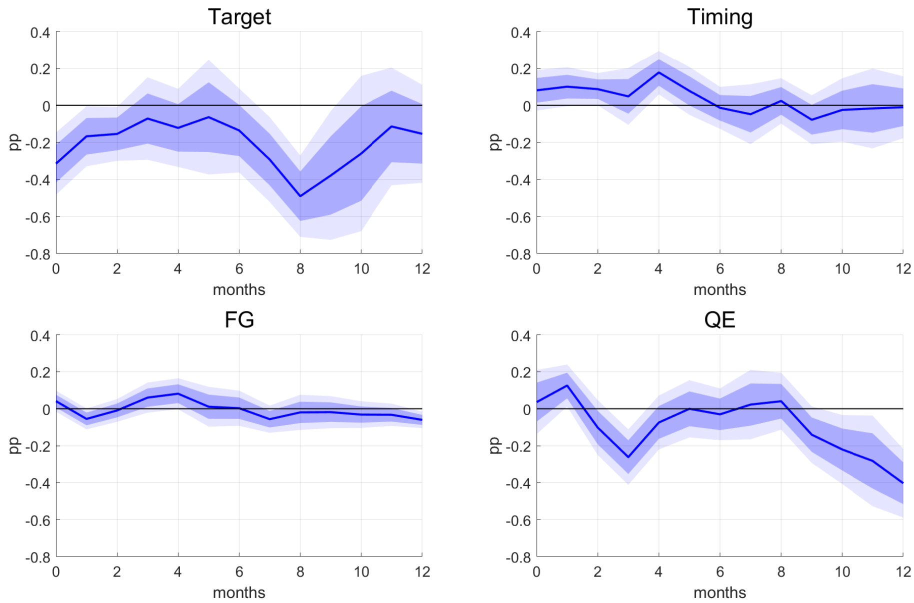


Figure 1.6 Response of inflation expectations by professional forecasters, Germany

Notes: Estimates based on local projections of one year ahead inflation expectations on monetary policy surprises and control variables as in Equation 2.4. Inflation expectations come from a monthly survey of professional forecasters conducted by Bloomberg. Sample starts only in February 2008. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points.

The results described above show that while household expectations mainly react to Target announcements, professional forecasters and especially financial markets also react to the other type of policy announcements. In particular, communication such as forward guidance has powerful effects on financial markets in line with a large existing literature also mentioned in the related literature earlier.

1.5 Inflation expectations and consumer spending

Ultimately, the mandate of central banks is inflation management/stabilization. In standard macroeconomic models expectations play an important role for the determination of households' consumption and saving choices and this ultimately also affects aggregate inflation and output. Inflation expectations could influence household consumption via different channels and I describe some possible channels in the following. First, the traditional Euler equation mechanism would suggest that higher inflation expectations should reduce real interest rates and create incentives for household to bring forward consumption, in particular durable consumption which is more interest rate sensitive. Second, higher inflation expectations might lead households to expect lower real incomes if they do not expect nominal wages to rise as well and therefore reduce consumption. Third, there might be additional effects in so far that higher inflation expectations also influence uncertainty. There are potentially additional relevant channels and overall the effect of household inflation expectations on consumption is not clear and the existing empirical literature has not reached a consensus yet.[20]

While the given dataset does not contain actual consumption data, it contains several questions on other expectations and in particular questions about consumer spending attitudes. In the following, I provide first some reduced-form evidence between inflation expectations and other household expectations and then estimate the effect of different types of policy announcements on consumer spending attitudes.

In order to study the reduced-form relationship between inflation expectations and other expectations, I use an ordered logit model with various expectation variables as dependent variable and inflation expectations as independent variable. Similar to inflation expectations the other expectation variables are also ordered categorical variables (see section A.1 for the detailed survey questions). Additionally, I include household controls and month fixed effects. Table 1.7 reports the marginal effects of an increase in inflation expectations on the probability that households answer the first category.

The results show that higher inflation expectations are significantly negatively related to a broad set of household expectations, i.e. households who expect higher inflation are more pessimistic about personal and general economic conditions. More specifically, the probability that the general economic

[20] See for example Bachmann et al. (2015) who find no or only a small negative relationship, while Coibion et al. (2022) find a negative relationship for durable consumption and Duca-Radu et al. (2021) and Armantier et al. (2015) find a positive relationship.

Table 1.7 Inflation expectations and personal and economic expectations

	(1) Economic situation A lot better	(2) Unemployment Much less	(3) Personal financial situation A lot better	(4) Time to spend Good
Inflation expectations	-0.002***	-0.003***	-0.001***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.002)
	(5) Plan to spend Much more	(6) Time to save Good	(7) Plan to save Much more	(8) Confidence
Inflation expectations	-0.001***	0.005***	-0.007***	-0.042***
	(0.000)	(0.001)	(0.000)	(0.003)

Notes: Results based on ordered logit model for columns (1)-(7) and linear regression for column (8). Marginal effect of a one unit change in (qualitative) inflation expectations on various measures of consumer expectations. Note that qualitative inflation expectations have been rescaled such that an increase corresponds to an increase in inflation expectations. Control variables include household controls and month fixed effects. Standard errors clustered at the monthly level are in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

situation gets a lot better, that there is much less unemployment and that households answer they expect their personal financial situation to get a lot better goes down. The probability that households answer it is a good time to spend or that they plan to spend much more is lower. The probability that households answer that it is a good time to save goes up which might be driven by precautionary reasons given that households seem to associate higher inflation with worse times. When asked about their actual plans to save the probability that households answer they plan to save much more goes down. This likely reflects that households expect a worse financial/income situation. Finally, higher inflation expectations are significantly related with a reduction in consumer confidence. Overall, these results highlight that households expect that the general and their own economic situation gets worse when inflation increases.

One reason behind this seemingly counter-intuitive relationship of inflation expectations and other expectations could be that households associate lower inflation with good times and high inflation with bad times. Especially for Germany with the hyperinflation in the 1920s this historical episode might still influence the way many households perceive inflation today. Moreover, there is some evidence in the literature that many households have a supply-side interpretation of inflation, i.e. they relate inflation with negative income effects and depressed economic activity (see for example Kamdar (2019) and Candia et al. (2020)).

A natural question is if the above shown reduced-form relationships between inflation expectations and consumer spending attitudes also hold in response to monetary policy announcements that affect inflation expectations. In order to answer this question, I estimate the ordered logit specification from Equation 1.3 and use three different dependent variables as proxies for consumer spending attitudes.

The first proxy is the readiness to spend. Readiness to spend is the measure most commonly used in the literature when testing the effects of changes in inflation expectations on consumer spending attitudes (see for example Bachmann et al. (2015)). The distribution of readiness to spend on durables over time is plotted in Figure A.6. Alternatively, I also consider the spending plans and a composite confidence indicator as proxies for consumer spending attitudes (see question 8 and 9 in section A.1 for the detailed questions).

Table 1.8 Effect of policy announcements on proxies for consumer spending attitudes

	(1) Time to spend Good	(2) Plan to spend Much more	(3) Confidence
Target	0.005	0.004***	0.047**
	(0.024)	(0.001)	(0.021)
Timing	-0.002	0.001	0.020
	(0.013)	(0.002)	(0.027)
FG	0.004	0.000	-0.003
	(0.013)	(0.001)	(0.015)
QE	0.019	-0.001	0.017
	(0.030)	(0.002)	(0.071)
N	195.560	191.159	182.548

Notes: Column (1) and (2) are based on an ordered logit model and show the marginal effect of a policy surprise that increases the respective reference rate by 25 basis points on the probability that it is the right moment to make major purchases and that one plans to spend much more on major purchases, respectively. Column (3) shows results from linear regression on consumer confidence indicator where a higher value indicates higher consumer confidence. Control variables include wave dummy, household controls and month fixed effects. Standard errors clustered at the monthly level are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table 1.8 shows the response of the three proxies for consumer spending attitudes. The coefficients show the effect of a 25 basis points surprise, i.e. one that in the case of the Target announcement reduces inflation expectations significantly. Column(1) shows the effect on the probability that it is a good time to make major purchases now. Except for the Timing announcement the coefficients are positive but not statistically significant and the magnitudes are rather small. These results are similar to the finding by Bachmann et al. (2015) who find that lower inflation expectations have a small positive but not significant effect on the willingness to spend.

Column (2) shows the effect on the probability that one has the plan to spend much more on major purchases over the next 12 months. The sign for Target announcements is positive as in column (1) but in this case it is significant. The effects of the other types of announcements are again imprecisely estimated. Finally, column (3) shows the response of consumer confidence which is often mentioned in the literature as good predictor for consumption growth.[21] Consumer confidence is constructed as a weighted statistic of four different questions in the survey about households past and expected financial situation, general economic expectations and spending plans (see Appendix A for details). Column (3) shows that Target announcements lead to a significant increase in consumer confidence at the 5% significance level while there is no significant response for the other policy announcements. However, the magnitude of the effect is very small if one considers that a 25 basis points Target surprise has a positive effect of 0.047 and the standard deviation of consumer confidence is 0.52.

Overall, all three proxies of consumer spending attitudes respond positively to the Target surprises which are shown to reduce household inflation expectations but the magnitude of the effects are generally small. This suggests that policies that try to engineer higher inflation expectations should not be expected to necessarily result in higher consumption as many conventional theories would predict.

1.6 Conclusion

This paper analyses the effect of different types of monetary policy announcements on household inflation expectations. While there has been a lot of research on the reaction of professional forecasters and financial markets to monetary policy, households and firms have been studied less. Studying the role of household expectations is relevant for several reasons. First, household survey data can provide a representative view of inflation expectations in the wider economy. Their expectations are likely to be also a good proxy of firms' expectations since many firms in countries like Germany are small or medium sized companies such that it is reasonable to assume that their knowledge and expectation formation is similar to households. Second, household expectations matter for economic activity. Many households participate in some form of wage bargaining processes and they take consumption and saving decisions that are not only influenced by financial market prices but also by their expectations (see Armantier et al. (2015) or Malmendier and Nagel (2016) among others). One issue is that household inflation expectations data are usually not available at high frequency such that a clean identification and estimation of the causal effect of monetary policy is challenging. My analysis exploits within month variation of interview dates that provides a natural experiment to identify the immediate effects of monetary policy announcements on household inflation expectations. Moreover, I use local projections to study the dynamic effects of policy announcements over the medium term.

In contrast to most of the existing literature on household inflation expectations, I find that households do adjust their expectations to some policy announcements. More specifically, policy rate

[21] See for example https://ec.europa.eu/info/sites/info/files/new_cci.pdf.

announcements lead to a quick and significant adjustment in inflation expectations. An announcement that increases the policy rate leads to a reduction in household inflation expectations. Forward guidance and quantitative easing, on the other hand, have no or only a small and delayed effect on inflation expectations of households. Household inflation expectations are linked with other expectations, in particular consumer spending attitudes. I find that households relate higher inflation expectations with bad times and there is no evidence that policy announcements that lead to higher household inflation expectations also have a positive effect on consumer spending attitudes. This contradicts the prediction of many conventional monetary/macroeconomic models with standard intertemporal Euler equation mechanics at its core.

My findings contribute to the discussion about central bank communication with the general public and highlight that there exist significant communication challenges. In particular, in recent years central banks have relied heavily on unconventional measures different from policy rate changes but these measures seem to have no or at least less of an effect on household inflation expectations.

Looking forward it would be important to understand better what is the optimal central bank communication. First, from a normative point of view how much should central banks try to reach the general public with their policy announcements and to what extent should they consider household inflation expectations as a policy tool. Second, if it is optimal to target the general public with policy announcements how to communicate effectively such that the policies have an effect and also in the desired direction.

2

Uncovering the heterogeneous effects of news shocks to underlying inflation

Joint with Evi Pappa and Alejandro Vicondoa

Abstract We identify in a SVAR shocks that best explain future movements in different measures of underlying inflation at a five-year horizon and label them as news augmented shocks to underlying inflation. Independently of the measure used, such shocks raise the nominal rate and inflation persistently, while they induce mild and short-lived increases in economic activity. The extracted inflation shocks have differential distributional effects. They increase significantly and persistently the consumption of mortgagors and homeowners. Differently from the traditional monetary policy disturbances, news augmented shocks to underlying inflation induce a positive wealth effect for mortgagors and homeowners, driven by a reduction in the real mortgage payments and a persistent increase in real house prices that they induce.

2.1 Introduction

Many economies have been experiencing inflation rates systematically below their inflation targets in a context of low interest rates. To achieve their inflation targets, central banks have been implementing unconventional monetary policies. These policies have significantly affected asset prices and long-run inflation expectations (see, for example, Ciccarelli et al., 2017), inducing redistributive effects. Although central banks are not charged with the task of addressing inequalities, it is essential for both academic and policymakers to be aware of all collateral effects – including the distributional ones. While previous works have shown that temporary exogenous changes in the interest rate rule induce heterogeneous effects (see, for example, Cloyne et al., 2020), there is no empirical evidence on how shifts in long-run inflation expectations and in underlying or trend inflation affect different types of households. Characterizing these effects is key to understand its aggregate implications and main transmission channels.

In this paper we identify news augmented shocks to underlying inflation (henceforth NASTI) in the US using a Bayesian Vector Autoregressive model (BVAR) with medium-run restrictions and estimate its aggregate and distributional effects. News shocks to underlying inflation are defined as the combination of the reduced-form residuals that best explain future movements in underlying inflation at a five-year ahead horizon that can affect underlying inflation contemporaneously. Our identification strategy relies on the assumption that agents may observe in advance possible changes in underlying inflation and adjust their decisions contemporaneously according to this change in their expectations. Mertens (2016) shows that trend/underlying inflation is a good proxy for the long-term inflation rate expected by economic agents. Thus, our shock can also be interpreted as a shock to long-run inflation expectations that can be altered due to monetary policy actions but also due to exogenous changes in agent's expectations per se, or external shocks to costs and prices.

News augmented shocks to underlying inflation relate to changes in the monetary policy stance and correlate positively with permanent shocks in the inflation target (see, e.g., Uribe (2021)) and unconventional monetary policy disturbances such as forward guidance and quantitative easing shocks (see, e.g., Swanson (2021)). They induce gradual and persistent increases in the nominal rates. They explain a significant fraction of the variations of PCE inflation at business cycle frequencies and consistently with the Fisher equation, also the longer run variation in 10- and 1-year rates. The effects on aggregate activity are only mildly positive and overall short-lived.

Then, we estimate the effects of the identified shock on consumption and income dynamics for households with different debt and asset positions. For this analysis, we use the Consumer Expenditure Survey (CEX). Following the analysis of Cloyne et al. (2020), we group households according to their housing tenure status. We find that NASTI shocks benefit mostly mortgagors and outright home owners.

We explore the channel behind these asymmetries and find that it is the persistent increase in real house prices coupled with the significant reduction in real mortgage payments prompted by the news shock to underlying inflation that induces positive wealth effects and favors mortgagors and owners. The channel we uncover is different from the liquidity constraint mechanism highlighted in the literature for the asymmetric responses to standard monetary policy shocks. Using household survey data for the U.S. and the U.K., Cloyne et al. (2020) find strong heterogeneity in the response of expenditure to monetary policy shocks. Households with mortgage debt increase their spending considerably following a cut in interest rates, while outright home owners without debt do not change their expenditure at all and renters also increase their spending, although by less than mortgagors. They highlight the composition of household balances sheets and the presence of illiquid assets as key for the heterogeneous responses observed. Our results reveal that anticipated changes in underlying inflation propagate differently. Mortgages transform expected underlying inflation shocks to shocks in real disposable income. The increase in real house prices in responses to NASTI shocks reinforces the positive wealth effect that brings about the heterogeneous responses between homeowners and renters.

A new wave of macroeconomic studies that examines the effects of persistent changes in monetary policy has recently emerged, which are often labeled as "Neo-Fisherian" shocks. The Neo-Fisher hypothesis suggests that inflation can be increased by increasing the nominal policy rate persistently. The reasoning is that the Fisher relation must hold in the long run and, given a constant steady-state real rate of interest, raising the nominal interest rate permanently will eventually lead to a higher inflation rate. Uribe (2021) investigates whether the Neo-Fisher effect is present in quarterly postwar U.S. data by estimating an empirical and a New-Keynesian model, both driven by transitory and permanent monetary and real shocks. He shows that a gradual and permanent increase in the nominal interest rate causes a fast adjustment of inflation to a permanently higher level, low real interest rates, and no output loss.[1] Unlike Uribe (2021), Mumtaz and Theodoridis (2019) do not introduce permanent shocks to the interest rate but identify shocks to the Federal Reserve's implicit inflation target as VAR innovations that make the largest contribution to future movements in the inflation target measured by spliced survey inflation forecast data, and reach similar conclusions as Uribe (2021). They show that inflation target shocks are an important driver of the decline in long-term interest rates over the last two decades. Our NASTI shock correlates positively with their identified shocks, but captures anticipated temporary shifts in underlying inflation. Previous studies have neither analyzed the heterogeneous effects of this type of shocks nor assess the different transmission mechanisms.

Another strand of the literature has documented that transitory monetary policy shocks, understood as transitory exogenous changes in the short-term interest rate, may induce significant distributive

[1]Earlier work by Ireland (2007), Cogley et al. (2010), and De Michelis and Iacoviello (2016) incorporates inflation target shocks within a New-Keynesian model and attributes an important role of movements in the inflation target for inflation dynamics. Schmitt-Grohé and Uribe (2022) show that permanent monetary policy shocks are key to understand exchange rate dynamics.

effects.[2] Auclert (2019) distinguishes, using a theoretical model, the following channels in response to temporary changes in inflation and the real interest rate: the unequal effects on income ("the earnings heterogeneity channel"), the impact of the real interest rate ("the real interest rate exposure channel"), and the impact of the unexpected inflation rate ("Fisher revaluation channel"). As previously mentioned, Cloyne et al. (2020) show that the expansionary effect of a transitory monetary policy shock on consumption is mainly driven by liquidity constraints. Wong (2021) further shows that mortgage refinancing is key to understand the aggregate dynamics of consumption in response to transitory interest rate shocks.[3]

However, persistent changes in the stance of monetary policy may work through different channels. Doepke et al. (2019) analyze the distributional effects of higher expected inflation in a life-cycle model with housing and find that they induce sizeable and heterogeneous welfare effects. In particular, they find that middle-aged, middle-class households, who currently have the largest mortgage debt burden, benefit at the expense of wealthy retirees due to the reduction in the real value of debt. Moreover, the responses of winners and losers do not cancel out in the aggregate; instead their model predicts a decline in aggregate consumption together with an increase in savings and the value of high quality houses. Using a two-agents (homeowners and capital owners) New-Keynesian model augmented with long-term debt, Garriga et al. (2017) and Garriga et al. (2021) also show that the real reduction in the value of debt is key for the transmission of persistent changes in the monetary policy stance while the real interest rate channel is key for transitory interest rate shocks. In particular, higher inflation benefits homeowners due to the reduction in the real value of their mortgage. Garriga et al. (2021) conclude that previous works have neither estimated these effects nor have quantified the role of each transmission channels in response to persistent changes in the stance of monetary policy. Our empirical analysis confirms these predictions regarding the real value of debt channel. However, it also highlights an additional channel stemming from the increase in real house prices that seems to be also operative benefiting homeowners independently of whether they hold a mortgage or not.

Finally, our results have important policy implications. We show that NASTI shocks relate to unconventional monetary policy disturbances and changes in the monetary policy stance. Such shocks

[2]Previous works have shown that transitory monetary policy shocks may affect wages and the labor share (see, for example, Cantore et al., 2020) and increase labor income inequality (see, for example, Dolado et al., 2021). The aggregate effects of transitory monetary policy shocks depend on the state of the business cycle (see, for example, Tenreyro and Thwaites, 2016) and on the production structure of the economy (see, for example, Galesi and Rachedi, 2019).

[3]Berger et al. (2021) and Eichenbaum et al. (2021) have also shown that mortgage refinancing is a key channel for the transmission of transitory monetary policy shocks. The transmission of monetary policy through movements in the wealth distribution has been also emphasized by Heterogenous Agents New-Keynesian (HANK) models (see, for example, Kaplan et al., 2018).

can be an effective tool in stimulating the economy and raising the level of inflation, without substantial real costs. However, we highlight that such policies will not benefit all households equally and in economies with fixed mortgage rates, as in the US, they will tend to benefit homeowners much more relative to renters. During the pandemic the housing market boomed in the US (and other economies)[4]. This surge in the home values could be driven by a steady fall in mortgage rates, most likely engineered by the Federal Reserve actions that pushed down interest rates to very low levels in early 2020, with a promise to keep rates ultra-low for years to come. Our paper talks to this promise: if such promise reflects a perceived change in underlying inflation, house prices might keep increasing persistently favoring homeowners, widening the existing inequality between these two population groups[5]. Finally, the US Federal Reserve has recently modified its monetary policy strategy committing itself to temporarily tolerating inflation rates above two percent and an inclusive view of the labour market. This change in strategy, although enacted to anchor longer term inflation expectations at two percent, given the current deflationary pressures, involves several challenges. One potential challenge of running inflation above the two percent target for a period of time is that it may begin to lift longer-term inflation expectations and, hence, underlying inflation. Given the change in the policy regime, the shocks that we identify in our econometric exercise might become more frequent in the new monetary policy era and it is of crucial importance to understand their propagation in the economy.

The rest of the paper is organized as follows: section 2.2 describes the data and the empirical framework for identifying news shocks to underlying inflation and discusses the nature of the extracted shocks. Section 2.3 describes the macroeconomic effects of the identified shocks. Section 2.4 presents the data and the methodology we use to evaluate the effects of our identified shocks to the different consumer groups we consider and their distributional effects, while section 2.5 examines in detail the differences in the propagation mechanism between the standard monetary policy shocks identified in the literature and the news shocks to underlying inflation we consider here. Finally, Section 2.6 concludes.

2.2 Identifying News Shocks to Underlying Inflation

2.2.1 Underlying Inflation

Underlying inflation is the rate of inflation that would be expected to eventually prevail in the absence of economic slack, supply shocks, idiosyncratic relative price changes, or other disturbances (see

[4]The S&P CoreLogic Case-Shiller National Home Price NSA Index, which tracks price changes of single-family homes (CSUSHPISA in the FRED database) has increased by 22 percent in December 2020 relative to the same month in 2019.

[5]According to the US Census Bureau, the median net worth for a homeowner is 89 times that of a renter.

Rudd (2020)). Since underlying inflation cannot be directly observed it must be inferred or estimated from actual inflation. Measures of underlying inflation are typically monitored by central banks to gauge trends in inflation and the likely evolution of inflation in the medium term. There are different approaches to measure underlying inflation.

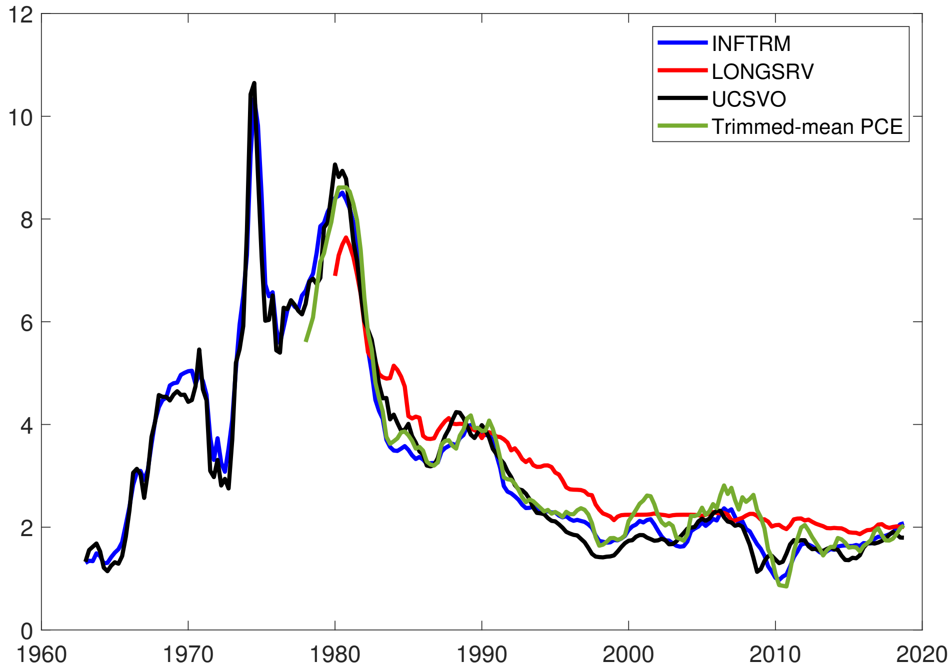
As baseline we consider estimates of underlying inflation based on a Beveridge and Nelson (1981) decomposition that condition jointly on realized and trimmed mean PCE and CPI realized inflation rates. To be more specific, we use the INFTRM trend series as computed by Mertens (2016) and updated them following the same procedure as a measure of underlying inflation.

Figure 2.1 depicts in blue the trend inflation series we employ in our baseline analysis (continuous blue line). The trend peaks twice, in the mid-1970s at double digit levels and in beginning of the 1980s, somewhat more moderately, before falling back toward about 4% by the mid-1980s and around 2% during the Great Moderation and in the later years of the sample. The high volatility of the trend inflation during the Great Inflation period (1965-1982) reconfirms that inflation expectations were unanchored during this period [6]. The drop in the inflation trend following Paul Volcker's disinflation is also evident. Figure 2.1 also depicts three other measures of underlying inflation: (i) another trend measure derived by Mertens (2016)), LONGSRV (red line), based on surveys for long-run forecast horizons that starts in 1980, (ii) a trend estimated based on the univariate unobserved-components stochastic volatility outlier-adjusted (UCSVO) model with core inflation by Stock and Watson (2016) (black line) and (iii) trimmed-mean PCE inflation (green line).

All measures of underlying inflation in Figure 2.1 share a common trend, however, they imply different dynamics from the movements in trend inflation. As discussed in Mertens (2016), compared to the trend inflation measured on realized inflation data, the trend measure derived from surveys changes more belatedly and is smoother, reflecting the relative smoothness of the survey series compared to observations on realized inflation. As argued also in Mertens (2016), the differences in the two trends reflect existing empirical results consistent with models of informational frictions in survey responses (see, e.g., Coibion and Gorodnichenko (2015c) and Coibion and Gorodnichenko (2015a)). Finally, differences can also be attributed to the different information sets embedded in the survey forecasts and the realized inflation series. Given our objective of recovering news augmented shocks to underlying inflation we found the series of inflation-based trend inflation more adequate to analyse in our benchmark

[6] Although, in general, trend inflation and long-run inflation expectations can be different, we implicitly assume that they move in lock step with each other.

Figure 2.1 Series of underlying Inflation



Note: INFTRM and LONGSRV are updated series of trend inflation as defined in the models INFTRM and LONGSRV by Mertens (2016). UCSVO is updated trend inflation series from UCSVO model in Stock and Watson (2016). Trimmed-mean PCE is calculated by staff at the Dallas Fed.[7]

exercise both due to their higher variability during the sample period and due to their superiority in predicting inflation[8].

The UCSVO series of Stock and Watson (2016) track pretty closely the INFTRM series we use in the baseline analysis. In the appendix we show that the INFTRM series is superior in forecasting PCE inflation out of sample and that our results are robust to using this alternative series to represent trend inflation variation in the VAR.

The series of trimmed-mean PCE inflation also follows a similar trend as our baseline measure INFTRM but it is overall more volatile. The forecasting power for PCE inflation is similar to the UCSVO series and worse than the INFTRM measure justifying our use of INFTRM as baseline.

Underlying inflation can be interpreted as the long-term inflation rate expected by economic agents. Movements in underlying inflation are usually attributed to the behavior of monetary policy, while short-run fluctuations of inflation reflect short-term dynamics related to price setting, external shocks, and monetary policy. As indicated in Figure 2.1 underlying inflation dynamics are in general related to the monetary policy stance. Policymakers may have targets that change over time, as for example, the disinflation of Paul Volcker, or may consider temporary deviations from their inflation targets, such

[8]In Appendix B.2 we show these series have a better forecasting power to predict inflation, reconfirming the original results of Mertens (2016) for our sample period. In Appendix B.6.1 we show that the main results are robust to the three alternative measures of underlying inflation.

as the recent change in the policy stance of the Fed. If the central bank's inflation target policy is fully credible, underlying inflation will converge to the target inflation rate in the long-run. However, in the short and medium-run, underlying inflation and the target rate can differ due to adaptive, or backward-looking, expectations and changes in the extent to which the inflation target is credible. Our scope is to extract news about changes in underlying inflation that could reflect deviations of monetary policy from the inflation target in the medium run, as well as other types of news that trigger movements in long-run inflation expectations.

2.2.2 Econometric Strategy

We apply the Maximum Forecast Error Variance (MFEV) identification approach put forward by Uhlig (2003) and later extended by Barsky and Sims (2011) and Kurmann and Sims (2021) to identify news shocks to underlying inflation as the VAR innovation that makes the largest contribution to the forecast error variance (FEV) of underlying inflation. The key observables that we examine are the INFTRM measure of trend inflation[9], PCE inflation, the growth rate of GDP per capita, the US 10Y yield, and the US 1Y yield. The PCE inflation rate and per capita GDP growth rate are expressed in annualized percentage points relative to the previous quarter. The US 10Y yield, and the US 1Y yield are included as annualized percentage points. The Appendix B.1 includes precise definitions and sources for all the data. We include both a short-term (1Y) and a long-term (10Y) yield to properly identify the shock and to characterize its transmission mechanism. The 1Y yield measures the response of monetary policy to macroeconomic conditions. Financial market data, like the levels of nominal interest rates, reflect to a great degree inflation expectations. In particular, nominal yields on longer-term securities should carry information about underlying inflation in the medium to long term horizon, since according to the Fisher equation nominal rates are the sum of expected inflation, a real interest rate, and a residual associated with the risk premium. Hence, via the expected-inflation term, changes in (future) underlying inflation should also influence long term nominal yields. The sample period for estimation is 1962:Q1-2018:Q4. The starting date is limited by the availability of the 10-Year Yield, a key variable to identify shocks to inflation expectations. We also examine the impact of the identified shock on financial variables, asset prices, house prices, the current account and the exchange rate, as well as on the fiscal deficit. In each case, we rotate these additional variables into the VAR one-by-one.

The main assumption behind our identification strategy is that agents may observe in advance possible changes in underlying inflation and that they adjust their decisions contemporaneously according to

[9]The INFTRM trend measure by Mertens (2016) is monthly and we aggregate it to quarterly frequency by taking the average in each quarter

this change in their expectations. As explained in Barsky and Sims (2011), an appealing way to identify an expected shock to a fundamental is to estimate a reduced-form multivariate VAR where all variables, including the fundamental itself, are regressed on their own lags, as well as the other variables' lags. Then, the resulting VAR innovations can be used to search for the structural shock that satisfies the medium run restrictions of the variable of interest. Following Kurmann and Sims (2021), we (a) extract a shock that accounts for the maximum forecast error variance (henceforth, FEV) share of underlying inflation at one truncation horizon, H=20 (i.e. five years) and (b) allow the news shock to influence underlying inflation contemporaneously. We have chosen five years for the anticipation horizon as a medium-run horizon and also show in the Appendix B.6.2, that our results are robust to different maximization horizons. According to our procedure, contemporaneous movements in macroeconomic variables are used to forecast changes in underlying inflation. We label the recovered structural shock as a news shock to underlying inflation that mainly reflects changes in long-run inflation expectations.

Given that inflation in the long run is commonly regarded as a monetary phenomenon, our shocks implicitly measure changes in monetary policy that trigger changes in underlying inflation in the medium run. Mumtaz and Theodoridis (2019) accept this view and name their shocks, identified with a similar procedure, shocks to the inflation target. We call the identified shock differently for several reasons. First, if one is willing to accept that long run inflation expectations do not react significantly and systematically to business cycle conditions, i.e., that the central bank's objective is relatively well anchored our identified shocks could be interpreted as persistent shocks to the inflation target. Since the period we consider is turbulent and it is not clear that expectations were always anchored our shock would be mislabeled for that period. Second, our shock might include more shocks that affect underlying inflation other than shocks to the inflation target. For example, forward guidance shocks might also affect inflation expectations and induce persistent deviations for underlying inflation. For example, Del Negro et al. (2015) show the estimated effects of forward guidance to output and inflation expectations to be non-trivial. Third, in the short and medium-run, underlying inflation and the target rate can differ due to adaptive, or backward-looking, expectations. Hence, shifts in beliefs, or expectation shocks which affect the formation of expectations by the private sector could also affect long run inflation expectations without any changes in the monetary policy stance or other fundamentals. Finally, although over the medium term, the overall rate of inflation in an economy is mainly determined by its central bank's monetary policy, inflation outcomes are also influenced by anticipated external cost and price shocks, such as commodity terms of trade news (see, e.g., Ben Zeev et al. (2017)) and import and export price shocks (see, e.g., Di Pace et al. (2021)).

Specifically, let the VAR in the observables be given by:

$$y_t = F_1 y_{t-1} + F_2 y_{t-2} + \ldots + F_p y_{t-p} + F_c + e_t \tag{2.1}$$

where y_t represents the vector of observables, where the first variable is the series of underlying inflation, F_i are 5×5 matrices, p denotes the number of lags, F_c is a 5×1 vector of constants, and e_t is the 5×1 vector of reduced-form innovations with variance-covariance matrix Σ. The reduced form moving average representation of (2.1) is:

$$y_t = B(L) e_t$$

where $B(L)$ is a 5x5 matrix polynomial in the lag operator, L, of moving average coefficients and e_t is a 5x1 vector of reduced-form innovations. Then, the h step ahead forecast error is:

$$y_{t+h} - \mathbb{E}_t y_{t+h} = \sum_{\tau=0}^{h} B_\tau e_{t+h-\tau},$$

where B_τ is the matrix of moving average coefficients at horizon τ. The contribution to the forecast error variance of variable i attributable to shock j at horizon h is then given by:

$$\Omega_{i,j} = \sum_{\tau=0}^{h} B_{i,\tau} \gamma \gamma' B'_{i,\tau}, \tag{2.2}$$

where γ is a $5x1$ vector corresponding to the jth column of a possible orthogonalization, and $B_{i,\tau}$ represents the ith row of the matrix of moving average coefficients at horizon τ. We index the shock to underlying inflation as 1 in the vector of structural shocks. The identification of the news shock to underlying inflation requires finding the γ which accounts for the maximum FEV contribution of underlying inflation at one horizon H (the truncation horizon), and is allowed to affect underlying inflation on impact. Formally, this identification strategy requires solving the following optimization problem

$$\begin{aligned} &\gamma^* = \max \Omega_{1,1}(H) \\ &\text{subject to} \quad \gamma' \gamma = 1 \end{aligned} \tag{2.3}$$

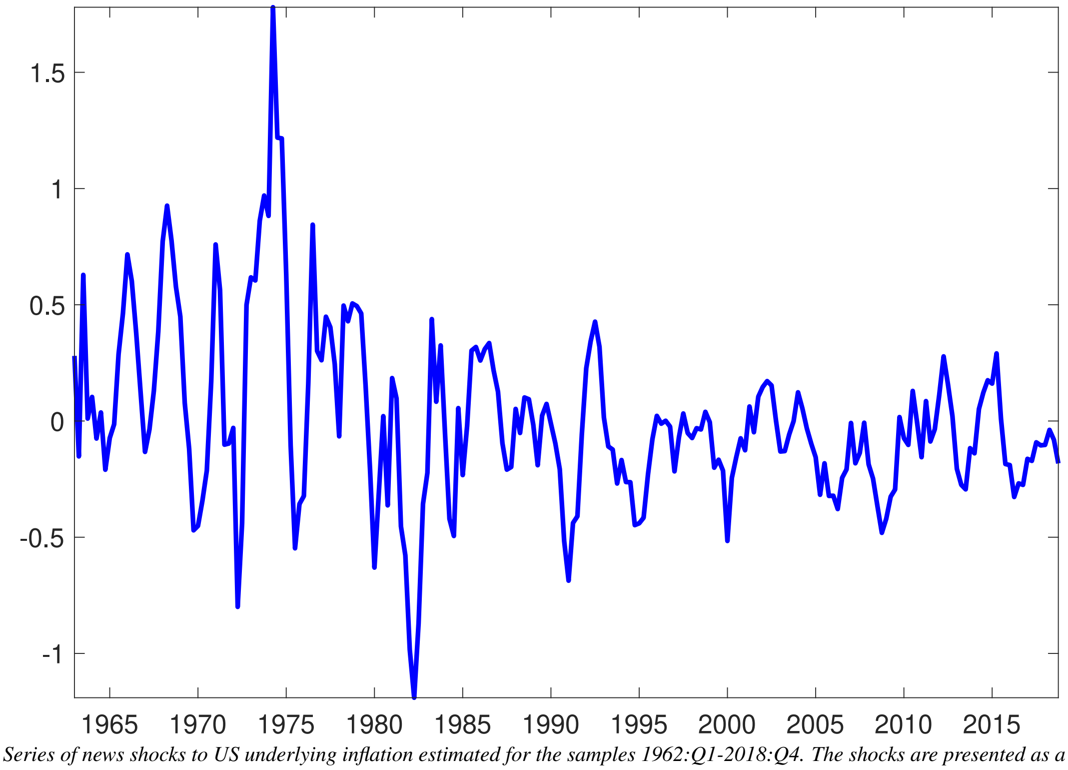
where $\Omega_{1,1}(H)$ is defined in equation (2.2). The restriction in equation (2.3) imposes on γ to have unit length, ensuring that γ is a column vector belonging to an orthonormal matrix. This normalization implies that the identified shocks have unit variance, but we do not restrict it to have a zero in its first entry, meaning that we allow the news shock to underlying inflation to be reflected on underlying inflation immediately.

We follow the conventional Bayesian approach to estimation and inference by assuming a diffuse normal-inverse Wishart prior distribution for the reduced-form VAR parameters. Specifically, we take 1000 draws from the posterior distribution of reduced form VAR parameters $p(F, \Sigma \mid data)$, where for each draw we solve optimization problem (2.3); we then use the resulting optimizing γ vector to compute impulse responses to the identified shock.[10] This procedure generates 1000 sets of impulse responses which comprise the posterior distribution of impulse responses to our identified shock. Our benchmark choices for the number of lags and truncation horizon are p=4 and H=20, respectively.[11]

2.2.3 The Series of Shocks to underlying Inflation

Figure 2.2 depicts the 5-quarter moving average of the identified series of news shocks to US underlying inflation extracted using the identification procedure described in section 2.2.2.

Figure 2.2 Smoothed Series of News Shocks to US underlying Inflation



Note: Series of news shocks to US underlying inflation estimated for the samples 1962:Q1-2018:Q4. The shocks are presented as a moving average to smooth the series and are identified using the strategy described in Section 2.2.2. Horizon is in quarters.

[10]Note that F here represents the stacked $(5 \times (p+1)) \times 5$ reduced form VAR coefficient matrix, i.e., $F = [F_1, \ldots, F_p, F_c]\prime$.

[11]Results are robust to the number of lags and also when using the two different samples in Section 2.2.3. See Online Appendix B.6.3 and B.6.4.

There is a significant shift in the volatility of the series of shocks after the mid 1980s. The spikes in 1970s and early 1980s correspond to the the Great Inflation period. Mertens (2016) estimates that uncertainty in trend inflation was measurably higher in the pre-1982 period indicating that changes in inflation largely reflected shocks to trend inflation. We reconfirm this finding with the identified news shock to underlying inflation. News shocks to underlying inflation have sizeable spikes in the Great Inflation period and the volatility of the shocks is reduced substantially at the end of the sample.

In order to externally validate our identification procedure, we look into FOMC transcripts for a more detailed description of the monetary policy decisions in the times of the observed spikes. Table 2.1 describes the main monetary policy events in the sample that could fit our concept of shocks to underlying inflation.

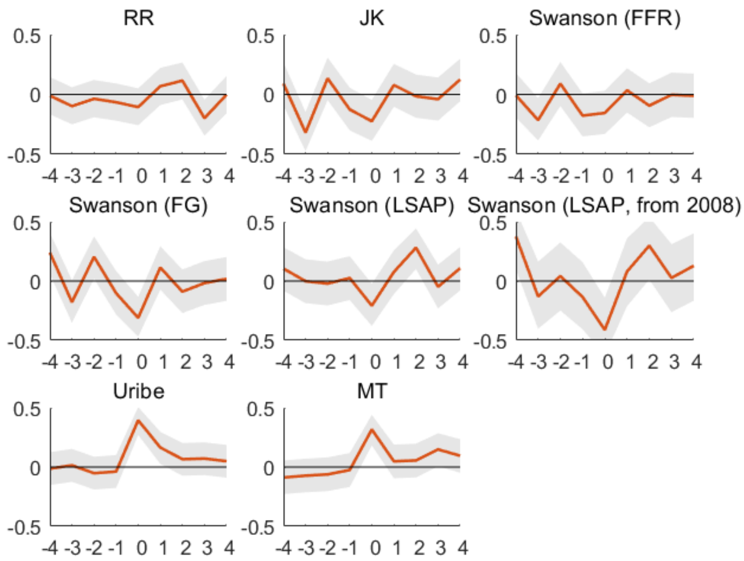
Table 2.1 Main News Shocks to underlying Inflation

Date	**Value of the Series**	**Description**
Q3 1971	-3.23	FED's discount rates were increased by 0.25% to 5% in order to "reduce inflation, moderate short-term capital outflows and reach an equilibrium in the country's balance of payments". The Nixon Shock and the 90-day price freeze helped to reduce inflationary expectations.
Q2 1974	5.45	In a context of large price increases (mainly oil), "The narrowly defined money stock increased sharply again in March. Broader measures of the money stock rose more moderately..."
Q3 1975	3.23	The FED was fostering financial conditions to stimulate economic recovery post 1973 recession. "Market interest rates raised appreciably due to indications of strengthening economic activity, more rapid inflation, and large prospective Treasury financing requirements".
Q2 1978	2.75	"M1, which had grown moderately in the first quarter, rose sharply in April."
Q2 1984	-1.34	The FED "seeks to foster monetary and financial conditions that will help to reduce inflation further reduce inflation further ...".
Q4 1991	1.28	The FED decided to decrease its discount rates by 1% to 4.5% seeking to foster economic growth (post 1991 recession) while "reducing the existing degree of pressure on reserve positions".
Q3 2008	-1.58	"Some measures of inflation expectations were down notably over the inter-meeting period."

The large news shocks we identify match with the reports from the Fed FOMC minutes transcripts. For example, in the second quarter of 1974 our procedure identifies a large positive news shock to underlying inflation. According to the FOMC minutes transcripts, the narrowly defined money stock increased sharply in March. Also, in the third quarter of 2008 we retrieve a negative shock to inflation expectations that is also reflected in the transcripts for this quarter.

Finally, to gain some intuition on the nature of the shock we recover, Figure 2.3 presents the correlation for four lead and lags of the news shock in underlying inflation with other shocks to monetary policy and shocks to the inflation target identified in the related literature (In the Appendix (see Table B.3) we provide point estimates for the contemporaneous correlations of the different shocks considered and the sample periods considered for each specification).

Figure 2.3 Serial correlation with monetary policy related shocks from previous works



Note: RR corresponds to the Romer and Romer (2004) monetary policy shock series extended by Coibion et al. (2017); JK to high-frequency monetary policy surprises identified via sign-restrictions from Jarociński and Karadi (2020); Swanson are Federal funds rate (FFR), Forward guidance (FG) and QE (LSAP) monetary policy surprises from Swanson (2021); Uribe concerns the permanent monetary policy shocks as identified in Uribe (2021);MT corresponds to the Inflation target shock identified as in Mumtaz and Theodoridis (2019)

In order to interpret the figure first note that a positive news shocks to underlying inflation raises the interest rate and as a result correlates negatively with standard expansionary monetary policy shocks. According to Figure 2.3, our series of news shocks to underlying inflation does not really correlate significantly with standard monetary policy shock series such as the Romer and Romer (2004). In turn, it exhibits a significant contemporaneous correlation with the high-frequency monetary policy surprises identified by Jarociński and Karadi (2020)[12]. Note that these monetary policy surprises are related to the three-months federal funds futures and therefore reflect both changes in the target rate and short-term forward guidance. The correlation depicted in the figure implies that some of the unexpected movements in monetary policy identified using high-frequency data correspond to changes in inflation expectations captured by news about underlying inflation reflected in our shock

[12] Jarociński and Karadi (2020) use sign restrictions on the high-frequency changes in interest rates and stock prices to separate monetary policy surprises from surprises that are related to central bank information.

measure. Swanson (2021) also identifies high-frequency monetary policy surprises and disentangles different types of monetary policy announcements. Similar to the Romer and Romer (2004) narrative series the high-frequency surprise about the current federal funds rate (Swanson (FFR)) is only weakly negatively correlated with our identified shock series. Interestingly, when we turn to the correlation of our news shocks series to underlying inflation with the surprise changes in forward guidance (FG), and large-scale asset purchases (LSAPs) for each FOMC announcement from July 1991 to June 2019 of Swanson (2021), we detect a significant contemporaneous correlation of the two series especially for the FG (-0.31) and the LSAPs after 2008 (-0.41). This high correlation implies that our identified news shocks to underlying inflation captures to a large extent changes in inflation expectations triggered by unconventional monetary policies such as forward guidance and quantitative easing.

As mentioned earlier, if monetary policy is well anchored our series can be interpreted as shocks to the inflation target, or persistent changes in monetary policy. The sample used for estimation (1962:Q1 to 2018:Q4) is comparable to the one used by Uribe (2021) and Mumtaz and Theodoridis (2019), enabling us to assess the properties of our identification strategy. While Uribe (2021) exploits long-run restrictions in a cointegrated system, the series of shocks he identifies as permanent monetary policy shocks are significantly positively correlated (0.40 contemporaneously) with our series over the common sample. The correlation with the shocks identified using the approach by Mumtaz and Theodoridis (2019) is 0.32. This evidence suggests that the identified news shocks to underlying inflation partially capture shocks to the inflation target or the monetary policy stance, but include also variations in underlying inflation that are unrelated to the monetary policy outlook.

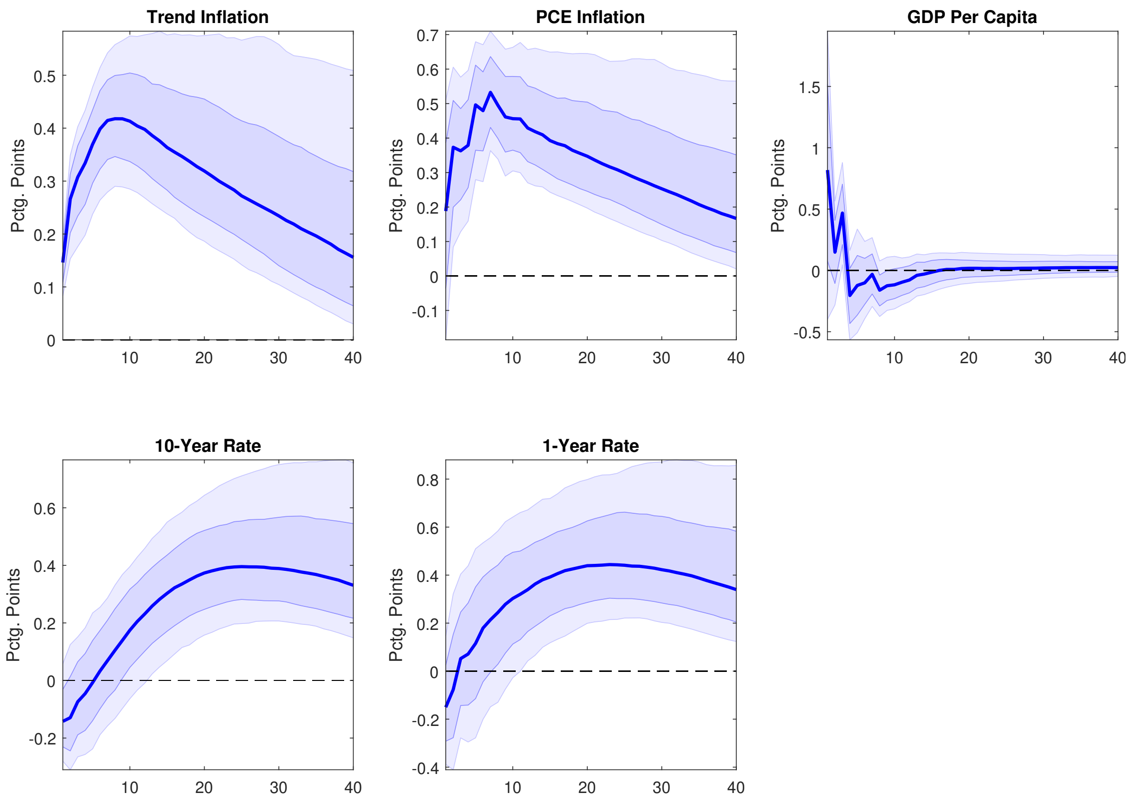
2.2.4 Validation of the Identified Shock

The analysis of the previous section reveals that the identified series of news shocks to underlying inflation may be contaminated with other series of shocks or extracted using an informational deficient VAR. To test for this hypothesis we perform two exercises. First, we test that the identified series of shocks are uncorrelated with leads and lags of TFP shocks, tax shocks, oil shocks, uncertainty shocks, financial shocks, and fiscal shocks identified by previous works. Figures B.1 and B.2 included in the Appendix B.4 display the serial correlation of our shock series with the corresponding series of those other disturbances. Second, we also test if the shocks are identified with a VAR with sufficient information, using the test developed by Forni and Gambetti (2014). The identified series of news shocks to underlying inflation cannot be explained by macroeconomic and financial factors. Results are presented in Table B.4 of the Appendix B.4. Thus, we cannot reject that the shock is identified using an informational sufficient VAR.

2.3 Macroeconomic Effects

2.3.1 Impulse Responses and Variance Decomposition

Figure 2.4 IRFs to a news shock to underlying inflation

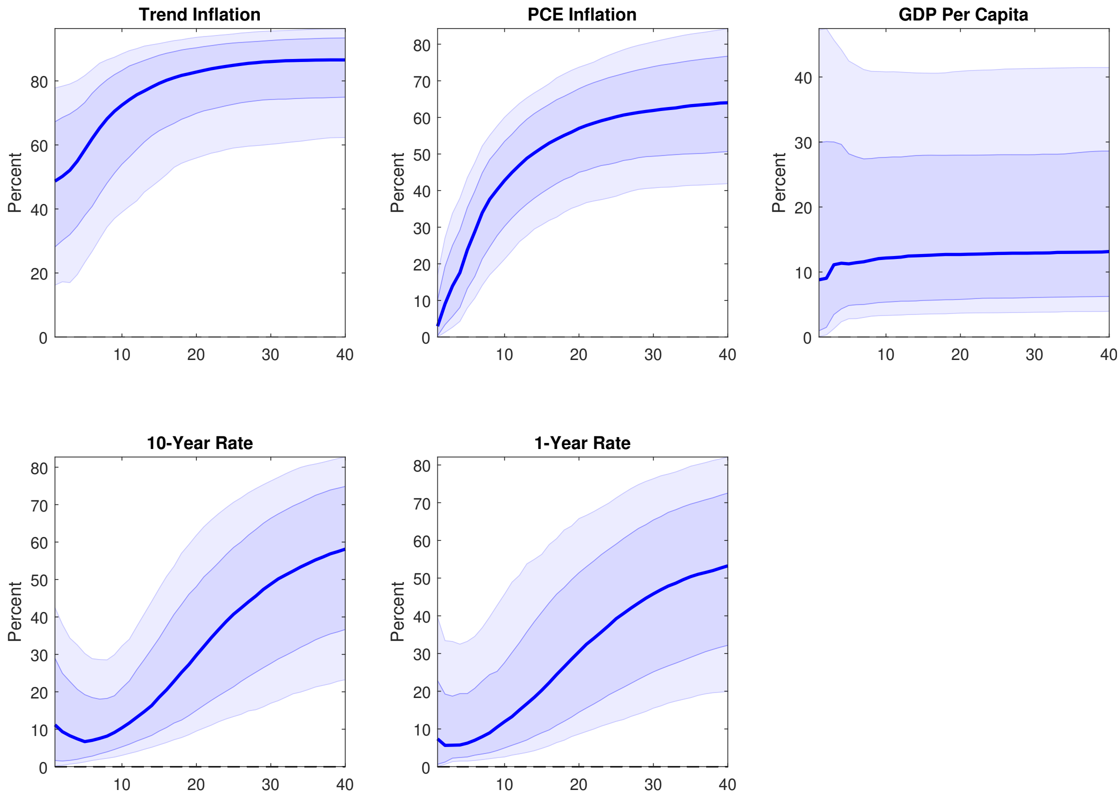


Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and includes the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Yield, and 1Y Treasury Yield. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The news shock to underlying inflation is identified using the strategy described in Section 2.2.2. Horizon is in quarters.

Figure 2.4 displays the impulse response functions (IRFs) to a one standard deviation news shock to underlying inflation for the baseline specification. The news shock induces an immediate positive response in underlying inflation of 0.2 percentage points that builds over time to 0.4 percentage points after 10 quarters. These dynamics of underlying inflation are closely related with the observed PCE inflation, both in terms of magnitude and persistence. Considering that both the 1Y and 10Y Treasury yields do not react on impact, the real interest rate initially decreases. This decline possibly explains the slight increase in GDP per capita growth rate in the first five quarters. Once the yields start to increase, the real interest rate converges back to its previous level and we do not find any significant effect on economic activity.

It is important to show that this is a shock to underlying inflation instead of any other type of shock that affects the real interest rate in the long run. Figure 2.5 displays the share of variance of each variable explained by the shock to underlying inflation. The news shock to underlying inflation explains a significant fraction of underlying inflation at all horizons: from 50 percent at 1 year up to 90 percent at 10 years ahead. Thus, the identified shock is a significant driver of underlying inflation.

Figure 2.5 FEV explained by a news shock to underlying inflation



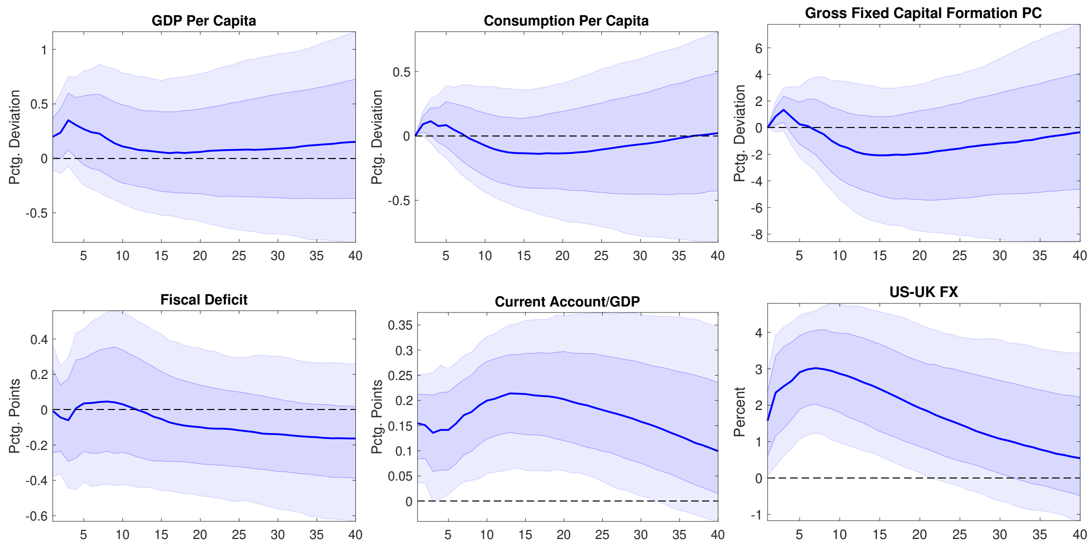
Note: Share of variance explained by the news shock to underlying inflation estimated using the BVAR(4) that includes a constant and includes the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Yield, and 1Y Treasury Yield. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The news shock to underlying inflation is identified using the strategy described in Section 2.2.2. Horizon is in quarters.

Although PCE inflation is significantly determined by news shocks to underlying inflation at long horizons (close to 65 percent at 10 years), the identified shock is not its main driver at short horizons (close to 15 percent at 1 year). Demand, price shocks and transitory monetary policy shocks are more likely the main drivers of PCE inflation at shorter horizons. In line with the FEV of inflation, the news shock to underlying inflation explains about 50 percent of the variability of interest rates in longer horizons, consistently with the Fisher effect. For shorter horizons, up to 20 quarters, the news shock has limited power on yield's dynamics. Finally, expected shocks to underlying inflation explain around 10 percent of the fluctuations in GDP per capita growth rates at all horizons.

2.3.2 Additional Aggregate Effects

In order to characterize better the aggregate implications of the news shock to underlying inflation, we augment the baseline VAR described in section 2.2.2 with consumption, gross fixed capital formation, fiscal deficit, the current account to GDP ratio, and the US-UK bilateral exchange rate. Consumption and Gross Fixed Capital Formation (GFCF) are expressed as per capita growth rates. For the Fiscal deficit we use the series computed by Hagedorn et al. (2018). We use the U.S. Dollars to One British Pound exchange rate as this is the longest historical series we have obtained. The data sources are described in the Appendix in section B.1. These three variables are included one by one in the baseline VAR and they are not used for the identification of the shock. Figure 2.6 displays the IRFs to each of these variables (The responses of all the variables of the VAR are presented in Appendix B.6).

Figure 2.6 IRF to a news shock to underlying inflation - Additional variables



Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the baseline BVAR(4) described in Section 2.2.2 plus the growth rate of Private Consumption, the growth rate of Gross Fixed Capital Formation, Fiscal Deficit, Current Account to GDP, and the US-UK Exchange Rate (including one variable at a time). The responses of the remaining variables of the BVAR(4) are presented in Appendix B.6. The responses of GDP, Consumption and Gross Fixed Capital Formation are accumulated. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The news shock to underlying inflation is identified using the strategy described in Section 2.2.2. Horizon is in quarters.

The shock induces a mild, barely significant transitory increase in consumption and gross fixed capital formation, which can be explained by output dynamics and the initial decrease in the real interest rate. The news shock to underlying inflation is not associated with a change in the fiscal deficit, indicating that the news about underlying inflation are not associated with fiscal policy. Finally, the increase in inflation expectations reflected in the news shock in underlying inflation induces a persistent improvement in the current account-to-GDP ratio, in line with the findings of Schmitt-Grohé and

Uribe (2022). The response of the current account couples well with the persistent depreciation of the exchange rate.

2.3.3 Sensitivity Analysis

The dynamics of the economy following news shocks to underlying inflation are robust to: employing a different measure of underlying inflation, different lag length in the VAR, using different maximization horizons, augmenting the VAR with fiscal variables, and restricting the sample to 1984-2018 period. All these results are presented in Appendix B.6.

2.4 Estimation of Heterogeneous Effects

The previous section established that news augmented shocks to underlying inflation result in mild and short-lived expansions in economic activity and eventually increase PCE inflation and interest rates persistently and lead to persistent depreciations of the currency and current account surpluses. In this section we characterize the disaggregated effects of news shocks to underlying inflation.

2.4.1 Econometric Strategy

In order to estimate the heterogeneous effects of the news shocks to underlying inflation we use local projections (Jordà (2005)).[13] We use local projections in the following analysis since the micro data starts in 1984 and we have fewer degrees of freedom to perform the SVAR analysis in the smaller sample. In particular, we estimate the following specification to obtain impulse response functions (IRFs) for 0$\leq$ h $\leq$ 16 quarters:

$$y_{i,t+h} = \alpha_{i,h} + \beta_{i,h}\epsilon_t^{NASTI} + \gamma_{i,h}X_t + u_{i,t+h} \tag{2.4}$$

where i, t and h denote household group, quarter and IRF horizon, respectively. In our main analysis households are grouped by housing tenure status such that i=renter, mortgagor, outright home owner. $y_{i,t+h}$ is our variable of interest from the Consumer Expenditure Survey (CEX). In our baseline we focus on the log of real per capita consumption by housing tenure status. The micro data and variables of interest are described in more detail in the next section. ϵ_t^{NASTI} is the identified series of news

[13] We show in the Appendix that using our shock identified from the VAR in local projections yields similar dynamic macro effects as the ones previously reported in section 2.3 (see Figure B.19 and Figure B.20).

shocks to underlying inflation from section 2. X_t includes 4 lags of log real GDP, the log PCE index, the 1-year Treasury rate, the 10-year Treasury rate, the news shock to underlying inflation and the dependent variable $y_{i,t}$. We use Newey-West standard errors to control for heteroscedasticity and serial correlation of the error term $u_{i,t+h}$.

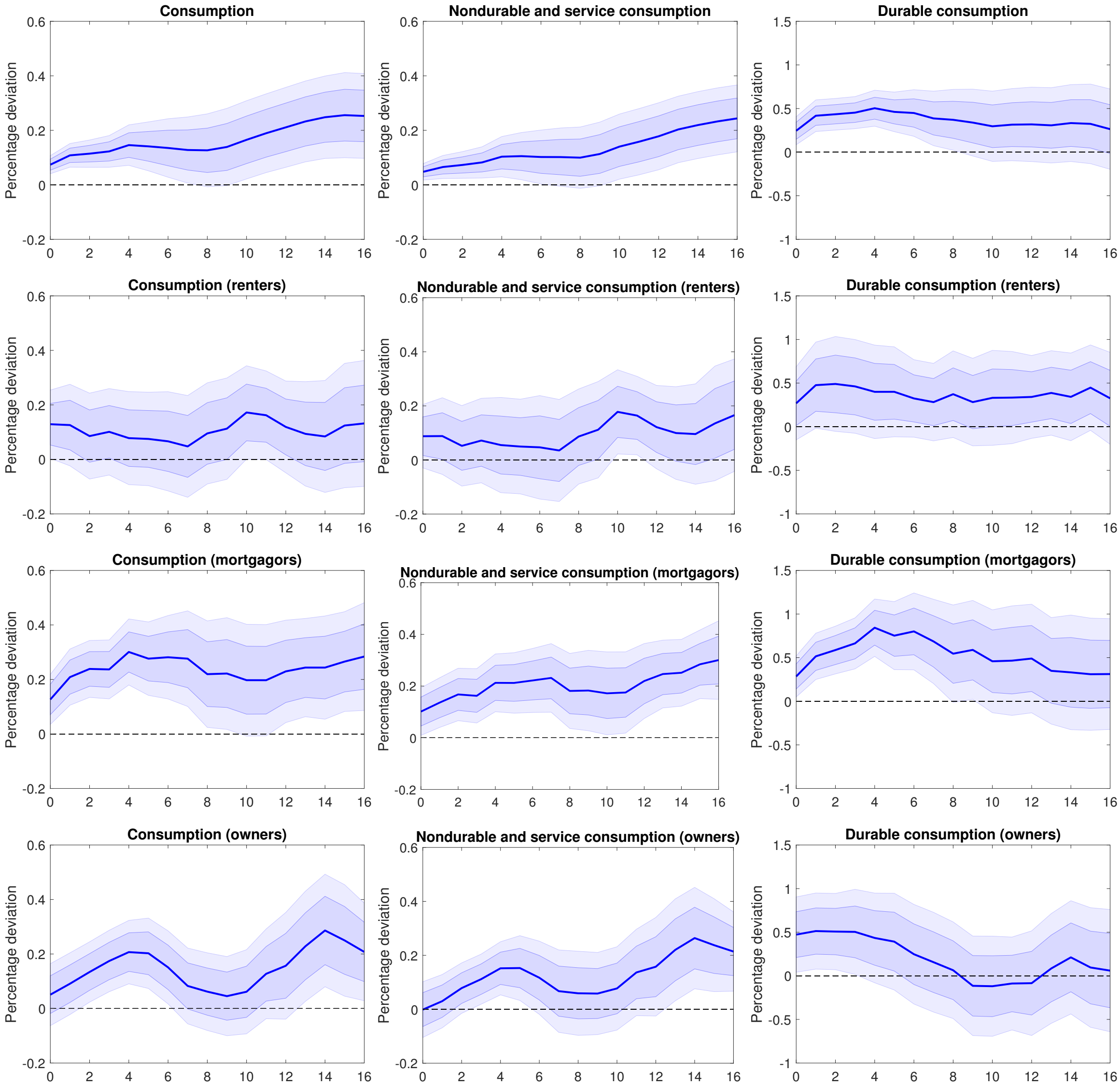
2.4.2 Micro data

We use data from the Consumer Expenditure Survey (CEX) interview sample conducted by the Bureau of Labor Statistics. The CEX is a monthly rotating panel, where households are selected to be representative of the US population. Our analysis sample goes from 1984 Q1 to 2018 Q4. The CEX contains information on household expenditures on detailed categories, household income, labor supply and a rich set of demographic characteristics. Expenditure categories include durable goods, nondurable goods and services. Following Coibion et al. (2017) our measure of nondurable and service consumption includes food, beverages, clothing, footwear, gasoline and other fuel, personal care, newspapers, tobacco, household operations, utilities, recreation services, financial services, accommodations, telecommunication services and transportation services. Durable consumption includes durable leisure goods, furniture and jewelry. Besides, we also consider households expenditures for mortgage and rent payments. All series are converted into real-per capita terms using the Consumer Price Index and family size and aggregated to quarterly frequency using the reference date of the interview. We then create pseudo cohorts to estimate the heterogeneous effects by household group. More specifically, in our baseline we group households by the variable housing tenure which classifies households as renters, mortgagors or outright home owners. See Section B.1.2 in the Appendix for more details on the data and construction of variables.

2.4.3 The heterogeneous response of consumption

In our baseline analysis we estimate the consumption response of households by housing tenure status. Housing tenure status can be seen as a proxy for wealth where renters are households with low wealth, mortgagors and owners have some wealth. While it is mainly illiquid wealth for mortgagors, owners also have liquid wealth. This dimension of heterogeneity has been also studied by Cloyne et al. (2020) who argue that there is a close link to the theoretical HANK literature with poor and rich hand-to-mouth consumers and non-hand-to mouth consumers.

Figure 2.7 Consumption response by housing tenure



Note: Effects of a news shock to underlying inflation on consumption by housing tenure status based on Equation 2.4. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

The first column of Figure 2.7 shows the IRFs to a 25 basis points positive news shocks to underlying inflation on aggregate consumption and by housing tenure status.[14] Total consumption increases persistently reaching it's peak by around 0.2 percent in 16 quarters[15] Looking at the different household groups the point estimates are positive for all the consumer groups considered. However, the

[14]For ease of exposition, we present 3-quarter backward looking moving averages of the IRFs. The results of the original series are in the Appendix (See Figure B.22).

[15]The difference in the shape and significance of total consumption responses between Figure 2.7 and Figure 2.6 is due to the different estimation strategies used to recover the IRFs. Local projections deliver more significant aggregate and persistent consumption responses. Plagborg-Møller and Wolf (2021) show that LP and VAR estimators are reduction techniques with common estimand but different properties. At short impulse response

responses of consumption for renters are smaller and less significant relative to the responses of the other two groups. For renters the effect is mostly statistically insignificant. For owners responses are more significant two to four quarters after the shock and the increase in consumption is more persistent relative to renters, however, its relatively smaller when compared with the response of mortgagors' consumption. Mortgagors consumption increases considerably, persistently and significantly over the IRF horizon with an effect of around 0.35 percent after 4 years.

We obtain qualitatively similar conclusions regarding the strong response of mortgagors' consumption in response to the news shock in underlying inflation if we distinguish between durable and nondurable and service consumption (see columns two and three of Figure 2.7).[16] For all groups of households, durable consumption seems to increase quickly while nondurable consumption moves more slowly. That is, nondurable consumption increases more persistently with peak effect at the end of the IRF horizon (especially for mortgagors and owners). Also, clearly the responses of both types of consumption is quantitatively larger and significant for mortgagors. It appears that both mortgagors and owners increase their nondurable consumption significantly and persistently in response to the news shock to underlying inflation, however, it is mortgagors consumption of durables that increases more considerably and persistently in response to the shock.

We also consider alternative dimensions of heterogeneity that have been studied in the literature to examine the heterogeneity in response to news shocks to underlying inflation. The results are included in the Appendix and only summarized shortly here. First, considering households by age we don't find strong evidence for heterogeneous consumption responses (see Figure B.24). Second, we group households by total after-tax income. We find that for total after-tax income low and middle income households increase consumption significantly while high income households do not respond significantly (see Figure B.25 in the Appendix). However, when we look at the response of households by housing tenure status in each income group, we find that for a given income group we reach a similar conclusion as in our baseline analysis: mortgagors significantly increase consumption while the effect is mostly not significant for the other housing tenure groups. The only exception are renters in the low income group that increase significantly their consumption after the news shock to underlying inflation.

Robustness Our baseline results presented in Figure 2.7 are robust to estimating the local projections without the macro control variables and to including a linear trend in Equation 2.4 (see Figure B.26 and Figure B.27). Herbst and Johannsen (2020) highlight that local projection estimates can be biased

horizons the two methods are likely to approximately agree if the same lag length is used for both methods. However, with finite lag lengths, the two methods may give substantially different results at long horizons.

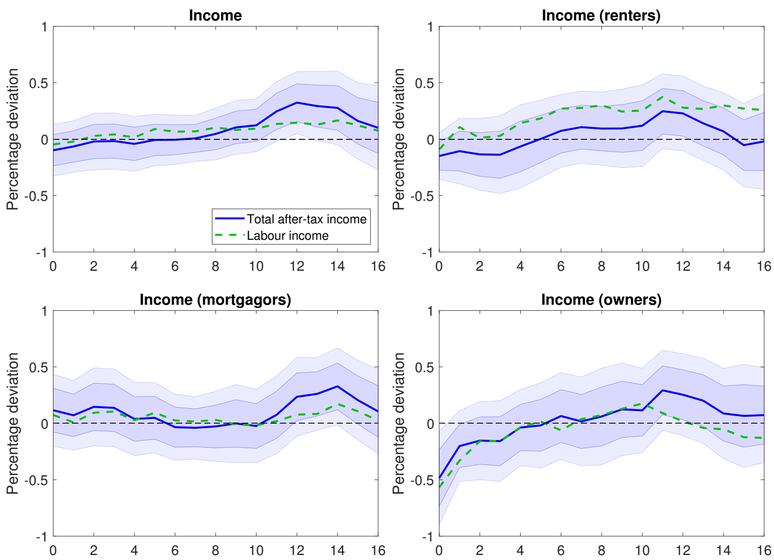
[16]Durable consumption does not include vehicle purchases. However, we show in the Appendix in Figure B.23 that results are robust to the inclusion of vehicle purchases in the definition of durable consumption.

in small samples and suggest a bias-corrected estimator. Applying this bias-correction yields similar IRFs (see Figure B.28). Moreover, they highlight that in short samples Newey-West standard errors are often downward biased and recommend to use only heteroscedasticity-robust standard errors such as Hubert-White standard errors. The results using Huber-White standard errors are displayed in Figure B.29 and are very similar to our baseline results.

2.4.4 Understanding the heterogeneous effects

Figure 2.8 shows the response of total after-tax income and labour income by housing tenure status after a positive news shock to underlying inflation. Overall, there is only a small response of income in both cases and little evidence for heterogeneity across housing tenure status. These responses imply that the heterogeneity in consumption responses does not seem to be driven by differences in labour or more general income such as business income.

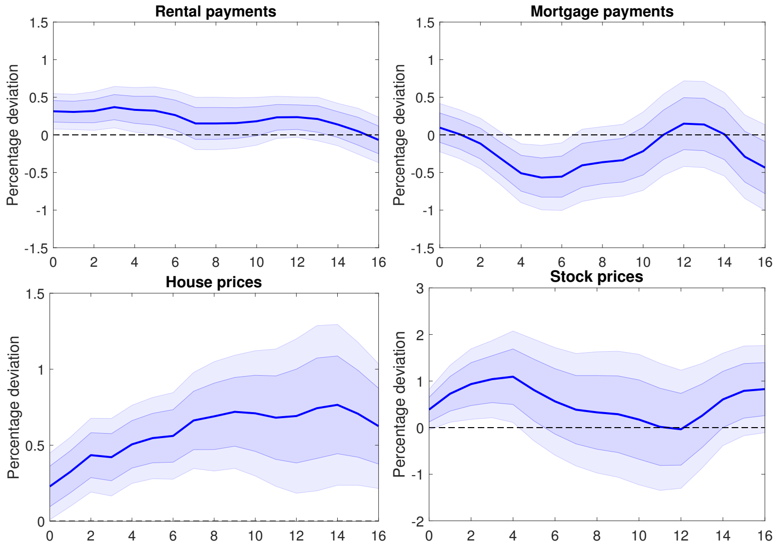
Figure 2.8 Income response by housing tenure



Note: Effects of a news shock to underlying inflation on income by housing tenure status based on Equation 2.4. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. For total after-tax income sample only goes until 2012Q4 due to structural break. 68% and 90% confidence bands based on Newey-West standard errors.

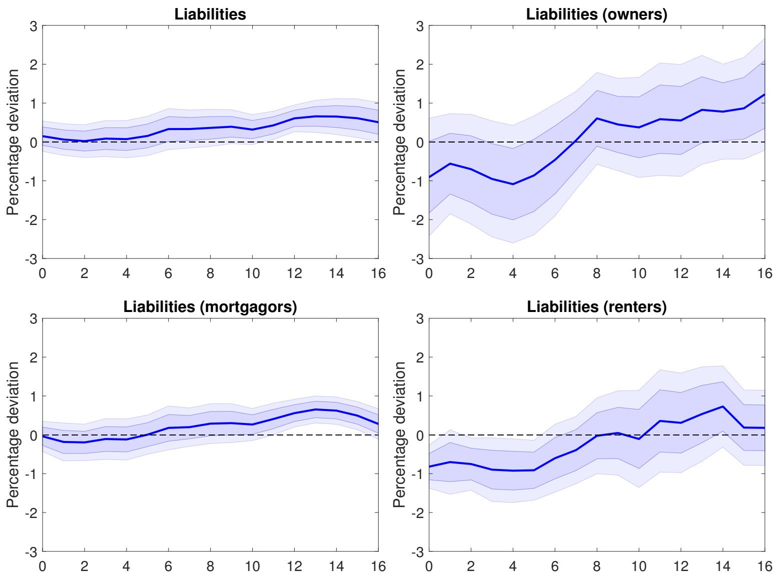
Instead, there is some evidence that housing related expenditures could be the driver behind the different consumption responses. Figure 2.9 displays the responses of rental and mortgage payments and real house prices and stock prices. While rental payments slightly increase following a 25bps expansionary news shock to underlying inflation, mortgage payments decline. House prices and stock prices increase. The persistent increase in real house prices coupled with the significant fall in mortgage payments is likely to benefit mortgagors and owners and could explain the differential consumption

Figure 2.9 Housing payments and prices



Note: Effects of a news shock to underlying inflation on rental and mortgage payments and house and stock prices based on Equation 2.4. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. Rental and mortgage payments are from CEX micro data while house prices are from US Census Bureau and stock prices are S&P500. 68% and 90% confidence bands based on Newey-West standard errors.

Figure 2.10 Liabilities by housing tenure



Note: Effects of a news shock to underlying inflation on liabilities based on Equation 2.4. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. Sample only goes until 2012Q4 due to structural break. 68% and 90% confidence bands based on Newey-West standard errors.

responses. Figure 2.10 shows the responses of liabilities by housing tenure status. Renters and owners slightly reduce their liabilities during the first quarters while mortgagors' liabilities increase at the end of the IRF horizon. Since mortgagors hold the largest share of liabilities their response also drives the response of aggregate liabilities.

2.5 Comparison with Monetary Policy Shocks

As analyzed earlier, the news shock to underlying inflation reduces the real interest rate and its dynamics resemble the dynamics induced by an expansionary monetary policy shock. In this section, we formally compare the heterogeneous effects of our news shocks with standard monetary policy shocks used in the literature in order to understand whether shifts in monetary policy that can induce changes in inflation expectations (regarded as news to underlying inflation) have different distributional effects than standard monetary policy actions .

First, we use the narrative monetary policy shock by Romer and Romer (2004) and extended by Coibion et al. (2017). This shock is about changes in the federal funds rate and does not measure the more recently introduced unconventional monetary policies. Therefore, it stops in 2008 and we focus our analysis only on the sample 1984Q1 until 2008Q4. Second, we use narrative high-frequency monetary policy surprises extracted by changes in asset prices around monetary policy announcements. More specifically, we use the surprises considered by Jarociński and Karadi (2020). These surprises are cleaned from information effects by imposing that monetary policy surprises lead to a negative co-movement between interest rates and the stock market around monetary policy announcements.[17]

Figure 2.11 and Figure 2.12 show the macro responses to the two monetary policy shocks together with the responses to a news augmented shock to underlying inflation over the same sample period.[18] In order to make the responses comparable we scale them by the impact on the real interest rate. All figures show the response to a shock that reduces the real interest rate by 25bps. Moreover, we follow Alloza et al. (2019) and include h leads of the shock in the local projections to control for persistence where h refers to the IRF horizon. This is important since especially the narrative monetary policy shock by Romer and Romer (2004) displays significant auto-correlation.[19]

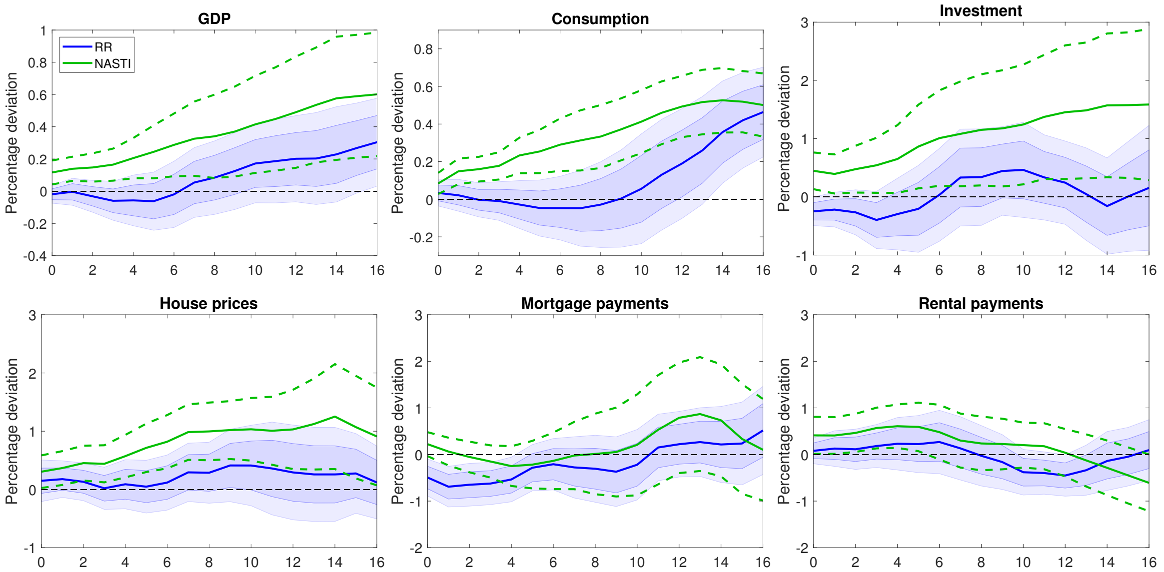
Apparently news augmented shocks to underlying inflation produce similar macro dynamics as standard expansionary monetary policy shocks. However, according to Figure 2.11 the news shock to underlying inflation has stronger effects on all components of demand and output and also induces

[17]We decided to use the shocks directly in local projections. Alternatively, for the high-frequency surprises we replicated the analysis by Jarociński and Karadi (2020) with quarterly data and added our variables of interest to the VAR one by one. The IRFs from this approach are included in the Appendix in Figure B.33 and Figure B.34.

[18]Note that the raw JK surprises have a correlation of -0.24 with our shock over the common sample, while the respective correlation for the RR shock equals -0.11.

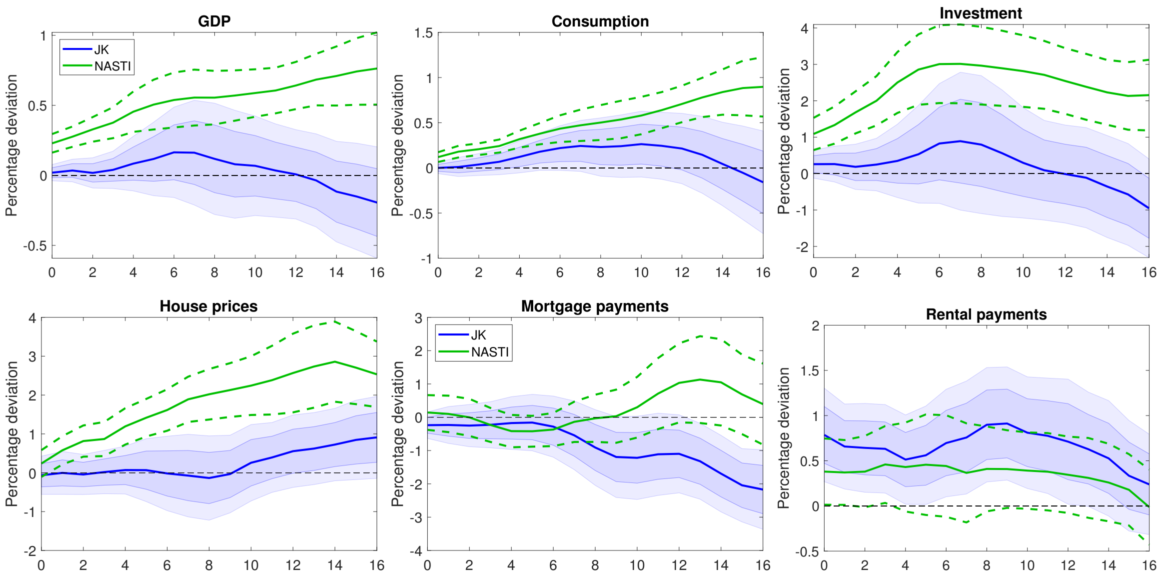
[19]Results without including leads of the shock can be found in the Appendix, section B.12.

Figure 2.11 Comparison with narrative Romer and Romer monetary policy shock



Note: Effects of a news augmented shock to underlying inflation (NASTI) and Romer and Romer monetary policy shock (RR) on macro variables using local projections. Romer and Romer shock is extended by Coibion et al. (2017). Based on Alloza et al. (2019) we include h leads of shocks to control for persistence. Sample period from 1984Q1-2008Q4. Response is scaled to expansionary shock that reduces real rate by 25bps. Real rate is computed as ex-post rate, i.e. difference between 1-year rate and PCE inflation. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

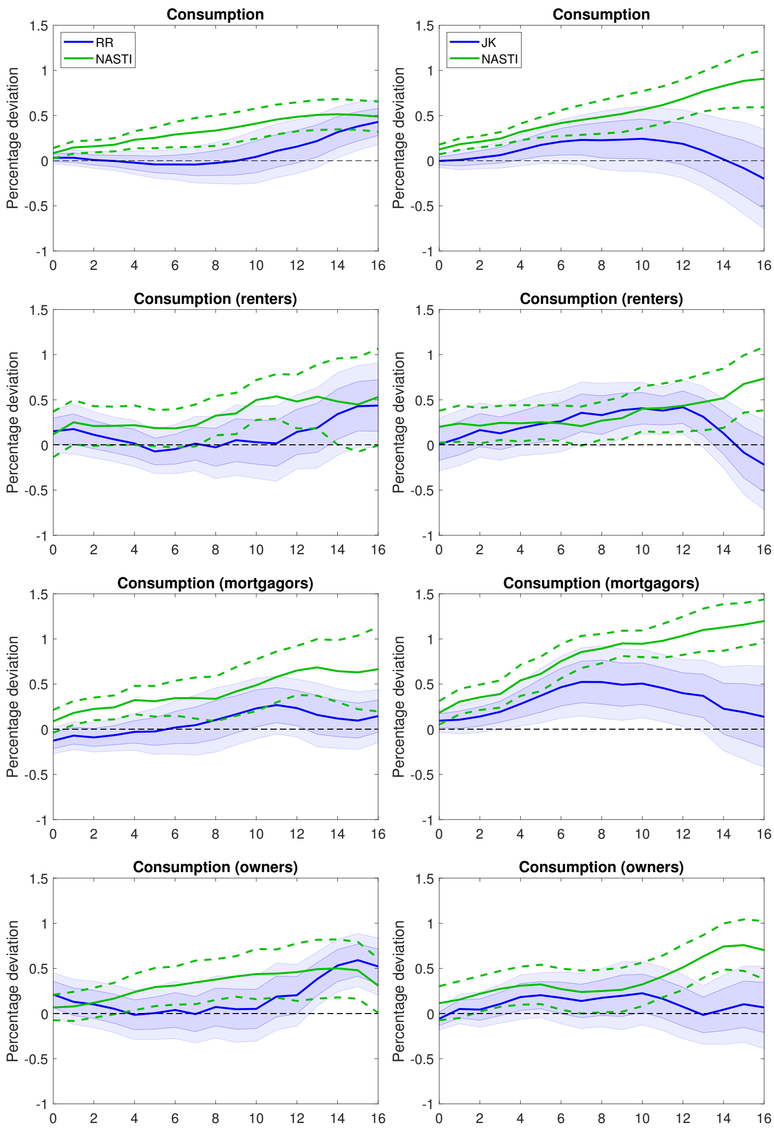
Figure 2.12 Comparison with high-frequency identified monetary policy shock



Note: Effects of a news augmented shock to underlying inflation (NASTI) and high-frequency monetary policy shock by Jarociński and Karadi (2020) (JK). Based on Alloza et al. (2019) we include h leads of shocks to control for persistence. Sample period from 1990Q1-2018Q4. Response is scaled to expansionary shock that reduces real rate by 25bps. Real rate is computed as ex-post rate, i.e. difference between 1-year rate and PCE inflation. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

a more persistent and considerable increase in real house prices, while it does not affect mortgage payments significantly, while the standard RR shock decreases significantly the latter the first year. Moreover, the identified shock to underlying inflation induces an immediate response for the macro variables, while the macroeconomic responses to the RR shock are very sluggish. Similarly, when comparing the effects of the news shock to underlying inflation with the high-frequency monetary policy shock, we still observe a more immediate, significant and persistent effect of the news shock on all variables.

Figure 2.13 Consumption responses by housing tenure status for different monetary policy shocks



Note: Comparison of consumption effects of news augmented shock to underlying inflation (NASTI) and monetary policy shocks. Left column shows Romer and Romer shock extended by Coibion et al. (2017) (RR) and right column shows high-frequency surprises by Jarociński and Karadi (2020) (JK). Based on Alloza et al. (2019) we include h leads of shocks to control for persistence. Sample period from 1984Q1-2008Q4 for left column and 1990Q1-2018Q4 for right column. Response is scaled to expansionary shock that reduces real rate by 25bps. Real rate is computed as ex-post rate, i.e. difference between 1-year rate and PCE inflation. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

Figure 2.13 shows the responses of consumption by housing tenure status for the two shocks that reduce the real interest rate by the same amount. Our estimates for the RR shock, contrary to the results of Cloyne et al. (2020), suggest that it is the owners that benefit the most from expansionary monetary policy.[20] When we turn to comparisons with the high-frequency identified monetary policy shock, it is the clearly the mortgagors that benefit the most from the monetary expansion. Now, relative to both standard monetary policy shocks, the news shock to underlying inflation raises more significantly and persistently the consumption of all household groups but clearly benefits mortgagors the most in both time periods.

2.6 Conclusion

According to the famous proposition of Milton Friedman, "Inflation is always and everywhere a monetary phenomenon". If Friedman's lemma is true, monetary policy must be the source of the change in the evolution of underlying inflation. Recent history suggests that this should be the case. The loose monetary policy stance during the 1960s and 1970s allowed both actual and expected inflation to drift up remarkably over many years. The shift in monetary policy stance in the late 1970s and the commitment to price stability has resulted not only in low and stable inflation but also a strong anchoring of long-run inflation expectations. Rephrasing Friedman, transitory movements in the measured rate of inflation can be driven by shocks of various kinds, but large and persistent movements in inflation cannot occur without a change in monetary policy. It is this type of monetary policy changes we identify in this work and we label as news shocks to underlying inflation and analyze their aggregate macroeconomic effects, as well as, their heterogeneous effects for different types of households. Identifying news shocks to underlying inflation as shocks that explain most of variations in the FEV of underlying inflation in medium term horizons, we investigate how such disturbances are propagated among agents with different levels of wealth, measured by housing tenure. News about an increase in underlying inflation raise more and more significantly the consumption of mortgagors (and somehow owners) relative to renters. This differential response is explained by the fact that news shocks to underlying inflation raise significantly and persistently real house prices and reduce significantly in the medium run mortgage payments, benefiting mortgagors and owners more relative to renters. Cloyne et al. (2020), performing

[20] The difference in results can be explained by various factors. This includes, in particular, the different sample period and our use of leads to account for the persistence in the RR shock. Our sample period only starts in 1984 while Cloyne et al. (2020) start their analysis in 1981 and results with RR shocks are often sensitive to the inclusion of the period around 1979-1983 (see for example Ramey (2016)). Moreover, the results without including leads of the shock in Figure B.32 display IRFs that are qualitatively more in line with Cloyne et al. (2020) in the sense that mortgagors react most.

a detailed and extensive evaluation of the effects of traditional monetary policy shocks a la Romer and Romer (2004) and using the same household survey data for the U.S. we use in this paper, also find that the increase in consumption after a standard monetary expansion is driven by the behavior of mortgagors. We show that news shocks to underlying inflation have stronger and often more persistent macroeconomic effects compared to standard monetary policy shocks identified through narratives (See, Romer and Romer (2004)), or using high-frequency identification methods (See, Jarociński and Karadi (2020)). We also show that mortgagors and owners are further benefited by such expansions since such shocks induce a persistent and considerable increase in real house prices and that the surge in the consumption of mortgagors and debtors in response to these disturbances is not linked to their liquidity constraint, but rather to an income effect associated to the increase in the value of their illiquid asset. The results we uncover are surprising. According to common wisdom increases in interest rates should drive up mortgage rates and, thus, undo the positive effects of the shocks on mortgagors and owners. Most mortgage contracts in the US are fixed rate and this is what could be the driver behind our results. Also, our results suggest that changes in monetary policy that induce future shifts in underlying inflation could increase inequalities as they benefit clearly mortgagors and owners relative to renters. Hence, we would like to conclude by raising a word of caution for the supporters of Neofisherian shocks. Those shocks can indeed lift (future) underlying inflation without inducing output costs, yet, they turn to bring an unequal distribution regarding the increase in consumption among the population in the US and policy makers should weight the costs and benefits before deciding to induce policy changes that affect long run inflation expectations.

3

Anchoring long-run inflation expectations in a panel of professional forecasters

Joint with Jonas Fisher and Leonardo Melosi

Abstract We use panel data from the U.S. Survey of Professional Forecasters to estimate a model of individual forecaster behavior in an environment where inflation follows a trend-cycle time series process. Our model allows us to estimate the sensitivity of forecasters' long-run expectations to incoming inflation and news about future inflation, and measure the coordination of beliefs about future inflation. We use our model of individual forecasters to study *average* long-run inflation expectations. Short term changes in inflation have small effects on average expectations; the sensitivity to news is over twice as large, but is still relatively small. These findings provide a partial explanation for why the anchoring and subsequent de-anchoring of average inflation expectations over 1991 to 2020 were such long-lasting episodes. Our model suggests coordination of beliefs also played a role, slowing down but not preventing the pull on average expectations from inflation running persistently below target. We apply our model to the case of a U.S. central banker setting policy in September 2021. Our results suggest the high inflation readings of mid-2021 would have to be followed by overshooting of the Fed's target generally at the high end of the Fed's Summary of Economic Projections to re-anchor long term expectations at their pre-Great Recession level.

3.1 Introduction

To assess their progress in maintaining price stability inflation-targeting central bankers look at a variety of indicators, including average and median long term expectations from surveys.[1] While survey data on average long-term inflation expectations are plentiful, the information that gets aggregated into them and the factors that can cause them to remain stable or drift away from the central bank's target are not well understood.[2] We describe a method to use panel data to estimate the sensitivity of forecasters' long term inflation expectations to incoming inflation and to news about future inflation, and measure the coordination of beliefs about future inflation. We estimate our model using panel data from the U.S. Survey of Professional Forecasters (SPF) and apply it to explore the historical drivers of average inflation expectations from 1991 to 2020, and to consider inflation anchoring from the stance of a hypothetical policymaker at the September 2021 meeting of the Federal Open Market Committee (FOMC).

In our model forecasting occurs within an environment in which inflation follows a standard trend-cycle time series process. Forecasters face a signal extraction problem to track the unobserved trend and cycle components of inflation which they use to form their long term expectations. We assume forecasters observe two signals. The first signal, which we call the *inflation signal*, is the current inflation rate that updates the forecasters' common knowledge of the history of inflation. This captures everything forecasters can learn about long-run inflation from observing inflation's historical behavior.

The second signal captures forward-looking information or *news* about long-run inflation not already captured in the historical behaviour of inflation. It is specified as the sum of future trend inflation and common and idiosyncratic shocks. The common shock coordinates beliefs about future inflation. Such coordination might reflect the central bank's communications regarding how it will seek to achieve its inflation objective, changes in public trust regarding the central bank's ability to stabilize inflation around its target, and animal spirits or sentiment. The variance of the common shock is time-varying to capture episodes when expectations are particularly sensitive or insensitive to the signals. The idiosyncratic shock has a forecaster-specific variance to capture the forecasters' heterogeneous sensitivity the signals.

[1]For example, see p. 27 of the January 2015 Tealbook available here: https://www.federalreserve.gov/monetarypolicy/files/FOMC20150128tealbooka20150121.pdf

[2]In the U.S. surveys that include longer term inflation expectations include Blue Chip Economic Indicators, Business Inflation Expectations from the Atlanta Fed, Livingston Survey, Michigan Survey of Consumers, and the Survey of Professional Forecasters. The New York Fed Survey of Consumer Expectations has medium term expectations.

We take this model to the data in two steps. First, we estimate the trend-cycle model using core CPI inflation over the sample period 1959q1 to 2020q3.[3] We combine this estimated model with the two signals just described to calculate the laws of motion of the individual forecasters' long-run inflation expectations. Second, we estimate this law of motion using the time series of CPI core inflation, trend inflation estimated in the first step, and our panel of SPF CPI 10-year inflation forecasts which covers the sample after 1991.

While we do not observe the second signal, it is identified by revisions to forecasters' expectations that cannot be rationalized by the historical behavior of inflation alone. This identification is facilitated by our assumption that we observe trend inflation when we estimate the laws of motion of individual forecasters' expectations, but forecasters do not. By making this assumption we can isolate the importance of news about trend inflation that is not yet reflected in historical inflation. The idiosyncratic component of the beliefs is identified by the cross-section of the SPF.

We estimate time-varying sensitivity of forecasters' long term inflation expectations to incoming inflation and news about future inflation. Forecasters' expectations respond little to incoming inflation. Averaging over the panel, they adjust their long-term expectations by only 10 basis points in response to a 100 basis point change in inflation. Forecasters are more than twice as sensitive to news about long term inflation but the elasticity of expectations to news is still relatively small. Averaging over the panel a 100 basis point increase in the news signal leads to an immediate 25 basis point increase in long term expectations.

The slow rate of learning reflected in these low elasticities provides a partial explanation for why the anchoring and subsequent de-anchoring of average inflation expectations over the period 1991 to 2020 were such long lasting episodes. Our model suggests coordination of beliefs also played a role, slowing down but not preventing the pull on average long term expectations from inflation running persistently below target from the early 2000s. The greater sensitivity to news than to actual inflation suggests that coordination of beliefs through effective communications about the central bank's commitment to keep inflation at or near target is a less expensive tool to keep inflation expectations anchored in the face of rising inflation than actually engineering a recession with persistently lower inflation.

In addition to providing a characterization of past average inflation expectations, our model can be used as a guide to central bankers looking to the future, and in particular those operating within an inflation targeting regime. The goal of such a regime is to anchor long term inflation expectations at the inflation target. Our estimated model can be used to study whether and under what conditions average

[3]The end of the sample period is the last quarter before the implementation of the Fed's new long run framework for monetary policy. This is discussed further below.

long term inflation expectations will be anchored going forward from the end of the sample period. Its parameters determine how quickly individual forecasters respond to incoming inflation and news about future inflation. Therefore we can use it to project average inflation expectations under different scenarios for the future paths of inflation and news.

We apply our model to the case of a central banker considering the stance of U.S. monetary policy in September 2021. At this time inflation had been running substantially above the inflation target for over half a year after a long period of running below target and average long term expectations drifting near to our sub-target estimate of trend inflation by 2020q3. But in the face of the high inflation readings in mid-2021 long term inflation expectations were rising too. These conditions presented the Fed with a key test of its credibility. In August 2020 Fed Chair Powell had announced a new long run framework for guiding US monetary policy. This framework is articulated in the Fed's Statement on Longer Run Goals and Monetary Policy, which includes the following passage: "In order to anchor longer-term inflation expectations at this level [2 percent PCE inflation], the Committee seeks to achieve inflation that averages 2 percent over time, and therefore judges that, following periods when inflation has been running persistently below 2 percent, appropriate monetary policy will likely aim to achieve inflation moderately above 2 percent for some time."[4] How much overshooting of the target does our model say the Fed should have been striving to achieve to implement this strategy as it set policy in September 2021?

In our model, expectations can be re-anchored if inflation runs for some time above the Fed's inflation target and the Fed coordinates beliefs by communicating that it will use policy to ensure this overshooting outcome. Our model's parameters determine how quickly individual forecasters respond to incoming inflation and news about future inflation. Therefore we can use it to project average inflation expectations under different scenarios for the future paths of inflation and news.

We explore two experiments to shed light on the overshooting question. In the first we calculate average long term inflation expectations implied by the highest, median, and lowest paths of inflation taken from the Fed's September 2021 Summary of Economic Projections (SEP).[5] Expectations in this experiment are determined solely by realized inflation and there is no role for the coordination of beliefs. We find that in all three cases average long term expectations fall persistently below 2.5 percent despite the sharp increase in inflation in mid-2021.

In the second experiment we find values of the permanent, cyclical, and news shocks that deliver paths for inflation and the inflation drift from 2021q4 that re-anchor average long term CPI inflation

[4] See https://www.federalreserve.gov/monetarypolicy/files/fomc_longerrungoals.pdf.

[5] The SEP are available at https://www.federalreserve.gov/monetarypolicy/fomc.htm.

expectations at 2.5%, the level of anchoring before the Great Recession.[6] We find that inflation need only come in at the high end of the SEP projections to re-anchor expectations due to the coordination of beliefs on higher inflation in the future. We interpret this as suggesting a role for policy communications. By signalling that inflation will come in higher than warranted by the underlying trend the central bank does not need as much of an inflation overshoot to re-anchor expectations.

The remainder of the paper proceeds as follows. In the next section we discuss the related literature. After this we describe our model of individual forecasters, how we estimate this model, the data we use, and our estimates. We then examine the history of inflation expectations through the lens of our estimated model. In the penultimate section we discuss our overshooting experiments, and then we conclude.

3.2 Relation to the literature

Our paper contributes to a large literature on the anchoring of inflation expectations. Broadly speaking the literature focuses on three concepts of anchoring. The first is the one we employ that considers expectations to be anchored when average inflation forecasts at long horizons remain stable and close to the inflation target. Ball and Mazumber (2018) and Kurmar et al. (2015) are two papers that also use this concept. The papers in this literature that are closest to ours study representative agents learning about the central bank's inflation objective. Some key work in this area includes Carvalho et al. (2020), Beechey et al. (2011), and Orphanides and Williams (2005). These papers consider signal extraction problems where agents seek to understand the central bank's inflation target using past data. Since they focus on the representative agent these papers consider mean or median of inflation expectations from surveys and ignore the cross-section information that is central to our study.

The second concept of anchoring that the literature has focused on is the one emphasized by Bernanke (2007). He described inflation expectations as being anchored when long-run expectations do not respond very much to incoming data. Corsello et al. (2021), Dräger and Lamla (2014), and Barlevy et al. (2021) have this concept in mind when they use panel data from surveys to estimate the time-varying elasticity of changes in long-run expectations with respect to changes in short-run expectations. Gürkaynak et al. (2007), Binder et al. (2019) and others analyze the response of inflation compensation in financial data to incoming macroeconomic news. We relate revisions of long-term

[6]CPI inflation runs higher than inflation in the personal consumption expenditures prices index from the National Income and Product Accounts which is the inflation measure targeted by the Fed. We assume a 50 basis point wedge between the two measures of inflation.

inflation expectations to incoming inflation and news about future inflation using data on inflation and long term expectations of individual forecasters facing a signal extraction problem.

The third strand of the anchoring literature emphasizes higher order moments of inflation expectations from surveys and financial market data. Reis (2021) relates inflation anchoring to changes in the cross-sectional variance and skewness of survey measures of inflation expectations. Grishchenko et al. (2019) use a trend-cycle model with time-varying volatility to relate anchoring to the probability of future inflation as measured by survey expectations being in a certain range of the inflation target. While we focus on a narrower notion of expectations anchoring resting only on first moments, our methodology leverages the entire distribution of individuals' long-run inflation expectations to measure the sensitivity of average inflation expectations to news. Our approach has several advantages. First, it allows us to distinguish between changes in the aggregate attention to news concerning long-run inflation from the fixed amount of attention paid by an individual forecaster to news compared to that paid by other forecasters. Second, estimating these fixed effects allows us to control for compositional effects in the distribution of attention. Accounting for compositional effects is particularly important in light of the critique of conditional mean forecasts highlighted by Engelberg et al. (2010). Our fixed effect is the variance of the forecaster-specific beliefs. Nechio (2015) studies composition in terms of the distribution of forecasters' root mean inflation forecast error.

We also contribute to the large literature that has sought to identify the role of central bank communications in aggregate dynamics, including the literature on the Fed information effect and forward guidance that builds on Nakamura and Steinsson (2018), Gürkaynak et al. (2005), and Campbell et al. (2012). We identify central bank communications as the news received by forecasters about the long-run dynamics of inflation that are not reflected in the historical dynamics of inflation. Central bank communications may not be understood or listened to by the public. Indeed Coibion et al. (2020b) show using survey data that, at least in a low inflation environment, households and firms pay little attention to monetary policy communications. This suggests that central bank communication does not flow directly through these channels. It seems more likely that professional forecasters pay attention to central bank communications and our framework allows us to measure that attention.

Finally, our work is related to the literature studying the dynamics of inflation with a trend-cycle model with unobserved components (Stock and Watson (2007)). Building on the idea by Beveridge and Nelson (1981), trend inflation in these models can be viewed as the long-run level of expected inflation. The papers in that field closest to ours link trend inflation with expectations from survey data to learn about the implications of changes in the inflation process for inflation forecasts and to study the anchoring of inflation expectations. This includes Henzel (2013), Mertens (2016), Mertens and Nason

(2020) and Nason and Smith (2021). Two notable differences between those papers and our paper is the focus on long-run inflation expectations and on the cross-sectional dimension of the survey data.

3.3 The Model

This section describes the stochastic environment confronting a collection of forecasters and how they forecast long-run inflation within that environment. We finish up by discussing our notion of inflation anchoring within this set up.

3.3.1 The forecasting environment

We assume forecasters form their long-term inflation expectations believing inflation outcomes are driven a particular trend-cycle time series model.[7] This process is as follows:

$$\pi_t = (1-\rho)\bar{\pi}_t + \rho\pi_{t-1} + \varepsilon_t \tag{3.1}$$

$$\varepsilon_t = \phi\varepsilon_{t-1} + \eta_t, \;\; \eta_t \backsim \mathcal{N}\left(0, \sigma_\eta^2\right) \tag{3.2}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \lambda_t, \;\; \lambda_t \backsim \mathcal{N}\left(0, \sigma_\lambda^2\right) \tag{3.3}$$

where π_t denotes inflation, ε_t denotes the cyclical component of inflation, and $\bar{\pi}_t$ denotes the trend or drift component of inflation. Cyclical inflation reflects transitory deviations of inflation from its long-run trend. Trend inflation reflects the long-run drivers of inflation that are already incorporated into the historical behavior of inflation. According to this process the expected value of inflation at long horizons equals the trend, $\bar{\pi}_t$.[8]

Forecasters make their long term forecast in each period with an information set that includes knowledge of the trend-cycle model, the history of inflation, and two signals. The *inflation signal* is received by all the forecasters and simply updates the history of inflation to include its current value.[9]

[7] The idea to model inflation with a trend-cycle model builds on a large literature including Stock and Watson (2007) and Harvey (1985). In this draft, we use a homoscedastic trend-cycle model of inflation even though Stock and Watson (2007) show that relaxing this assumption would help the model fit the US postwar data. Recent papers studying trend-cycle models with stochastic volatility include Mertens (2016) and Stock and Watson (2016). We are currently working on expanding the model to allow for heteroscedasticity.

[8] In a New Keynesian model trend inflation would be determined by perceptions of the behavior of the central bank and would be incorporated into long-run inflation expectations of price setters, $E_t\pi_\infty$, as described by Hazell et al. (2022).

[9] The forecasters in the SPF do not know inflation in the quarter they are surveyed because they submit their forecasts in the second month of each quarter. We address this by lagging SPF forecasts when we estimate the model. For example, we measure long term expectations in the 2020q3 using forecasts from the November 2020 survey.

The second signal $y_t(i)$ is given by:

$$y_t(i) \quad = \quad \bar{\pi}_{t+h} + u_t(i), \;\; h > 0. \tag{3.4}$$

This signal is private as it depends on the identity of the forecaster, denoted i. The dependence on the identity of the forecaster reflects differences in their beliefs, $u_t(i)$, given by

$$u_t(i) \equiv v_t + z_t(i). \tag{3.5}$$

The forecaster-specific component is $z_t(i) \sim \mathcal{N}\left(0, \sigma_z^2(i)\right)$ and the common component v_t is driven by

$$v_t = \rho_v v_{t-1} + \nu_t \tag{3.6}$$

with $\nu_t \sim \mathcal{N}\left(0, \sigma_{\nu,t}^2\right)$. The shocks $z_t(i)$ are homokedastic and orthogonal to each other and ν_t.[10] Since the private signal provides news about the future long-run dynamics of inflation we refer to it as the *news signal*. The forecasters are assumed to know the parameters of the signals.

The news signal $y_t(i)$ is designed to gauge the importance of news or forward-looking information about long-term inflation in forecasters' inflation expectations. To see how the private signal reflects news about long-term inflation, use equation (3.3) to decompose the first term on the right-hand side equation (3.4) as follows:

$$\bar{\pi}_{t+h} = \bar{\pi}_t + \sum_{j=1}^{h} \lambda_{t+j}. \tag{3.7}$$

The first term of this decomposition captures all forward-looking factors that affect the current value of the drift, and therefore are already reflected in the historical dynamics of prices. The second term captures the news received by forecasters about the long-run dynamics of inflation that are not yet known by agents in the economy and, therefore, are not reflected in historical inflation. It should be noted that this specification does not imply that forecasters know more about trend inflation than other agents in the economy. Indeed trend inflation likely also reflects news received by other agents in the economy, for example by price-setters, that is not observed by the forecasters.

The second term in equation (3.4), $u_t(i)$, includes common and idiosyncratic shocks that affect the forecasters' beliefs about long term inflation which may or may not come to pass. Since these shocks are autonomous (i.e. orthogonal to the variables in equation 3.7), they can be thought of as animal spirits or

[10] In principle the forecast-specific component of beliefs could be also modelled as serially correlated. We follow the above approach since for the majority of forecasters in our estimation we do not find evidence of serial correlation in the forecast-specific component of beliefs.

sentiments. Sentiments that coordinate beliefs about long term inflation (ν_t) may be triggered by central bank communications and media influencing public opinion about long-run inflation in a particular direction, for instance by criticizing or backing the strategy of the central bank. The idiosyncratic shock $z_t(i)$ affects the beliefs of a specific forecaster i. This shock accounts for compositional effects in average inflation expectations due to forecasters with different idiosyncratic variances moving into and out of our survey sample.

The volatility of $u_t(i)$ (which depends on the variances of ν_t and $z_t(i)$) influences the sensitivity of expectations to the two signals. If the volatility of $u_t(i)$ is zero a forecaster knows the inflation drift $\bar{\pi}_{t+h}$ perfectly and their long-term expectations will respond one for one with the drift. If the volatility of $u_t(i)$ is very high, the news signal is close to useless. In this situation forecasters rely almost exclusively on the historical behavior of inflation to form their long-term inflation expectations.

Note that the standard deviation of the innovations to the common component of beliefs, $\sigma_{\nu,t}$, is time-varying and the same across forecasters while the standard deviation of the idiosyncratic component, $\sigma_z(i)$, is constant and specific to each forecaster.[11] The volatility of common beliefs captures episodes when long term expectations of *all* the forecasters are particularly sensitive or insensitive to the signals. The volatility of idiosyncratic beliefs captures forecaster-specific sensitivity to the signals.

At each date t forecasters observe the signals with knowledge of the history of inflation and the trend-cycle model. They use this information to update their expectations about $\bar{\pi}_t$ using Bayes rule. We assume their objective is to minimize the variance in their estimates of the underlying state variables. Given our model is linear and its shocks are normally distributed this implies that it is optimal for forecasters to update their expectations using the Kalman filter. It is important to note that the resulting expectations do not feedback into the trend-cycle model and so do not affect the dynamics of inflation.

The volatilities of the two shocks ν_t and $z_t(i)$ help determine the magnitudes of the Kalman gains and therefore the sensitivities of individual expectations to the two signals. These variances cannot be estimated directly because we do not observe the realizations of the shocks. Rather, they are identified from the observed sensitivity of average and individual expectations to current and future changes in the drift. In this sense, these shocks can be thought of as shocks to average and individual expectations.

3.3.2 Forecasters' long-run inflation expectations

The environment confronted by forecaster i has a state-space representation given by

$$\xi_t = \mathbf{\Phi}\xi_{t-1} + \mathbf{R_t} e_t \tag{3.8}$$

[11] For the majority of forecasters in our data the null hypothesis of homoskedasticity for $z_t(i)$ is not rejected.

$$s_t(i) = \mathbf{D}\xi_t + \Psi(i)z_t(i) \tag{3.9}$$

where

$$\begin{aligned}
\xi_t &= [\pi_t, \varepsilon_t, \bar{\pi}_{t+h}, \bar{\pi}_{t+h-1} \cdots, \bar{\pi}_{t+1}, v_t]' \\
e_t &= [\eta_t, \lambda_{t+h}, \nu_t]' \\
s_t(i) &= [\pi_t, y_t(i)]'.
\end{aligned}$$

Here $\mathbf{\Phi}$ is a $k \times k$ matrix which depends on ρ, ϕ, and ρ_v, where $k = h + 3$ is the number of state variables; $\mathbf{R_t}$ is $k \times 3$ and depends on σ_η, σ_λ and $\sigma_{\nu,t}$; $\mathbf{D}$ is a $2 \times k$ matrix of zeros and ones; and $\Psi(i)$ is 2×1 and depends on $\sigma_z(i)$. These matrices are defined in section C.1.

At each date t forecasters observe the signals with knowledge of the history of inflation. They use this information to update their expectations about ξ_t using Bayes rule. We assume they seek a linear rule that minimizes the variance in the estimated states. Given the Gaussian structure of our shocks this implies that it is optimal for forecasters to update their expectations using the Kalman filter. Specifically, expectations of forecaster i following the date t signals are updated as follows:

$$\xi_{t|t}(i) = (\mathbf{I}_k - \mathbf{K}_t(i)\mathbf{D})\,\xi_{t|t-1}(i) + \mathbf{K}_t(i)\,s_t(i), \tag{3.10}$$

where $\xi_{t|t}(i) \equiv \mathbb{E}\left(\xi_t | s_t(i), \pi^{t-1}\right)$ denotes forecaster i's expectations conditional on their signals and the history of inflation π^{t-1}; $\mathbf{I}_k$ denotes the $k \times k$ identity matrix; and the $k \times 2$ matrix $\mathbf{K}_t(i)$ denotes forecaster i's Kalman gain at date t, which is defined in section C.2. The third element of the vector $\xi_{t|t}(i)$ is forecaster i's long-run inflation expectation. Correspondingly, the two elements of the third row of $\mathbf{K}_t(i)$ are the i'th forecaster's Kalman gains for the inflation and news signals that are associated with their long-run inflation expectations.

3.3.3 Inflation anchoring in the model

Forecasters' inflation expectations are considered anchored when their average long-term expectations do not drift away from the central bank's inflation target. Conversely, de-anchoring occurs when average long-term inflation expectations do drift away from the target. Note that the inflation drift $\bar{\pi}_t$, which is central to long term inflation expectations, is different from the concept of an inflation target.

One way in which de-anchoring could occur in our model is when the central bank lets inflation run persistently away from its target. Sooner or later the inflation drift will start diverging from the target and de-anchoring occurs as forecasters learn that the inflation drift is changing. The role played by the inflation and news signals in this type of de-anchoring is quite different. As the inflation drift keeps deviating from the the central bank's target, the inflation signal reveals a persistent deviation of inflation from the central bank's target, leading to a progressive de-anchoring of inflation expectations. This de-anchoring is typically slow as the cyclical component of inflation, ε_t, is generally more volatile than the trend component, $\bar{\pi}_t$.

The role of the news signal is more nuanced and depends on the volatility of the common belief, v_t. If the volatility of this component is large, the news signal plays essentially no role and forecasters' expectations are updated at a pace consistent with only observing the historical behavior of inflation.

If the volatility of the aggregate component is smaller, long-run inflation expectations move more autonomously from the observed dynamics of inflation (encoded in the inflation signal). As a result, the news signal can either accelerate or decelerate de-anchoring depending on the news the forecasters receive regarding the long-run behavior of inflation. For instance, even though inflation has been running high for a period of time, de-anchoring might not occur because forecasters remain confident that the central bank will soon tighten monetary policy ($\sum_{j=1}^{h} \lambda_{t+j} + v_t < 0$). However, if forecasters' trust in the central bank's ability or willingness to quash the rising inflation is waning ($\sum_{j=1}^{h} \lambda_{t+j} + v_t > 0$), the news signal can even accelerate the de-anchoring.

It should be noted that news that keeps expectations anchored may turn out to be wrong, implying that the central bank will eventually fail to tighten (loosen) monetary policy when inflation runs persistently above (below) target. However, this assessment can be done only with the benefit of hindsight, i.e. after having observed or estimated the future shocks to the inflation drift.

3.4 Estimation

To estimate forecasters' long-term inflation expectations resulting from the signal extraction problem of section 3.3 we follow a two-step approach. In the first step we estimate the parameters of the trend-cycle model (ρ, ϕ, σ_η, and σ_λ) summarized by equations (3.1)-(3.3) using only inflation as an observable to obtain estimates of the drift and cyclical components conditional on all the sample observations using the Kalman smoother.

In the second step, we estimate the a panel model assuming that forecasters know the trend-cycle model estimated in the first step and observe inflation and their private signals $y_t(i)$. We as the econometricians observe inflation, the inflation drift obtained from the first step, and a measure of long term inflation expectations, but we do not observe the private signals. Therefore, we estimate a state space model that combines equations (3.1)-(3.3) with N equations corresponding to equation (3.10) for each of the N forecasters in our sample. This yields estimates of (ρ_v, $\sigma_{\nu,t}$, and $\sigma_z(i)$, $i = 1,2,\ldots,N$).

The transition equation we use in our panel estimation reads

$$\begin{bmatrix} \xi_t \\ \overrightarrow{\xi}_{t|t} \end{bmatrix} = \widetilde{\mathbf{\Phi}}_t \begin{bmatrix} \xi_{t-1} \\ \overrightarrow{\xi}_{t-1|t-1} \end{bmatrix} + \widetilde{\mathbf{R}}_t \begin{bmatrix} e_t \\ \overrightarrow{z}_t \end{bmatrix} \tag{3.11}$$

where $\overrightarrow{\xi}_{t|t}$ and $\overrightarrow{z}_t$ are column vectors stacking $\xi_{t|t}(i)$ and $z_t(i)$ of every forecaster and the matrices $\widetilde{\mathbf{\Phi}}_t$ and $\widetilde{\mathbf{R}}_t$ are defined in section C.1. These matrices are constructed from Φ and R_t along with the the matrices describing the evolution of each forecaster's expectations in equation (3.10).

The measurement equations for our panel estimation are

$$\begin{bmatrix} \pi_t^{cpi} \\ \bar{\pi}_{t+h}^{est} \\ \mathbb{E}_t\pi_t^{long}(1) \\ \mathbb{E}_t\pi_t^{long}(2) \\ \vdots \\ \mathbb{E}_t\pi_t^{long}(N) \end{bmatrix} = \begin{bmatrix} \mathbf{1}_1 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \ldots & \mathbf{0}_{1\times k} \\ \mathbf{1}_3 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \ldots & \mathbf{0}_{1\times k} \\ \mathbf{0}_{1\times k} & \mathbf{1}_3 & \mathbf{0}_{1\times k} & \ldots & \mathbf{0}_{1\times k} \\ \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \mathbf{1}_3 & \ldots & \mathbf{0}_{1\times k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \ldots & \mathbf{1}_3 \end{bmatrix} \begin{bmatrix} \xi_t \\ \xi_{t|t}(1) \\ \xi_{t|t}(2) \\ \vdots \\ \xi_{t|t}(N) \end{bmatrix}, \tag{3.12}$$

where $\mathbf{1}_n$ denotes the $1 \times n$ row vector with elements all equal to zero except the n-th one which is equal to one. The observable variables in the vector on the left hand side of (3.12) include an empirical measure of inflation such as CPI core inflation, π_t^{cpi}, our estimate of the inflation drift, $\bar{\pi}_t^{est}$, and an empirical measure of long-term inflation expectations of forecasters such as the SPF 10 year inflation forecasts, $\pi_t^{long}(i)$. Our inflation drift estimate is explained in detail below. Note that we keep the number of forecasters N fixed over time and we adjust the matrix in equation (3.12) to take into account the missing forecasts of forecasters, including gaps in their forecast histories.

3.5 Data

This section describes the inflation and inflation expectation data we use. Our choices are guided by the fact that CPI inflation forecasts from the SPF are available for a longer period than forecasts of inflation in the personal consumption expenditure index, which is the inflation measure targeted by the Fed. We use data on year over year core CPI inflation from the U.S. Bureau of Labor Statistics spanning the sample 1959q1–2021q3. Our long-term inflation expectations are from the SPF and cover the sample 1991Qq–2021Q4. We use the 10-year average CPI inflation forecasts to measure long-term inflation

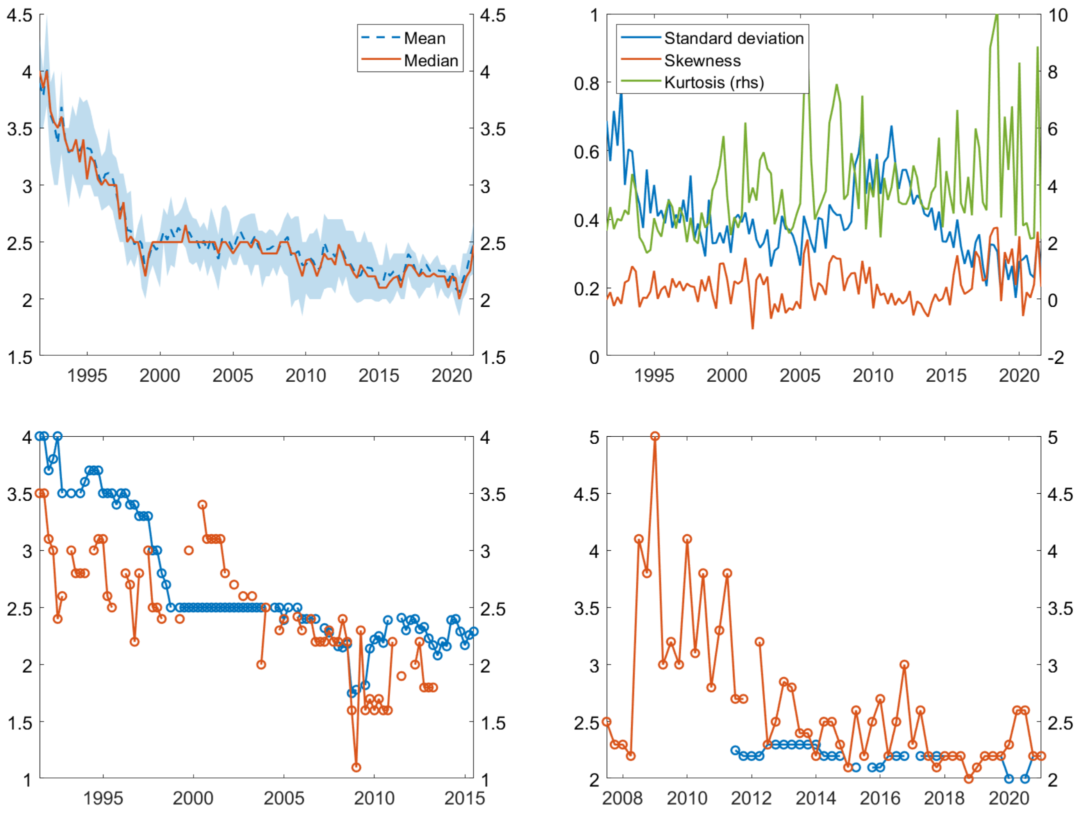


Figure 3.1 Time series summary of 10-year CPI inflation expectations

Notes: Top left chart shows mean and median together with the interquartile range, top right chart shows higher moments. The two bottom charts show the time series of 4 individual forecasters.

expectations in our model.[12] This measure does not directly correspond to the long-term inflation expectations $\bar{\pi}_{t+h}$ in our model, which is the inflation trend 10 years ahead. However, if the cyclical term is sufficiently small and short lived (ϕ and σ_η are small) it should be a good approximation. To have a sufficient number of observations to measure the variances of idiosyncratic beliefs we consider only those forecasters with at least 32 forecasts (we consider 16 as well and the results are little changed). This leaves us with an unbalanced panel of 48 forecasters. Note that in some cases there are gaps in the time series of forecasts for individual forecasters.[13] In Appendix C.4 we show that average and median long-term expectations in our sample of forecasters corresponds closely to their values in the full SPF sample.

[12]We can use the SPF to construct average inflation expected between 5 and 10 years ahead which might more closely align with the long term concept in our model. However, this requires using the SPF 5-year CPI inflation forecasts which are only available starting from 2005.

[13]The Philadelphia Fed must decide whether a forecaster ID should follow a forecaster when they change employer. Information on the Philadelphia Fed's website indicates that such decisions are based on judgments as to whether the forecasts represent the firms or the individual's beliefs. See http://www.phil.frb.org/econ/spf/Caveat.pdf.

The top row in Figure 3.1 shows how the the distribution of long-term inflation expectations evolved over the sample from 1991q4 until 2021q3. Average long-term inflation expectations at the beginning of the 1990s were near 4%. For the first years of the sample there was a steady decline, then from the beginning of the 2000s expectations were stable around 2.5% until the Great Recession after which there was again a downward trend, towards 2%. In the most recent quarter, after several quarters of unusually high inflation, inflation expectations have reached their pre-Great Recession levels again. Generally average expectations have been fairly stable over the last 20 years.

Behind these aggregate dynamics there is substantial heterogeneity across forecasters. The standard deviation is high in the beginning of the sample and around the Great Recession. The distribution is right-skewed and the kurtosis is most of the time above 3 indicating fat-tails. The bottom row in Figure 3.1 shows the time series of 4 selected forecasters. This highlights two points. First, there can be substantial differences in the level of expected inflation. Second, some forecasters have fairly stable inflation expectations and only adjust smoothly (blue lines) while other forecasters change their expected inflation in nearly every period.

3.6 Estimates

This section describes our parameter and unobserved component estimates of our time series and panel models. These estimates will be used to measure the factors driving inflation over the last 30 years and to conduct the overshooting experiments.

3.6.1 Time-series estimates

We estimate the trend-cycle model summarized by equations (3.1)-(3.3) using π_t^{cpi} as the observable and the sample period 1959Q1-2020Q3.[14] The initial level of trend inflation, $\bar{\pi}_{t_0}$, is treated as a parameter to be estimated. The priors and estimated posterior modes for all the parameters are shown in Table 3.1.

Parameter	Prior	Posterior mode
ρ	Beta(0.5,0.2)	0.785
ϕ	Beta(0.5,0.2)	0.623
σ_η	Inverse Gamma (0.25,4)	0.427
σ_λ	Inverse Gamma (0.25,4)	0.300
$\bar{\pi}_{t_0}$	Uniform	2.187

Table 3.1 Parameter estimates for the time series model

[14]We describe how we initialize the state vector of this model in section C.3.

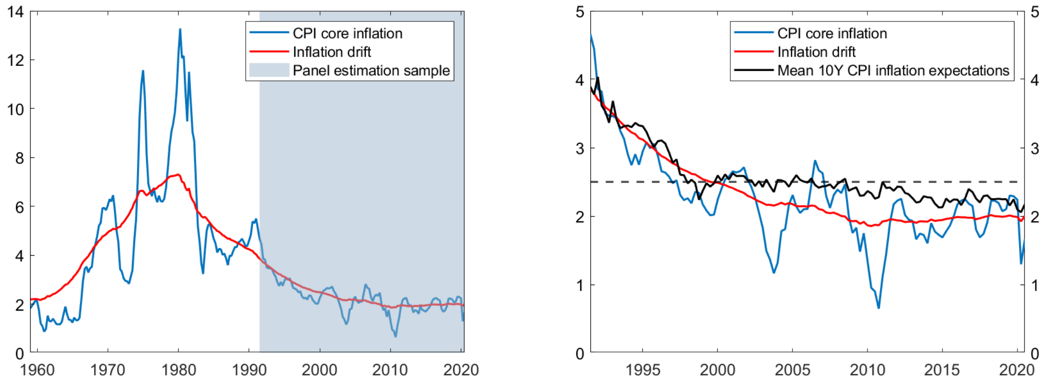


Figure 3.2 Core inflation, inflation drift and long-term expectations

Notes: The inflation drift is obtained by using the Kalman smoother. The shaded area in the left chart indicates the sample period for the panel estimation.

Once the model is estimated, we use the Kalman smoother to obtain an estimate of the inflation drift, $\bar{\pi}_t^{est}$. Figure 3.2 shows the time series of core CPI inflation and our estimate of the inflation drift over the full estimation sample. The shaded area shows the sample period we will use to estimate the panel model. The inflation drift reaches its peak of around 7% in 1980 and then declines over the following years.

The right chart in Figure 3.2 shows the mean of long-term CPI inflation expectations from the SPF. It is important to highlight that in the first part the sample the inflation drift and average expectations are very close. From around 2000, the decline of the trend inflation has been faster than that of the long-run inflation expectations, which, in fact, remained anchored to 2.5% from the end of 1990s through to the onset of the Great Recession.

3.6.2 Panel estimates

We estimate the state-space model in equations (3.11)-(3.12) over the sample period 1991q3-2020q3 assuming $h = 4$. The first period where the 10-year CPI inflation expectations are available is 1991q4. Since forecasters in the SPF do not observe contemporaneous inflation when they submit their forecasts, we shift the SPF data one period backward. For instance, in 1991q3, we are using inflation and the estimated inflation drift in 1991q3 and the SPF expectations for 1991q4. If a forecaster enters the Survey after 1991q4, its initial beliefs are updated by the Kalman filter assuming omitted observations. section C.3 describes how we set the initial conditions. These initial conditions are set so that we as the econometricians have the same priors about the initial state as the forecasters.

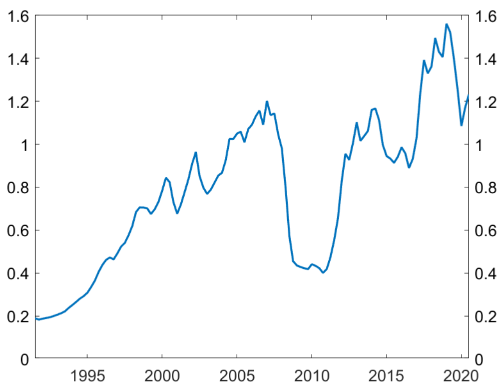
In Table 3.2 we summarize the priors and estimated parameters of the panel estimation. As indicated in the table the prior for $\sigma^2_{\nu,t}$ is a Gaussian random walk. This prior should induce a smooth change in

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.384
$\sigma_{\nu,t}$	$\ln\sigma^2_{\nu,t} \backsim \mathcal{N}\left(\ln\sigma^2_{\nu,t-1}, \sigma^2_{\nu,\text{prior}}\right)$	see Figure 3.3, lhs
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.220
$\sigma_z(i)$	Inverse Gamma (0.5,4)	see Figure 3.3, rhs
$\sigma_{\nu,\text{prior}}$	Calibrated	0.2

Table 3.2 Parameter values for panel estimation

the forecasters' common attention to news about inflation drift over time, which reflects our belief that drastic changes in overall attention are not likely *a priori*. In the baseline we set $\sigma_{\nu,\text{prior}}$ – the standard deviation of the Gaussian random walk prior – to 0.2, but we also show the robustness to alternative values. The initial condition for the variance $\sigma^2_{\nu,0}$ is assumed to be distributed as inverse gamma with moments shown in Table 3.2.

Table 3.2 shows we estimate a persistence of around 0.4 for the v_t process. The time series of $\sigma_{\nu,t}$ is shown in the left of Figure 3.3. From the estimated initial value there has been an upward trend with a large drop around the Great Recession. This suggests that the sensitivity of expectations to the news signal has declined as inflation became more stable. During the turbulent developments of the Great Financial Crisis and the ensuing Great Recession, the exogenous common beliefs were substantially less volatile suggesting greater sensitivity to news. The right chart in Figure 3.3 plots the distribution of the variance of forecaster-specific beliefs, $\sigma_z(i)$. This distribution suggests that the degree of sensitivity to the signals is quite heterogeneous.



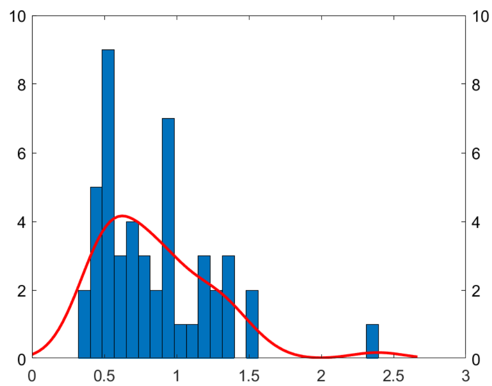


Figure 3.3 Time series of $\sigma_{\nu,t}$ (lhs) and histogram of σ_z (rhs)

3.7 Inflation expectations through the lens of the model

This section discusses three aspects of the historical behavior of inflation expectations. We first describe how the sensitivity of forecasters to the signals varies over time and across forecasters based on the estimated Kalman gain matrices. Next we use the Kalman matrices to compute impulse responses to study the effect of the model's different shocks on forecasters' long term inflation expectations. Finally, we analyze the historical contribution of the different shocks to the evolution of long-term inflation expectations over time and the anchoring and de-anchoring of average US inflation expectations over the last 30 years.

3.7.1 Forecasters' sensitivity to inflation and news

As described in the previous section, a key ingredient of the panel estimation is the Kalman gain matrix for each forecaster. The Kalman gain matrix is based on the solution of the signal extraction problem of each forecaster and is a $(h+3) \times 2$ matrix (see derivation in Appendix C.2, equation (C.5)). The different rows correspond to the state variables and the two columns to the signals. The elements of this matrix tell us how much each forecaster learns from the two signals about the state variables. A large Kalman gain reflects a high degree of sensitivity to the inflation and news signals and fast learning about the underlying state variables. Our focus is on the third row of the Kalman gain matrix which corresponds to the Kalman gain for the inflation drift h period ahead and shows how much a given forecaster adjusts her long-term inflation expectations in response to changes in the two signals.

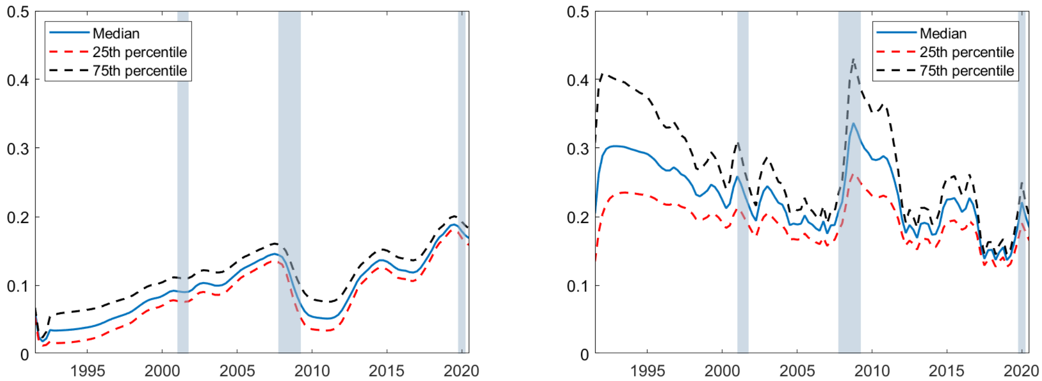


Figure 3.4 Kalman gains for the inflation drift due to the inflation (lhs) and news (rhs) signals

Notes: Shaded areas indicate NBER recession dates.

Figure 3.4 plots the distribution of the Kalman gain regarding the inflation drift over time. The left figure shows the Kalman gain from observing the inflation rate. The right figure plots the Kalman gain

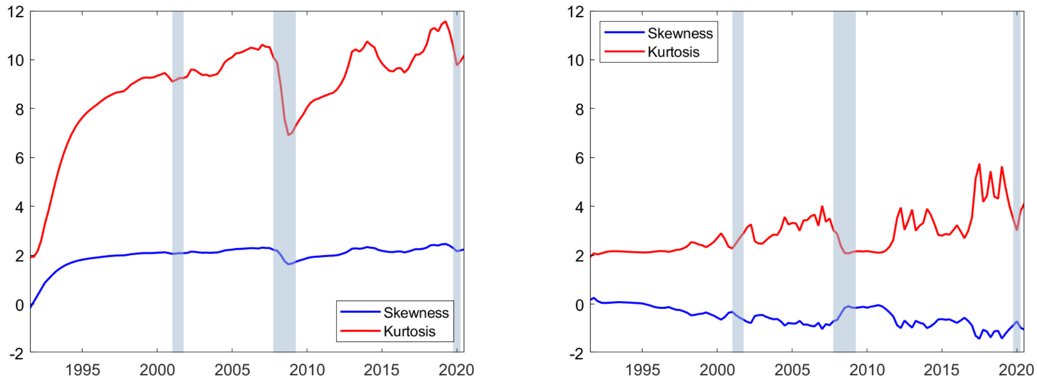


Figure 3.5 Higher moments of Kalman gain distribution for inflation drift: inflation signal (lhs), news signal (rhs)
Notes: Shaded areas indicate NBER recession dates.

from receiving news about long-term inflation. There are a number of things we can learn from this figure.

First, the median Kalman gain for inflation is smaller than for news. News about an increase in trend by 100 basis points moves average long-term inflation expectations by about 25 basis points on average compared to 10 basis points for the inflation signal. This suggests that news plays a larger role in shaping professional forecasters' long-run inflation expectations in the sample period. Forward-looking information is more important for forecasters to form beliefs about the long-term. Nevertheless, the difference between the Kalman gains has fallen in recent years as the Kalman gain for the inflation signal has a positive trend in the sample period while it is roughly stationary for news.

Second, the gains vary over time and generally in opposite directions. The shaded areas in Figure 3.4 indicate NBER recessions dates and illustrate that while the sensitivity of expectations to the inflation signal is pro-cyclical, it is counter-cyclical for news. This is especially noteworthy during the Great Recession where we observe a large increase in the median Kalman gain for the news signal. These findings suggest that individual and therefore average inflation expectations are particularly responsive to news about long-run inflation during recessions and when the Federal Funds rate reaches its effective lower bound. During such times the central bank has to rely more on other monetary policy tools including forward-looking communication about how to stabilize inflation. The relative size of the estimated Kalman gain from the inflation and news signals suggests that central bank communication can be an effective tool for anchoring long-term inflation expectations in large recessions.

Third, heterogeneity in attention to the news signal is counter-cyclical as indicated by the widening in the 25th and 75th percentile bands in the recessions, particularly the Great Recession.

Figure 3.5 shows the skewness and the kurtosis of the distributions of Kalman gains from the inflation signal (left panel) and from the news signal (right panel) across forecasters. While the distribution of Kalman gains from the inflation signal is positively skewed, the distribution of Kalman gains from the long-run inflation news is generally negatively skewed. Both distributions became more symmetric during the past two recessions. The kurtosis of both distribution of Kalman gains is counter-cyclical, meaning that the tails of the distribution of Kalman gains become thinner in recessions.

3.7.2 The effects of the different shocks on inflation expectations

Our model allows us to estimate how forecasters' inflation expectations respond to the different shocks. Figure 3.6 plots the impulse response functions to one-time one standard deviation shocks to each of the four shocks of the model. All model parameters are set to the estimated values except for the time-varying parameter $\sigma_{\nu,t}$ which we set to the average value estimated over time which is 0.79. We assume that inflation and the inflation drift are both equal to the value of the inflation drift in 1991Q3. In addition, we simulate the model for several burn-in periods to make sure that initial conditions do not affect the Kalman gain and the parameter matrices in equation (3.11) anymore. Each chart shows the impulse response function of inflation expectations for a forecaster with σ_z calibrated to the median, the 25th-percentile and the 75th-percentile estimated value of σ_z, respectively. We study shocks to the cyclical component η, permanent component λ, common beliefs ν, and idiosyncratic beliefs, z, which is indicative of how important the composition of the survey is to average inflation expectations.

The top left chart shows the response to a transitory shock to inflation η. The transitory shock leads to a very small temporary rise in long-term inflation expectations. Note that a one standard deviation shock in η increases actual inflation by more than 60 basis points. The magnitude in this chart shows that this increase only partly feeds through to long-term inflation expectations with a peak effect of around 5 basis points.

The top right chart plots the response to a permanent shock to inflation λ that leads to a jump in the inflation drift $h = 4$ periods ahead by around 30 basis points. Forecasters learn about this change fairly slowly over time. Inflation expectations of the median forecaster rise by 7 basis points in the period when the shock materializes and within the first 6 quarters they complete half of their adjustment. After around 7 years the median forecaster has learned the new level of trend inflation.

The bottom two charts depict the impulse response functions for shocks to the common beliefs ν_t (left plot) and to the idiosyncratic beliefs $z_t(i)$ (right plot). In both cases, a one standard deviation shock moves median inflation expectations away from the inflation drift by about 20 basis points. The effects of these shocks are a similarly persistent. This illustrates that shocks to beliefs can move away

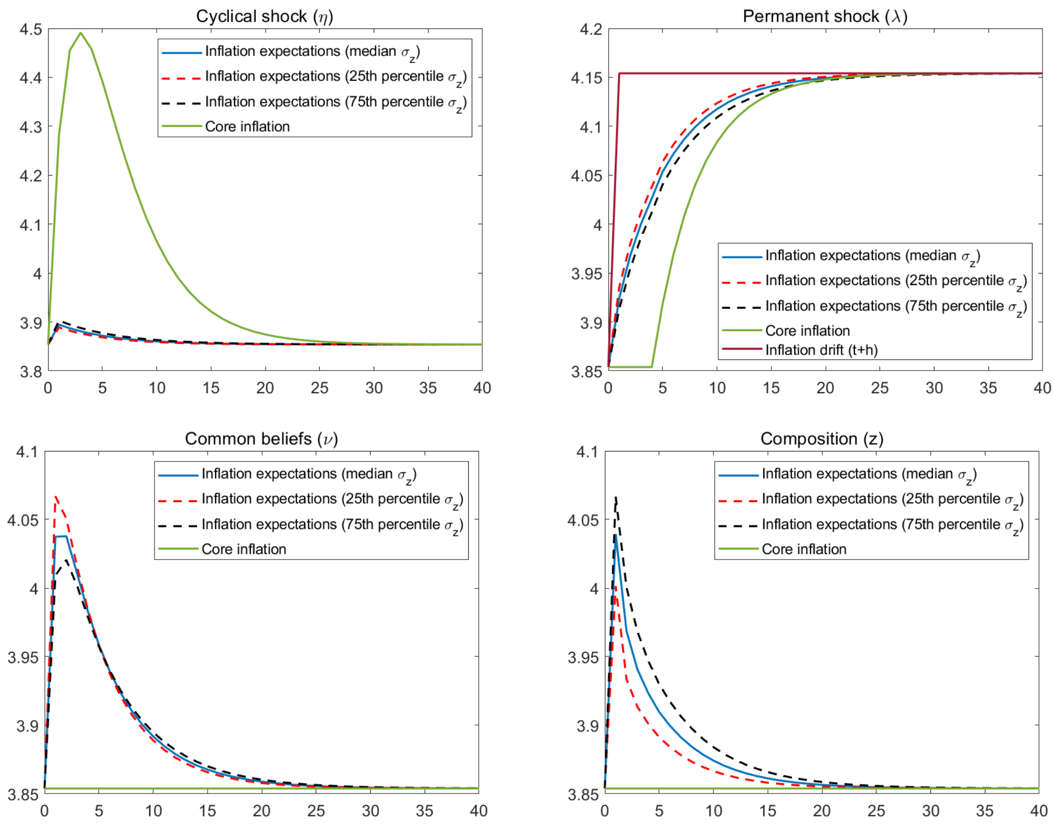


Figure 3.6 Impulse response functions to one standard deviation shocks

Notes: IRFs to one time shock that happens in period 1. The blue and red/black dashed lines correspond to the IRFs of inflation expectations of forecaster with median and 25th/75th percentile of the distribution of estimated σ_z, respectively. The green and the dark red line show the IRF of core inflation and the inflation drift, respectively.

median inflation expectations for a significant period of time from the inflation drift. The similarity of the responses to the idiosyncratic shock suggests that composition is likely to have a relatively small effect on average inflation expectations.

3.7.3 Historical drivers of long-term inflation expectations

In this section we use our model to learn more about the historical drivers of long-term inflation expectations. Figure 3.7 shows the historical shock decomposition of forecasters' average inflation expectations together with the inflation drift. We study the role of the cyclical and permanent shocks, common beliefs, and composition by considering the effect of one shock at a time assuming all the other shocks are set to zero. The detailed procedure to obtain the historical shock decomposition is described in section C.6.

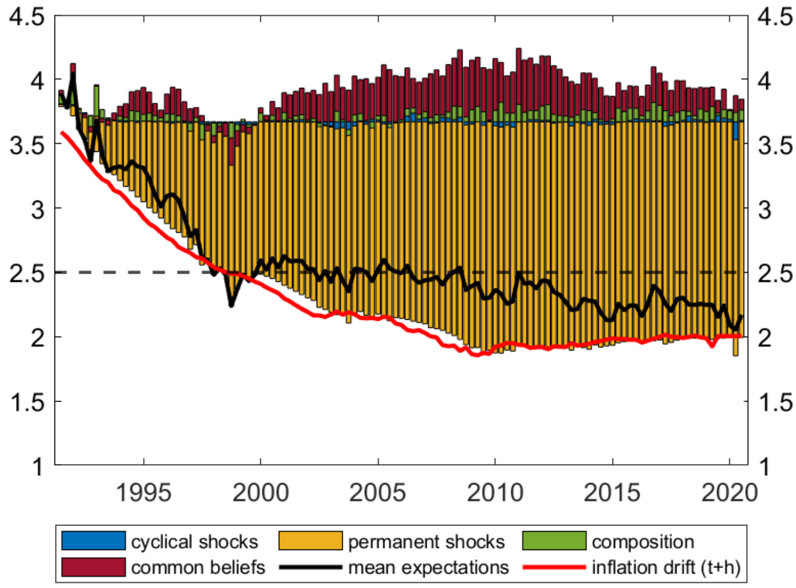


Figure 3.7 Historical decomposition of average inflation expectations

Notes: Simulation of model based on smoothed estimates with different shocks active.

Figure 3.7 shows the primary driver of the long term decline in average inflation expectations is permanent shocks to inflation λ_t. After the drift reached 2.5 percent in the late 1990s it declined further but inflation expectations remained fairly stable. The main driver behind this discrepancy between trend inflation and average inflation expectations is common beliefs, news not yet reflected in current inflation, ν_t. This pattern of common beliefs led forecasters to keep their average inflation expectations stable and close to the Fed's objective.[15]

We interpret this result as suggesting indicating that communication has played an important role in stabilizing average long-term inflation expectations around the Fed's target notwithstanding the low inflation rates observed over the last two decades. However, at the onset of the Great Recession long-term inflation expectations started to fall slowly below the value they settled around at the end of the disinflation period. By the end of the post-Great Recession recovery, the gap between average inflation expectations and the sub-target estimated trend of inflation has shrunk considerably.

In line with the results described in subsection 3.7.2, cyclical shocks to inflation played a minor role as drivers of inflation expectations in the last 30 years. The composition of the SPF panel through idiosyncratic beliefs $z_t(i)$ has had a mainly positive and small effect on long term expectations. Still,

[15]In this paper, we assume that core CPI inflation at 2.5% is consistent with price stability. This is because long-term CPI inflation expectations have settled around that level following the long US disinflation until the beginning of the Great Recession. See the left plot of Figure 3.2.

absent these composition effects the post Great Financial Crisis de-anchoring of average long term expectations would have come earlier and faster.

In Appendix C.6, we show the historical decomposition of individual expectations for a subset of forecasters. The forecaster-specific beliefs $z_t(i)$ plays an important role as a driver of inflation expectations at the forecaster level. As shown in Figure 3.7, this source of volatility may also contribute to explain average inflation expectations given that the number of forecasters in our sample is finite.

3.8 Re-Anchoring U.S. Inflation Expectations

The previous section shows that our model provides a plausible characterization of the historical behavior of average long term inflation expectations. Our model can also be used as a guide for central bankers looking to the future, and in particular those operating within an inflation target regime. The goal of such a regime is to anchor long term inflation expectations at the inflation target. Our estimated model can be used to study whether and under what conditions average long term inflation expectations will be anchored going forward from the end of the period data are available. Its parameters determine how quickly individual forecasters respond to incoming inflation and news about future inflation. Therefore we can use it to project average inflation expectations under different scenarios for the future paths of inflation and news.

We now apply our model to the case of a central banker considering the stance of US monetary policy in the third quarter of 2021. From the late 1990s to the Great Recession SPF average long term CPI inflation expectations appear to have been anchored at 2.5 percent. However for the two decades prior to the pandemic CPI inflation almost always ran below these expectations. This persistent deflationary bias led to progressive declines in the inflation drift and in average expectations. By 2020q3 long term CPI inflation expectations had fallen to near 2 percent, roughly the same level as our estimated inflation drift, as shown in the right plot of Figure 3.2. In mid-2021, as the economy emerged from the pandemic recession, year-on-year core CPI inflation rose sharply from a near pandemic low of 1.5 percent in 2020q1 to 3.9 percent in 2021q2 and 4.1 percent in 2021q3. These high readings coincided with a substantial increase in SPF average long term inflation expectations from 2.1 percent in the May survey, 2.4 percent in the August survey, and 2.6 percent by the time of the November survey.[16] These conditions presented the Fed with a key test of the credibility of its new long run framework for guiding U.S. monetary policy announced by Fed Chair Powell in August 2020. This framework tries to commit

[16]These expectations do not correspond exactly to the SPF headline rates because they are averages not medians and because they are based on our sample of forecasters which is a subset of the survey's sample.

the Fed to overshooting its target if necessary to re-anchor expectations. How much overshooting of the target does our model say the Fed should have been striving to achieve to implement this strategy as it set policy in September 2021? We now consider two experiments with our model to address this question.[17]

3.8.1 Alternative paths of inflation

In the first experiment we consider the evolution of average expectations under alternative paths of inflation taken from the Fed's September 2021 SEP. We obtain our model's predictions for average long term inflation expectations conditional on alternative paths of inflation in two steps. In the first step we use our estimated trend-cycle model to calculate the inflation drift with inflation data from 2020q4 (the quarter after the end of our estimation sample and the announcement of the Fed's new long run framework) through 2021q3 and September SEP inflation projections from 2021q4 through 2024q4. In addition we linearly interpolate inflation to 2.5 percent in 2025q5 where it stays until 2026q4. The latter step facilitates the calculation of the drift through 2025q4 which we need to construct the news signal in 2024q4 (with $h = 4$).[18] In the second step we use our estimated model of individual inflation forecasters to calculate average long-run inflation expectations launching from 2021q3 and conditioning on core CPI inflation in 2021q3, the November 2021 SPF (recall we lag SPF projections to account for the timing of the survey), the SEP inflation paths from 2021q4, and the inflation drift estimated in the previous step. Note that these steps are the same as those we followed to estimate our model of individual forecasters except for the fact that we do not use the distribution of SPF inflation expectations as they are not available.

Estimation of the inflation drift in the first step is complicated by the sharp rise in inflation in mid-2021. This rise in inflation appears to be a result of a surge in aggregate demand from fiscal and monetary stimulus and negative shocks to aggregate supply coming from a contraction in labor supply and disruptions to the supply of goods. Our linear and Gaussian setup is unlikely to properly capture these unusual developments. Consequently we adapt the method Lenza and Primiceri (ming) propose to estimate VAR models with samples that include the pandemic-driven wild swings in data starting in 2020q2.[19] In particular, we scale the variances of the cyclical and permanent components starting in 2021q2 by the factor β that decays at rate γ. When we calculate average inflation expectations we

[17] See section C.8 for details of the calculations underlying these experiments.

[18] The September 2021 SEP reports FOMC participants' projections (under their individual views about appropriate monetary policy) for the q4 over q4 inflation rate in 2021q4, 2022q4, 2023q4, and 2024q4. We linearly interpolate between projections to obtain quarterly values.

[19] See Ferroni et al. (2020) for a related approach to estimating DSGE models with unusual shocks.

assume the forecasters know this scaling. We estimate values of β near 4.75 and γ near 0.1 (meaning the scaling factor falls quickly back to 1) using uniform priors taken as given paths of inflation from 2021q4 to 2026q4. With these coefficients in hand we calculate the inflation drift from 2020q4 to 2024q4 by running the Kalman smoother backward from 2024q4.

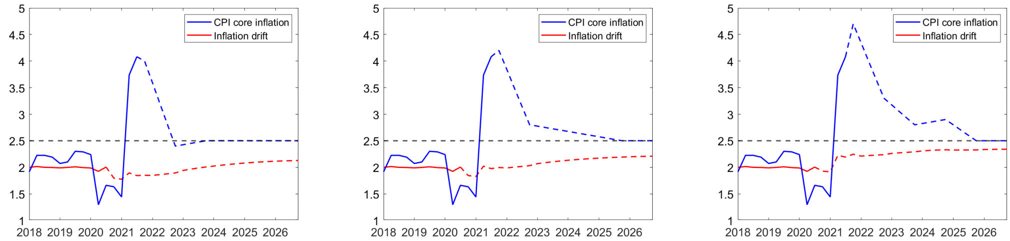


Figure 3.8 Inflation path and estimated inflation drift based on SEP lower range (lhs), median (middle) and upper range (rhs)

From left to right Figure 3.8 shows the paths of inflation corresponding to lowest, median, and highest projections along with the inflation drifts implied by these paths. The key takeaway from this figure is that all three paths of the drift adjust very slowly back toward 2.5 percent.[20] This slow convergence means that in all three scenarios the drift exerts a downward bias to average inflation expectations.

Figure 3.9 illustrates the impact of this on the predicted paths of average inflation expectations. In all three cases these drop quickly below 2.5 percent, stay low, and end up between 2.1 and 2.4 percent in 2024q4. Evidently, according to our model, the inflation projected by FOMC participants in September 2021 should not have been projected to re-anchor expectations at 2.5 percent.

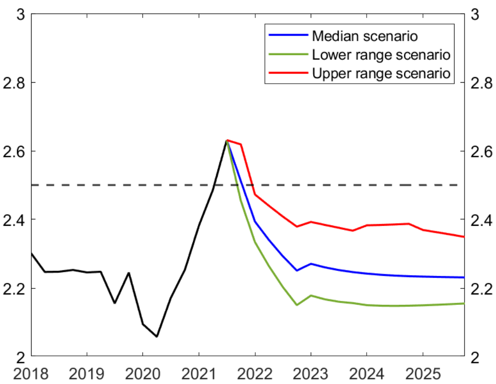


Figure 3.9 Mean inflation expectations under different SEP inflation scenarios

[20]Note that if the variances of the cyclical and permanent shocks do not change, the drifts in all three scenarios rise quickly to above 2.5 percent in 2021q2 and stay at or above that level throughout the remainder of the projection period (not shown).

3.8.2 The path of inflation consistent with re-anchoring expectations

In the second experiment we study the path of inflation that would re-anchor average expectations at their pre-Great Recession level of 2.5 percent starting from 2021q4.[21] We impose in the measurement equations that the average long-run expectations of the forecasters are equal to 2.5 percent from 2021q4-2025q4. We then assume an initial path for the inflation drift from 2020q4 to 2026q4 and find the values of the permanent and cyclical shocks to inflation and the shocks to beliefs, that deliver a path for inflation from 2021q4 and rationalize the joint behavior of the drift and expectations. Since $\bar{\pi}_{t+h}$ is predetermined by our assumed path for the drift, the path of the news signal $y_t(i)$ is pinned down by $u_t(i)$, that is the common and idiosyncratic beliefs. Since we only impose a restriction on the mean of the forecasts and the sample of forecasters is unchanged, $z_t(i)$ plays essentially no role. Given the calculated path of inflation we can infer a path of the drift as we do in the first experiment. The resulting path of the drift will not necessarily equal the path of the drift we assumed initially. We iterate on the assumed path of the drift until it converges.

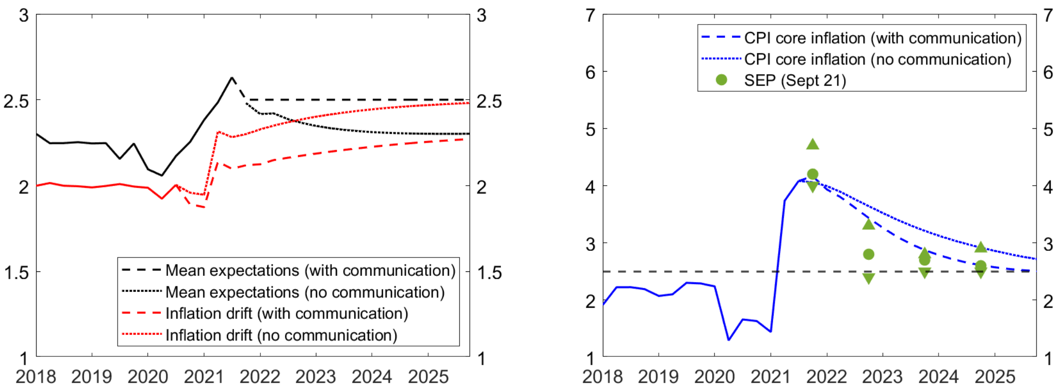


Figure 3.10 Inflation consistent with re-anchoring average long-term inflation expectations at 2.5 percent from 2021q4.

Notes: SEP (Sept 21) corresponds to the Summary of Economic Projections from September 2021 and is the year over year core PCE inflation projection for the fourth quarter of 2021-2024, rescaled by 50 basis points to be consistent with core CPI inflation. The dots correspond to the median projections and the arrows to the highest and lowest projections.

Figure 3.10 displays our findings. The blue dashed line in the right hand plot shows the inflation that is consistent with anchoring mean inflation expectations at 2.5 percent. The corresponding inflation drift is shown in the left hand plot. This experiment reveals that to re-anchor expectations inflation must overshoot 2.5 percent by 150 to 50 basis points in 2022 and 2023. To gauge the magnitude of this overshoot the right hand plot also shows the largest, median, and smallest inflation projection from the

[21] Bianchi et al. (2021) show that in New Keynesian models, a low interest rate environment can bring about deflationary spirals as the risk of hitting the ZLB increases.

SEP (solid arrow heads and circle). We can see that the overshoot is close to the upper range of the SEP inflation in 2022 and 2023.

How can we square this finding with the declines in expectations observed in Figure 3.9? The reason is common beliefs. The news signals need to come in stronger ($v_t > 0$) than justified by the path of the inflation drift alone. This can be seen in the left plot of Figure 3.10 where the black dotted line shows the path of expectations when we set $\nu_t = 0$.[22] Absent the common beliefs expectations would fall below 2.5 percent much as they do in Figure 3.9. The blue dotted line in the right plot shows the inflation that would be necessary to re-anchor expectations without the lift from beliefs (the red dotted line in the left hand plot shows the implied value of the drift). This is notably higher than the path with common beliefs. We interpret this finding as indicating a potential role for forward looking communication by the FOMC in re-anchoring expectations while ensuring inflation returns to 2.5 percent faster than otherwise.

3.9 Conclusion

In this paper, we show how to use panel survey data to estimate how sensitive forecasters' long term inflation expectations are to incoming inflation and news about future inflation, and measure the coordination of beliefs about future inflation. We apply our method to the U.S. Survey of Professional Forecasters and find that observed changes in inflation have small effects on long term inflation expectations. News has larger effects but they are still relatively small. These features of our estimated model provide a partial explanation for why the anchoring and subsequent de-anchoring of average long term inflation expectations over the period 1991 to 2020 were long lasting episodes. Our model suggests coordination of beliefs also played a role, slowing down but not preventing the pull on average expectations from inflation running persistently below target.

Professional forecasters' inflation expectations respond to news about long-run inflation that is not fully reflected by the historical behavior of inflation. This type of news affects common and idiosyncratic beliefs about future inflation. We interpret the common beliefs we estimate as reflecting the forecasters trust regarding the central bank's commitment to its inflation target and effect communications about how the central bank will seek to achieve price stability in the long run. We find that common beliefs that the Fed would attain its target played an important role keeping inflation expectations anchored over the past two decades.

[22] This means that until 2021Q3 common beliefs are active but afterwards not. Due to the low serial correlation in v_t this means the role of beliefs vanishes quickly.

In addition to providing a characterization of past average inflation expectations, our model can be used as a guide to central bankers looking to the future, and in particular those operating within an inflation targeting regime. We apply our model to the case of a central banker considering the stance of U.S. monetary policy in September 2021. We consider two experiments with our model. With the first we find that while the high inflation readings of mid-2021 boosted average inflation expectations close to the seemingly anchored values from before the Great Recession, the September SEP projections imply expectations would fall back down to pre-pandemic levels because they return to target too quickly. In our second experiment we use our model to assess the degree of overshooting of the inflation target that is necessary to re-anchor long term expectations at pre-Great Recession levels. Generally inflation must be at least as large as the highest SEP inflation projections in 2022 and 2023. Our model suggests that effective central bank communications that coordinate beliefs about future inflation reduces the size of overshooting necessary to re-anchor expectations.

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A

Appendix to Chapter 1

A.1 GfK household survey

A.1.1 Survey questions

The full set of survey questions used in this paper beyond inflation expectations are

Q1: How has the financial situation of your household changed over the last 12 months? It has...

1. Got a lot better
2. Got a little better
3. Stayed the same
4. Got a little worse
5. Got a lot worse
6. Don't know

Q2: How do you expect the financial position of your household to change over the next 12 months? It will...

1. Get a lot better
2. Get a little better
3. Stay the same

4. Get a little worse

5. Get a lot worse

6. Don't know

Q4: How do you expect the general economic situation in this country to develop over the next 12 months? It will...

1. Get a lot better

2. Get a little better

3. Stay the same

4. Get a little worse

5. Get a lot worse

6. Don't know

Q7: How do you expect the number of people unemployed in this country to change over the next 12 months? The number will...

1. Increase sharply

2. Increase slightly

3. Remain the same

4. Fall slightly

5. Fall sharply

6. Don't know

Q8: In view of the general economic situation, do you think that now it is the right moment for people to make major purchases such as furniture, electrical/electronic devices, etc.?

1. Yes, it is the right moment now

2. It is neither the right moment nor the wrong moment

3. No, it is not the right moment now 4. Don't know

Q9: Compared to the past 12 months, do you expect to spend more or less money on major purchases (furniture, electrical/electronic devices, etc.) over the next 12 months? I will spend...

1. Much more

2. A little more

3. About the same

4. A little less

5. Much less

6. Don’t know

Q10: In view of the general economic situation, do you think that now is...?

1. A very good moment to save

2. A fairly good moment to save

3. Not a good moment to save

4. A very bad moment to save

5. Don’t know

Q11: Over the next 12 months, how likely is it that you save any money?

1. Very likely

2. Fairly likely

3. Not likely

4. Not at all likely

5. Don’t know

Q12: Which of these statements best describes the current financial situation of your household?

1. We are saving a lot

2. We are saving a little

3. We are just managing to make ends meet on our income

4. We are having to draw on our savings

5. We are running into debt

6. Don’t know

The confidence indicator used in section 4.2 is constructed as weighted some of questions 1, 2, 4 and 9.

A.1.2 Descriptive statistics

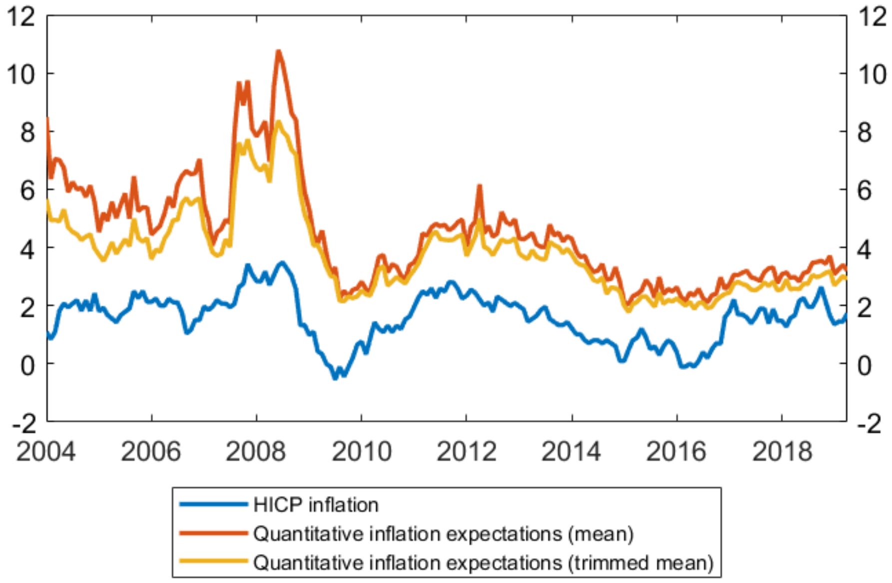


Figure A.1 Quantitative inflation expectations and actual HICP inflation

Notes: HICP inflation is year on year growth rate of seasonally adjusted HICP index for Germany. Trimmed mean of quantitative inflation expectations is excluding top and bottom 2%. of values.

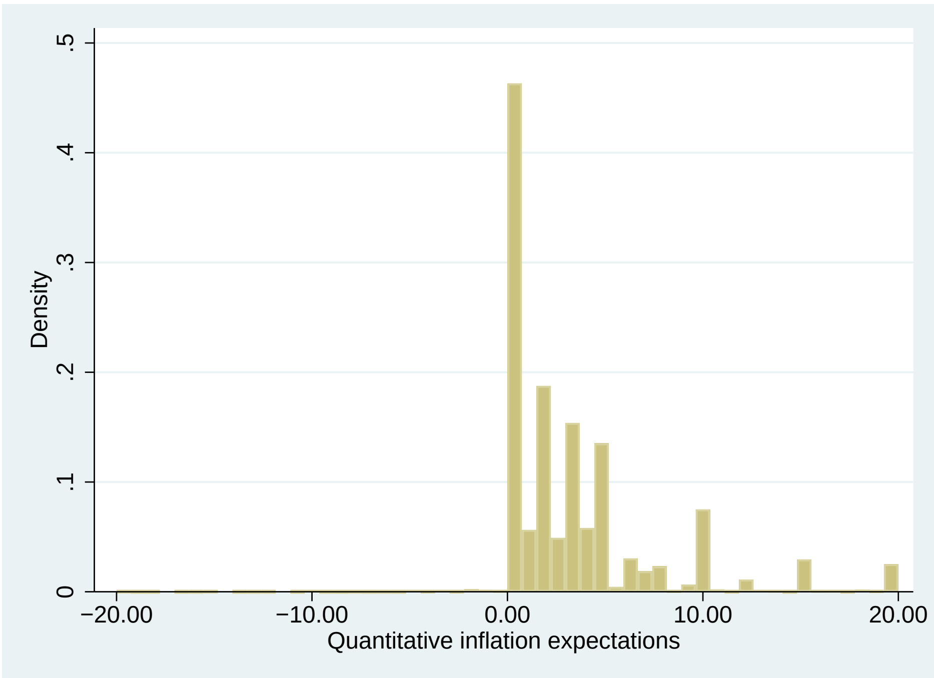


Figure A.2 Distribution of quantitative inflation expectations

Notes: Distribution is trimmed at absolute value of 20. Overall reported values range between -100% and 100%. Sample: January 2004 until April 2019.

Table A.1 Summary statistics of demographic characteristics

		Mean
Age		47.86
Gender	female	54.66%
	male	45.44%
Household net income (Euro per month)	<500	1.21%
	(500,749)	1.70%
	(750,999)	5.00%
	(1.000,1.249)	4.57%
	(1.250,1.499)	9.21%
	(1.500,1.999)	10.71%
	(2.000,2.499)	14.00%
	(2.500,2.999)	9.50%
	(3.000,3.499)	8.59%
	(3.500,3.999)	4.46%
	>=4.000	7.69%
	No answer	23.34%
Education	Volks-/Hauptschule	38.82%
	Höhere Schule ohne Abitur	40.06%
	Abitur/Hochschulreife	10.73%
	Universität	8.92%
	No answer	1.47%
Household size	1 person	22.83%
	2 person	38.39%
	3 person	18.50%
	4 person	14.98%
	5 person or more	5.30%
City size	<2000	7.13%
	(2.000,2.999)	3.46%
	(3.000,4.999)	8.10%
	(5.000,9.999)	9.69%
	(10.000,19.999)	14.78%
	(20.000,49.999)	19.77%
	(50.000,99.999)	7.91%
	(100.000,199.999)	7.02%
	(200.000,499.999)	7.12%
	>=500.000	15.04%
Occupation	farmer	1.44%
	liberal profession	0.26%
	self-employed	5.69%
	civil servant	2.09%
	white-collar worker	30.59%
	blue-collar worker	15.02%
	student	6.37%
	trainee	2.39%
	housewife	5.89%
	retiree	24.25%
	unemployed	5.99%
	No answer	0.02%
Housing situation	own house	44.11%
	own apartment	6.47%
	rented house/apartment	49.42%
Marital status	single	22.41%
	living together	10.77%
	married	49.75%
	divorced/widowed	17.03%
	No answer	0.04%
Household head	yes	59.94%
State	16 German states	

Notes: Sample from January 2004 until April 2019. Total number of observations is 338.778.

The cross-correlation of qualitative inflation expectations with core inflation 12 months ahead is 0.53 for the full sample and 0.72 for the sample until December 2014. Note that this is not just driven by some predictive power of food and energy inflation for core inflation. The 12-month ahead correlation of food and energy inflation with core inflation is 0.27 and 0.11 for the full sample and 0.41 and 0.34 for the sample until December 2014.

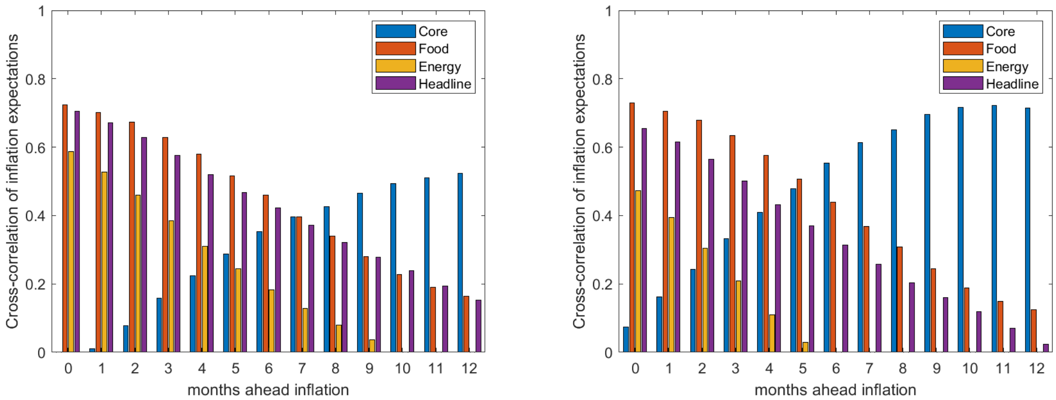


Figure A.3 Predictive power of qualitative inflation expectations for realized inflation

Notes: Cross-correlations of **qualitative** inflation expectations (balanced statistic) with realized inflation at different future horizons. Sample: January 2004 until April 2019 (lhs) and December 2014 (rhs), respectively.

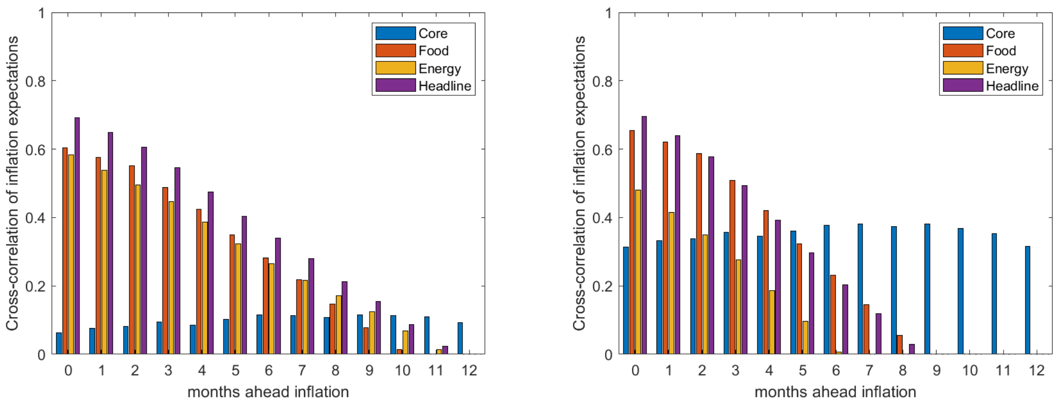


Figure A.4 Predictive power of quantitative inflation expectations for realized inflation

Notes: Cross-correlations of **quantitative** inflation expectations (trimmed mean) with realized inflation at different future horizons. Sample: January 2004 until April 2019 (lhs) and December 2014 (rhs), respectively.

Figure A.5 Inflation expectations and actual realized inflation

Notes: Qualitative inflation expectations by households are calculated as balanced statistic following Arioli et al. (2017): (P[1]+0.5 P[2]-0.5 P[4]-P[5])*100 where P[i] is the frequency of response. Inflation expectations by professional forecasters are from Bloomberg and start only in February 2008.

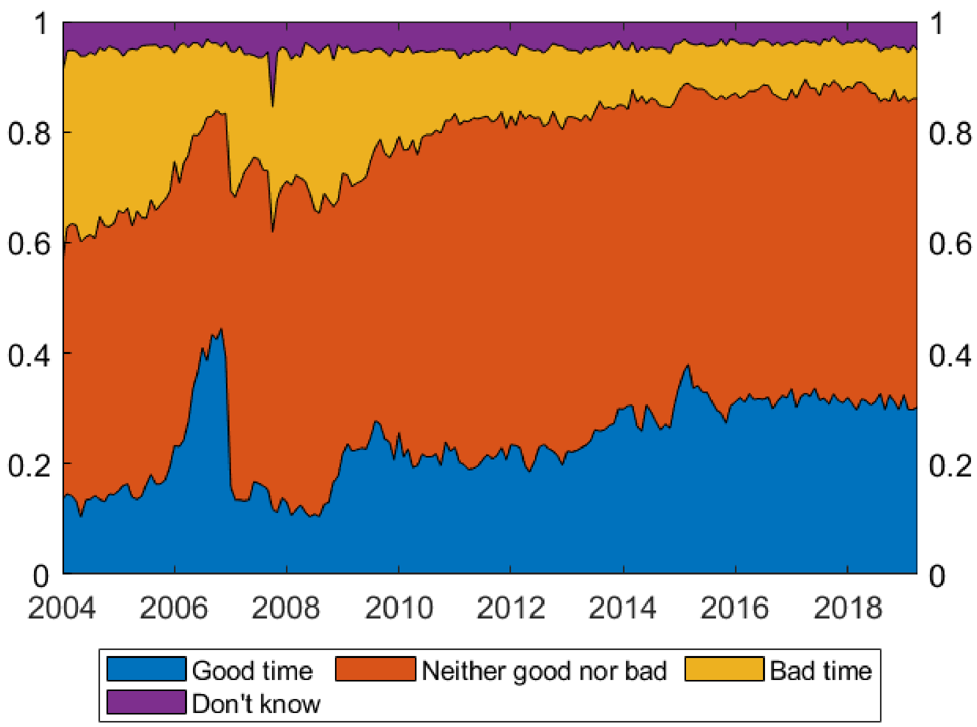


Figure A.6 Distribution of readiness to spend on durables over time

A.2 Monetary policy surprises

The monetary policy surprises are identified using the methodology by Altavilla et al. (2019). I extended their analysis until April 2019 using data on interest rate changes around ECB Governing Council meetings from the Euro Area Monetary Policy Event-Study Database (EA-MPD). This database has been originally compiled by Altavilla et al. (2019) and is regularly updated.[1]

Figure A.1 and Figure A.2 shows the factor loadings and monetary policy surprises from the estimated factor model.

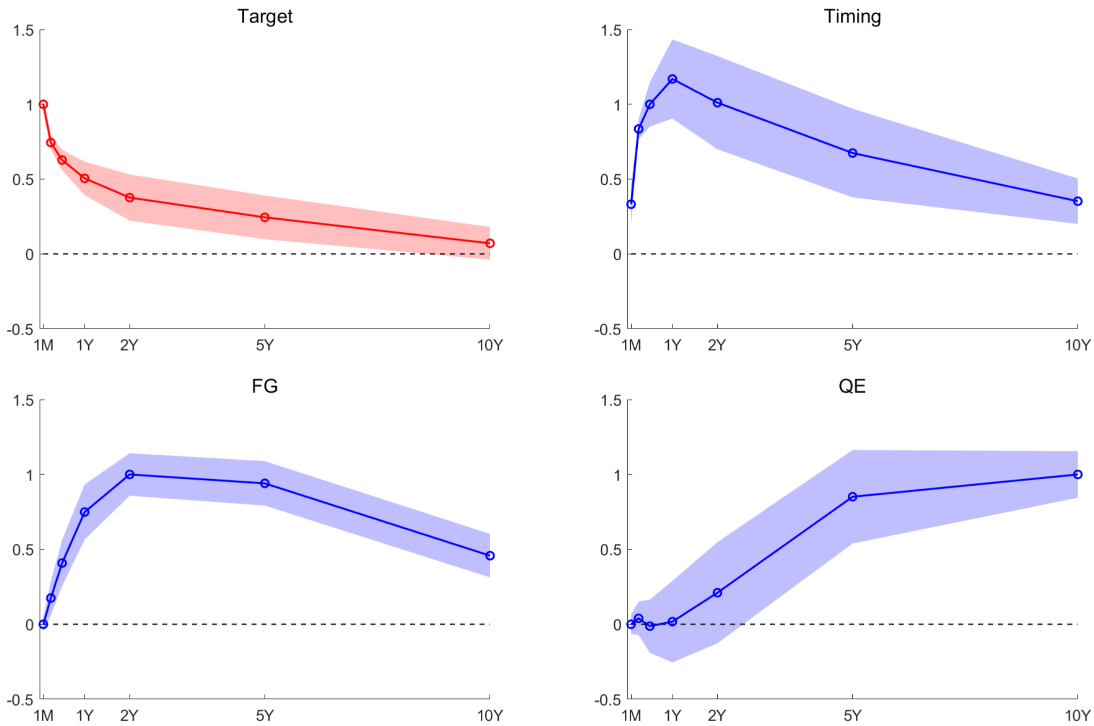


Figure A.1 Factor loadings

[1]https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx

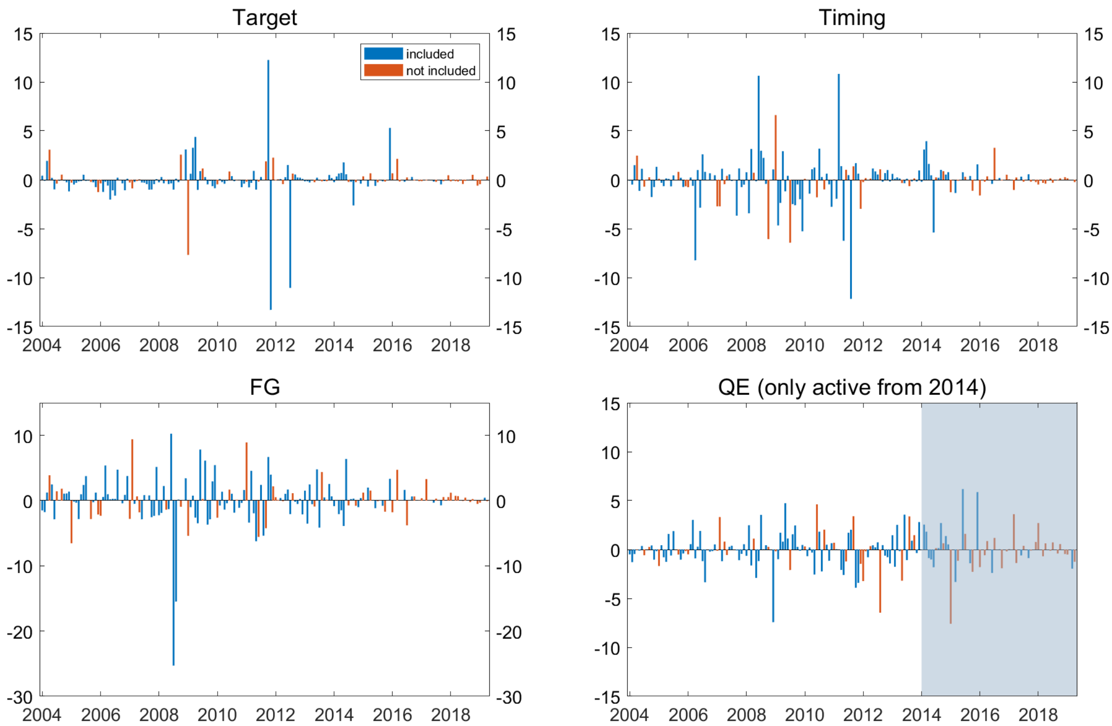


Figure A.2 Monetary policy surprises (in basis points)

Notes: Estimation based on methodology and data by Altavilla et al. (2019). Surprises are normalized to have unit effect on 1-month, 6-month, 2-year and 10-year OIS, respectively. Blue bars indicate events that are included in the event study approach, i.e. there is one survey wave before the Governing Council meeting and one survey wave directly after.

A.3 Additional event study results

Table A.1 Detailed marginal effects from Table 1 based on ordered logit model

	(1) Increase more rapidly	(2) Increase by approximately same rate	(3) Increase less strongly	(4) Stay about the same	(5) Fall
Target	-0.027***	-0.024***	0.009***	0.040***	0.002**
	(0.010)	(0.009)	(0.003)	(0.015)	(0.001)
Timing	0.002	0.002	-0.001	-0.003	-0.000
	(0.016)	(0.014)	(0.005)	(0.024)	(0.001)
FG	-0.008	-0.007	0.002	0.012	0.001
	(0.007)	(0.007)	(0.002)	(0.011)	(0.001)
QE	-0.017	-0.015	0.006	0.026	0.001
	(0.015)	(0.013)	(0.005)	(0.023)	(0.001)

Notes: Results based on ordered logit model. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points. Standard errors clustered at the monthly level are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table A.2 Main results from Table 1 based on alternative model specification

	(1) Logit model	(2) Linear regression model
Target	-0.025***	-0.112**
	(0.007)	(0.050)
Timing	0.005	-0.000
	(0.017)	(0.070)
FG	-0.001	-0.029
	(0.008)	(0.032)
QE	-0.013	-0.074
	(0.034)	(0.068)
N	220.414	203.778
Month FE	Yes	Yes
Wave dummy	Yes	Yes
HH controls	Yes	Yes
Past expectations	Yes	Yes
Sample	2004-2019	2004-2019

Notes: Results in column (1) based on logit model with dependent variable being 1 if consumers say prices increase more rapidly and 0 otherwise. Results in column (2) based on linear regression model with qualitative inflation expectations as dependent variable. Note that qualitative inflation expectations have been rescaled such that an increase corresponds to an increase in inflation expectations. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points. Standard errors clustered at the monthly level are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table A.3 Effect of announcements on proportion of "Don't know" answers

	(1)
Target	0.000
	(0.008)
Timing	-0.004
	(0.010)
FG	-0.006
	(0.006)
QE	-0.004
	(0.014)
N	220.414
Month FE	Yes
Wave dummy	Yes
HH controls	Yes
Past expectations	Yes
Sample	2004-2019

Notes: Results based on logit model with dependent variable being 1 if consumers say they don't know and 0 otherwise. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points on probability that households answer "Don't know". Standard errors clustered at the monthly level are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table A.4 The role of inflation perceptions

	(1) Controlling for inflation perception	(2) Inflation perceptions as dependent variable
Target	-0.023**	-0.016
	(0.011)	(0.022)
Timing	0.004	-0.008
	(0.014)	(0.021)
FG	-0.004	-0.008
	(0.006)	(0.013)
QE	-0.015	-0.003
	(0.011)	(0.026)
N	203.778	215.122
Month FE	Yes	Yes
Wave dummy	Yes	Yes
HH controls	Yes	Yes
Past expectations	Yes	Yes
Sample	2004-2019	2004-2019

Notes: Results based on ordered logit model. Column (1) shows the effect of different types of announcements on inflation expectations when controlling for inflation perceptions. Column (2) shows the effect of different types of announcements on inflation perceptions. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points. Standard errors clustered at the monthly level are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table A.5 Main results from Table 1 controlling for QE factor before 2014

	(1)
Target	-0.028**
	(0.012)
Timing	0.000
	(0.016)
FG	-0.009
	(0.008)
QE	-0.016
	(0.034)
QE (pre-2014)	-0.022
	(0.034)
N	203.778
Month FE	Yes
Wave dummy	Yes
HH controls	Yes
Past expectations	Yes
Sample	2004-2019

Notes: Results based on ordered logit model. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points. Standard errors clustered at the monthly level are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table A.6 Robustness of main results to dropping large Target surprises

	Baseline	Drop Oct 2011	Drop Nov 2011	Drop July 2012
	(1)	(2)	(3)	(4)
Target	-0.027***	-0.031**	-0.036***	-0.021**
	(0.010)	(0.014)	(0.013)	(0.010)
Timing	0.002	0.002	0.003	0.002
	(0.016)	(0.016)	(0.016)	(0.016)
FG	-0.008	-0.008	-0.006	-0.008
	(0.007)	(0.008)	(0.008)	(0.007)
QE	-0.017	-0.016	-0.016	-0.018
	(0.015)	(0.016)	(0.016)	(0.015)
N	203.778	201.913	201.964	201.909
Month FE	Yes	Yes	Yes	Yes
Wave dummy	Yes	Yes	Yes	Yes
HH controls	Yes	Yes	Yes	Yes
Past expectations	No	Yes	Yes	Yes
Sample	2004-2019	2004-2019	2004-2019	2004-2019

Notes: Results based on ordered logit model. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points on probability that prices increase more rapidly (=inflation goes up). Standard errors clustered at the monthly level are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Table A.7 Robustness of main results to excluding Great Recession (March 2008-June 2009)

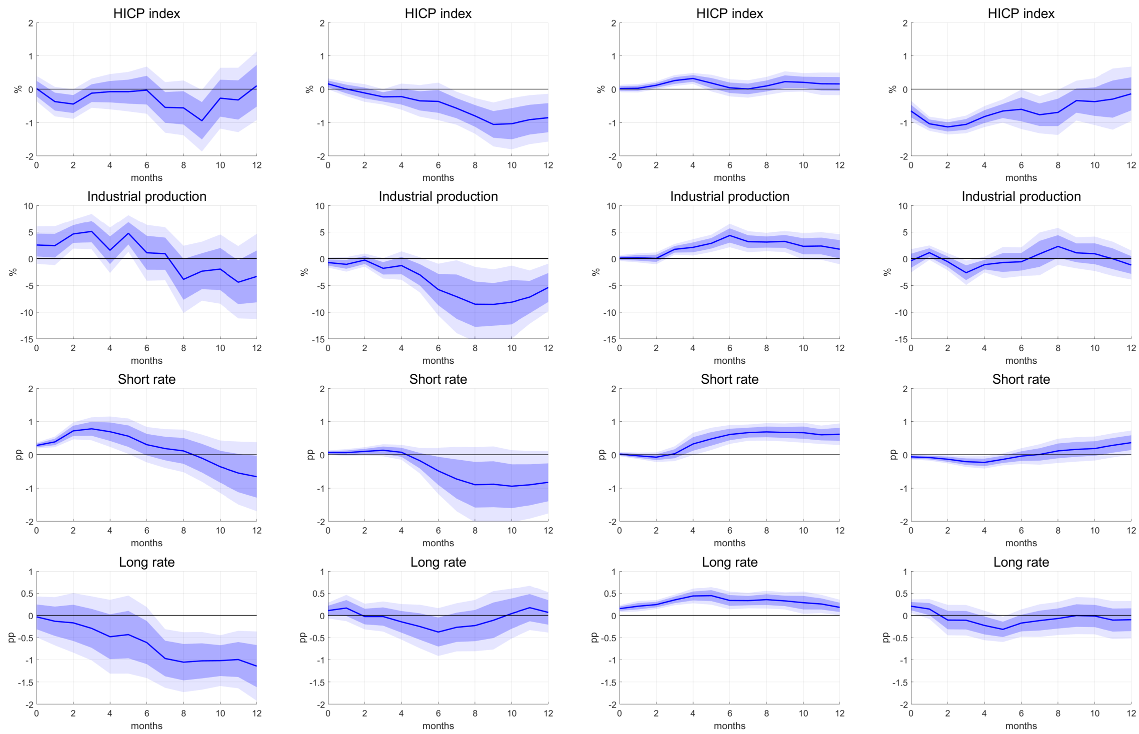
	(1)
Target	-0.029**
	(0.012)
Timing	-0.018
	(0.016)
FG	-0.007
	(0.014)
QE	-0.008
	(0.016)
N	180.367
Month FE	Yes
Wave dummy	Yes
HH controls	Yes
Past expectations	Yes
Sample	2004-2019

Notes: Results based on ordered logit model. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points on probability that prices increase more rapidly (=inflation goes up). Standard errors clustered at the monthly level are in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

A.4 Additional local projection results

A.4.1 Macro results

Figure A.1 presents the response of German HICP, Industrial production, the short rate and the long rate to the four types of monetary policy surprises based on Equation 2.4.



(a) Target **(b)** Timing **(c)** FG **(d)** QE

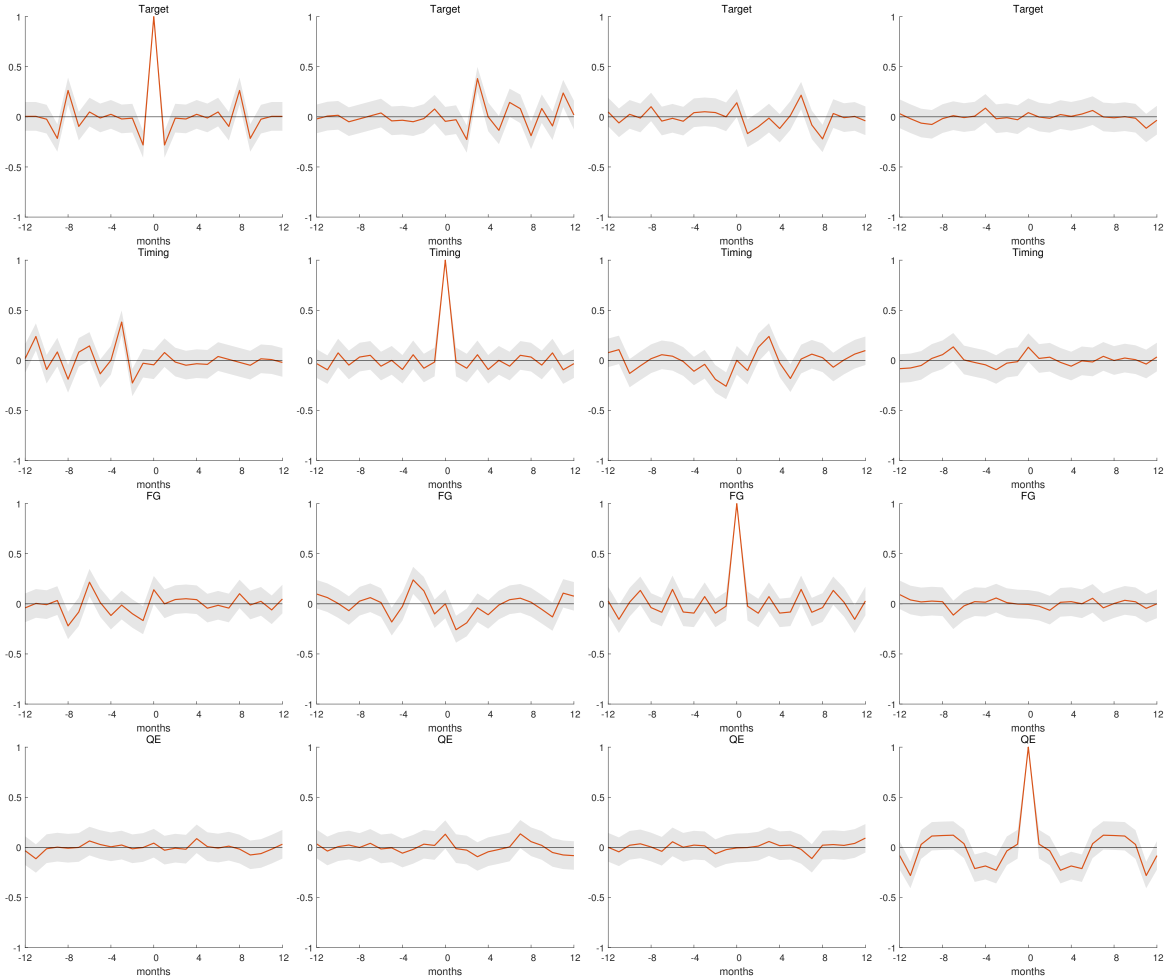
Figure A.1 Response of macro variables and interest rates to monetary policy surprises

Notes: Estimates based on local projections as in Equation 2.4. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points.

A.4.2 Robustness

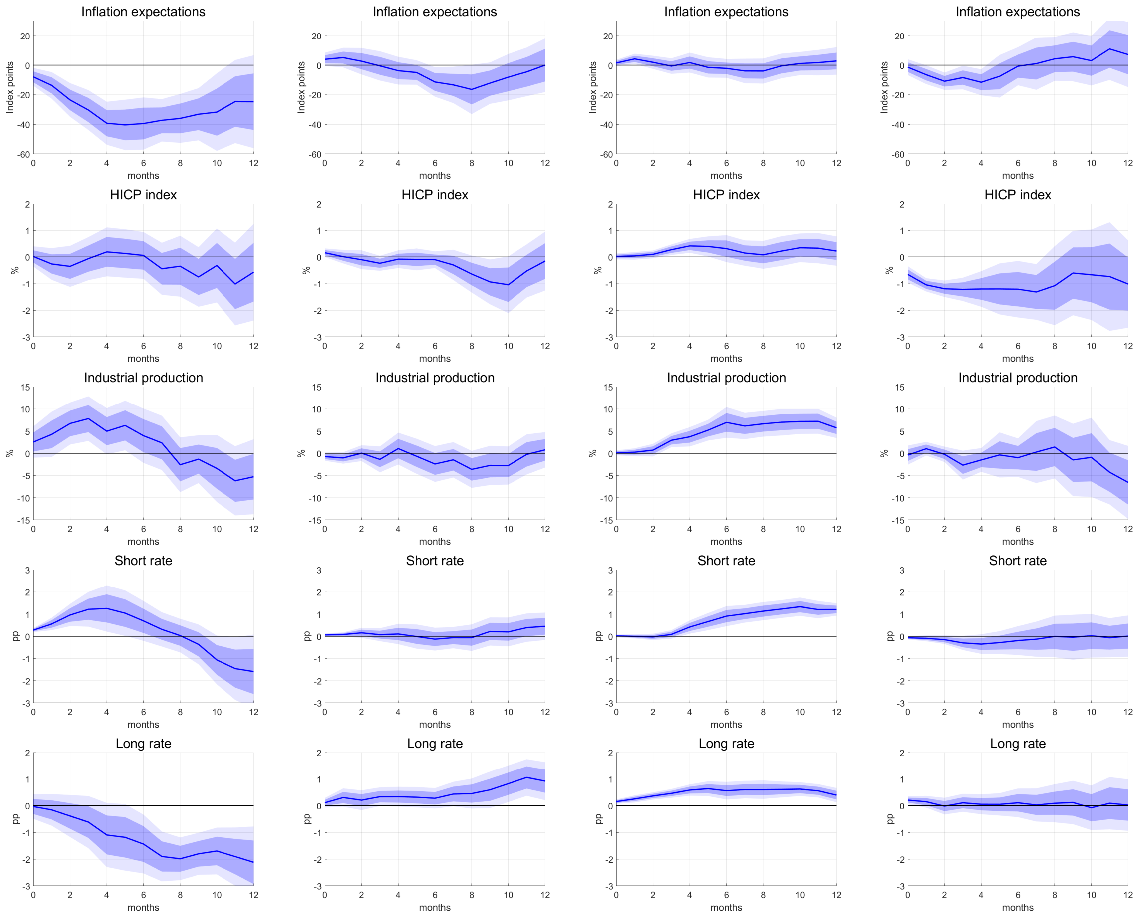
Figure A.2 shows the serial and cross-correlation of the different surprises. The specification in Equation 2.4 already includes lags of the surprises to control for potential correlations with past surprises. However, their can be also correlation with future surprises. In particular, Figure A.2 highlights that the Timing surprises exhibit a positive correlation with leads of Target surprises. This can be problematic when estimating the dynamic effects. Therefore, as robustness I follow Alloza et al. (2019) who suggest to include h leads of the shock in the regression to control for persistence. The results are shown in Figure A.3. The main difference to the baseline results is the much smaller and more reasonable output response of the Timing surprise. The magnitude of the response of inflation expectations to the four different surprises changes slightly but overall the qualitative conclusions are very similar in the sense that Target announcement have the strongest effect.

Figure A.4 and Figure A.5 shows the robustness to choosing different number of lags and to controlling for the surprises in the QE factor before 2014.



(a) Target **(b)** Timing **(c)** FG **(d)** QE

Figure A.2 Serial and cross-correlation of surprises



(a) Target **(b)** Timing **(c)** FG **(d)** QE

Figure A.3 Response of macro variables and interest rates to monetary policy surprises (controlling for persistence)

Notes: Estimates based on local projections as in Equation 2.4. Following Alloza et al. (2019) I include h leads of the surprises to control for the persistence. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points.

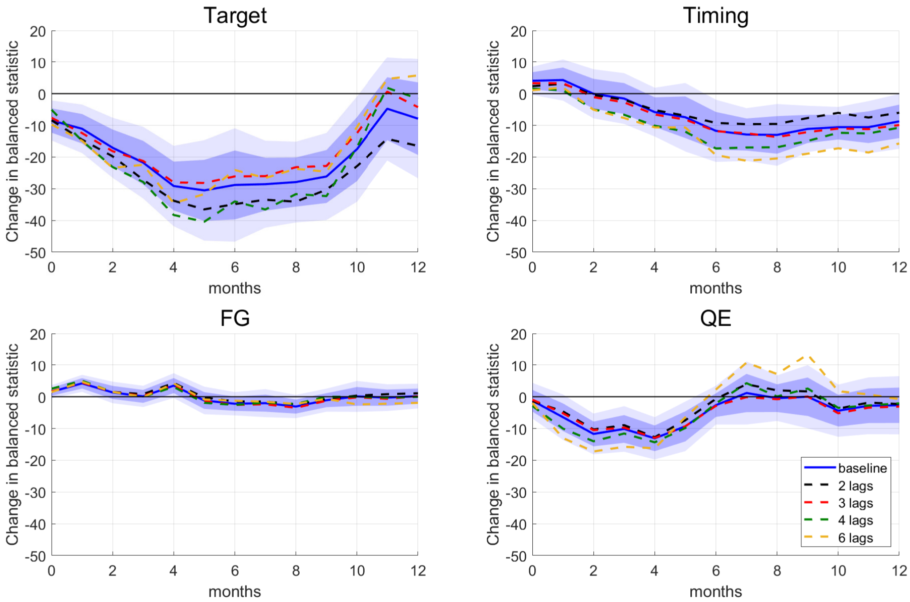


Figure A.4 Robustness to different lag lengths

Notes: Estimates based on local projections of qualitative inflation expectations (balanced statistic) on monetary policy surprises and control variables as in Equation 2.4. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points.

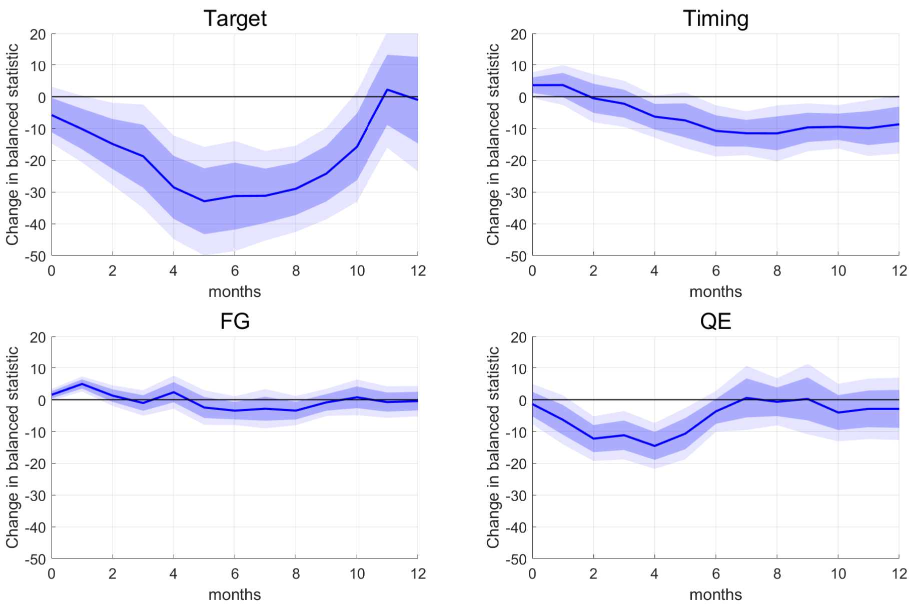


Figure A.5 Robustness to controlling for pre 2014 QE surprises

Notes: Estimates based on local projections of qualitative inflation expectations (balanced statistic) on monetary policy surprises and control variables as in Equation 2.4. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points.

A.4.3 Euro area results

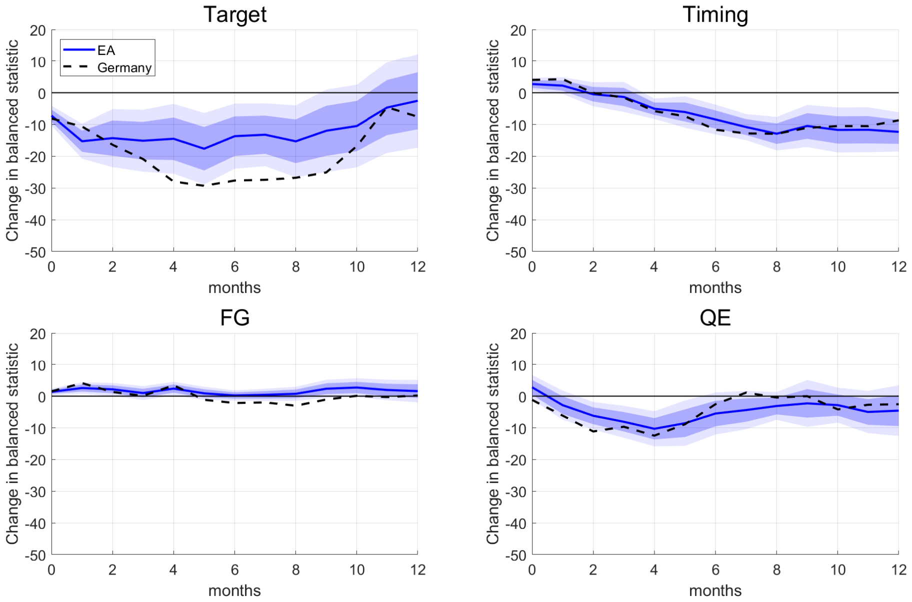


Figure A.6 Response of qualitative inflation expectations (balanced statistic), euro area

Notes: Estimates based on local projections of qualitative inflation expectations (balanced statistic) on monetary policy surprises and control variables as in Equation 2.4. Black dashed line corresponds to IRFs for Germany. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that surprise increases corresponding interest rate by 25 basis points.

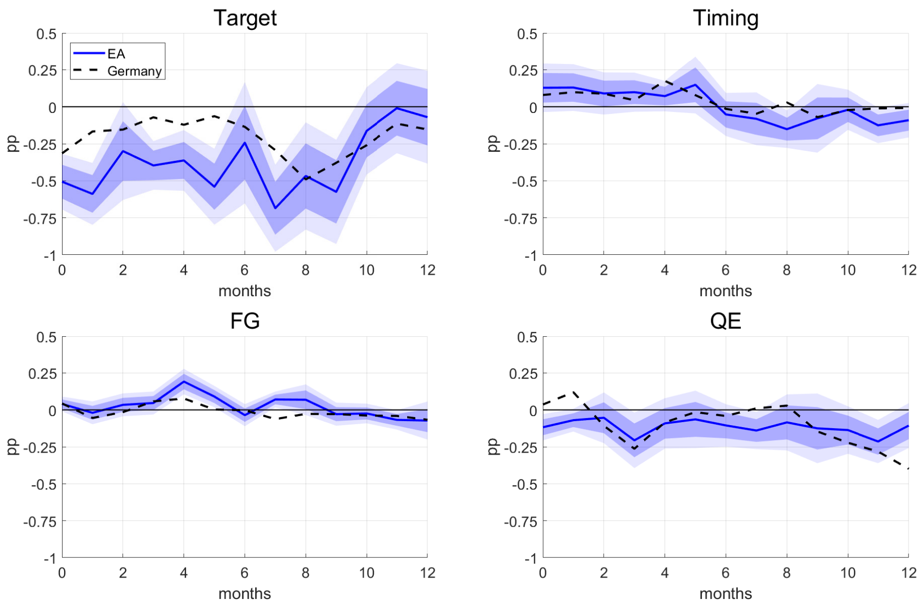


Figure A.7 Response of inflation expectations by professional forecasters, Euro area

Notes: Estimates based on local projections of one year ahead inflation expectations on monetary policy surprises and control variables as in Equation 2.4. Inflation expectations come from a monthly survey of professional forecasters conducted by Bloomberg. Sample starts only in October 2005. Black dashed line corresponds to IRFs for Germany. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points.

A.5 Dynamic effects based on pseudo panel approach

An alternative to aggregating cross-sectional survey data at monthly frequency to one time series is to create a pseudo panel based on the approach by Deaton (1985). The idea is to track groups of households over time instead of individuals since the latter is not possible. More specifically, they suggest to create cohorts with fixed membership and then take at every given point the sample cohort means to obtain time series for every cohort.

I create cohorts based on birth year, gender and education. There is a trade-off between number of cohorts and number of households per cohort required for the estimation of accurate cohort means. Therefore, for the year of birth I choose 10-year bands, i.e. born before 1940,1940-1949,1950-1959,1960-1969,1970-1979,1980-1989 and born after 1989. For education there are in principle 4 categories: Volks-/Hauptschule, Realschule, Gymnasium, Universität. Since the number of households in the last two categories is relatively small I group them together in one category. Together with the two categories for gender this gives me overall 42 cohorts. In order to make sure that the cohort means are accurate and not just based on few observations I also set monthly cohort observations to missing if there are less than 30 households in a cohort in a given month.

I estimate impulse response functions to the different monetary policy announcements using panel local projections with cohort fixed effects and macro control variables as in Equation 2.4. In addition, I include household expectations as controls. Figure A.8 shows that the results are similar to the ones based presented in subsection 1.3.2.

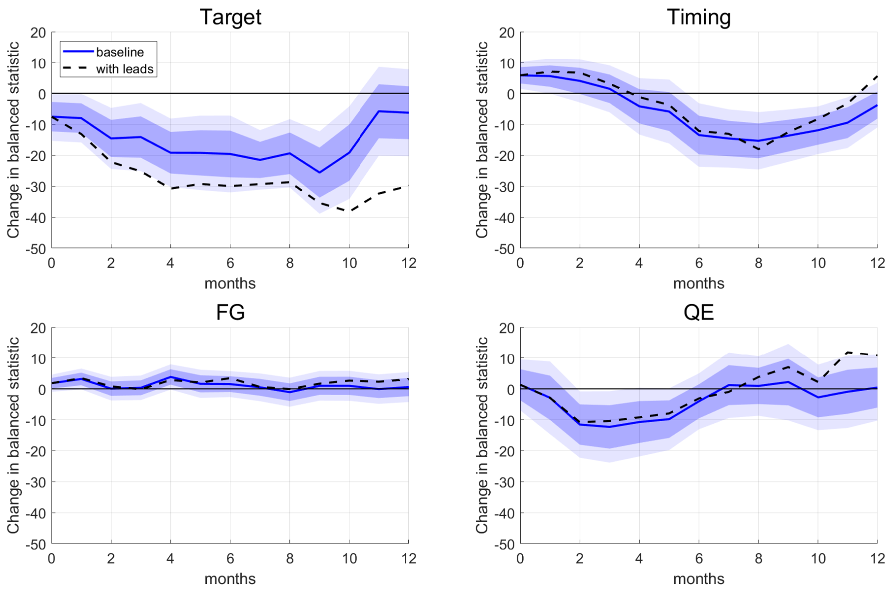


Figure A.8 Response of inflation expectations: Pseudo panel approach

Notes: Estimates based on panel local projections of qualitative inflation expectations (balanced statistic) on monetary policy surprises and control variables as specified in the text above. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points. Black dashed line shows IRFs when including h leads of the surprises.

A.6 The effects on quantitative inflation expectations

Comparing these results to the existing literature on monetary policy and household inflation expectations might look contradictory. However, most existing studies focus on quantitative inflation expectations. As is well documented in the literature, quantitative inflation expectations of households are very dispersed and often unreasonably large. In the given survey, I find that a lot of consumers answer that they do not know the value of inflation or they answer a level of inflation that is unreasonable and ranges from -100 to 100 (see Figure A.2 for distribution of quantitative inflation expectations). This makes the analysis using quantitative inflation expectations more difficult as one has to take a stance on how to treat outliers that would otherwise bias the estimation results. Moreover, the GfK survey is designed such that the quantitative question builds on the qualitative question. For households who answer that they expect prices to stay about the same, the answer to the quantitative question is set automatically to zero and only the other households are asked to provide a point estimate. This is problematic as there are a lot of households who answer that they expect prices to stay about the same and it is not possible to distinguish if they really mean a point estimate of zero or values of very low inflation as observed during parts of the sample period.

Keeping the aforementioned aspects in mind, I shortly present the effects of policy announcements on quantitative inflation expectations. Table A.8 shows the effects of policy announcements on quantitative inflation expectations using the event study approach. Column (1) highlights that the effects of the different types of policy announcements on quantitative inflation expectations are generally very imprecisely estimated and there is no significant effect for any of the announcements. This is also true if I trim the data to remove the largest outliers (column (2)) or if I consider the difference between expected and perceived inflation as proposed by Duca-Radu et al. (2021) (see columns (3) and (4)).

Figure A.9 shows the medium-term response of quantitative inflation expectations based on local projections. The measure of inflation expectations used is a trimmed mean where the top and bottom 2% of values are excluded. As alternative Figure A.10 also shows the response using the median of inflation expectations. On impact the effect is not significant for any of the policy announcements. The overall dynamics are similar to the response of qualitative inflation expectations shown in Figure 1.4 (especially when using the median of inflation expectations). A 25 basis points Target surprise reduces quantitative inflation expectations by almost 2 percentage points but only after 9 months.

Overall, comparing the results for quantitative and qualitative inflation expectations illustrates that getting the direction right might be simpler and require less information and time than giving a precise

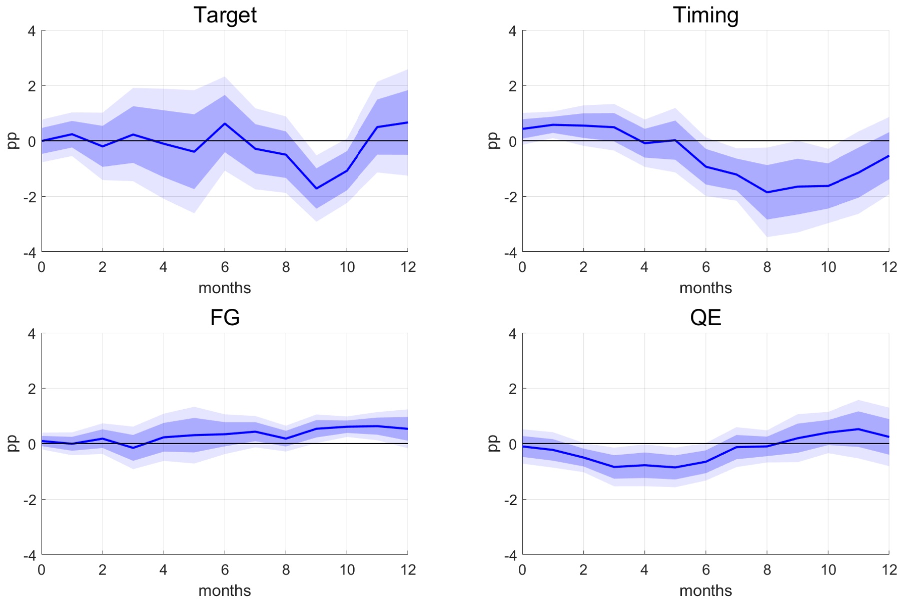


Figure A.9 Response of quantitative inflation expectations (trimmed mean), Germany

Notes: Estimates based on local projections of quantitative inflation expectations (trimmed at top and bottom 2%) on monetary policy surprises and control variables as in Equation 2.4. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points.

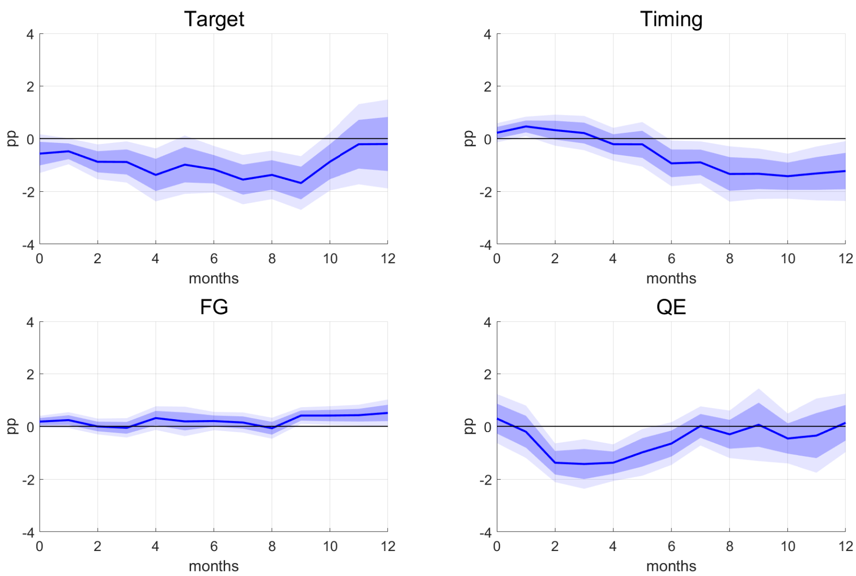


Figure A.10 Response of quantitative inflation expectations (median), Germany

Notes: Estimates based on local projections of quantitative inflation expectations (median) on monetary policy surprises and control variables as in Equation 2.4. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled such that a surprise increases the corresponding interest rate by 25 basis points.

Table A.8 The response of quantitative inflation expectations

	(1)	(2)	(3)	(4)
Target	-0.228	-0.452	-0.178	-0.302
	(0.633)	(0.520)	(0.546)	(0.289)
Timing	0.325	0.393	0.362	0.236
	(0.383)	(0.375)	(0.303)	(0.354)
FG	-0.316	-0.009	-0.316	0.118
	(0.466)	(0.250)	(0.333)	(0.294)
QE	-0.330	-0.901	0.043	-0.459
	(0.664)	(0.586)	(0.401)	(0.317)
N	180.003	175.908	175.956	169.650

Notes: Results based on linear regression model with quantitative inflation expectations (columns 1 and 3) or the difference between quantitative inflation expectations and perceptions (columns 2 and 4) as dependent variable. Columns 3 and 4 use data that is trimmed at top and bottom 2%. Marginal effect of a policy surprise that increases the respective reference rate by 25 basis points. Standard errors clustered at the monthly level are in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

inflation point estimate. At the same time it highlights that more household surveys could be helpful that include for example probabilistic questions or provide households with intervals that they can choose.

A.7 Financial market responses

Figure A.11 shows the daily time series of German inflation linked bonds for maturities 1, 2, 3 and 4 years. Figure A.12 shows the dynamic effects of the different types of monetary policy announcements on German inflation linked bonds. The impulse response functions are estimated based on daily local projections.

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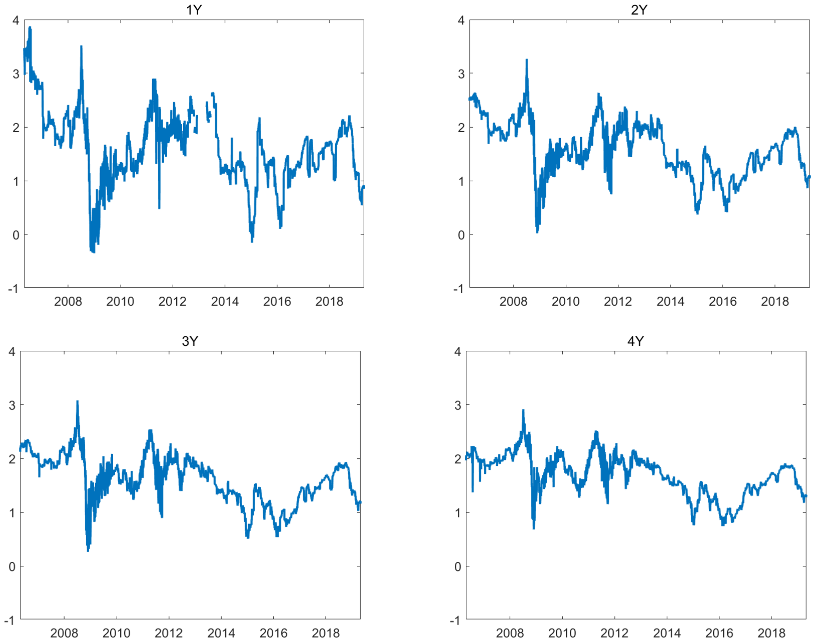
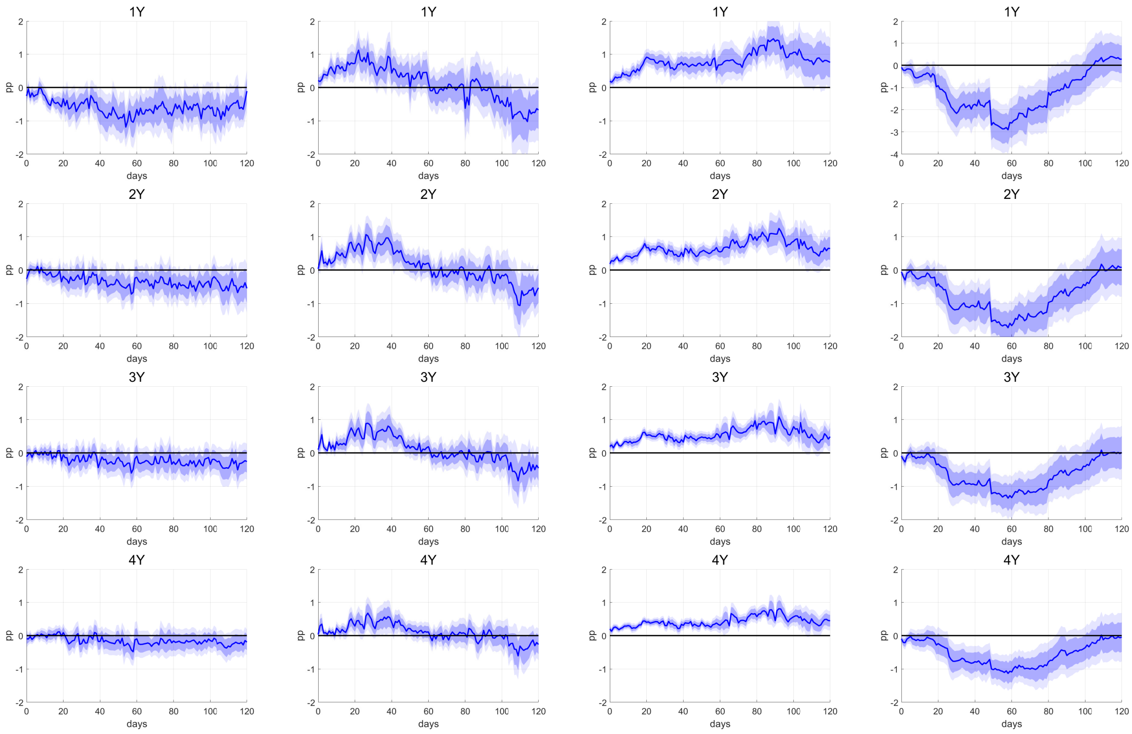


Figure A.11 Time series of German inflation linked bonds



(a) Target **(b)** Timing **(c)** FG **(d)** QE

Figure A.12 Response of German inflation linked bonds

Notes: Estimates based on daily local projections. Blue areas correspond to 68% and 90% confidence intervals based on Newey-West standard errors. Responses are scaled to a policy surprise that increases the respective reference rate by 25 basis.

B

Appendix to Chapter 2

B.1 Data Appendix

B.1.1 Macroeconomic Variables

These are the variables included in the specification of the baseline VAR:

- Underlying inflation: the trend of headline PCE inflation. The trend is extracted using a Beveridge-Nelson decomposition following Mertens (2016). We update the original series from Mertens until June 2019 using the original codes available from the author. The monthly trend series is aggregated to quarterly frequency by taking quarterly averages.
- Real per capita GDP growth: Annualized quarterly growth rate of Seasonally Adjusted US real gross domestic product per capita. Source: FRED. Code: A939RX0Q048SBEA.
- PCE Inflation: Annualized quarterly growth rate of Seasonally Adjusted Personal Consumption Expenditures: Chain-Type Price Index. Source: FRED. Code: PCEPI.
- 1-Year Rate: 1-Year Treasury Constant Maturity Rate. Source: FRED. Code: DGS1.
- 10-Year Rate: 10-Year Treasury Constant Maturity Rate. Source: FRED. Code: DGS10.

We also employ the following variables in the additional exercises:

- Private Consumption: Private Final Consumption Expenditure in the United States divided by total population, annualized percentage change relative to previous quarter, seasonally adjusted. SOurce: FRED. Code: USAPFCEQDSMEI
- Investment: Real gross private domestic investment divided by total population, annualized percentage change relative to previous quarter, seasonally adjusted. Source: FRED. Code: GPDIC1.
- Fiscal Deficit: US fiscal deficit as computed by Hagedorn et al. (2018).
- Current Account/GDP: Balance on Current Account as a % of GDP, NIPA's, Quarterly, Seasonally Adjusted Annual Rate. Source: FRED. Code: NETFI divided by GDP.
- US-UK exchange rate: U.S. / U.K. Foreign Exchange Rate in the United Kingdom, U.S. Dollars to One British Pound, Quarterly. Source: FRED. Code: USUKFXUKM.
- House Prices: Median sales price of houses sold in the United States deflated by PCE, annualized % change with respect to previous quarter. Source: FRED. Code: MSPUS.

B.1.2 Consumer Expenditure Survey

We use the Consumer Expenditure Survey (interview section) from 1984-2018.[1] The files from 1984-1995 are obtained from the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan, and the files starting from 1996 from the website of the Bureau of Labor Statistics (BLS).

The CEX is a monthly rotating panel, where households are selected to be representative of the US population. Each household is interviewed once per quarter, for at most five consecutive quarters, although the first interview is used for pre-sampling purposes and is not available for analysis. While expenditure is reported at the household level, demographics are reported for individuals. These include age, income, labor supply, family size, and year of birth of the head of household.

In each interview, the reference period for expenditures covers the three months prior to the interview month. Income and most labor supply question are only asked during the second and fifth interview and the reference period covers the twelve months prior to the interview month.

Our data preparation procedure broadly follows Coibion et al. (2017). All expenditure data is aggregated up from the disaggregated MTAB files and income and demographic data is derived from the MEMB and FMLY files. Starting from the raw data files the following steps are carried out:

[1] It is possible to find CEX data back to 1980 Q1 but there are several changes in methodology in the first years and issues regarding data quality.

1. All expenditure data is aggregated up from the disaggregated MTAB files. We aggregate the monthly UCC expenditures by household and generate expenditure aggregates for the different categories such as food following the BLS documentation.
2. We correct for breaks in the expenditure variables. In particular, between 1982 and 1987 food at home is adjusted following Aguiar and Bils (2015).
3. We deflate all series using the Consumer Price Index (CPI).
4. Then, we convert the expenditure data into a quarterly time series using the reference date of the interview. We merge the expenditure data with the income and demographic data from the MEMB and FMLY files by household and interview date.
5. We define consumption and income variables following Coibion et al. (2017):
   - Non-durable goods and services: food, alcohol, tobacco, clothing and footwear, household utilities, fuel, personal care, public transport, household services and nondurable household goods, leisure services and goods (e.g. entertainment services, reading)
   - Durable goods: durable leisure goods (e.g. entertainment equipment) and durable household goods (e.g. furniture and electrical appliances).[2]
   - Labor-related earnings and total disposable income: Labor-related earnings only include wages and salaries, income from farm and non-farm business, self-employment. Social security benefits and pensions are not part of earnings but are together with income from investments included in non-labor income. Then, total disposable income consists of labor and non-labor income and net (disposable) income is calculated as gross income - (taxes - rebates/refunds). Following Coibion et al. (2017) tax is computed using the NBER TAXSIM calculator.
   - mortgage and rental payments: mortgage payments are defined as interest and capital repayments for mortgages on the main house (the house currently lived in) and rental payments are equal to the rent paid and do not include any services.
6. Household variables are transformed into real-per capita values using family size
7. We use the household weights provided within the survey and normalize these so that they sum up to 1 within each housing tenure group and quarter. Then, we apply these normalized weights to the household level variables to construct cohort-level series.

[2] This definition of durable consumption does not include large purchases such as car or house purchases. However, in Figure B.23 we also consider a broader definition of durable consumption that includes vehicle purchases and maintenance expenditures.

8. In order to deal with under-reporting trends over time and following Cloyne et al. (2020), the cohort-level series for non-durable and durable expenditures are adjusted each quarter using the ratio of aggregate national accounts to aggregated household data (NIPA/CEX). The same ratio is used to adjust the three cohort series (mortgagors, owners and renters).

B.2 Series of underlying inflation

In this section we assess the informational content of our baseline measure of underlying inflation (the INFTRM trend inflation) to explain future values of PCE inflation. First, we regress the 5-year ahead realized value of PCE inflation on the INFTRM. Table B.1 displays the results. Contemporaneous values of underlying inflation are statistically significant to explain 5-year ahead realized values of PCE inflation. Second, we run a Granger causality test using our baseline VAR(2). While we reject the hypothesis that underlying inflation does not Granger cause realized PCE inflation, we cannot reject the null-hypothesis that PCE inflation does not Granger cause underlying inflation. Thus, we conclude that underlying inflation has significant predictive power to explain realized PCE inflation.

Table B.2 presents the root mean squared error (RMSE) of out-of-sample forecasts for quarterly inflation measured by the PCE headline inflation for the different underlying inflation measures we consider in Figure 2.1. The results are shown relative to a benchmark model, where a relative RMSE number less than one indicates improvement compared to the benchmark. We use INFTRM as our benchmark and report results for both the long sample from 1960 (except ptr which starts only in 1968) as well as the sample post 1984 to account for the possible structural break and the fact that we use the shorter sample in the heterogeneous responses analysis. In both samples the INFTRM does better in forecasting inflation. RMSE number less than one indicates improvement compared to the benchmark and these are only observed in the later sample for the UCSVO index for 4 and 8 horizons ahead. We

Table B.1 Forecasting power of the series of underlying inflation

	5-Year Ahead PCE Inflation
ndxINFTRM	0.169***
	(0.024)
Constant	0.284***
	(0.073)
N	212
adj. R^2	0.287
F-stat	47.91***

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

show in the following sections that results for the effects of shocks identified using the alternative UCSVO trend inflation series in our procedure are robust.

Table B.2 Forecasting power of the series of underlying inflation (RMSE)

horizon (quarters)	INFTRM	LONGSRV	ptr	UCSVO	Trimmed-mean PCE
4	1		2.13	1.05	
8	1		1.31	1.10	
12	1		1.28	1.09	
16	1		1.33	1.09	
20	1		1.35	1.10	
24	1		1.28	1.07	
4	1	1.54	1.99	0.87	1.24
8	1	1.45	1.73	0.99	1.14
12	1	1.40	1.60	1.08	1.09
16	1	1.44	1.66	1.11	1.08
20	1	1.51	1.82	1.14	1.10
24	1	1.58	2.01	1.17	1.18

Notes: RMSE for headline PCE inflation over different forecast horizons. The top part shows for the sample from 1960-2018 (1968-2018 in the case of ptr) and the bottom part from 1984-2018. INFTRM and LONGSRV correspond to inflation trend measures based on trimmed and realized inflation measures and long-run inflation expectations from Mertens (2016), respectively. PTR corresponds to long-run inflation expectations from the FRB/US model and used by Mumtaz and Theodoridis (2019). UCSVO corresponds to extended univariate trend measures based on core PCE from Stock and Watson (2016). Trimmed-mean PCE is from the Dallas Fed and starts only in 1978. All values are normalized with respect to the RMSE of INFTRM trend series.

Mumtaz and Theodoridis (2019) use a series for long-horizon inflation expectations that is a spliced survey based measure of long horizon PCE inflation expectations used in the Federal Reserve board model. This measure (with mnemonic PTR) is available on a quarterly basis from 1968Q1. In the earlier part of the sample, PTR uses estimates of the inflation target from Kozicki and Tinsley (2005), for the the 1980s series for inflation expectations of 5 to 10 year ahead of participants in the financial markets are obtained from the discontinued Decision Makers poll (DMP) and from 1991Q4 onwards, the series is based on 10 year average inflation expectations taken from the Survey of Professional Forecasters. In Figure 2.1 those series are smoother and exhibit much lower variation relative to the series estimated using the Beveridge-Nelson decomposition, especially during the Great Inflation period and they return extremely slowly to a lower target during the Paul-Volcker disinflation. Although the procedure to recover the shocks in our and Mumtaz and Theodoridis (2019)' paper is very similar we have decided to disregard these series in our analysis for several reasons. First, they suffer from missing observations, especially in first two parts of the sample. Second, such series are subject to noise and measurement error, especially the series coming from financial markets. Finally, the series contained in PTR comprise both short-term and long-term forecasts horizons and we are interested in identifying shocks to underlying inflation which is more about the medium to long-term horizon. As it is obvious in table B.2, the forecasting power of these series is pretty low compared with the alternative series we consider. In the last column we show the forecasting power of trimmed-mean PCE inflation. This series only starts in 1978. Overall, the forecasting power is better than for survey-based measures of underlying inflation but also worse than our baseline measure INFTRM.

B.3 Correlation with monetary policy/inflation target shocks

Table B.3 presents the correlation of the identified news shocks to underlying inflation with the existing series for monetary policy and inflation target shocks. Since shock series are available for different sample periods the first column of Table B.3 indicates the relevant sample period considered to compute the cross correlations also presented in Figure 2.3 in the main text.

Table B.3 Correlation of shock to inflation expectations with monetary policy related shocks

Shock	**Sample**	**Correlation**
Romer and Romer (2004)[3]	1970-2008	-0.11
Jarociński and Karadi (2020)	1990-2018	-0.22
Swanson (2021):		
FFR	1991-2018	-0.16
Forward Guidance	1991-2018	-0.31
LSAP	1991-2018	-0.21
LSAP (just QE period)	2008-2018	-0.41
Uribe (2021)	1954-2018	0.41
Approach by Mumtaz and Theodoridis (2019)	1969-2016	0.32

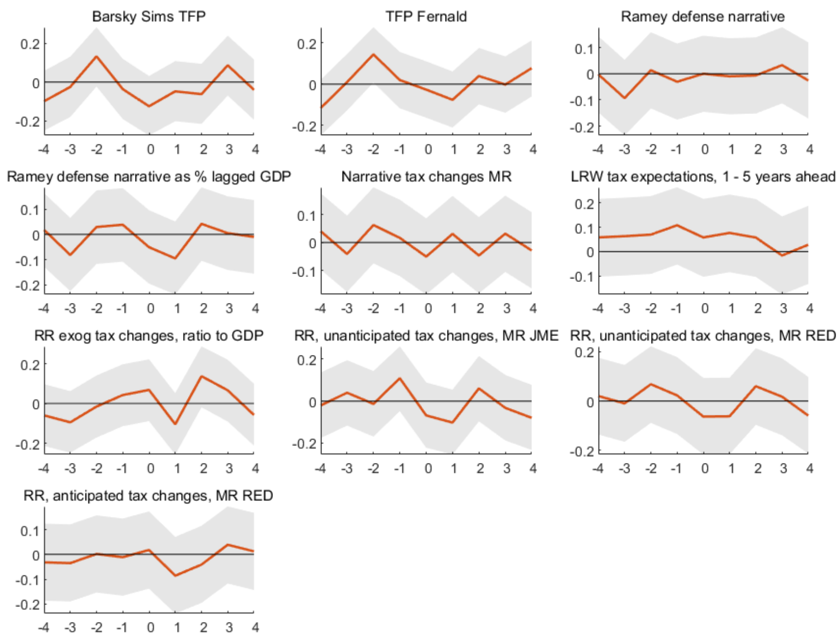
B.4 Validation of the Identified Shock

An important check on our results is the extent to which the identified inflation expectations shock may be confounded with other shocks. In this section we investigate the correlation of the identified shock with other structural shocks identified as important sources of cyclical fluctuations in the literature. Figure B.1 presents the correlation of 4 leads and lags of the identified shock with:

- Barsky Sims TFP: TFP series are extracted as in Barsky and Sims (2011)
- TFP Fernald: this is the utilization-adjusted TFP series of Fernald and Wang (2016)
- Ramey defense narrative: narrative shock from Ramey and Zubairy (2018)
- Ramey defense narrative as a % lagged GDP: see Ramey and Zubairy (2018)

- Narrative tax changes MR: series of tax shocks as in Mertens and Ravn (2013)
- LRW tax expectations 1-5 years ahead: series from Leeper et al. (2012)
- RR exog tax changes, ratio to GDP: narrative tax shock series from Romer and Romer (2010)
- RR, unanticipated tax changes MR JME: shocks series on unanticipated tax changes from Mertens and Ravn. (2014)
- RR, unanticipated tax changes MR RED: shocks series on unanticipated tax changes from Mertens and Ravn (2011)
- RR, anticipated tax changes MR RED: shocks series on anticipated tax changes from Mertens and Ravn (2011)

Figure B.1 Serial correlation with series of shocks from previous works - I



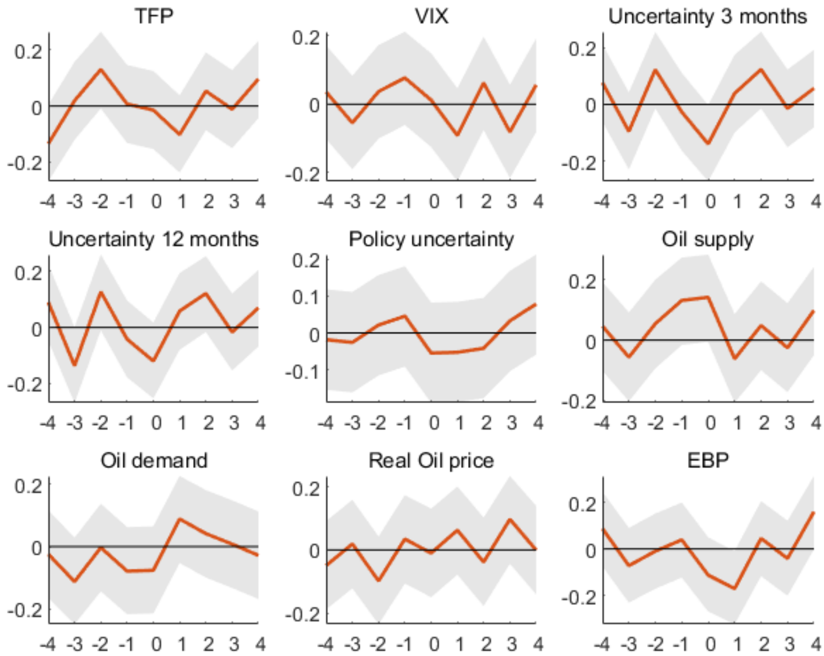
NOTE. If not already structural shock series quarterly shock series calculated as residuals from autoregressive regression.

Figure B.2 presents the correlation of 4 leads and lags of the identified shock with:

- VIX: CBOE Volatility Index
- Uncertainty 3 months: Jurado et al. (2015)'s 3- month macroeconomic uncertainty index
- Uncertainty 12 months: Jurado et al. (2015)'s 12- month macroeconomic uncertainty index
- Policy Uncertainty: Economic policy uncertainty, as measured by news coverage about policy-related economic uncertainty by Baker et al. (2016).

- Oil Supply and Oil demand: structural shocks from Baumeister and Hamilton (2019)
- Real Oil Price: residuals from AR model of log-difference in real oil price
- EBP: shock to excess bond premium identified as in Gilchrist and Zakrajšek (2012)

Figure B.2 Serial correlation with series of shocks from previous works - II



NOTE. Except from Oil supply, oil demand and EBP shock, shocks are calculated at monthly frequency as residuals from autoregressive regression and then aggregated to quarterly frequency.

Forni and Gambetti (2014) estimate the state variables of the economy by using the principal components of a large dataset, containing all available macroeconomic information and subsequently test whether the estimated principal components Granger cause the variables included in the VAR. According to their procedure, the variables are informationally sufficient if and only if the null hypothesis of no Granger causality is not rejected. Table B.4 reports the results. The F-statistic for the joint significance of all factors is 1.2 and we can therefore not reject the null hypothesis of no Granger causality.

Table B.4 Fundamentalness Test (Forni and Gambetti (2014))

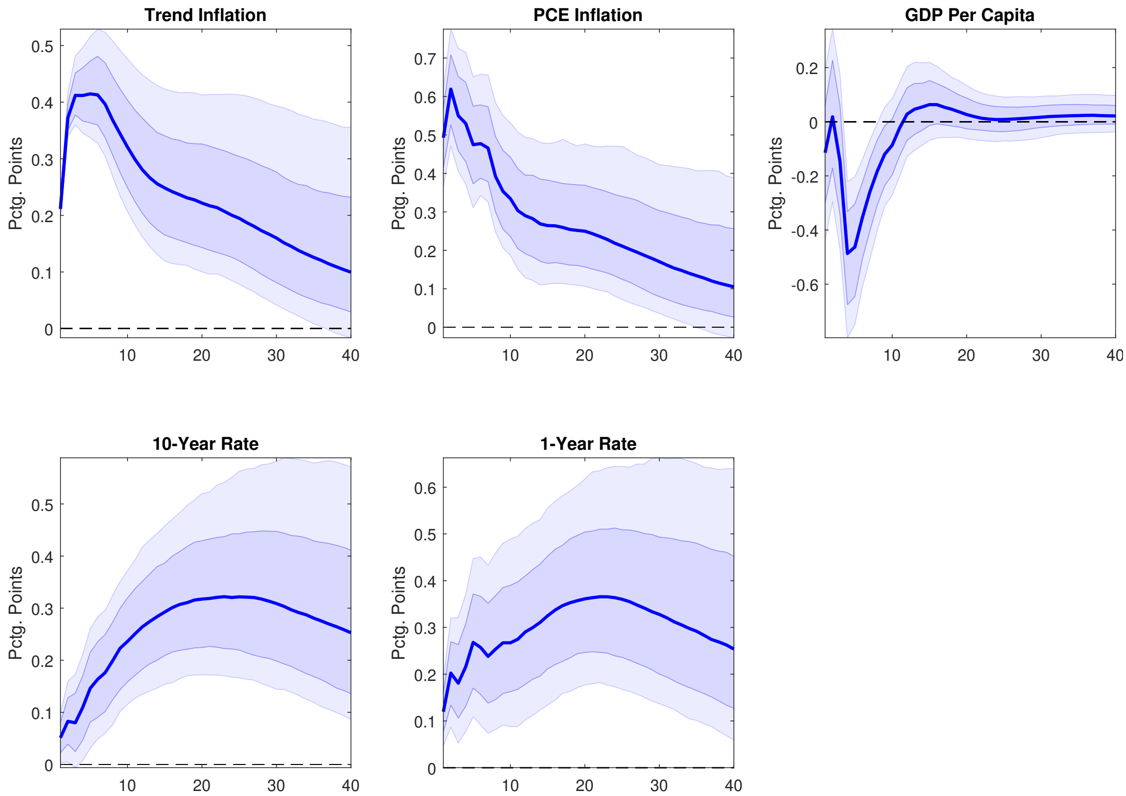
	News shock to underlying inflation
L.factor1	-0.0118
	(0.1994)
L.factor2	-0.0972
	(0.3816)
L.factor3	-0.1306
	(0.1743)
L.factor4	0.8423**
	(0.3360)
L.factor5	-0.0840
	(0.4698)
L.factor6	0.3437
	(0.3515)
L.factor7	0.0456
	(0.4007)
L.factor8	0.1437
	(0.4841)
N	224
adj. R^2	**0.009**
F-stat	**1.2**

Robust standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

B.4.1 Comparison with a Cholesky Decomposition

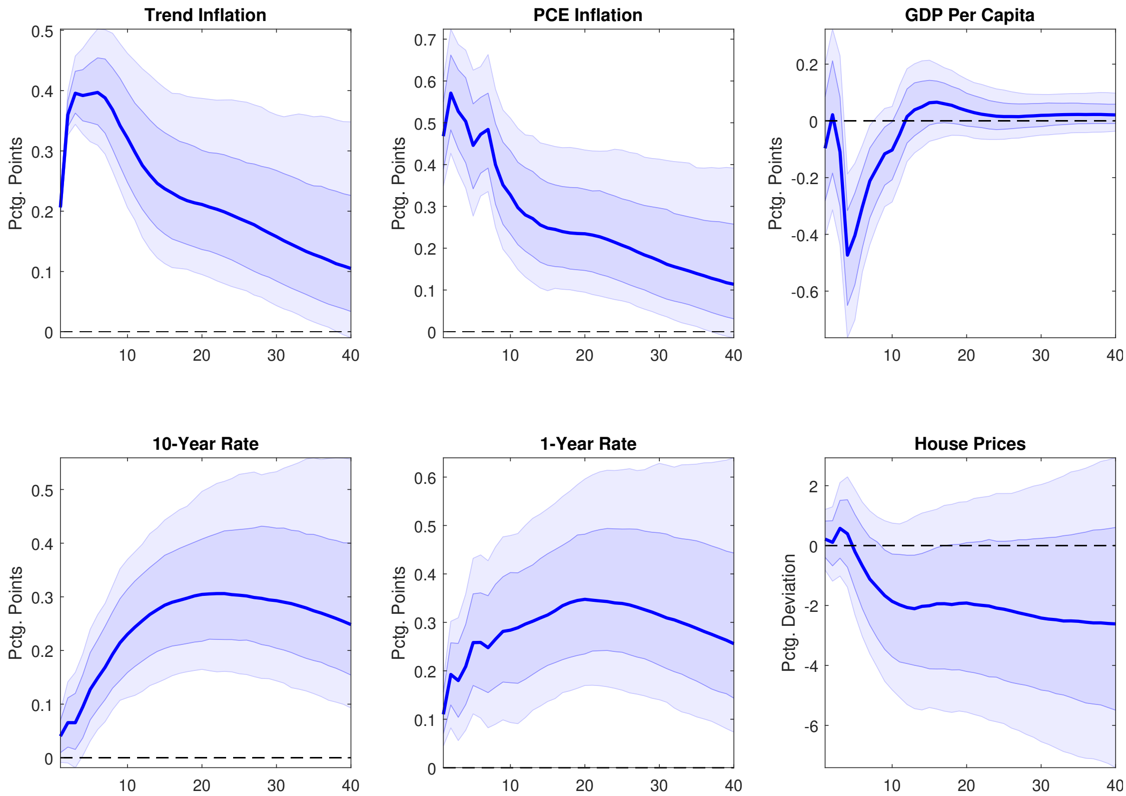
In order to assess the identification strategy of the news augmented shock to underlying inflation based on medium-run restrictions, we compute the IRFs using a Cholesky decomposition where the measure of underlying inflation is ordered first in the system. Figure B.3 displays the results. The responses of output and the 1Y rate look different relative to the baseline ones. These differences may be explained by the dynamics of asset prices, which may reflect persistent changes in expected underlying inflation. To assess this hypothesis, we augment the VAR with real house prices. Figure B.4 displays the IRF for this case. Unlike the augmented baseline case where real house prices increase significantly in response to the news shock to underlying inflation, in this case the response of real house prices is not statistically significant. The differential response of real house prices may be reflecting the fact that our baseline shock, due to the differential identification strategy, captures shocks to underlying inflation that are perceived as more persistent relative to the shocks identified with the Cholesky decomposition. These results also suggest that the response of house prices is key to understand output dynamics.

Figure B.3 IRF to a shock to underlying inflation - Cholesky



Note: IRFs to a one standard deviation shock to inflation expectations estimated using the BVAR(4) that includes a constant and includes the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. The identification of the inflation expectation shocks is with a Cholesky decomposition. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. Horizon is in quarters.

Figure B.4 IRF to a shock to underlying inflation - Cholesky - House Prices

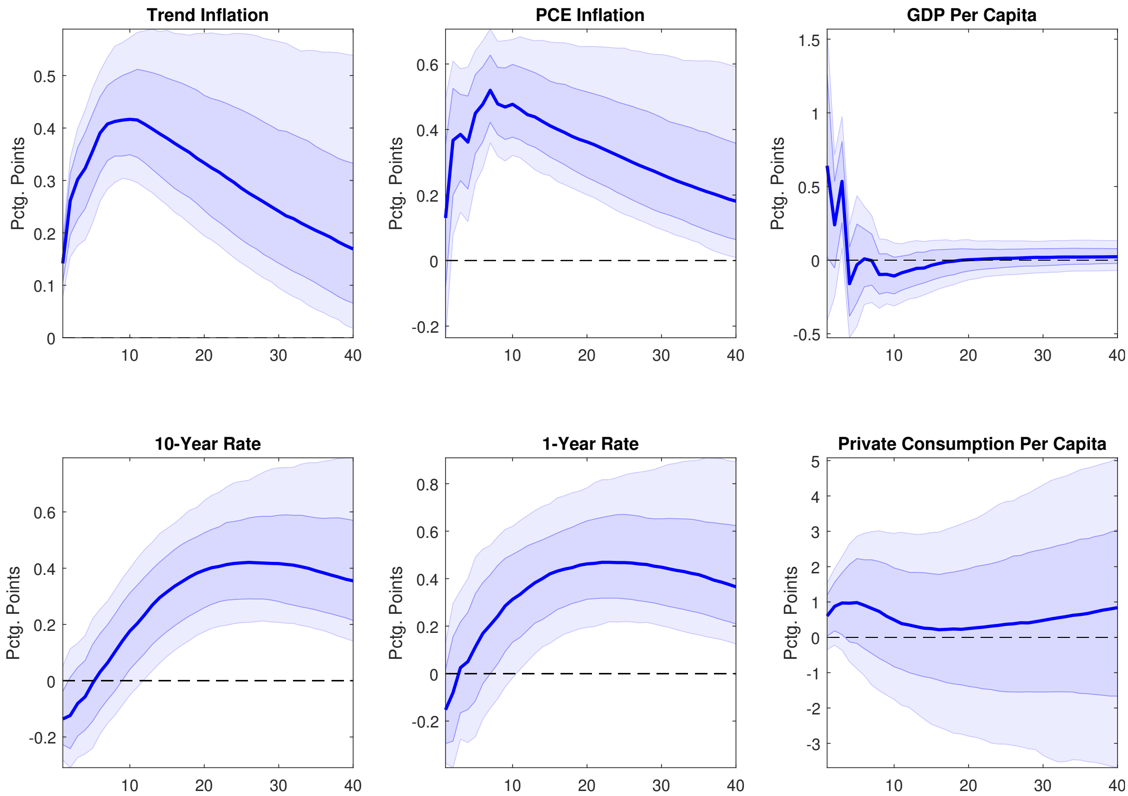


Note: IRFs a one standard deviation shock to inflation expectations estimated using the BVAR(4) that includes a constant and includes the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, 1Y Treasury Rate, and real house prices. The identification of the inflation expectation shocks is with a Cholesky decomposition. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. Horizon is in quarters.

B.5 IRFs Additional Variables

In order to characterize better the aggregate implications of the news shock to underlying inflation, we augment the baseline VAR described in section 2.2.2 with consumption, gross fixed capital formation, fiscal deficit, the current account to GDP ratio, and the US-UK bilateral exchange rate. These three variables are included one by one in the baseline VAR and they are not used for the identification of the shock. Figure B.5 displays the IRFs of the VAR when we augment it with the private consumption, which is included as per capita growth rates. For private consumption we present the cumulative IRF.

Figure B.5 IRF to a news shock to underlying inflation including Private Consumption

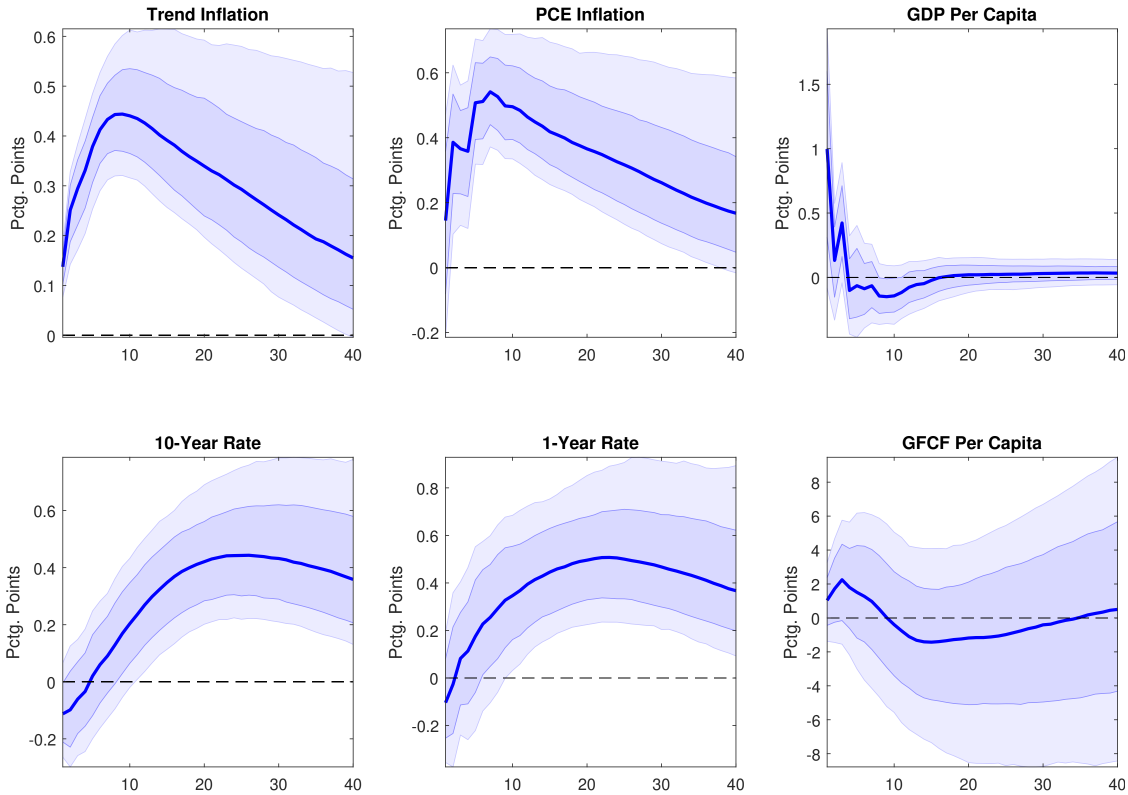


Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, private consumption per capita growth rate, 10Y Treasury Yield, and 1Y Treasury Yield. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The response of consumption is the cumulative IRF. The news shock to underlying inflation is identified using the strategy described in Section 2.2.2 and the specification is explained in Section 2.3.2. Horizon is in quarters.

Figure B.6 displays the IRFs of the VAR when we augment it with the Gross Fixed Capital Formation (GFCF) series, which is included as per capita growth rates. For the GFCF we present the cumulative IRF.

The Fiscal deficit series we use are computed by Hagedorn et al. (2018). Figure B.7 displays the IRFs of the VAR when we augment it with the fiscal deficit series.

Figure B.6 IRF to a news shock to underlying inflation including Investment

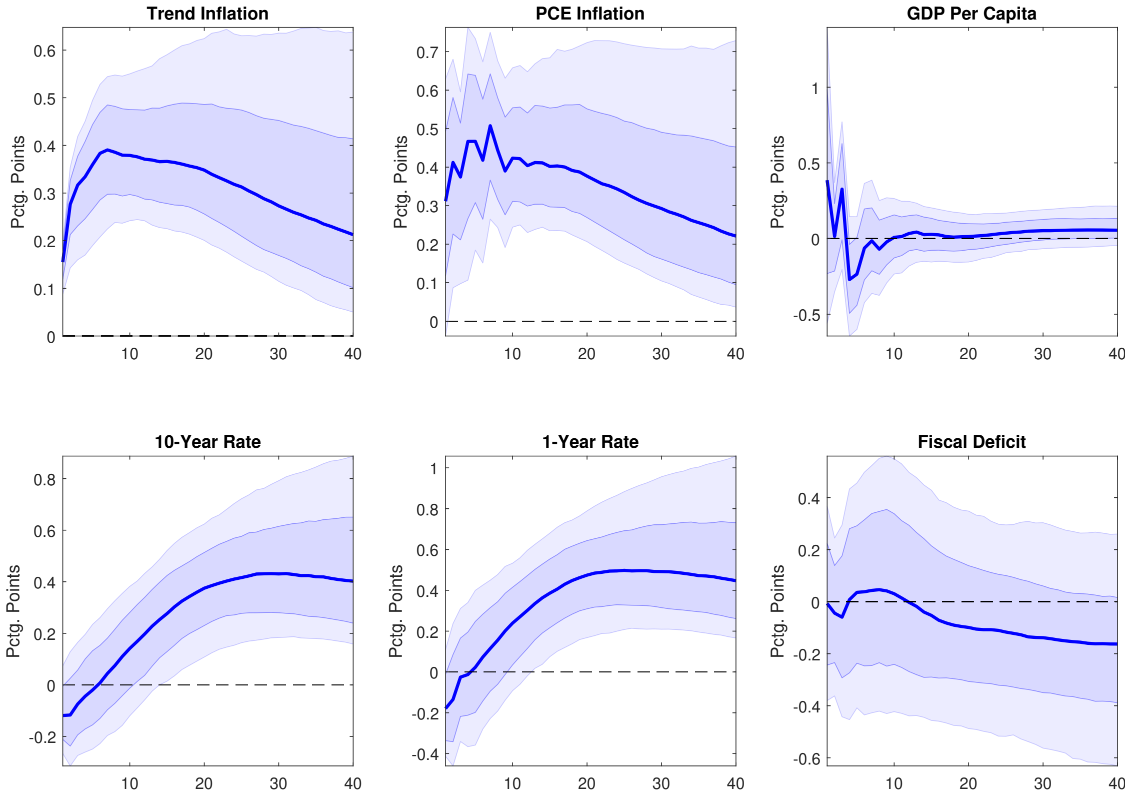


Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, GFCF per capita growth rate, 10Y Treasury Yield, and 1Y Treasury Yield. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The response of GFCF is the cumulative IRF. The news shock to underlying inflation is identified using the strategy described in Section 2.2.2 and the specification is explained in Section 2.3.2. Horizon is in quarters.

Figure B.8 displays the IRFs of the VAR when we add the current account-to-GDP ratio series.

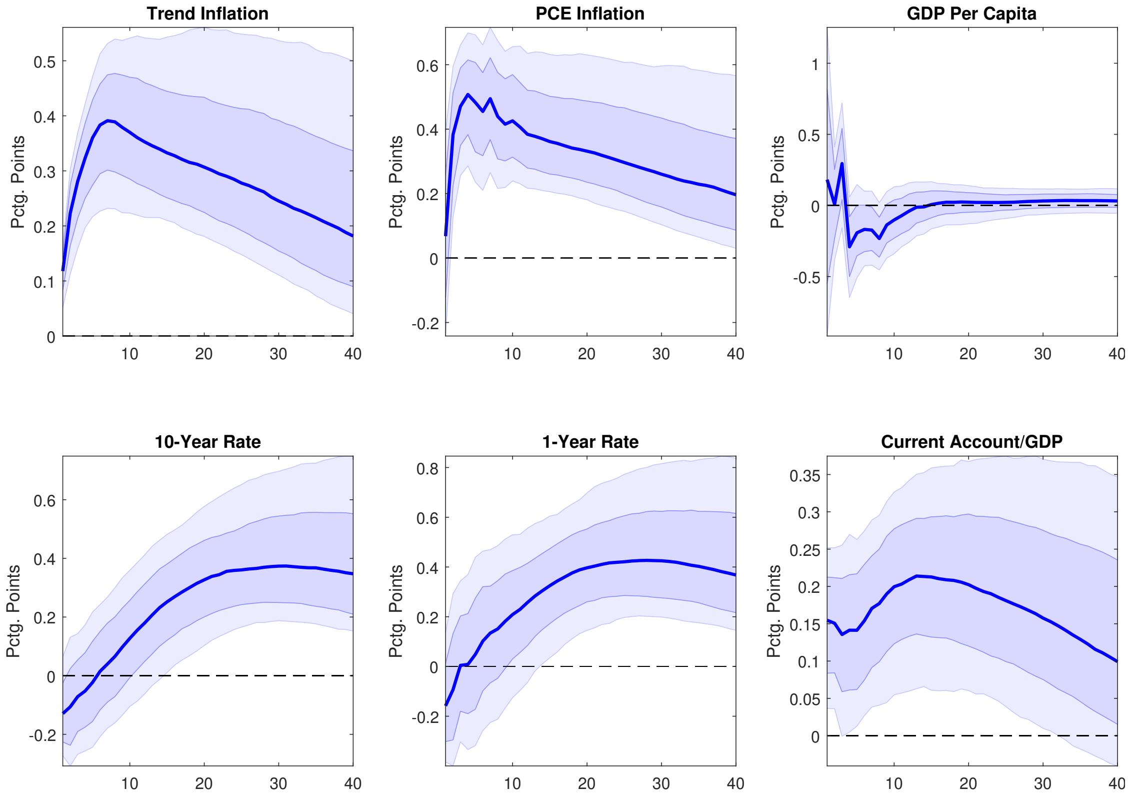
Figure B.9 displays the IRFs of the VAR when we add the nominal exchange rate as an additional variable in the BVAR. We use the U.S. Dollars to One British Pound exchange rate as this is the longest historical series we have obtained. Results show that the news shock to underlying inflation depreciates the US Dollar.

Figure B.7 IRF to a news shock to underlying inflation including Fiscal Deficit



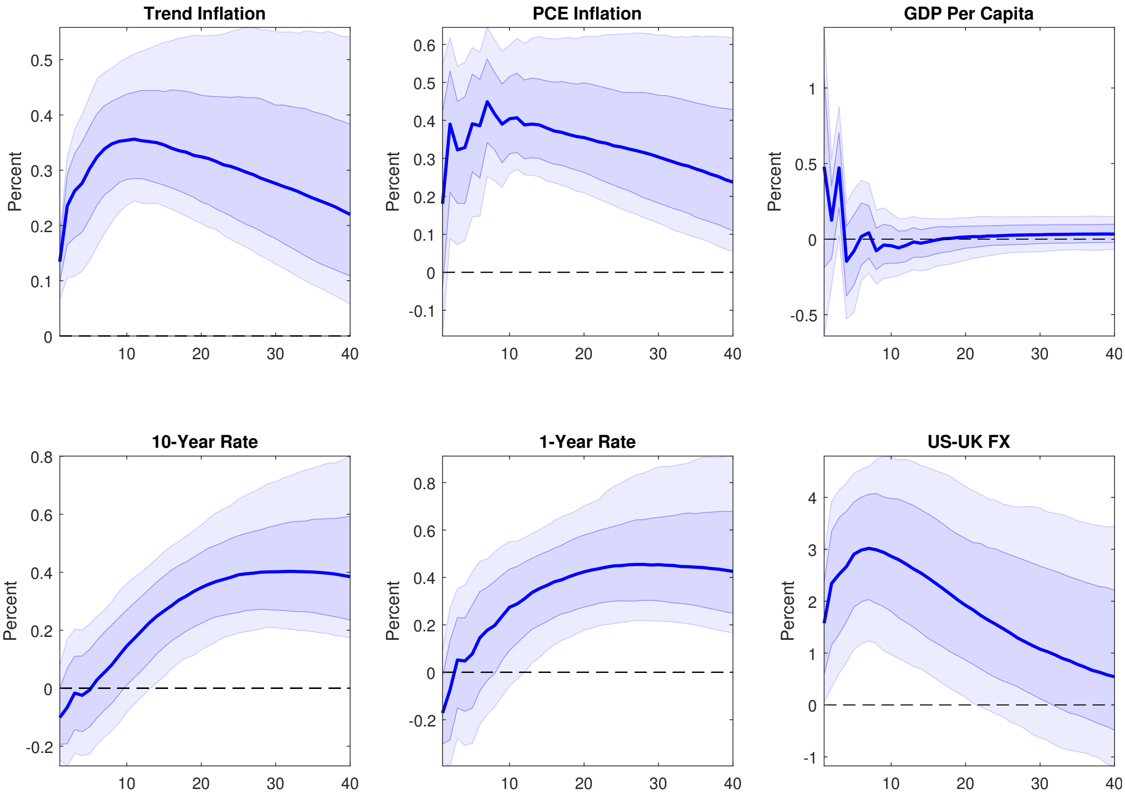
Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Yield, 1Y Treasury Yield, and fiscal deficit. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The news shock to underlying inflation is identified using the strategy described in Section 2.2.2 and the specification is explained in Section 2.3.2. Horizon is in quarters.

Figure B.8 IRF to a news shock to underlying inflation including Current Account to GDP



Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Yield, 1Y Treasury Yield, and the current account-to-GDP ratio. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The news shock to underlying inflation is identified using the strategy described in Section 2.2.2 and the specification is explained in Section 2.3.2. Horizon is in quarters.

Figure B.9 IRF to a news shock to underlying inflation including Exchange Rate



Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Yield, 1Y Treasury Yield, and the exchange rate US Dollar to one British Pound. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The news shock to underlying inflation is identified using the strategy described in Section 2.2.2 and the specification is explained in Section 2.3.2. Horizon is in quarters.

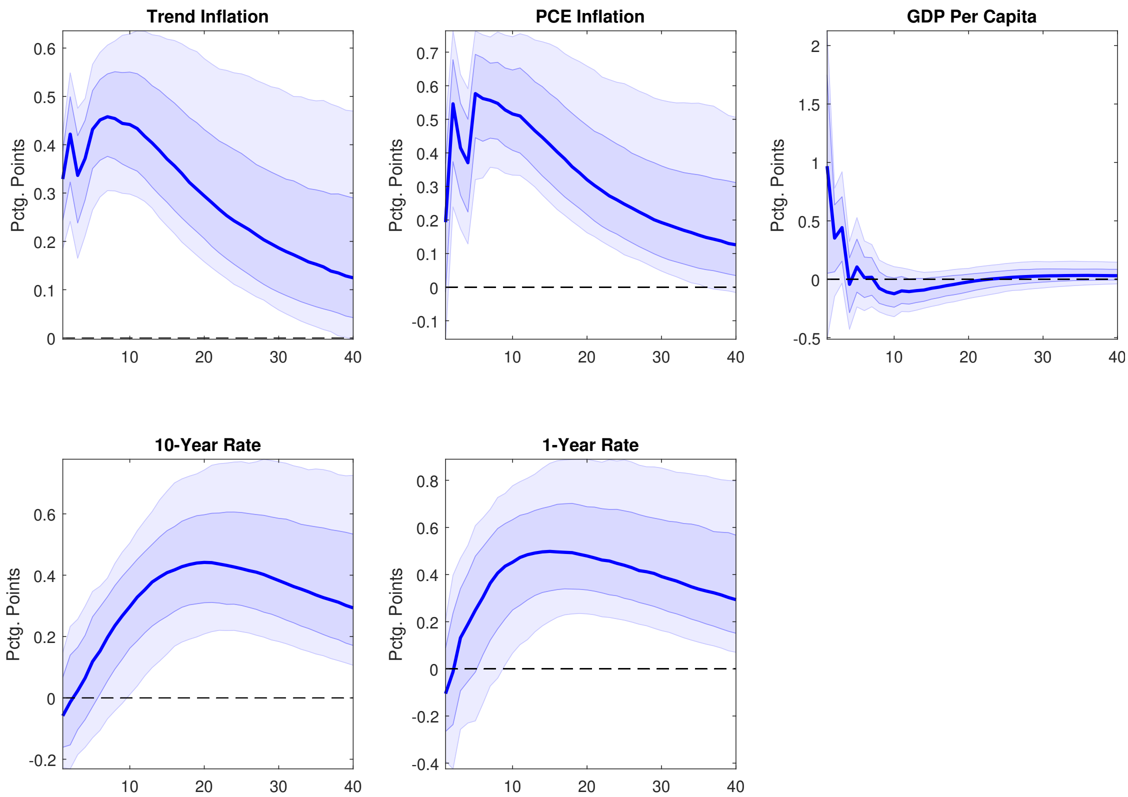
B.6 VAR Robustness Analysis

In this section, we investigate the robustness of our baseline results to the series used for underlying inflation, the maximization horizon, the lag length of the VAR and the sample period considered.

B.6.1 IRFs using an alternative measure of underlying inflation

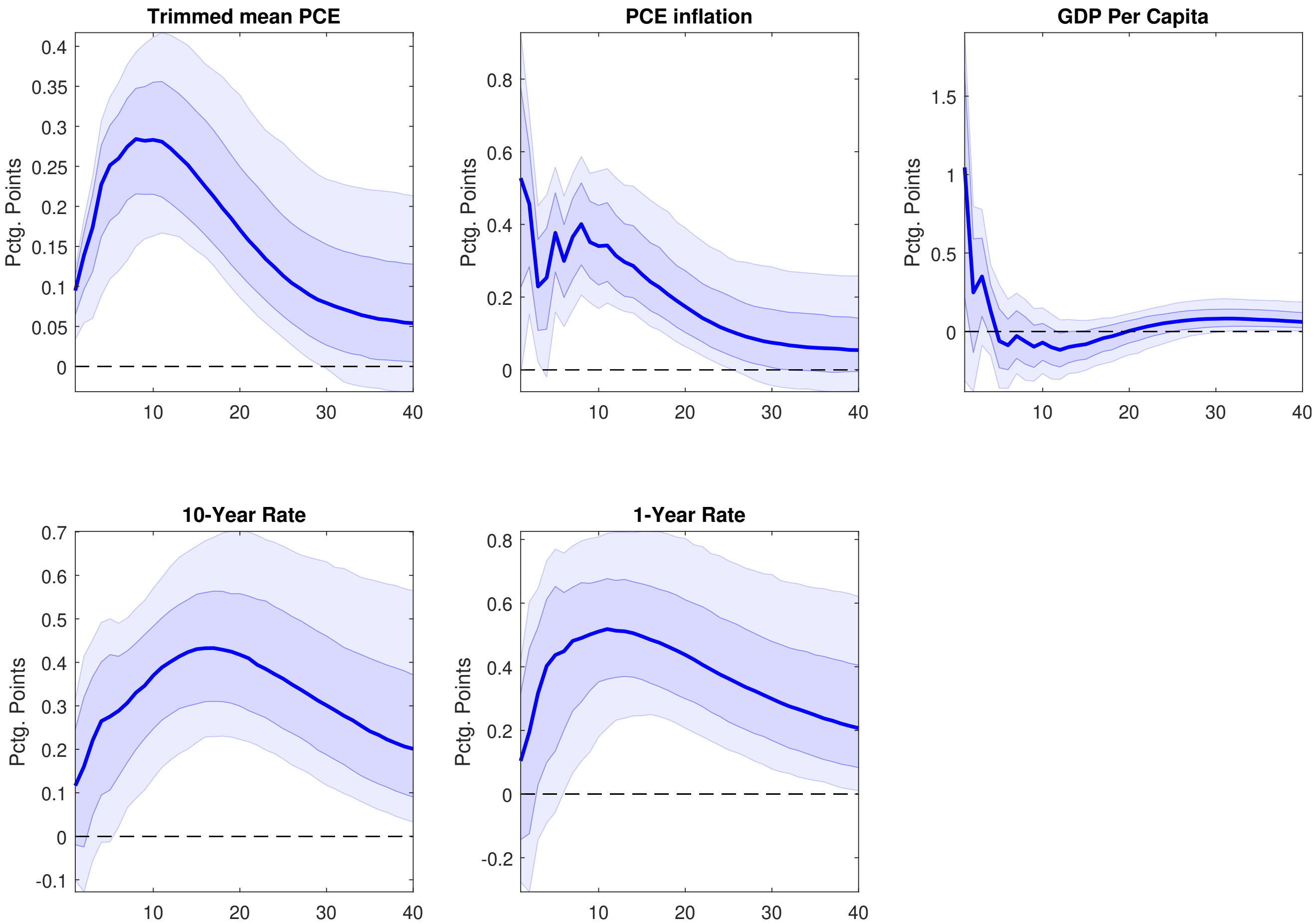
In order to assess the robustness of the main results of this paper to different measures computed by the literature, we estimate the baseline BVAR (4) using the series of trend/underlying inflation computed by Stock and Watson (2016). As we show in section B.4, this series has a good forecasting power specially in short horizons. Figure B.10 displays the IRFs. The results remain almost unchanged with respect to the baseline ones using the series INFTRM computed by Mertens (2016). As additional robustness check we also consider trimmed-mean PCE inflation as measure of underlying inflation and results are also broadly similar (see Figure B.11).

Figure B.10 IRF to a news shock to underlying inflation - Stock and Watson (2016) trend inflation



Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. Horizon is in quarters.

Figure B.11 IRF to a news shock to underlying inflation - trimmed-mean PCE inflation

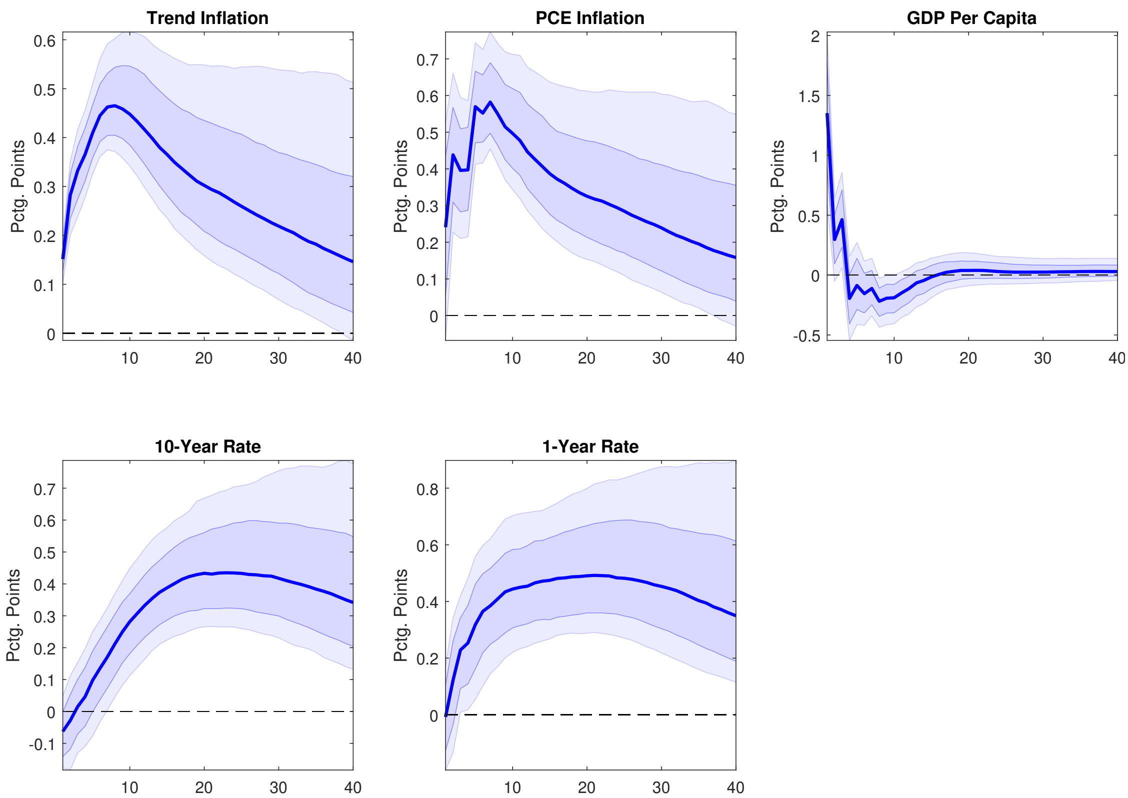


Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. Horizon is in quarters. Note that sample period is from 1978 since trimmed-PCE inflation only starts then.

B.6.2 Alternative maximization horizon H

The horizon might affect the robustness of our results since at long horizons there are (cumulative) errors in the MA coefficients on which the identification rests. In other words, VARs can produce biased and uncertain impulse responses as the horizon increases. On the other hand, the MFEV approach, in addition to capturing the medium-run shock of interest, it also captures aspects of other shocks in the data. In light of these considerations, we consider two alternative maximization horizons H=10 and H=30 to challenge the sensitivity of our results. Figures B.12 and B.13 present the IRFs and FEV when we consider H=10 when identifying the shock, while Figures B.14 and B.15 present the respective figures for H=30.

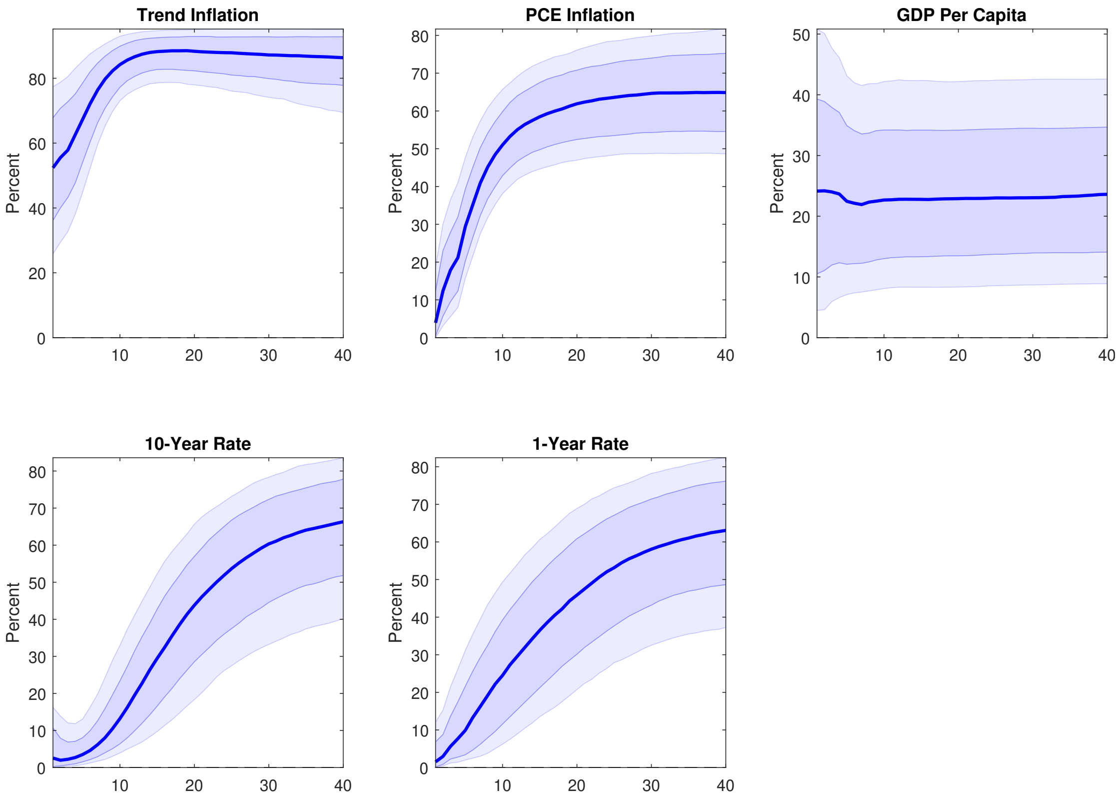
Figure B.12 IRF to a news shock to underlying inflation - Maximization horizon $H = 10$



Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The maximization horizon is 10 periods ahead. Horizon is in quarters.

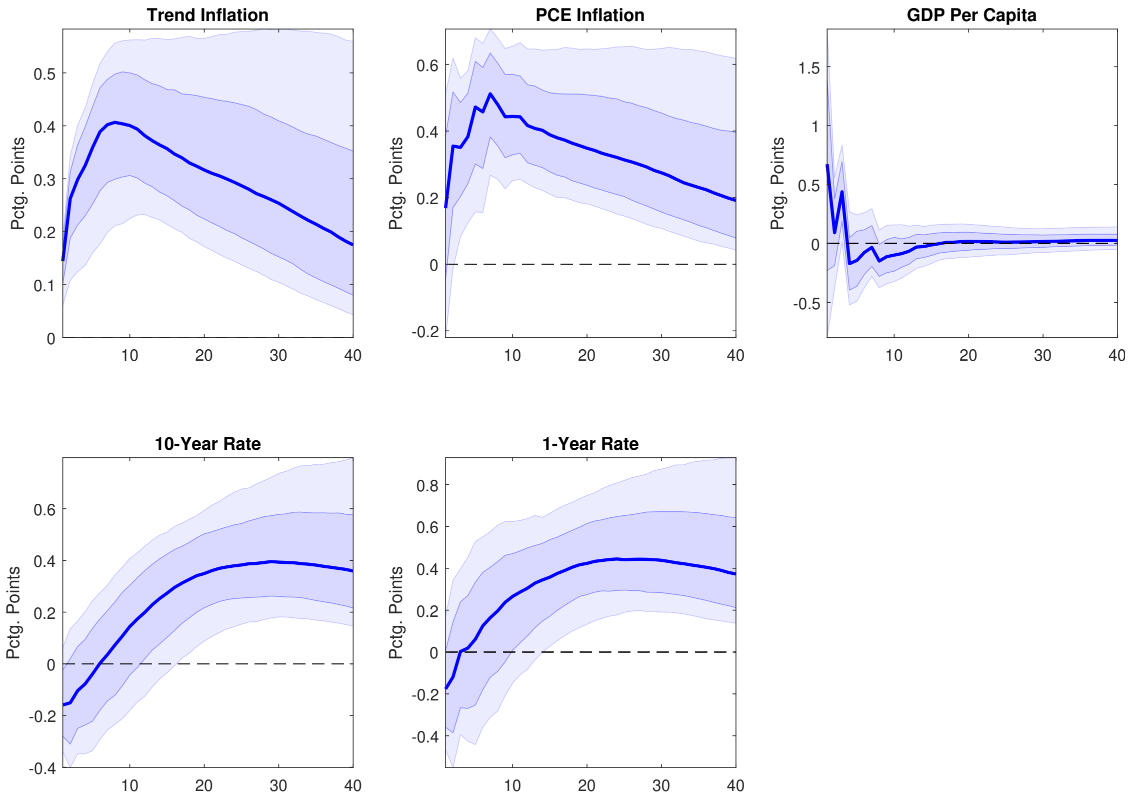
Clearly the maximization horizon affects the persistence of the recovered shock and, hence, its effects on PCE inflation and the importance of the shock in generating business cycle fluctuations.

Figure B.13 FEV to a news shock to underlying inflation - Maximization horizon $H = 10$



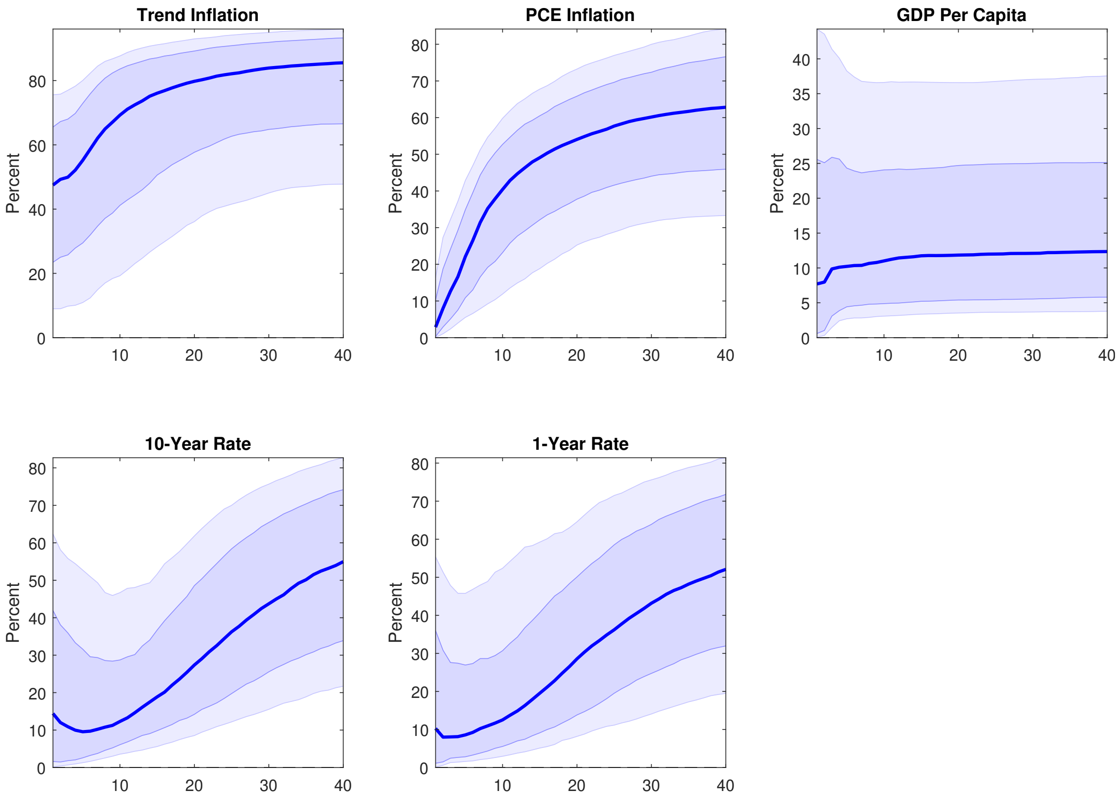
Note: Forecast error variance explained by news shocks to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The maximization horizon is 10 periods ahead. Horizon is in quarters.

Figure B.14 IRF to a news shock to underlying inflation - Maximization horizon $H = 30$



Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The maximization horizon is 30 periods ahead. Horizon is in quarters.

Figure B.15 FEV to a news shock to underlying inflation - Maximization horizon $H = 30$

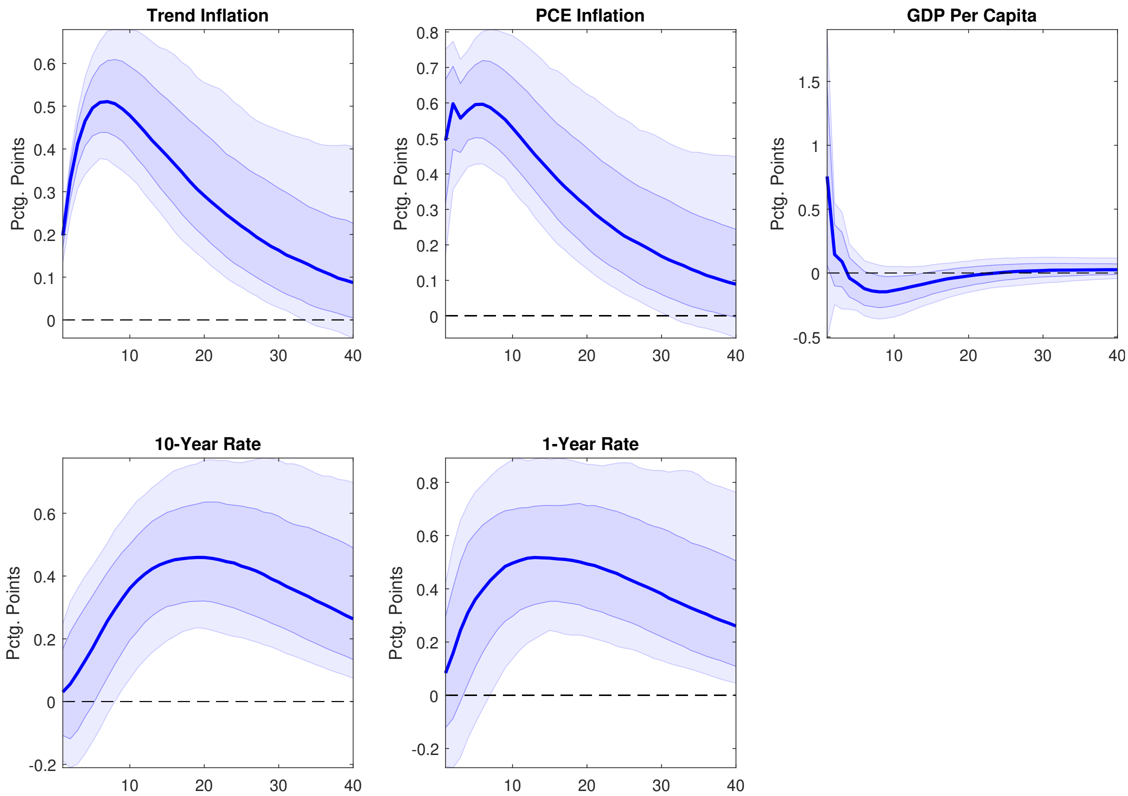


Note: Forecast error variance explained by news shocks to underlying inflation estimated using the BVAR(4) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The maximization horizon is 30 periods ahead. Horizon is in quarters.

B.6.3 Alternative Lag-Length

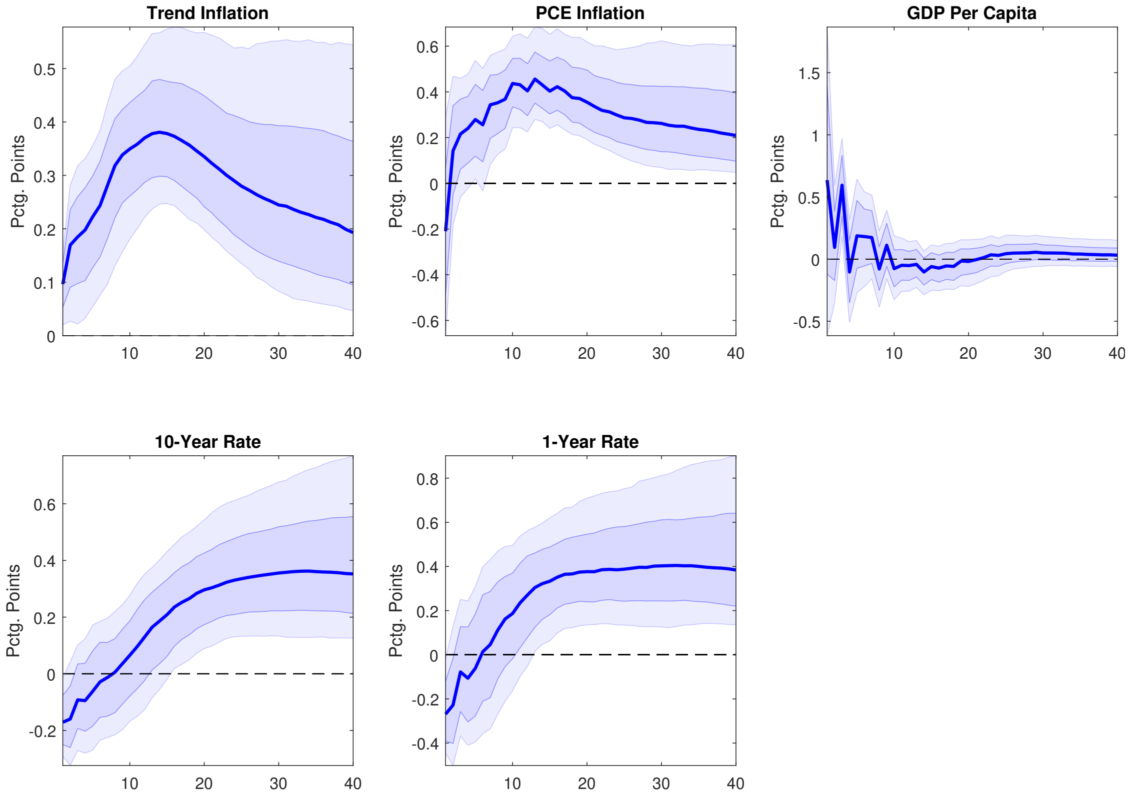
In this section we investigate whether the lag-length of the VAR affects the robustness of our results. Figures B.16 and B.17 present the impulse responses of the baseline VAR when we change the lag length to two and six periods, respectively. Apart for some kinks in the latter case, results are similar to the ones presented in the benchmark VAR.

Figure B.16 IRF to a news shock to underlying inflation - BVAR(2)



Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(2) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. Horizon is in quarters.

Figure B.17 IRF to a news shock to underlying inflation - BVAR(6)

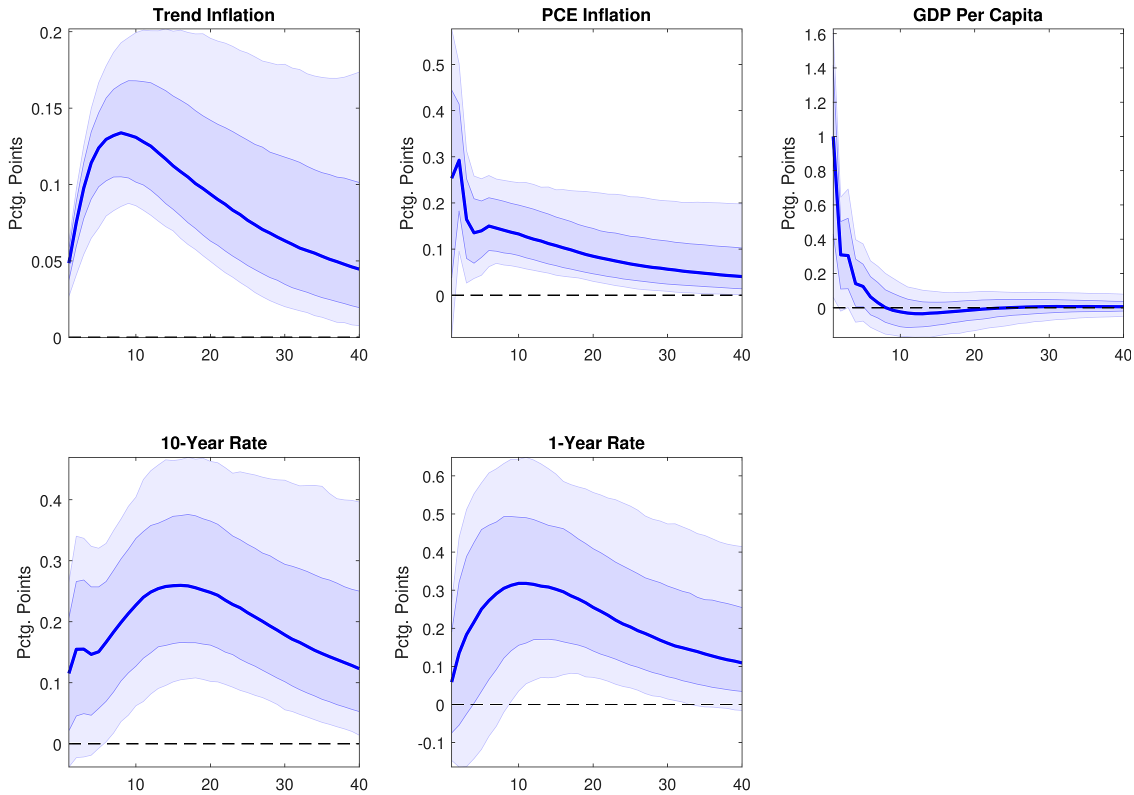


Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(6) that includes a constant and the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. Horizon is in quarters.

B.6.4 Post-1984 Sample

Our benchmark includes part of the Great Inflation period (1965-1982). We now show results when we limit the sample in time. Figure B.18 presents results when we limit the sample between the mid 1980s and the end of the sample.

Figure B.18 IRF to a news shock to underlying inflation - Sample 1984-2018



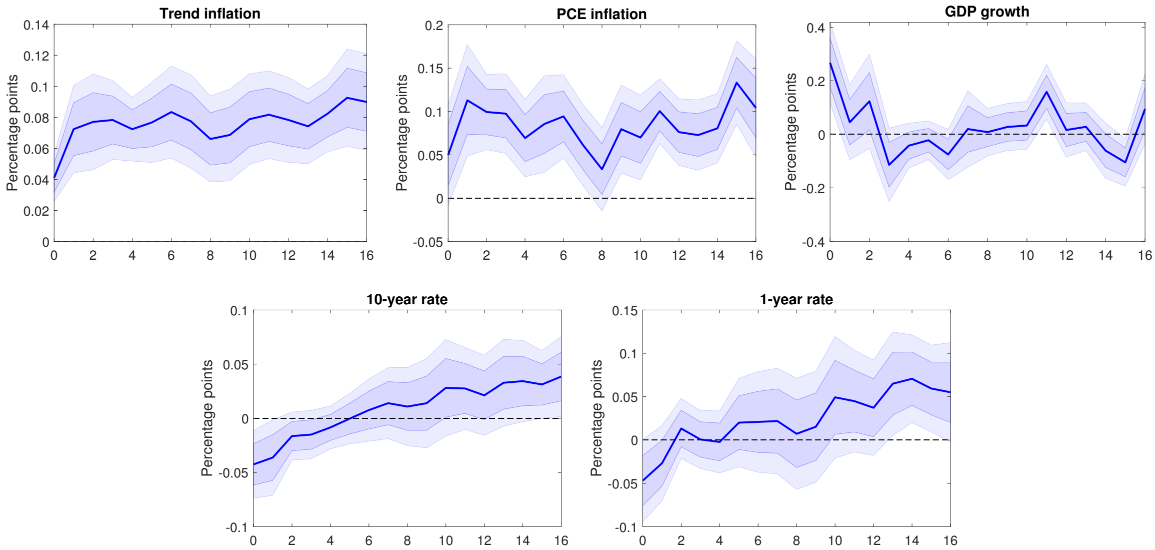
NOTE. IRFs to a one standard deviation news shock to underlying inflation estimated using the BVAR(4) that includes a constant and includes the following variables: underlying inflation, PCE inflation rate, GDP per capita growth rate, 10Y Treasury Rate, and 1Y Treasury Rate. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. The BVAR is estimated using a the restricted sample 1984-2018. Horizon is in quarters.

The IRFs are similar in shape with the ones presented in Figure 2.4 in the main text, but there are also important quantitative differences. The effect of the identified shock on PCE inflation is smaller and less persistent and the response of the 1-Year and 10-Year rates is positive on impact in the recent sub-sample. We conjecture that the better anchoring of inflation expectations by the monetary policy in the latest sample should be responsible for the differential response of PCE inflation in the two specifications.

B.7 LP IRFs of VAR variables

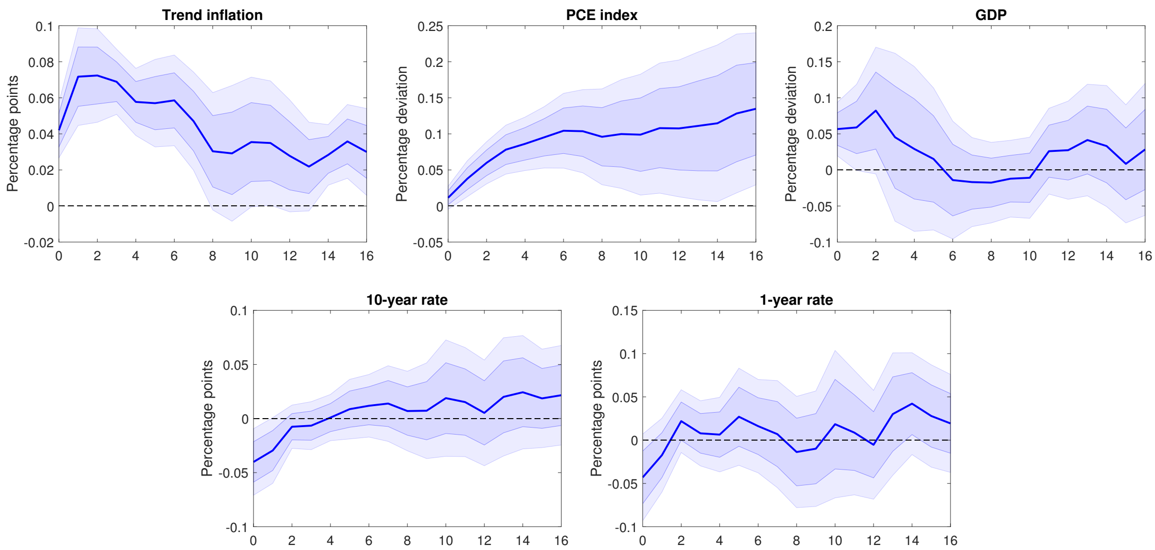
This section presents the responses of the macro variables if we employ local projections to analyze the effects of the extracted news shocks to underlying inflation.

Figure B.19 Dynamic effects from local projections: replication



Note: Effects of a news shock to underlying inflation from BVAR(4) estimated using local projections based on Equation 2.4 but with GDP growth and PCE inflation as controls instead of log-levels. The sample period is 1963Q1-2018Q4 and responses are scaled to expansionary shock of 25bps. 68% and 90% confidence bands based on Newey-West standard errors.

Figure B.20 Dynamic effects from local projections: baseline

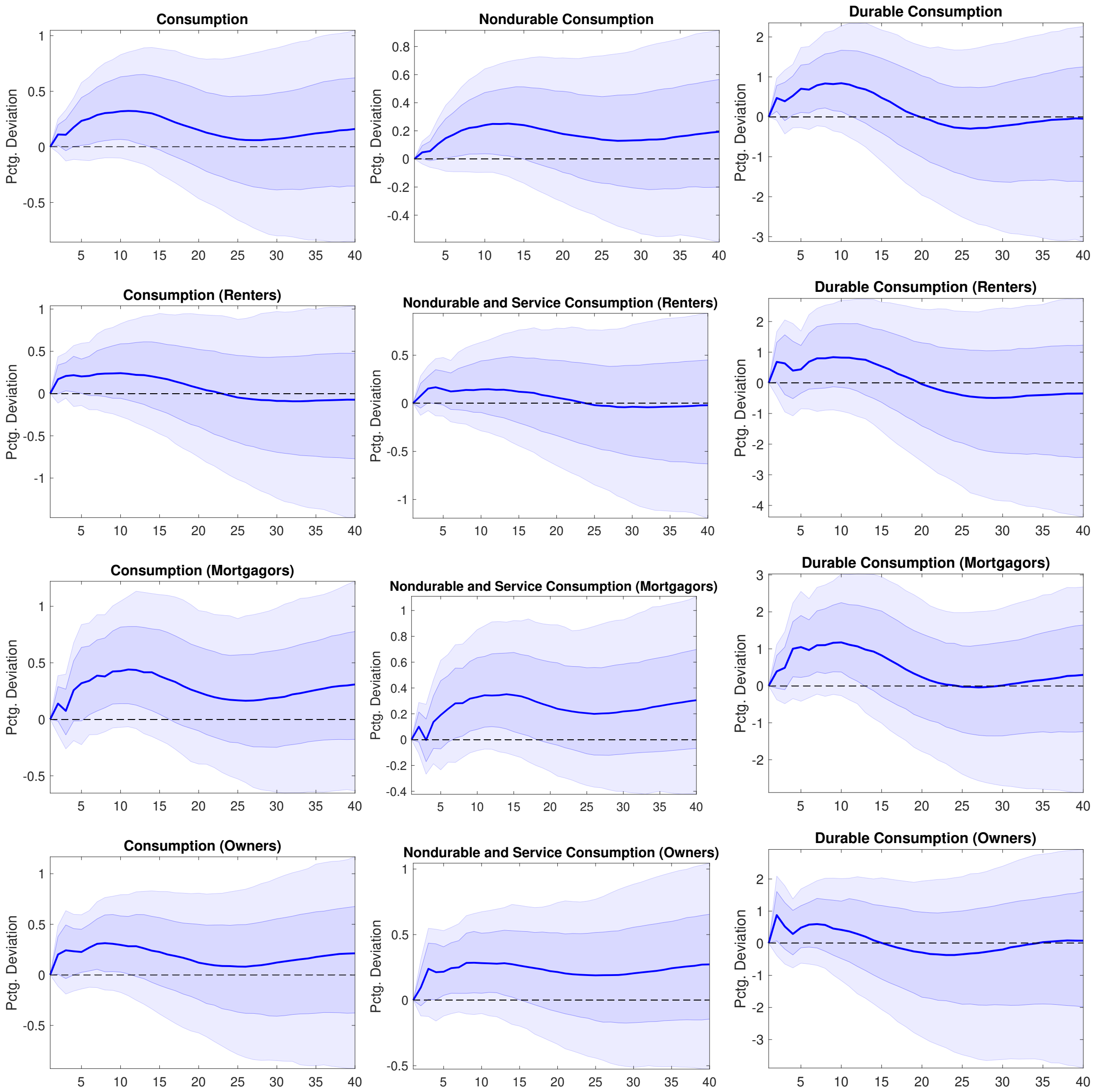


Note: Effects of a news shock to underlying inflation from BVAR(4) estimated using local projections based on Equation 2.4. The sample period is 1963Q1-2018Q4 and responses are scaled to expansionary shock of 25bps. 68% and 90% confidence bands based on Newey-West standard errors.

B.8 VAR IRFs of consumption responses by housing tenure

This section presents the responses of consumption for different types of households computed with the baseline VAR presented in Section 2.3 augmented with one variable at the time. Figure B.21 displays the IRFs to a one standard deviation news shock to underlying inflation. Responses are consistent with the ones presented in Figure 2.7.

Figure B.21 Consumption response by housing tenure - computed with the VAR



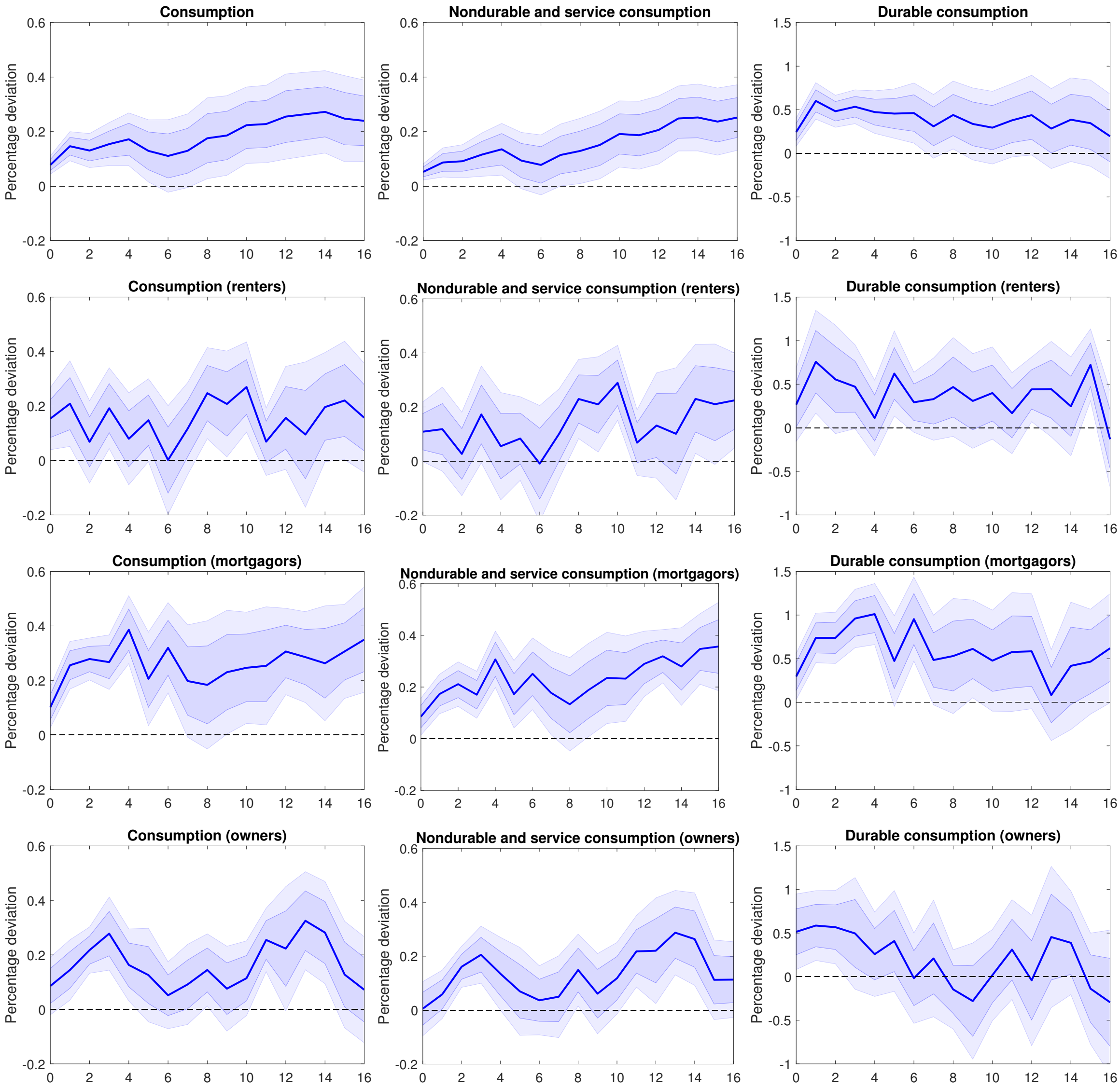
Note: IRFs to a one standard deviation news shock to underlying inflation estimated using the baseline BVAR (4) described in Section 2.2.2 plus each consumption series (including one variable at a time). The responses of the remaining variables of the BVAR(4) are the same as in Figure 2.5. The responses of consumption are presented as cumulated. Continuous blue line denotes the median IRFs. Blue and light blue shaded areas denote 68% and 90% credible sets based on 1,000 draws from the posterior distribution of the parameters. Horizon is in quarters.

B.9 Additional LP results

B.9.1 Non smoothed responses

Figure B.22 plots the IRFs of a news shock to underlying inflation on consumption by housing tenure status when we do not smooth the impulse responses.

Figure B.22 Consumption response by housing tenure (non-smoothed IRFs)

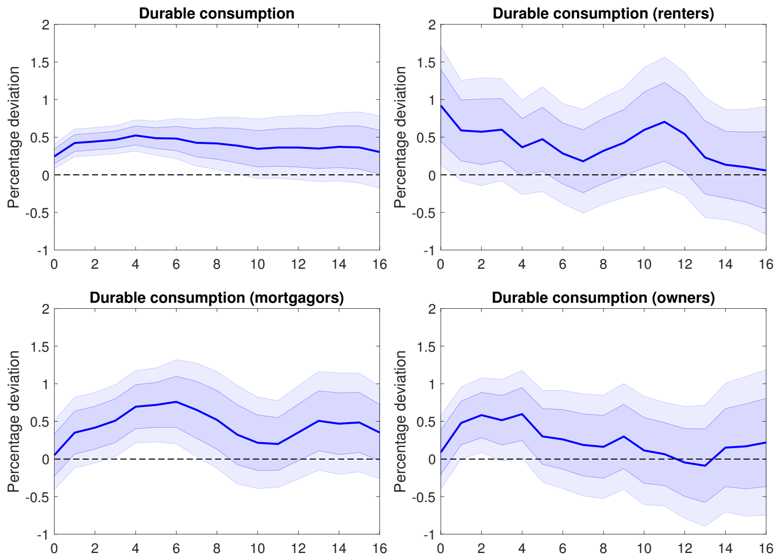


Note: Effects of a news shock to underlying inflation on consumption by housing tenure status based on Equation 2.4. Response is scaled to expansionary shock of 25bps. 68% and 90% confidence bands based on Newey-West standard errors.

B.9.2 Durable consumption IRFs including vehicle purchases

Figure B.23 plots the IRFs of a news shock to underlying inflation on durable consumption for different household groups when we include vehicle purchases in durables.

Figure B.23 Durable consumption (including vehicle purchases) response by housing tenure

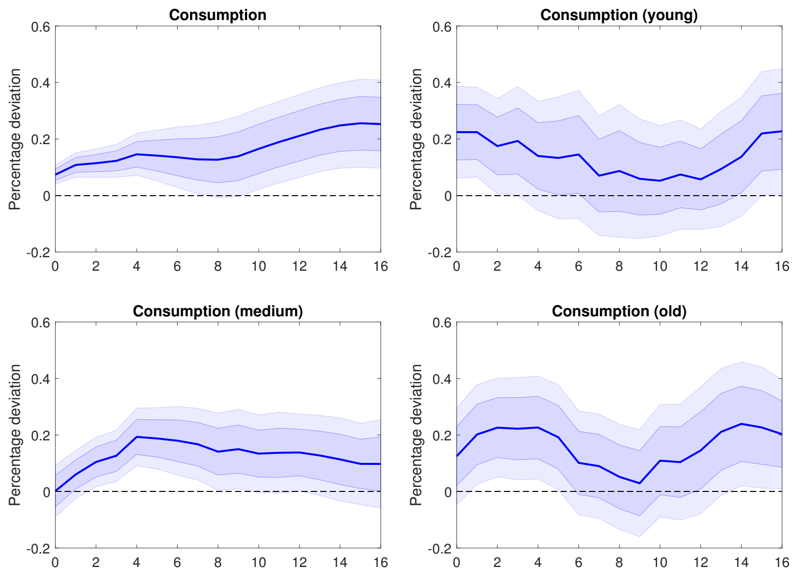


Note: Effects of a news shock to underlying inflation on durable consumption including vehicle purchases by housing tenure status based on Equation 2.4. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

B.10 Alternative dimensions of heterogeneity

In the related literature on the heterogeneous effects of monetary policy shocks, many studies analyze age and income as relevant dimensions of heterogeneity. Figure B.24 explores the heterogeneous responses of consumption to news shocks to underlying inflation when we cluster consumers according to their age. Figure B.25 explores the heterogeneous responses of consumption to news shocks to

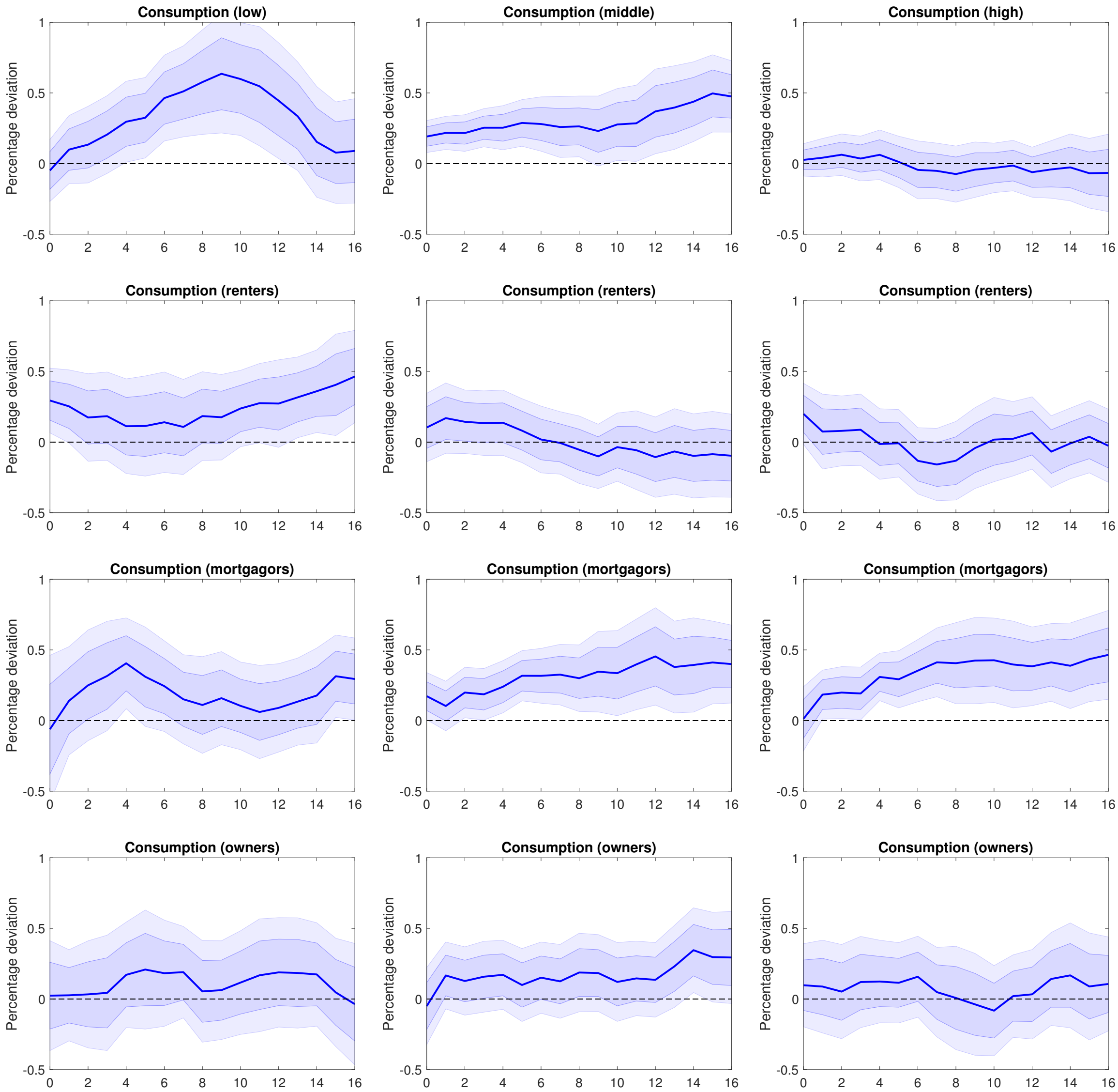
Figure B.24 Consumption response by age



Note: Effects of a news shock to underlying inflation on consumption by age based on Equation 2.4. Young is below 35 and old above 65. Response is scaled to expansionary shock of 25bps. 68% and 90% confidence bands based on Newey-West standard errors.

underlying inflation when we cluster consumers by their total after tax income (first row) and also distinguish between renters (second row), mortgagors (third row) and owners (last row).

Figure B.25 Consumption response by total after tax income



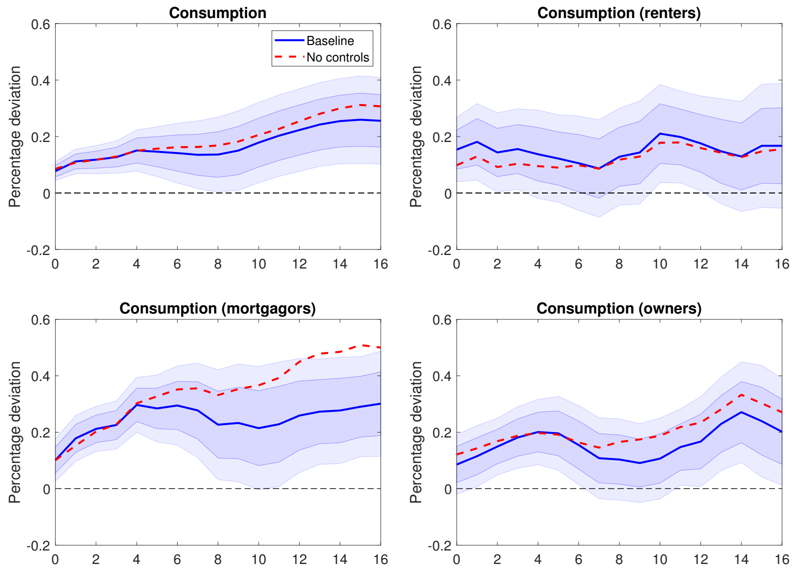
Note: Effects of a news shock to underlying inflation on consumption by total after-tax income based on Equation 2.4. Low, medium and high income correspond to below 33th, 33th-66th and above 66th percentile of income distribution, respectively. Each column corresponds to one of the income groups. First row shows response for all households in that income group, following rows show the response of the given income group differentiating by housing tenure status. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

B.11 Robustness of Baseline Heterogeneous Effects

Figure B.26 plots the IRFs of consumption by housing tenure status when we do not include controls in Equation 2.4.

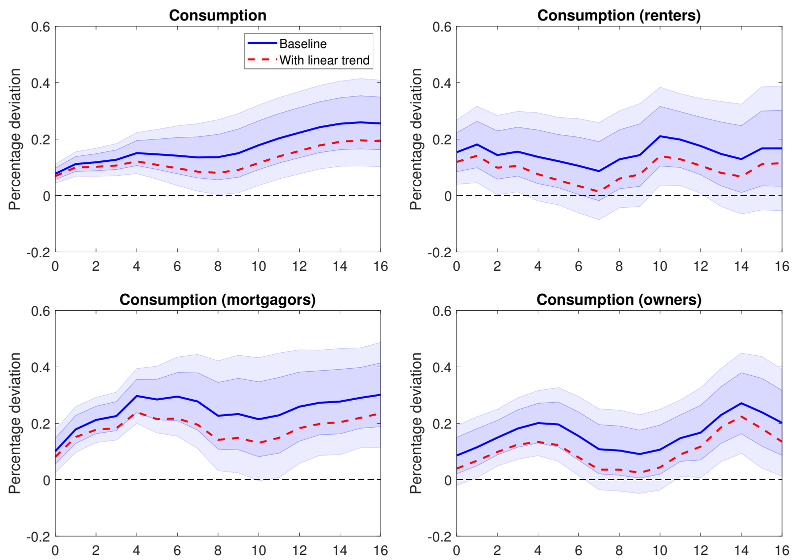
Figure B.27 plots the IRFs of consumption by housing tenure status when we include a linear trend in Equation 2.4.

Figure B.26 Robustness to excluding controls



Note: Effects of a news shock to underlying inflation on consumption by housing tenure status based on Equation 2.4. Red line shows estimates based on local projections without controls. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

Figure B.27 Robustness to including linear trend

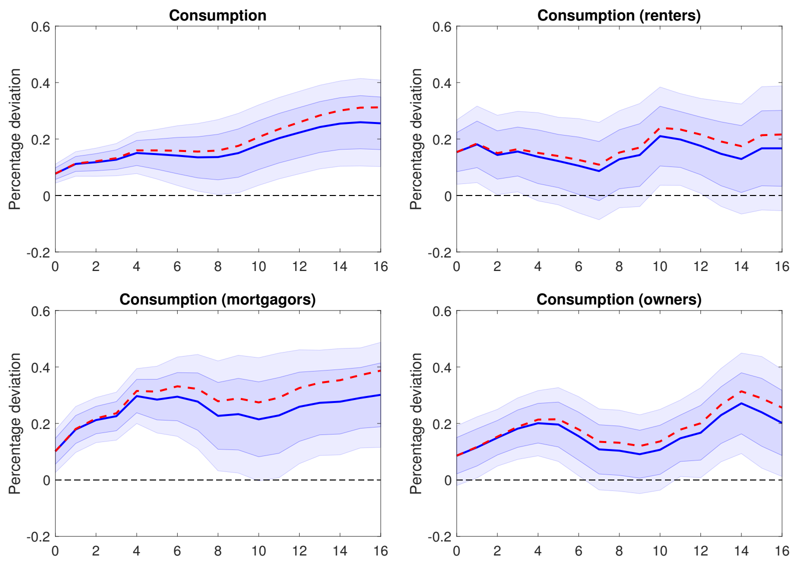


Note: Effects of a news shock to underlying inflation on consumption by housing tenure status based on Equation 2.4. Red line shows estimates based on local projections with linear trend. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

Figure B.28 plots the IRFs of consumption by housing tenure status when we correct for small-sample bias in Equation 2.4.

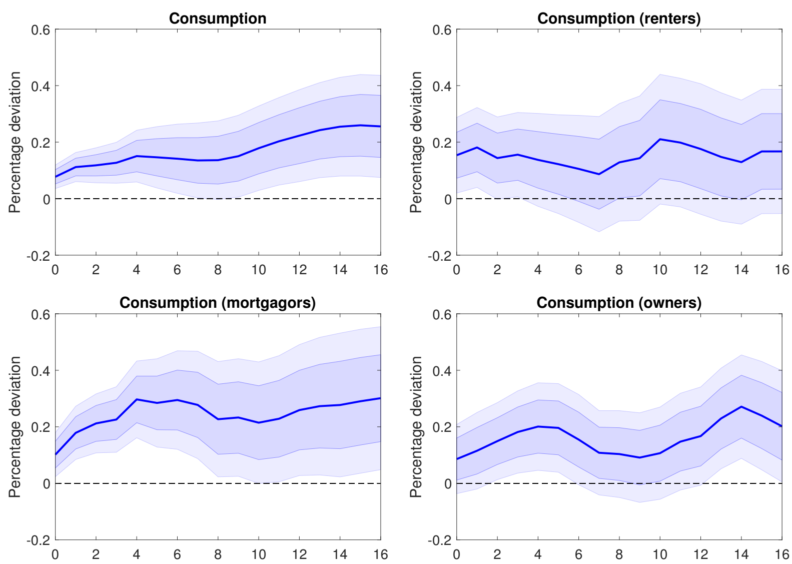
Figure B.29 plots the IRFs of consumption by housing tenure status when we use heteroscedasticity-robust standard errors for confidence in Equation 2.4.

Figure B.28 Robustness to small-sample bias correction



Note: Effects of a news shock to underlying inflation on consumption by housing tenure status based on Equation 2.4. Red line shows estimates that are corrected for small-sample bias as suggested by Herbst and Johannsen (2020). Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

Figure B.29 Robustness to using Huber-White standard errors

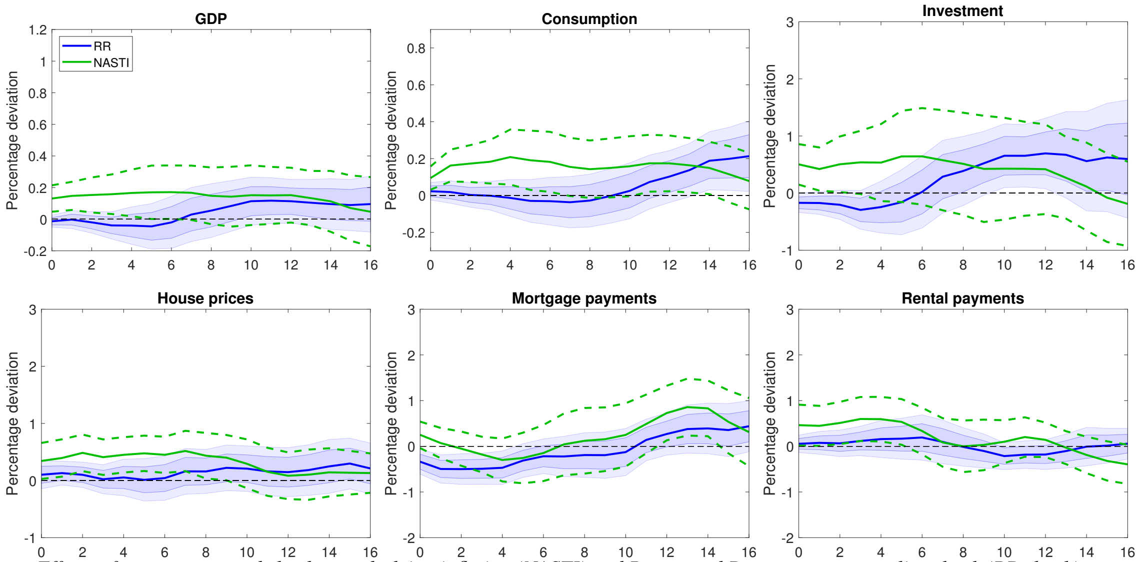


Note: Effects of a news shock to underlying inflation on consumption by housing tenure status based on Equation 2.4. Response is scaled to expansionary shock of 25bps. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Huber-White standard errors.

B.12 Comparison with monetary policy shocks

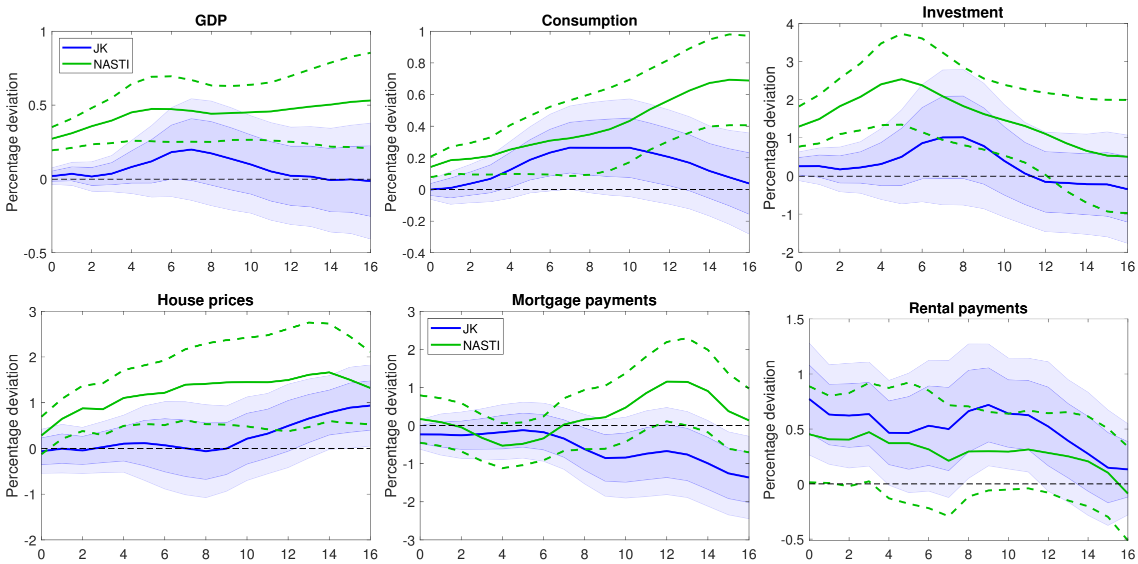
The next three graphs present the comparisons of macroeconomic and individual responses to narrative monetary policy and news shocks to underlying inflation when we do not use leads of the shock in the local projections to control for the persistence of the shock series.

Figure B.30 Comparison with narrative Romer and Romer monetary policy shock, no leads of shock



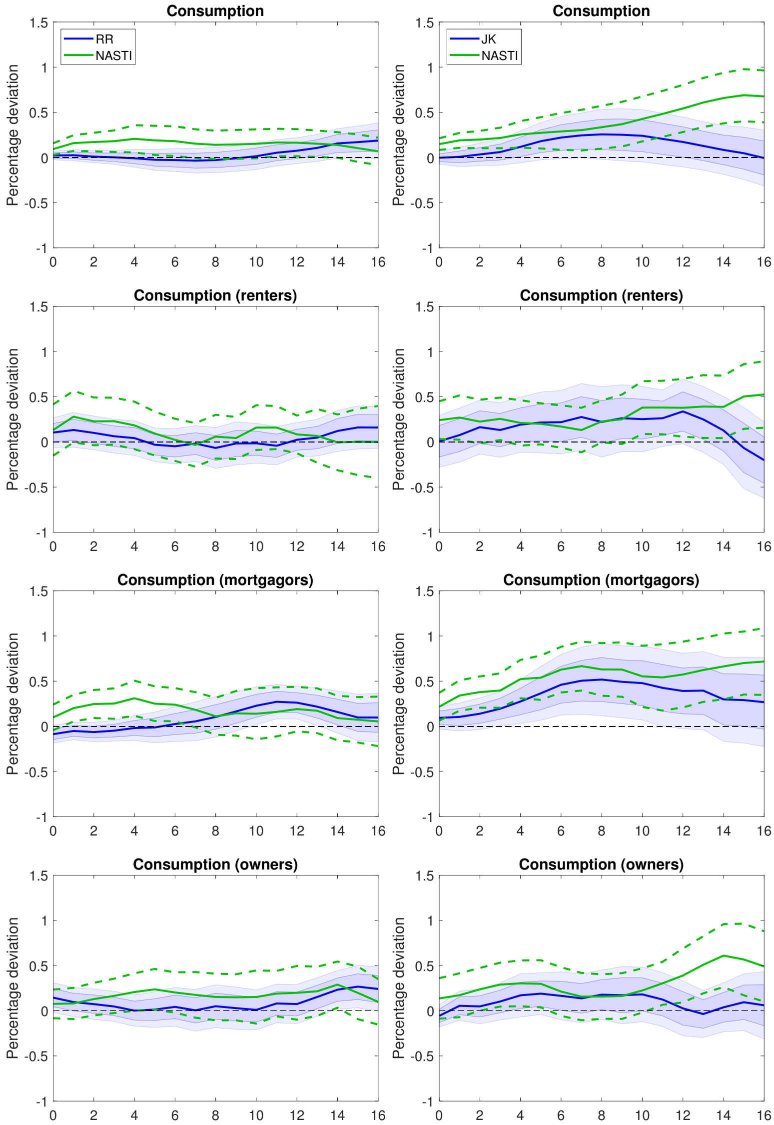
Note: Effects of news augmented shock to underlying inflation (NASTI) and Romer and Romer monetary policy shock (RR shock) on macro variables using local projections. Romer and Romer shock is extended by Coibion et al. (2017). Sample period from 1984Q1-2008Q4. Response is scaled to expansionary shock that reduces real rate by 25bps. Real rate is computed as ex-post rate, i.e. difference between 1-year rate and PCE inflation. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

Figure B.31 Comparison with high-frequency identified monetary policy shocks, no leads of shocks



Note: Effects of news augmented shock to underlying inflation (NASTI) and high-frequency monetary policy shock by Jarociński and Karadi (2020) (JK). Sample period from 1990Q1-2018Q4. Response is scaled to expansionary shock that reduces real rate by 25bps. Real rate is computed as ex-post rate, i.e. difference between 1-year rate and PCE inflation. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

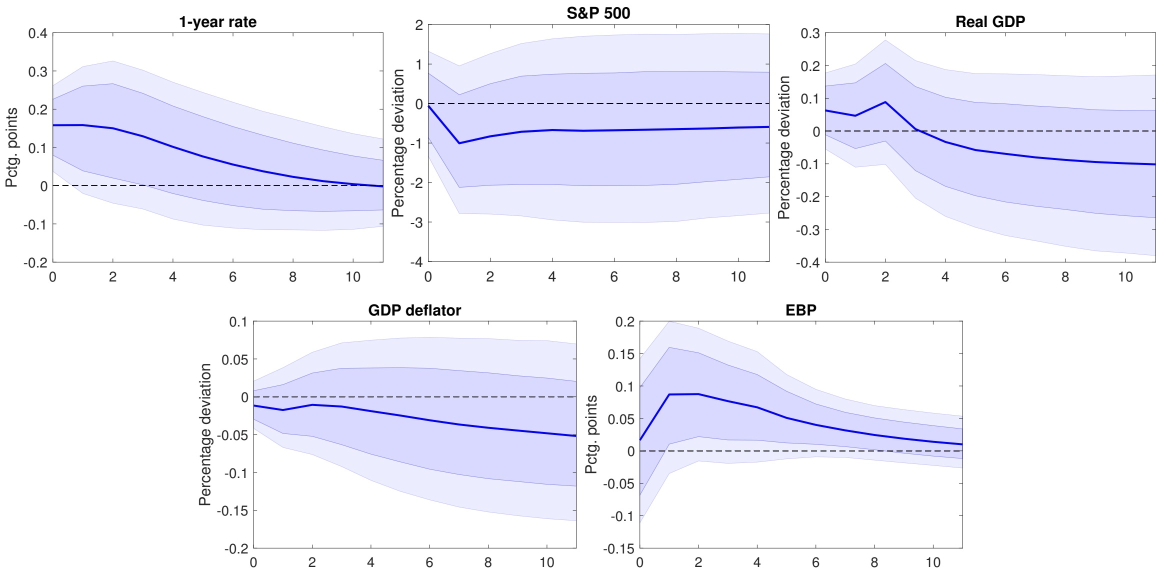
Figure B.32 Consumption responses by housing tenure status for different monetary policy shocks, no leads of shock



Note: Comparison of consumption effects of a news augmented shock to underlying inflation (NASTI) and monetary policy shocks. Left column shows Romer and Romer shock extended by Coibion et al. (2017) (RR) and right column shows high-frequency monetary policy shocks by Jarociński and Karadi (2020) (JK). Sample period from 1984Q1-2008Q4 for left column and 1990Q1-2018Q4 for right column. Response is scaled to expansionary shock that reduces real rate by 25bps. Real rate is computed as ex-post rate, i.e. difference between 1-year rate and PCE inflation. IRFs smoothed using 3-quarter backward looking moving average. 68% and 90% confidence bands based on Newey-West standard errors.

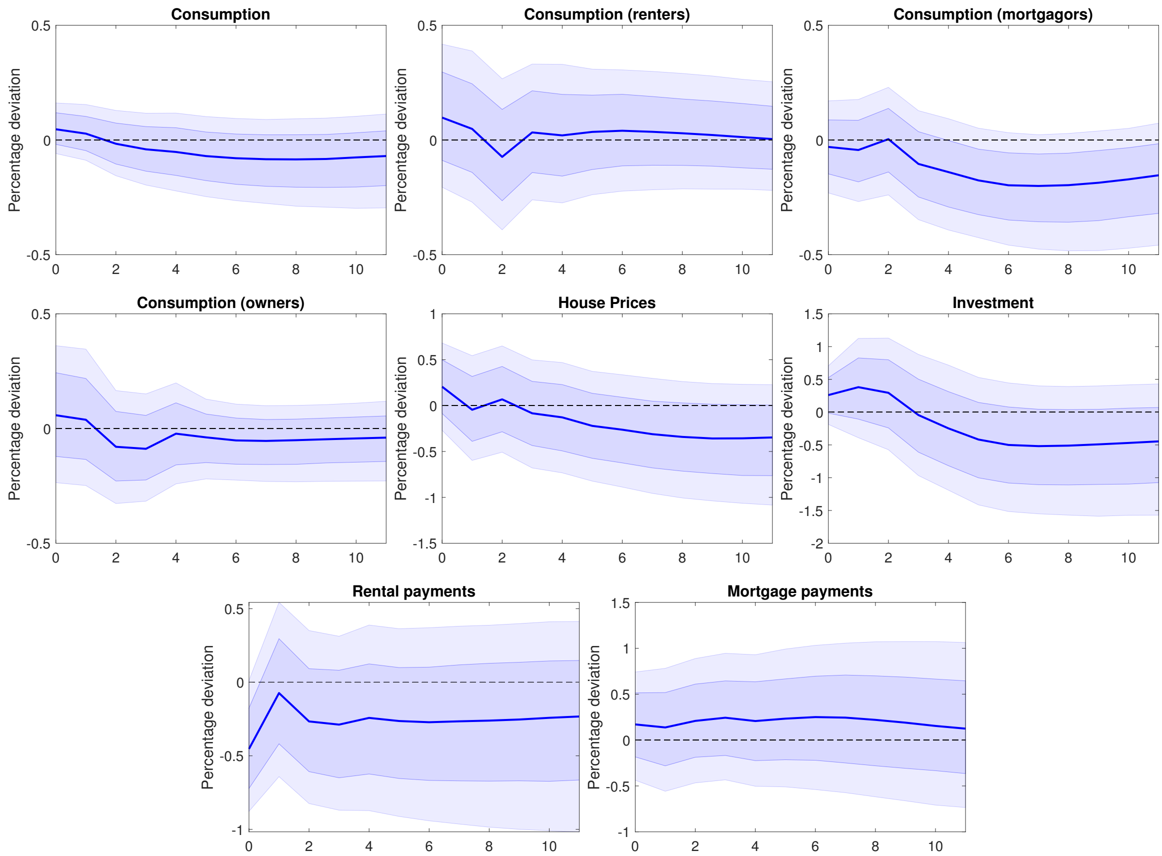
The next two graphs present the IRFs for the high-frequency monetary policy shocks by Jarociński and Karadi (2020) if we use exactly their framework (an internal VAR approach) on quarterly data.

Figure B.33 Replication of baseline specification in Jarociński and Karadi (2020)



Note: Replication of baseline analysis by Jarociński and Karadi (2020) in quarterly frequency. Sample period from 1984Q1-2016Q4. Response is scaled to one standard deviation (contractionary) shock 68% and 90% confidence bands.

Figure B.34 Adding additional variables to baseline specification in Jarociński and Karadi (2020)



Note: Replication of baseline analysis by Jarociński and Karadi (2020) in quarterly frequency. We add additional variables one at a time. Sample period from 1984Q1-2016Q4. Response is scaled to one standard deviation (contractionary) shock 68% and 90% confidence bands.

C

Appendix to Chapter 3

C.1 Definition of matrices in subsection 3.3.2 and section 3.4

The matrices in equations (3.8) and (3.9) are defined as follows:

$$\xi_t = \begin{bmatrix} \pi_t \\ \varepsilon_t \\ \bar{\pi}_{t+h} \\ \bar{\pi}_{t+h-1} \\ \vdots \\ \bar{\pi}_{t+2} \\ \bar{\pi}_{t+1} \\ v_t \end{bmatrix}, \mathbf{\Phi} = \begin{bmatrix} \rho & \phi & 0 & 0 & \dots & 0 & 1-\rho & 0 \\ 0 & \phi & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & \rho_v \end{bmatrix}, \mathbf{R}_t = \begin{bmatrix} \sigma_\eta & 0 & 0 \\ \sigma_\eta & 0 & 0 \\ 0 & \sigma_\lambda & 0 \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \sigma_{\nu,t} \end{bmatrix}$$

$$e_t = \begin{bmatrix} \eta_t \\ \lambda_{t+h} \\ \nu_t \end{bmatrix}, \mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}, \Psi(i) = \begin{bmatrix} 0 \\ \sigma_z(i) \end{bmatrix}$$

The matrices in equation (3.11) are defined as follows:

$$\widetilde{\mathbf{\Phi}}_t \equiv \begin{bmatrix} \mathbf{\Phi} & \mathbf{0}_{k\times k} & \mathbf{0}_{k\times k} & ... & \mathbf{0}_{k\times k} \\ \mathbf{K}_t(1)\mathbf{D\Phi} & (I-\mathbf{K}_t(1)\mathbf{D})\Phi & \mathbf{0}_{k\times k} & ... & \mathbf{0}_{k\times k} \\ \mathbf{K}_t(2)\mathbf{D\Phi} & \mathbf{0}_{k\times k} & (I-\mathbf{K}_t(2)\mathbf{D})\mathbf{\Phi} & ... & \mathbf{0}_{k\times k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{K}_t(N)\mathbf{D\Phi} & \mathbf{0}_{k\times k} & \mathbf{0}_{k\times k} & ... & (I-\mathbf{K}_t(N)\mathbf{D})\mathbf{\Phi} \end{bmatrix}$$

$$\widetilde{\mathbf{R}}_t = \begin{bmatrix} \mathbf{R}_t & \mathbf{0}_{k\times 1} & \mathbf{0}_{k\times 1} & ... & \mathbf{0}_{k\times 1} \\ \mathbf{K}_t(1)\mathbf{DR}_t & \mathbf{K}_t(1)\mathbf{\Psi}(1) & \mathbf{0}_{k\times 1} & ... & \mathbf{0}_{k\times 1} \\ \mathbf{K}_t(2)\mathbf{DR}_t & \mathbf{0}_{k\times 1} & \mathbf{K}_t(2)\mathbf{\Psi}(2) & ... & \mathbf{0}_{k\times 1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{K}_t(N)\mathbf{DR}_t & \mathbf{0}_{k\times 1} & \mathbf{0}_{k\times 1} & ... & \mathbf{K}_t(N)\mathbf{\Psi}(N) \end{bmatrix}$$

C.2 Model derivations

Based on equations (3.8)-(3.9) the Kalman filter recursion is given by:

$$\xi_{t|t-1}(i) = \Phi\xi_{t-1|t-1}(i) \tag{C.1}$$

$$P_{t|t-1}(i) = \Phi P_{t-1|t-1}(i)\Phi' + R_t R_t' \tag{C.2}$$

$$s_{t|t-1}(i) = D\xi_{t|t-1}(i) \tag{C.3}$$

$$F_{t|t-1}(i) = DP_{t|t-1}(i)D' + \Psi(i)\Psi(i)' \tag{C.4}$$

$$\xi_{t|t}(i) = \xi_{t|t-1}(i) + \underbrace{P_{t|t-1}D'\left[F_{t|t-1}(i)\right]^{-1}}_{K_t(i)}\left[s_t(i) - D\xi_{t|t-1}(i)\right] \tag{C.5}$$

$$P_{t|t}(i) = P_{t|t-1}(i) - P_{t|t-1}(i)D'\left[F_{t|t-1}(i)\right]^{-1}DP_{t|t-1}(i) \tag{C.6}$$

Then, re-arrange the Kalman equation as follows to obtain equation (3.10):

$$\xi_{t|t}(i) = \xi_{t|t-1}(i) + K_t(i)\left[s_t(i) - D\xi_{t|t-1}(i)\right] \tag{C.7}$$

$$= (\mathbf{I}_{h+3} - K_t(i)D)\xi_{t|t-1}(i) + K_t(i)s_t(i) \tag{C.8}$$

$$= (\mathbf{I}_{h+3} - K_t(i)D)\xi_{t|t-1}(i) + K_t(i)[D\xi_t + \Psi(i)z_t(i)] \tag{C.9}$$

$$= (\mathbf{I}_{h+3} - K_t(i)D)\xi_{t|t-1}(i) + K_t(i)[D(\Phi\xi_{t-1} + R_t e_t) + \Psi(i)z_t(i)] \tag{C.10}$$

C.3 Initial conditions for estimation

Define the state vector of the trend-cycle model as $\xi_t = [\pi_t, \epsilon_t, \bar{\pi}_t]'$. We initialize the state as follows:

$$\xi_{0|0} \equiv E\left(\begin{bmatrix} \pi_0 \\ \epsilon_0 \\ \bar{\pi}_0 \end{bmatrix}\right) = \begin{bmatrix} \pi_{t_0} \\ 0 \\ \bar{\pi}_{t_0} \end{bmatrix}$$

$$\mathbf{P}_{0|0} \equiv E\left(\begin{bmatrix} \pi_0 \\ \epsilon_0 \\ \bar{\pi}_0 \end{bmatrix}\begin{bmatrix} \pi_0 & \epsilon_0 & \bar{\pi}_0 \end{bmatrix}\right) = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{\sigma_\eta^2}{1-\phi^2} & 0 \\ 0 & 0 & \varsigma \end{bmatrix}$$

where t_0 denotes the last quarter before the estimation starts. We set π_{t_0} to the CPI core inflation rate in the last quarter before the estimation starts (1958Q4) and ς is set to σ_λ^2.[1] The expected initial level of trend inflation, $\bar{\pi}_{t_0}$, is dealt with as parameter to be estimated.

The initial conditions for the panel estimation are assumed to be

$$\begin{aligned} \tilde{\xi}_{0|0} &\equiv E\left(\begin{bmatrix} \xi_0 \\ \overrightarrow{\xi}_{0|0} \end{bmatrix}\right) = \mathbf{1}_{(N+1)\times 1} \otimes \bar{\xi}_{0|0} \\ \widetilde{\mathbf{P}}_{0|0} &\equiv E\left(\begin{bmatrix} \xi_0 \\ \overrightarrow{\xi}_{0|0} \end{bmatrix}\begin{bmatrix} \xi_0 & \overrightarrow{\xi}_{0|0} \end{bmatrix}\right) = \mathbf{I}_{(N+1)\times 1} \otimes \bar{\mathbf{P}}_{0|0} \end{aligned}$$

where $\mathbf{1}_{(N+1)\times 1}$ is a $(N+1)\times 1$ vector of ones, $\mathbf{I}_{N+1}$ is the $(N+1)\times(N+1)$ identity matrix and

$$\bar{\xi}_{0|0} \equiv E\left(\begin{bmatrix} \pi_0 \\ \epsilon_0 \\ \bar{\pi}_{0+h} \\ \bar{\pi}_{0+h-1} \\ \vdots \\ \bar{\pi}_{0+2} \\ \bar{\pi}_{0+1} \\ v_0 \end{bmatrix}\right) = \begin{bmatrix} \pi_{t_0} \\ 0 \\ \bar{\pi}_h \\ \bar{\pi}_{h-1} \\ \vdots \\ \bar{\pi}_2 \\ \bar{\pi}_1 \\ 0 \end{bmatrix} \quad \text{and}$$

[1] The estimated parameters are robust to alternative values for ς.

$$
\bar{\mathbf{P}}_{0|0} \equiv E\left(\begin{bmatrix} \pi_0 \\ \epsilon_0 \\ \bar{\pi}_{0+h} \\ \bar{\pi}_{0+h-1} \\ \vdots \\ \bar{\pi}_{0+2} \\ \bar{\pi}_{0+1} \\ \upsilon_0 \end{bmatrix} \begin{bmatrix} \pi_0 & \epsilon_0 & \bar{\pi}_{0+h} & \bar{\pi}_{0+h-1} & \dots & \bar{\pi}_{0+2} & \bar{\pi}_{0+1} & \upsilon_0 \end{bmatrix} \right)
$$

$$
= \begin{bmatrix} 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & \frac{\sigma_\eta^2}{1-\phi^2} & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \varsigma & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 0 & \varsigma & 0 & 0 & 0 & 0 \\ \vdots & 0 & 0 & 0 & \ddots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & \varsigma & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & \varsigma & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & \frac{\sigma_{\nu,0}^2}{1-\rho_v^2} \end{bmatrix}
$$

where π_{t_0} is set to the core inflation rate in 1991 Q2 (the last quarter before the start of the panel estimation sample) and $\bar{\pi}_0$ corresponds to the inflation drift in 1991 Q2 and $\bar{\pi}_1$, etc. are set accordingly. The interpretation of these initial conditions is that they are set so that we as the econometricians have the same priors about the initial state as those about the forecasters' initial beliefs. Therefore, forecasters' initial beliefs at the beginning of the sample, i.e. 1991Q3, are denoted by $\bar{\xi}_{0|0}$ and $\bar{\mathbf{P}}_{0|0}$. If a forecaster enters the Survey after 1991Q4, its initial beliefs are updated by the Kalman filter assuming omitted observations. Recall that forecasters are heterogeneous in their level of attention, the Kalman filter will assign different prior uncertainty $\bar{\mathbf{P}}_{t-1|t-1}(i)$ across forecasters who enter the Survey in the same quarter.

C.4 Selection of forecasters

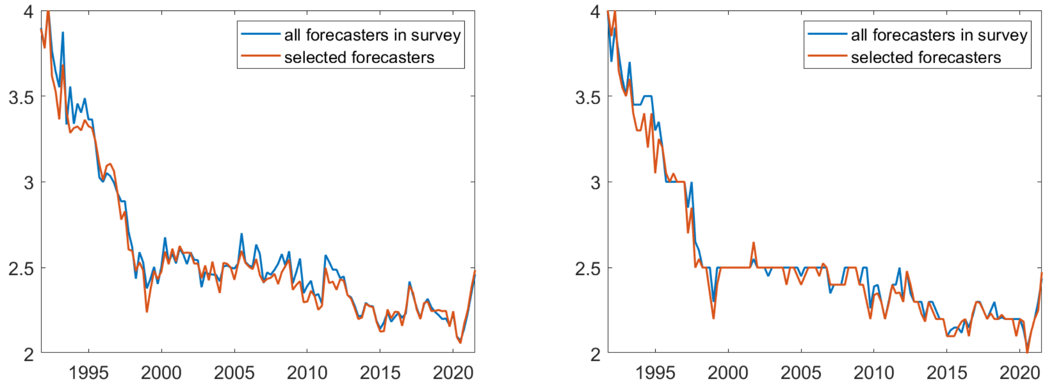


Figure C.1 Time series of inflation expectations: mean (lhs) and median (rhs)

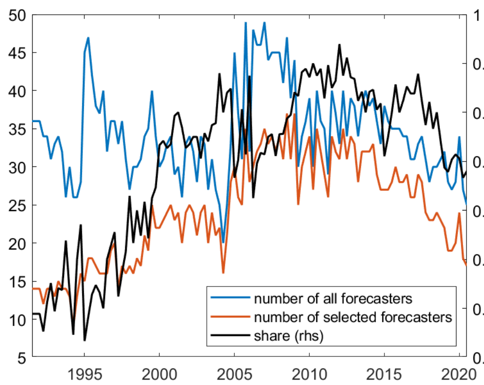


Figure C.2 Number of total and selected forecasters in the US SPF survey

C.5 Volatility of Expectations

In order to understand better what determines the estimated parameters we analyze their relationship with the inflation expectations data. As illustrated by Figure C.3 the estimated parameters of the process $u_t(i) \equiv v_t + z_t(i)$ in equation (3.4) are related to the second moment of the distribution of inflation expectations. The left chart shows that forecasters with a higher standard deviation of expectations over time tend to have a higher σ_z. This result suggests that periods in which the average cross-sectional volatility increases, the likelihood selects a larger volatility of the idiosyncratic beliefs, $z_t(i)$. The right chart plots the estimated σ_ν as a function of the standard deviation across forecasts at a given point in time and points to a negative relationship between the standard deviation of expectations across forecasts and the volatility of the forward-looking component v_t. If the volatility of the forward-looking component is low, forecasters pay more attention to the information coming from news about long-run inflation (the second signal) and consequently, expectations react more to news (larger Kalman gains).

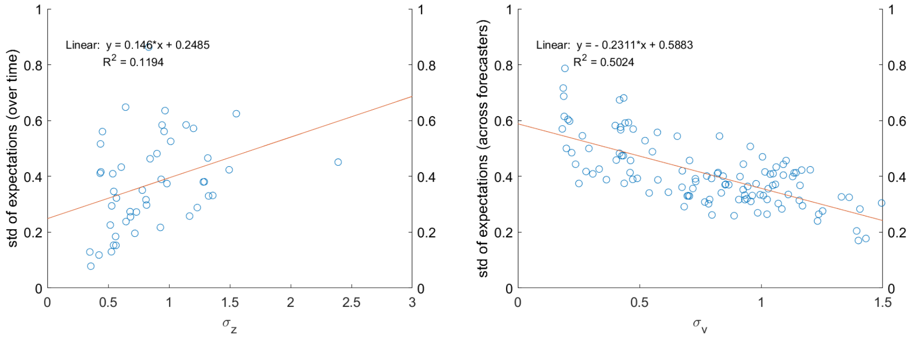


Figure C.3 Relationship of estimated parameters with distribution of expectations

C.6 Historical decomposition

The following describes the procedure to obtain the historical shock decomposition:

1. We add the shock series $z_t(i)$ and ν_t as state variables to the model in equation (3.11) and then use the Kalman smoother to obtain the smoothed estimates of all shock series.

2. We derive the initial states in period 0 by inverting the transition equation for period 1 and using the smoothed estimates for the parameter matrices and shock series from period 1 in this equation to get the initial states in period 0.

3. We simulate the model based on the smoothed estimates of the parameter matrices and shock series. Figure C.4 shows the simulated average inflation expectations together with the average inflation expectations in the data and the inflation drift.

4. We replace the smoothed estimates of all shock series by zero and simulate the model to obtain the series of inflation expectations in the absent of any shocks.

5. We simulate the model by allowing one shock to be non-zero at the time and then compute the deviation of this simulated series of inflation expectations from the series obtain in step (iv) before.

6. For each shock, we compute the average of these deviations across forecasters to obtain the bars in Figure 3.7.

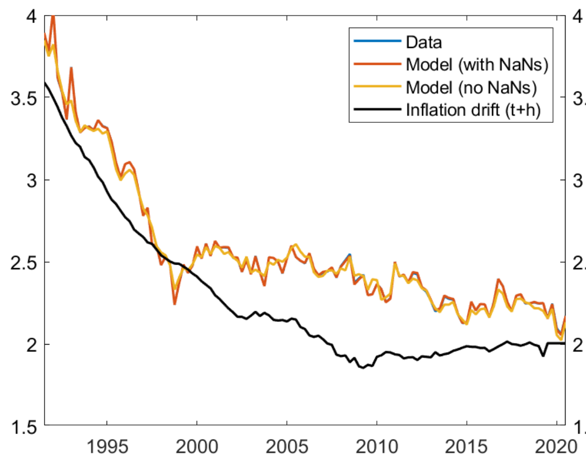


Figure C.4 Average inflation expectations: data vs model

Notes: Data corresponds to average inflation expectations by all forecasters. Model (with NaNs) corresponds to the average of the model simulated inflation expectations where periods without forecasts are replaced by missing values. Model (no NaNs) corresponds to the average of the model simulated inflation expectations where periods without forecasts are filled by the Kalman smoother.

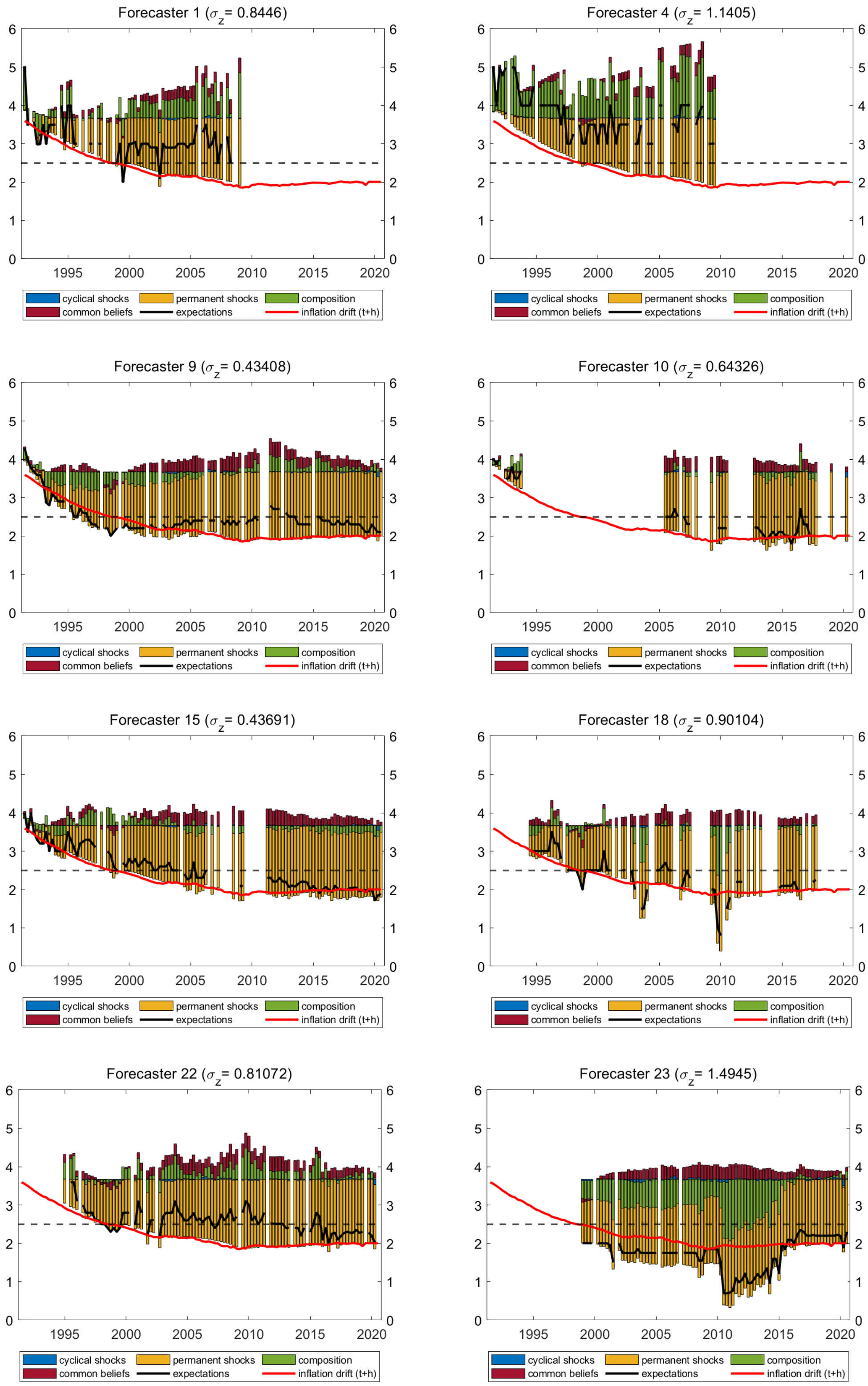


Figure C.5 Historical decomposition of inflation expectations for different forecasters

Notes: Simulation of model based on smoothed estimates with different shocks active.

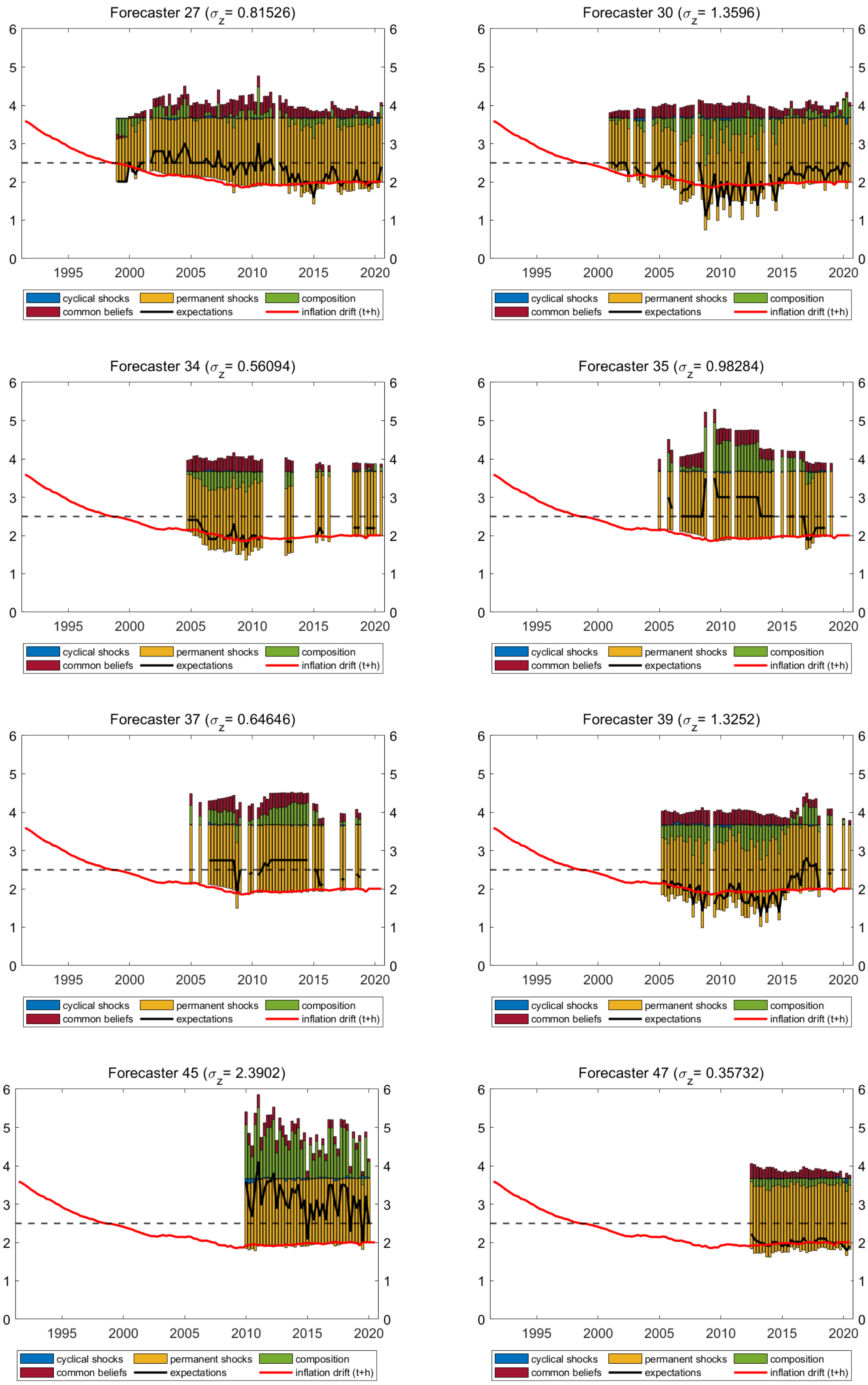


Figure C.6 Historical decomposition of inflation expectations for different forecasters (continued)

Notes: Simulation of model based on smoothed estimates with different shocks active.

C.7 Robustness of panel estimation

This section shows some robustness analysis of the panel estimates (see Table C.1 and Figure C.7), the implied Kalman gain for the inflation drift (see Figure C.8 and Figure C.9) and the historical decomposition of average inflation expectations (see Figure C.10). Our results are robust to setting h=8, no serial correlation in the common belief component (v_t), alternative prior specifications and different forecasters selections. The different robustness analyses are defined in the table below from (2)-(8).

(1) Baseline

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.384
$\sigma_{\nu,t}$	$\ln \sigma^2_{\nu,t} \backsim \mathcal{N}\left(\ln \sigma^2_{\nu,t-1}, \sigma^2_{\nu,\text{prior}}\right)$	see Figure C.7, top
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.220
$\sigma_z(i)$	Inverse Gamma (0.5,4)	see Figure C.7, bottom
$\sigma_{\nu,\text{prior}}$	Calibrated	0.2

(2) h=8

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.428
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.233

(3) ρ_v=0

Parameter	Prior	Posterior mode
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.233

(4) $\sigma_{\nu,\text{prior}} = 0.4$

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.369
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.249
$\sigma_{\nu,\text{prior}}$	Calibrated	0.4

(5) Select forecasters with at least 16 quarters

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.387
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.210

(6) Select forecasters with at least 48 quarters

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.446
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.230

(7) larger prior mean of $\sigma_z(i)$

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.381
$\sigma_{\nu,0}$	Inverse Gamma (0.5,4)	0.223
$\sigma_z(i)$	Inverse Gamma (**0.75**,4)	see Figure C.7, bottom

(8) Larger prior standard deviation of beliefs

Parameter	Prior	Posterior mode
ρ_v	Beta(0.5,0.2)	0.396
$\sigma_{\nu,0}$	Inverse Gamma (0.5,**8**)	0.257
$\sigma_z(i)$	Inverse Gamma (0.5,**8**)	see Figure C.7, bottom

Table C.1 Robustness of parameter values for panel estimation

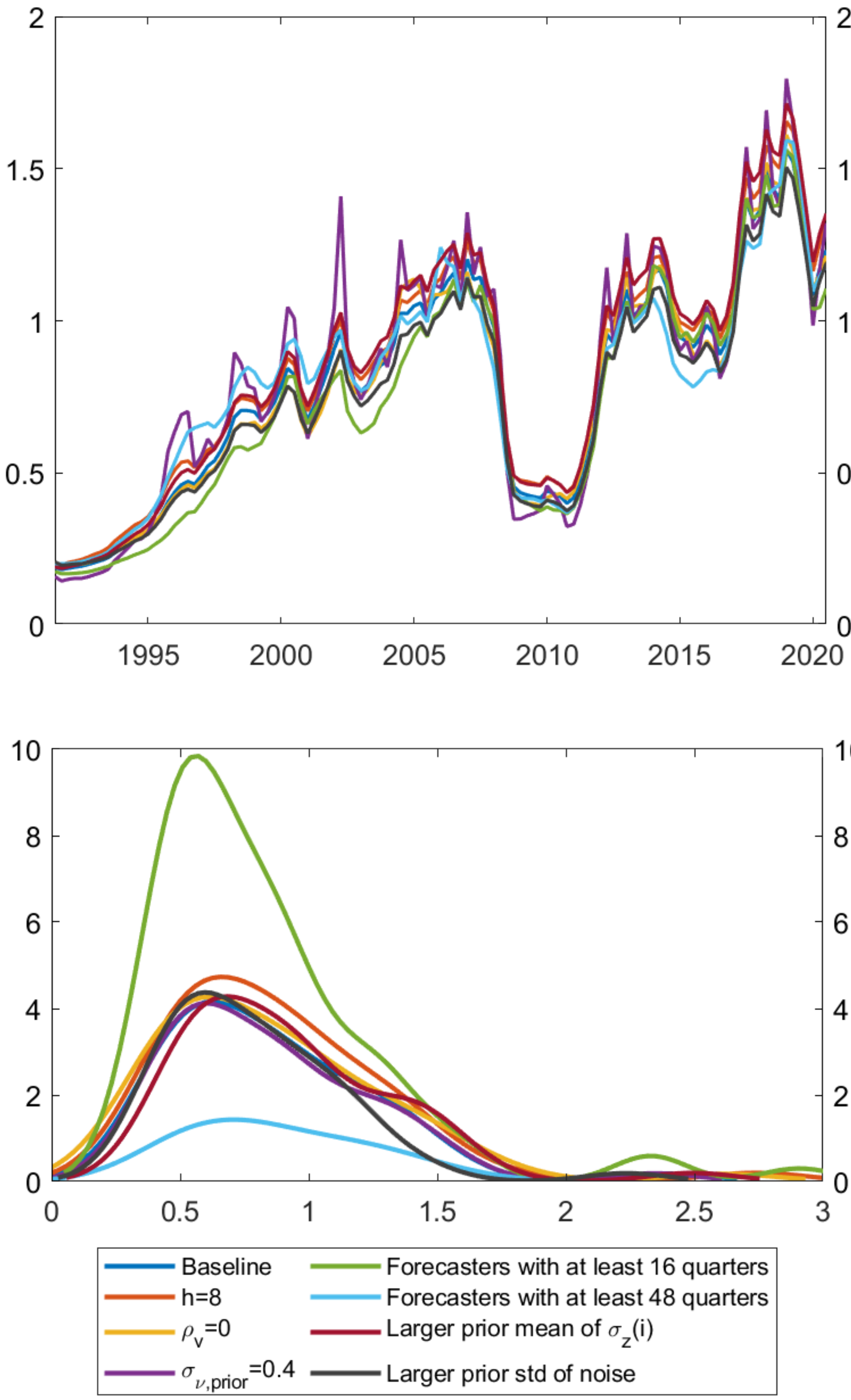


Figure C.7 Robustness of $\sigma_{\nu,t}$ (top) and $\sigma_z(i)$ (bottom)

Notes: Bottom chart shows kernel-smoothing distribution fitted to histogram with 25 bins.

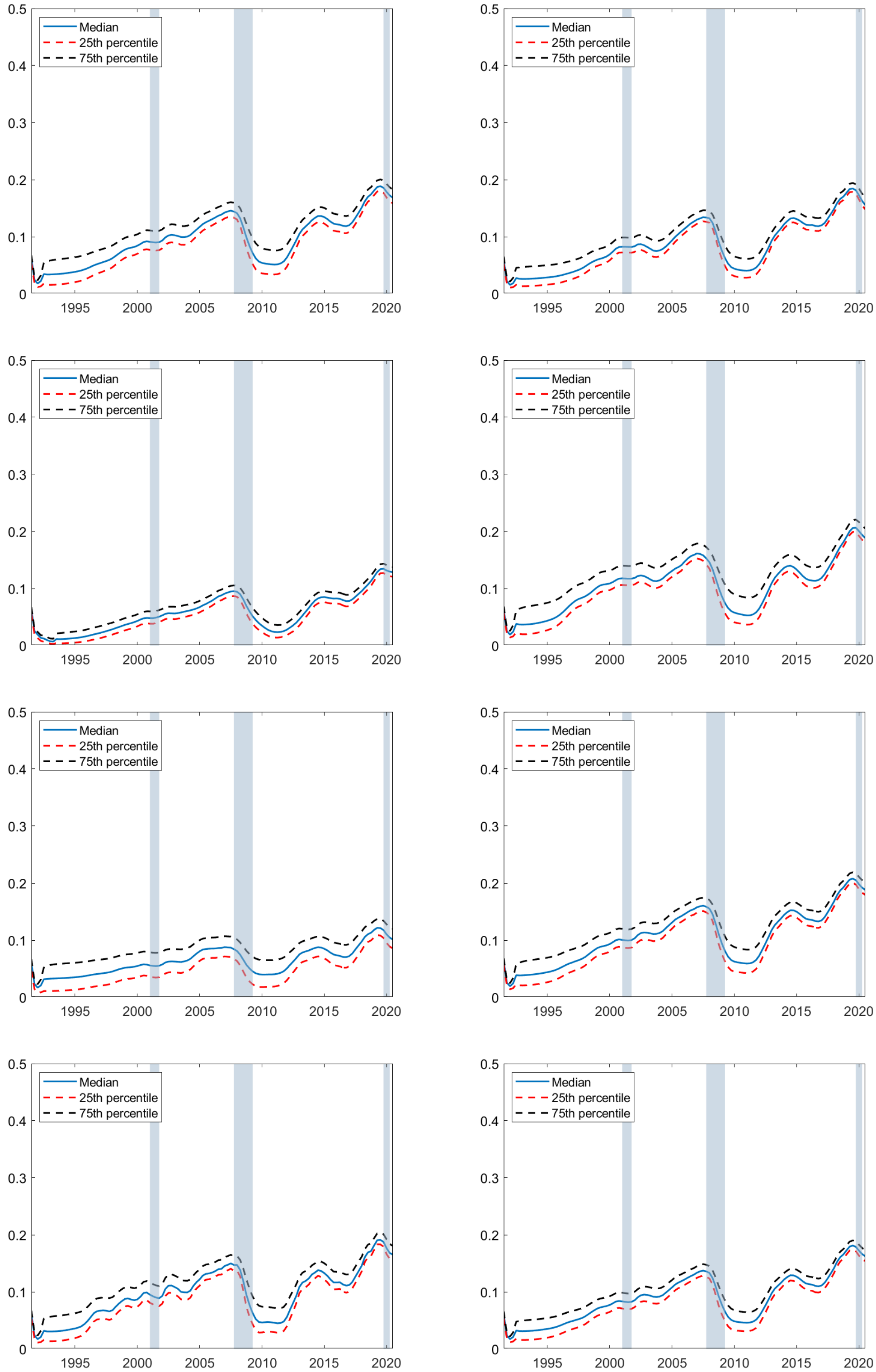


Figure C.8 Robustness of estimated Kalman gains for the inflation drift due to inflation signal. (1)-(4) are shown in left column and (5)-(8) in right column.

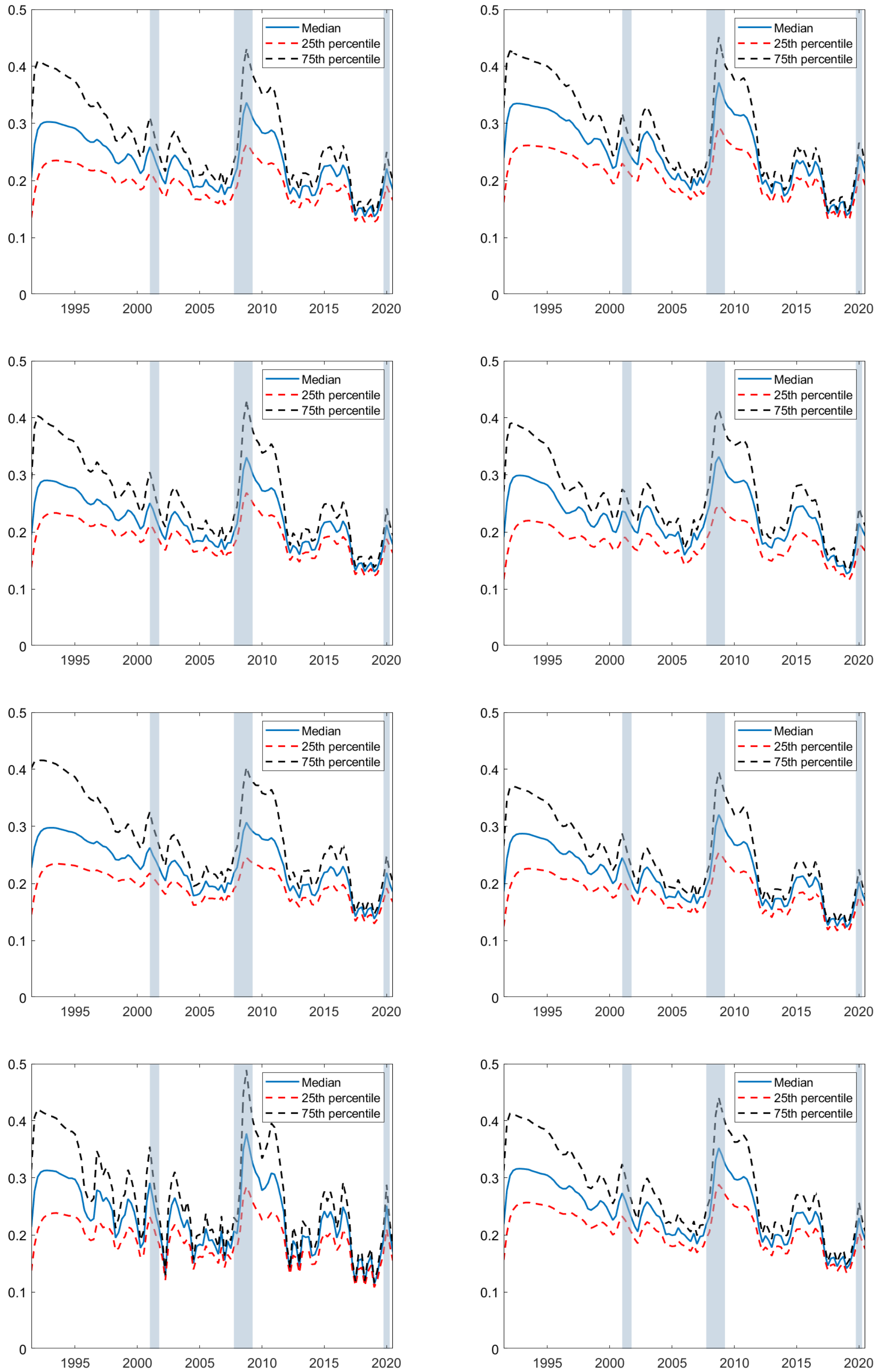


Figure C.9 Robustness of estimated Kalman gains for the inflation drift due to news signal. (1)-(4) are shown in left column and (5)-(8) in right column.

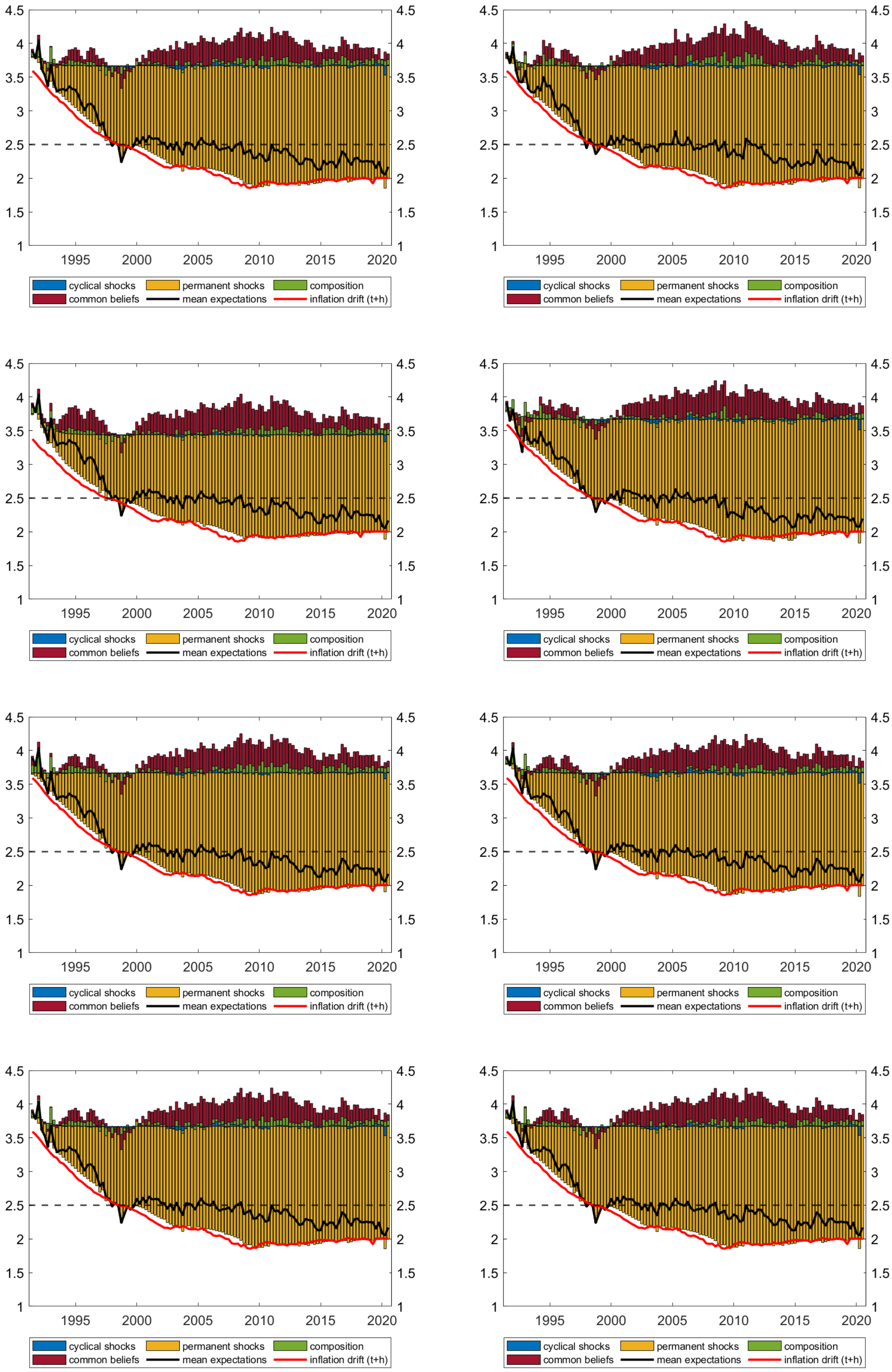


Figure C.10 Robustness of estimated historical decomposition of average inflation expectations. (1)-(4) are shown in left column and (5)-(8) in right column.

C.8 Projection exercise

In the following we describe the detailed procedure underlying the projection exercise in section 3.8. The projection exercise starts in 2020Q4 since our estimation sample goes until 2020Q3.

Part 1: Path of inflation expectations based on SEP inflation paths

1. Construction of **inflation paths** from 2020Q4-2026Q4:
   (a) 2020Q4-2021Q3: we use the realized core CPI inflation rate
   (b) 2021Q4-2026Q4: we use the median, lower or upper range path for PCE core inflation from the September 2021 Summary of Economic Projections. For each year from 2021-2024, the forecasts refer to the year-on-year growth rate of the fourth quarter and we rescale the forecasts by 50 basis points to be consistent with core CPI inflation. From 2025Q4 onwards we assume that inflation is equal to the longer run projection of 2% rescaled again by 50 basis points to be consistent with core CPI inflation. For the missing quarters we obtain the inflation path based on linear interpolation.
2. Estimation of **inflation drift**: We estimate the inflation drift using the estimated trend-cycle model in equation (3.1)-(3.3). The sample goes from 2020Q4-2026Q4 and we use the parameter estimates from the time series estimation and the estimates of the state and co-variance matrix in 2020Q3 as initial conditions. In order to handle the extremely large shock in 2021Q2, we follow the approach by Lenza and Primiceri (ming) and allow for a rescaling of the shock volatilities σ_η and σ_λ. Denoting the scaling factor by s_t, $s_t = 1$ before 2021Q2, $s_{2021Q2} = \beta$ and from 2021Q3 onward $s_{2021Q2+j} = 1 + (\beta - 1)\gamma^j$ with j>0. We estimate the parameters s_0 and ρ using uniform priors. For the median SEP scenario we obtain β=4.758 and γ=0.088. Finally, we use the Kalman smoother to obtain an estimate of the unobserved inflation drift. The estimated inflation drifts together with the corresponding inflation paths are shown in Figure 3.8.
3. Estimation of **inflation expectations**: We use the inflation and inflation drift series obtained in the previous two steps as observables in the state-space model of the econometrician (see equations (3.11)-(3.12)). Note that the sample goes until 2025Q4 but we only observe SPF inflation expectations until 2021Q3. Afterwards they are treated as missing values. We keep all parameter estimates equal to the estimated values shown in Table 3.2 and assume $\sigma_{\nu,t}$ is equal to the value estimated for 2020Q3 until the end of the sample. Applying the Kalman smoother we

obtain estimates of all the state variables. We compute mean inflation expectations across forecasters as plotted in Figure 3.9.[2]

Part 2: Inflation path required to cement expectations at 2.5% (anchoring)

1. Estimation of **inflation drift**: We follow steps (i)-(ii) in Part 1 but only focus on the SEP median inflation path.
2. Using the drift from step (i), we have all observables in the panel estimation available from 2020Q4 until 2021Q3. We use the Kalman filter of the state-space model of the econometrician as defined in Equation (3.11)-(3.12) to obtain filtered estimates of the state variables. We assume $\sigma_{\nu,t}$ is equal to the value estimated for 2020Q3.
3. Now we use the states from the previous step as initial conditions to run the Kalman filter from 2021Q4 until 2025Q4. We only observe the inflation drift from step (i) for the whole sample. Individual inflation expectations are not available and since we want to cement expectations at 2.5% we impose that average inflation expectations are equal to 2.5%.[3] We use the same state-space model as defined in Equation (3.11)-(3.12) except that we append the shocks as state variables and then we use two scenarios for communication that imply the following measurement equations:

   (a) **with communication:**

$$\begin{bmatrix} \hat{\pi}_t \\ \bar{\pi}_{t+h} \\ 2.5N \end{bmatrix} = \begin{bmatrix} \mathbf{1}_1 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & ... & \mathbf{0}_{1\times k} & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{1}_3 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & ... & \mathbf{0}_{1\times k} & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{0}_{1\times k} & \mathbf{1}_3 & \mathbf{1}_3 & ... & \mathbf{1}_3 & 0 & 0 & 0 & \mathbf{0}_{1\times N} \end{bmatrix} \begin{bmatrix} \xi_t \\ \xi_{t|t}(1) \\ \xi_{t|t}(2) \\ \vdots \\ \xi_{t|t}(N) \\ \epsilon_t \\ \lambda_{t+h} \\ \nu_t \\ \overrightarrow{z}_t \end{bmatrix}$$

[2]Note that we compute the mean across the inflation expectations of all forecasters even if they have only been in the survey many years ago. Computing just the mean across forecasters who have been active in the survey in 2021 yields very similar results.

[3]In 2021Q2 and 2021Q3 mean inflation expectations are close to 2.5 with values of 2.485 and 2.631, respectively.

(b) **no communication (ν_t=0):**

$$\begin{bmatrix} \hat{\pi}_t \\ \bar{\pi}_{t+h} \\ 2.5N \\ 0 \end{bmatrix} = \begin{bmatrix} \mathbf{1}_1 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{1}_3 & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{0}_{1\times k} & \mathbf{1}_3 & \mathbf{1}_3 & \dots & \mathbf{1}_3 & 0 & 0 & 0 & \mathbf{0}_{1\times N} \\ \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \mathbf{0}_{1\times k} & \dots & \mathbf{0}_{1\times k} & 0 & 0 & 1 & \mathbf{0}_{1\times N} \end{bmatrix} \begin{bmatrix} \xi_t \\ \xi_{t|t}(1) \\ \xi_{t|t}(2) \\ \vdots \\ \xi_{t|t}(N) \\ \epsilon_t \\ \lambda_{t+h} \\ \nu_t \\ \overrightarrow{z}_t \end{bmatrix}$$

4. Using the Kalman smoother we obtain smoothed estimates of $\hat{\pi}_t$ from step (iii) for both cases.
5. Since these inflation paths are not necessarily consistent with the inflation drift used as input we apply a bisection algorithm to solve for a "fixed point". Using the obtained inflation path as input to step (i) we iterate over steps (i)-(iii) until convergence for each of the two cases with and without communication.[4] The implied inflation paths are plotted in the rhs of Figure 3.10 together with the SEP projections. The estimated inflation drift paths are plotted in the lhs of the same figure.
6. In order to assess the contribution of communication to average inflation expectations we estimate the historical decomposition of average inflation expectations using the Kalman smoother based on the measurement equations defined in the case with communication above (see also section C.6). We start from 2021Q3 as initial condition. The historical decomposition is shown in Figure C.11. Then, the black dotted line in the lhs of Figure 3.10 is computed as the mean expectations minus the contribution of communication (red bars).

[4]Since we need an inflation path until 2026Q4 for step (i) we assume that inflation in 2026Q1-2026Q4 is the same as in 2025Q4.

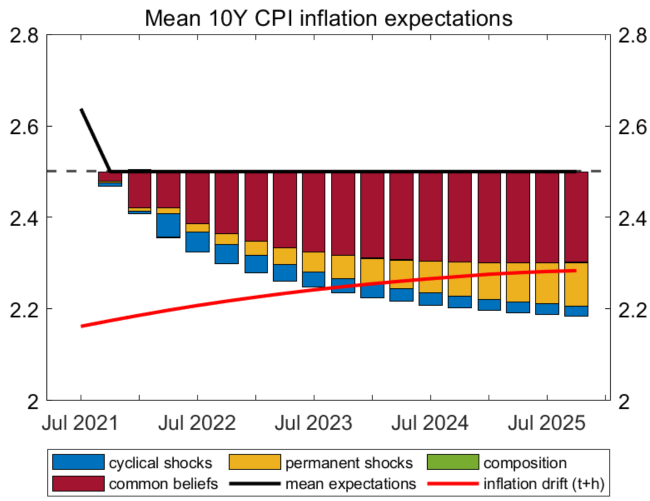


Figure C.11 Historical decomposition of mean expectations under projection exercise