Year: 2024

THREE ESSAYS IN MACROECONOMICS

Lauper Christoph

UNIL | Université de Lausanne

FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT D'ÉCONOMIE

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THÈSE DE DOCTORAT

présentée à la

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pour l'obtention du grade de

Doctorat en économie

par

Christoph LAUPER

Directeur de thèse
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Prof. Boris Nikolov, président
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Prof. Burçin Kısacıkoğlu, expert externe

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Three Essays in Macroeconomics

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Acknowledgements

I am deeply grateful to my PhD supervisor, Prof. Jean-Paul Renne, for his invaluable guidance and support over the years. His dedication and insights have been instrumental in the completion of this thesis. My sincere thanks also go to my thesis committee members, Prof. Kenza Benhima and Prof. Burçin Kısacıkoğlu, for their precise comments and insightful feedback, which have significantly improved the quality of this work. I would also like to thank Prof. Philipp Bacchetta, Prof. Aurélien Eyquem, and Prof. Pascal St-Amour for sharing their knowledge, time, and experience with me.

This journey would not have been possible without the constant support, help, and encouragement of many fellow doctoral students. Aleksandra and Giacomo were great companions and friends during a very intense first year at the University of Zurich. Their camaraderie has been an important source of strength and motivation. I would also like to thank my co-authors, Giacomo and Adrien, for our fruitful exchanges and good collaboration. Working with them has been a rewarding experience from which I have learned a lot.

I am also indebted to many colleagues in the Department of Economics for the good team spirit, encouragement, and enriching discussions. While many deserve mention, I am particularly grateful to Pauline and Pascal, who have been extremely helpful to me personally and have worked tirelessly to also improve the situation for all PhD students in the department.

Special thanks go to Mathieu Grobéty for giving me the opportunity to work with him at CREA during the last year. This has been a great help to me in completing my dissertation.

Finally, I would like to express my deepest gratitude to my family. To my parents, Gabriela and Jürg, for their unconditional love and support, which has been a constant source of strength. To my siblings, Jacqueline and Marco, for their encouragement and understanding. And to my partner, Nadja, for her unwavering support, patience, and encouragement, which have been invaluable to me. Your love and belief in me have made this possible.

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Introduction

Traditionally, monetary policy analysis has revolved around assessing the aggregate effects of conventional monetary policy shocks, typically characterized by changes in short-term interest rates. This approach abstracts from several important aspects. First, it ignores the distributional effects of monetary policy shocks, as different demographic groups and economic sectors are affected very differently by these policy actions, which highlights the need for a more nuanced understanding of their impact. Second, monetary policy is more complex than simple changes in interest rates. Central bank communication can play a crucial role, introducing significant information effects that influence market expectations and the effectiveness of monetary policy. Third, the nature of the underlying shocks, to which monetary policy responds, is often not sufficiently taken into account in simplified structural frameworks, where monetary policy is independent from underlying shocks to the economy. This requires more careful consideration of the relative importance of different macroeconomic shocks.

For these reasons, there has been a growing recognition in recent years that a more granular view of monetary policy is needed, in order to better understand its effects and implications, and to also understand better the distributional aspects of these policies. This thesis aims to improve the understanding of monetary policy and the underlying shocks in multiple dimensions, by delving deeper into different aspects and shortcomings around the analysis of monetary policy. More generally, it aims to contribute to a more thorough understanding of monetary policy, its transmission, and the macroeconomy.

To this end, I employ a variety of different methods to disentangle the dynamic causal effects of monetary policy, using tools such as Local Projections, proxy VAR, and noisy information models. I draw upon various data sources to empirically derive exogenous shocks. Monetary policy shocks are derived from narrative methods, as documented by Romer and Romer (2004), as well as from high-frequency asset price surprises around monetary policy announcements, as outlined by, among many, Gertler and Karadi (2015). In addition, to assess the relative importance of supply and demand shocks, the thesis uses survey data from the US Survey of Professional Forecasters, enriching the analysis with real-time, forward-looking expectations data to gain a more nuanced view on macroeconomic dynamics.

The thesis applies these different methodologies to examine the effects on a wide range of macroeconomic data series, including household-level inflation rates and various measures of inflation dispersion, high and low-frequency exchange rate data, and other macroeconomic time series such as GDP and inflation. The subsequent chapters of this thesis are structured as follows:

Chapter 1 examines the relationship between monetary policy and the heterogeneity of individual inflation rates across households. We compute household-level inflation rates and show that contractionary monetary shocks strongly reduce inflation dispersion, while the median of individual inflation rates closely follows the official, aggregate inflation rate. Focusing on the underlying sectoral inflation rates, we show that expenditure categories such as energy, water, and gasoline are highly sensitive to monetary policy, while at the same time, these are categories where the fraction of household expenditures varies strongly across households. Combined, this explains why these three sectors play a crucial role in driving the observed decline in inflation dispersion after a contractionary monetary policy shock.

In light of these findings, the first chapter examines further how monetary shocks affect inflation rates across different demographic groups, shedding light on inflation inequality. We show that inflation tends to be lower and more sticky for high-income households, when compared to low and middle-income households. We then use these findings to demonstrate that the effect of monetary policy on (real) expenditure inequality is significantly dampened when controlling for differences in individual inflation rates. By taking inflation heterogeneity into account, this chapter provides new insights into the dynamics of inflation inequality in response to monetary policy shocks.

Chapter 2 focuses on the informational components of monetary policy and, in particular, their impact on exchange rates. By distinguishing between conventional and informational monetary policy shocks, the chapter highlights the influence of central bank communication on market expectations and thus on exchange rate dynamics. Through an analytical exchange rate decomposition, it is shown that exchange rates are expected to react strongly to informational shocks, taking into account not only the interest rate differential but also changes in the expected path of inflation, and hence the stance of monetary policy.

The empirical analysis uses a factor model and high-frequency asset price changes around monetary policy announcements, and derives different monetary policy shocks by applying zero and sign restrictions. This methodology disentangles Delphic and Odyssean shocks: While Delphic shocks capture changes in the market's economic outlook, Odyssean shocks represent an exogenous change in future monetary policy. I find that exchange rates are highly sensitive to central bank information shocks, appreciating after both positive Delphic and Odyssean shocks. Both shocks are more meaningful for exchange rates when compared to conventional monetary policy shocks.

Finally, Chapter 3 addresses the time variation in the relative importance of supply and demand shocks in the US over the past 50 years. The effectiveness of monetary policy depends on the underlying nature of the shocks to which it seeks to respond. While monetary policy can effectively mitigate demand shocks, its ability to counter supply shocks comes at a much greater cost. Recognizing this, the chapter creates additional insights by challenging the assumption of constant relative importance of supply and demand shocks, or homoscedasticity, over time.

The chapter proposes a novel measure to quantify changes in the relative importance of these shocks over time, based on the covariation of individual GDP and inflation forecasts. In doing so, the chapter offers a novel perspective on the long-run changes in the importance of different macroeconomic fluctuations over time. By using survey data and departing from the perfect information assumption, the chapter provides insights into how professional forecasts can be used to establish a measure of the importance of supply and demand shocks, providing new insights into the impact on GDP and inflation dynamics. It shows theoretically, using a synthetic model that uses noisy information and agents that form predictions based on the Kalman filter, how the covariation between forecasts and the relative importance of different underlying shocks are connected. The empirical part shows that the derived measure of supply or demand dominance correlates with ex-post measures of the relative importance of supply and demand shocks, as well as its effect on the term premium. This research contributes to a more nuanced understanding of the underlying drivers of business cycles.

Each chapter in this thesis contributes to a deeper understanding of the functioning of the economy and the effects of monetary policy, providing insights for policymakers and researchers. The thesis contributes to a more refined understanding of monetary policy in several dimensions. First, it addresses the distributional effects of monetary policy, highlighting the differential effects of monetary policy that are transmitted through differential effects on the inflation rate faced by individual households. Second, it explores the informational components inherent in central bank communications and decisions and their influence on exchange rates. Finally, it introduces a novel measure to quantify changes in the relative importance of demand and supply shocks over time, providing new insights into the drivers of macroeconomic fluctuations.

Taken together, these contributions advance the understanding of monetary policy in multiple directions, shedding light on its drivers and effects more generally. By examining the underlying shocks, the potential information effects that stem from central bank communication, and the important distributional effects caused by monetary policy actions, this research provides a more refined picture of monetary policy in general, but also suggests multiple directions with high potential for future research. This is laid out in more detail in the subsequent chapters.

Chapter 1

Monetary Policy Shocks and Inflation Inequality[†]

1.1 Introduction

The relationship between monetary policy and heterogeneity has become increasingly important in macroeconomic research, both from a theoretical and empirical point of view. Changes in interest rates do not impact households homogeneously. Renters and homeowners, savers and hand-to-mouths, high-skilled and low-skilled workers are only a few examples of different demographic groups that have been found to bear the consequences of the decisions made by the monetary authorities in completely different ways. Therefore, in the last few years, both economic researchers and central bankers have shifted their focus from aggregate to more granular effects to better understand the different channels through which monetary policy can affect individual households and firms. However, the importance of inflation heterogeneity, i.e., the different inflation rates experienced by households due to the variations in the consumption baskets they purchase, for the distributional effects of monetary policy has so far received limited attention.

This paper studies how monetary policy influences the distribution of the individual inflation rates to which different households are exposed. We compute a measure of the inflation rate at the household level and we document that contractionary monetary shocks reduce the median as well as the cross-sectional standard deviation of the distribution of inflation rates. The decrease in inflation dispersion is almost entirely driven by expenditures on *Energy*, *Water*, and *Gasoline*. The inflation rate of these sectors, despite the fact that they account for a relatively small share of the aggregate consumption bundle, is extremely sensitive to changes in interest rates. We then study how the inflation rates of different demographic groups are heterogeneously affected by monetary shocks. We show that *inflation inequality*, defined as the cross-sectional standard deviation of the decile-specific inflation rates across expenditure, salary, and income deciles, decreases after a contractionary monetary

[†]This chapter is co-authored with Giacomo Mangiante from the Banca d'Italia.

shock. The reason is that households at the bottom of the distribution are exposed to a higher inflation rate which tends at the same time to decrease more following a monetary shock. Finally, we find that the increase in expenditure inequality in response to monetary shocks is significantly more muted once inflation heterogeneity is taken into account.

The first contribution of this paper is to evaluate how monetary policy influences the distribution of household-level inflation rates. To compute individual inflation rates, we combine item-level price data from the Bureau of Labor Statistics (BLS) with individual expenditure data from the CEX for the U.S. from 1980 onward. We evaluate how the different moments of the inflation rates distribution, i.e., the median and the standard deviation, react to monetary policy shocks by adopting a Local Projection approach à la Jorda (2005). Exogenous variations in interest rate are captured using the Romer and Romer (2004) monetary shocks series. We document that contractionary monetary policy shocks decrease the median inflation rate as well as significantly reduce the dispersion of the distribution.

The second contribution is to assess which sectors are mainly responsible for the decrease in inflation dispersion. The price indexes of different sectors have different sensitivity to monetary policy shocks. We document that *Energy*, *Water* and *Gasoline* are by far the most influenced by contractionary shocks and they explain almost entirely the response of inflation dispersion to monetary shocks even though they account for only a relatively small expenditure share.

The third contribution is to study whether the inflation rates of different demographic groups are heterogeneously affected by monetary policy. We demonstrate that contractionary shocks lead to a sizable decrease in inflation inequality. On the one hand, the inflation rates of low- and middle-income households tend to be higher than those one of high-income households. On the other hand, it is more reactive to shocks and therefore decreases relatively more after a monetary shock. The same result holds for salary and expenditure deciles, confirming the important role of endowments in the dynamics of individual inflation rates.

The fourth contribution of the paper is to evaluate how these new findings on inflation heterogeneity influence real expenditure inequality and its response to monetary shocks. We compute two measures of real expenditure at household-level: one deflating nominal expenditure by the aggregate price level (as is common in the literature, neglecting inflation heterogeneity) and one deflating each expenditure category by the relative sectoral price level. As expected, we find that assuming all households are exposed to the same inflation rate overestimates the impact of monetary policy shocks on expenditure inequality. Although the nominal expenditure of low- and middle-income households decreases more after a shock compared to that of high-income households, their inflation rates also decrease relatively more, partially offsetting this decrease in real terms. It is important to underline that real consumption heterogeneity is still found to increase after a monetary shock corroborating again the evidence of the sizable distributional effects that central banks can have on the economy.

The level as well as the sensitivity of household-level inflation rates to changes in interest rates are strongly correlated with demographic characteristics. Therefore, abstracting from also considering how the individual inflation rates adjust in response to shocks would lead to systematic biases by the monetary authorities against specific demographic groups. For instance, since low-income households experience a higher inflation rate relative to high-income households, they would benefit from a more aggressive monetary policy than the one implemented by focusing only on the aggregate inflation rate. This problem could even be exacerbated by the fact that central banks usually design their policies targeting a specific subset of the price indexes. As we document, core measures of inflation, i.e., excluding energy and food, greatly underestimate the overall level of inflation dispersion in the economy. Finally, the empirical findings we provide suggest that central banks should pay close attention to inflation heterogeneity as whether it is taken into account or not has important implications for the magnitude of the distributional effects caused by the monetary authorities' decisions.

Related literature. This paper contributes to two strands of the literature. The first one is the research agenda on inflation inequality. Households are exposed to different levels of price increases given the heterogeneous consumption baskets they consume. For the U.S., Thesia et al. (1996), Hobijn and Lagakos (2005), Leslie and Paulson (2006), Johannsen (2014), and Orchard (2022) measure inflation inequality using the CEX data which covers the full consumption basket. More recently, Kaplan and Schulhofer-Wohl (2017), Argente and Lee (2021), and Jaravel (2019) compute inflation inequality from scanner data which is available for a much more limited time period but provides information at a higher level of granularity. The differences in inflation rates across households have been found to be substantial over time as well as related to demographic characteristics. For instance, high-income households are exposed to lower inflation rates compared to low- and middle-income households. See Jaravel (2021) for a review of the growing literature on inflation inequality.

Particularly related to the results of our paper, Cravino et al. (2020) show that the inflation rate of high-income households reacts significantly less than that of middle-income households following a monetary shock. We contribute to this literature by studying how inflation dispersion across households responds to monetary policy shocks. We document that contractionary shocks decrease the cross-sectional dispersion in household inflation rates. Almost the entire effect is due to the higher sensitivity of the prices of *Energy*, *Water*, and *Gasoline* to changes in the interest rate. Combining two results from the existing literature regarding the fact that lower- and middle-income households are exposed to a higher inflation rate, as documented by Kaplan and Schulhofer-Wohl (2017) and Jaravel (2019), and that at the same time, their inflation rate decreases relatively more following a monetary shock, as shown in Cravino et al. (2020), we find that inflation inequality across income, salary, and expenditure deciles decrease in response to a monetary shock.

The second strand is the growing literature on the distributional aspects of monetary policy. With an approach analogous to the one we adopt, Coibion et al. (2017) document that consumption and income inequality in the U.S. increase following a contractionary monetary shock. Similar findings have also been found in other countries and in different time periods, e.g., Mumtaz and Theophilopoulou (2017) for the United Kingdom, Guerello (2018) and Samarina and Nguyen (2023) for the Euro Area, Furceri et al. (2018) for a panel of 32 advanced and emerging economies. A summary of the current empirical and theoretical literature on the relationship between monetary policy and inequality is provided by Colciago et al. (2019).

We show that neglecting inflation heterogeneity results in an overestimation of the impact of monetary policy shocks on expenditure inequality. In response to a contractionary monetary shock, the stronger decrease in the inflation rate of low-income households partially offset the decrease in their nominal consumption resulting in a more muted response in real terms. It follows that the distributional effects of monetary policy on expenditure inequality are more limited once inflation heterogeneity is taken into consideration.

Road map. The paper is structured as follows. Section 1.2 describes the dataset used, as well as the construction of individual inflation rates and dispersion measures. In Section 1.3 we discuss the empirical strategy and show the main results in terms of the impact of monetary policy shocks on the cross-sectional inflation distribution. Section 1.4 studies the heterogeneous responses across different demographic groups. Section 1.5 evaluates how inflation heterogeneity influences the response of real consumption inequality to monetary shocks. In Section 1.6, we perform a battery of different robustness checks to evaluate the reliability of our findings. Section 1.7 concludes.

1.2 Individual Inflation Rates

This section shows the computation of individual inflation rates at the household level by exploiting the differences in consumption patterns across households. There are three steps needed for the computation of any inflation rate. First, we need information on prices for different goods. Second, we need detailed information on (individual) consumer expenditure, which allows computing the share of different goods in an aggregate index and therefore provides weights.[1] Third, statistical agencies have to decide on a methodology to combine price data to get a meaningful measure of inflation. In the following, we discuss each step separately.

1.2.1 Inflation Data

We use data from the CPI as computed by the BLS at a monthly frequency. In particular, we use the not-seasonally-adjusted *US City Average for all urban consumers* (CPI-U). The BLS collects price data on 211 different subgroups of goods and services, which they call item strata. This is the most disaggregated level for which it publishes information on prices. However, these item strata over the period from 1980 to today undergo regular revisions or their definition is changed. Some disappear entirely and some get newly introduced. For this reason and for data availability we need to combine these basic price indices with more aggregate ones. We follow Hobijn and Lagakos (2005) and Johannsen (2014) in creating 21 indices, for which we get consistent inflation rates during our time sample. We call the

[1] The CEX proves rich enough to provide data on expenditure, going back to 1980.

inflation rates for subgroups of the consumer basket *inflation subindices*.[2] The construction of these inflation rates is subject to a tradeoff between consistent and sufficiently long time series and finely disaggregated time series that capture as much of the difference in inflation as possible. Jaravel (2019) finds that only 20% of inflation inequality is captured when using 22 expenditure categories instead of 256 for the period from 2004 to 2015. In Subsection 1.6.1 we show that increasing the number of categories considered from 21 to 121 significantly increases the *level* of inflation dispersion across households but does not affect its *sensitivity* to monetary policy shocks.

In Table 1.A1 we report the mean, median, standard deviation, the 10th and the 90th percentile of the 21 inflation subindices we compute, as well as of the Official CPI-U for the period 1980-2008. The observed sectoral inflation heterogeneity will be one of the key components in explaining the evolution of inflation dispersion. Households spend different shares of their overall expenditure on each category and, since these categories differ in terms of price volatility and price level, this will lead to differences in terms of experienced inflation.[3] In what follows, we have to find reliable weights with which we can combine the inflation subindices to get household-level inflation rates across all items.

1.2.2 Expenditure Data

For the computation of expenditure weights, we use the CEX provided by the BLS. This is the same dataset that is used to compute the official CPI of the U.S. The CEX is a quarterly survey of household expenditures and is divided into a diary and an interview survey. The diary survey covers small expenditures on daily items over a period of two weeks. The interview survey is more comprehensive, with detailed questioning every three months yielding up to a year of data for a single household. Since our goal is to get inflation rates that are as comprehensive as possible, we solely rely on data from the interview survey.

There are some limitations to the CEX data. The BLS removes consumption data from the 100th percentile (it is top-coded) to ensure anonymity. Additionally, since we deal with survey data, there are likely more measurement errors in the CEX compared to other data sources.[4] However, the CEX allows us to get a comprehensive picture of virtually all consumer expenditures and it is also sufficiently large in the time dimension (starts in 1980) and along the cross-section (roughly 5000-7000 households each wave).

[2]The list and definitions of these subindices can be found in Appendix 1.A.1.

[3]The biggest limitation of using inflation subindices is that they are not individual prices. While we capture the inflation that is due to different consumption baskets, we are not able to capture inflation differences within a subindex. It is conceivable that taking the category *Food away* as an example, high-end restaurants have different price developments from low-end ones. This problem is circumvented with Nielsen scanner data. The dataset reports product-level information on both prices and quantities so it is more granular than the CEX data. However, two major limitations made the Nielsen data a non-viable solution for our analysis. First of all, the data covers only purchases in department stores, grocery stores, drug stores, convenience stores, and other similar retail outlets which account for approximately 15% of total household expenditures. Moreover, the dataset is available only from 2004 onward.

[4]See Bee et al. (2013) for an assessment of the quality of our consumer dataset.

Like the inflation subindices, we aggregate the expenditure data into 21 groups[5], matching the classification of the CEX with the one from the price indices. In the next step, we aggregate the household-level expenses from monthly to yearly. By doing this, we get rid of seasonal patterns in expenditures, while at the same time "averaging out" extraordinary expenses and hence improving the quality of our data. With this approach, almost the entire variation in individual inflation rates comes from price changes, rather than from changes in consumption patterns. Hence, the variation in individual inflation rates is mainly driven by the dynamics of sectoral inflation rates, as opposed to being driven by changes in the consumption bundle, as we intend. The relevance of the substitution effects is studied in Subsection 1.6.1 where we compute the expenditure shares at higher frequencies.

1.2.3 Computation of Individual Inflation Rates

In the third step, we combine the expenditure data with the inflation data. For this, we compute consumption shares w_j^i for household i and item subgroup j, which are calculated by dividing the yearly consumption expenditure in a certain period by the total expenditure reported in the same period. In the baseline analysis, we use all 21 categories. We compute the individual inflation rate for household i as:

$$\pi_{t-k,t}^i = \sum_{j \in J} w_j^i \pi_{j,t-k,t}, \tag{1.1}$$

where j denotes the item subgroup as defined in Section 1.2.2. The inflation rate of the subindex for good j in period t with base period $t-k$ is denoted by $\pi_{j,t,t-k}$. We set $k = 12$, meaning year-on-year inflation rates, which removes seasonality in the inflation subindices. Additionally, we winsorize the individual inflation rates at the 1st and the 99th percentile. In the next step, we analyze the statistical properties of individual inflation rates.

1.2.4 Properties of Individual Inflation Rates

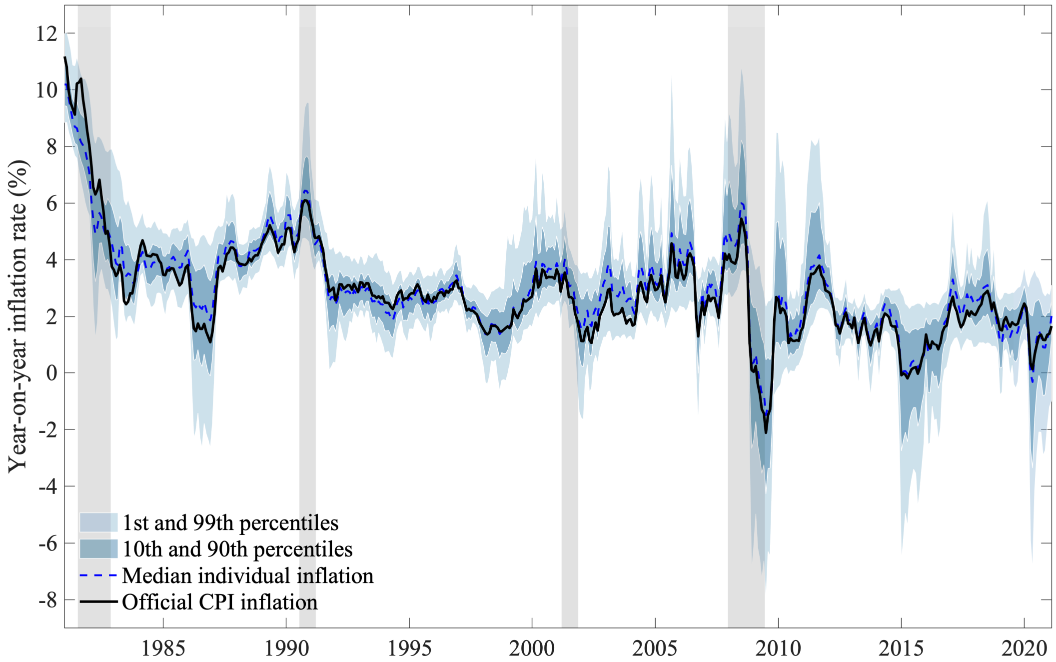
We assess the validity of the measures of individual inflation computed above by comparing the official CPI inflation rate with the median of individual inflation rates in Figure 1.1.[6] In the same figures, we also show different percentiles of the calculated household-specific rates of inflation.

The median of the distribution of household-specific rates of inflation closely tracks the headline value of CPI inflation. Hence, our approach gives, in an aggregate world, very similar results to the official CPI inflation rate. This result shows why for many years economic models mainly focused on the representative agent: The time series of the experienced

[5] In computing household-level inflation rates we have to alter the *Housing* group and omit the *Vehicle* group altogether. In particular, we follow Johannsen (2014) and we use the question on rental equivalence for the owned dwelling expenditures of the homeowners. Moreover, we exclude expenditures on new and used vehicles since in a given year the purchase of a vehicle could dominate all other expenditures. When we compute the inflation rate across deciles, vehicle purchases are included since it is less likely this category can bias the decile-level inflation rates. See Appendix 1.A.3 and Appendix 1.B for more details.

[6] Similar results are obtained for the mean of the distribution.

Figure 1.1: Official CPI Inflation, Cross-Sectional Distribution, and Median Individual Inflation Rate Over Time



Notes: This figure shows the evolution over time of the official CPI inflation as well as the median and selected percentiles (1st, 10th, 90th, and 99th) of the winsorized cross-sectional distribution in individual inflation rates. The gray shaded areas depict U.S. recessions.

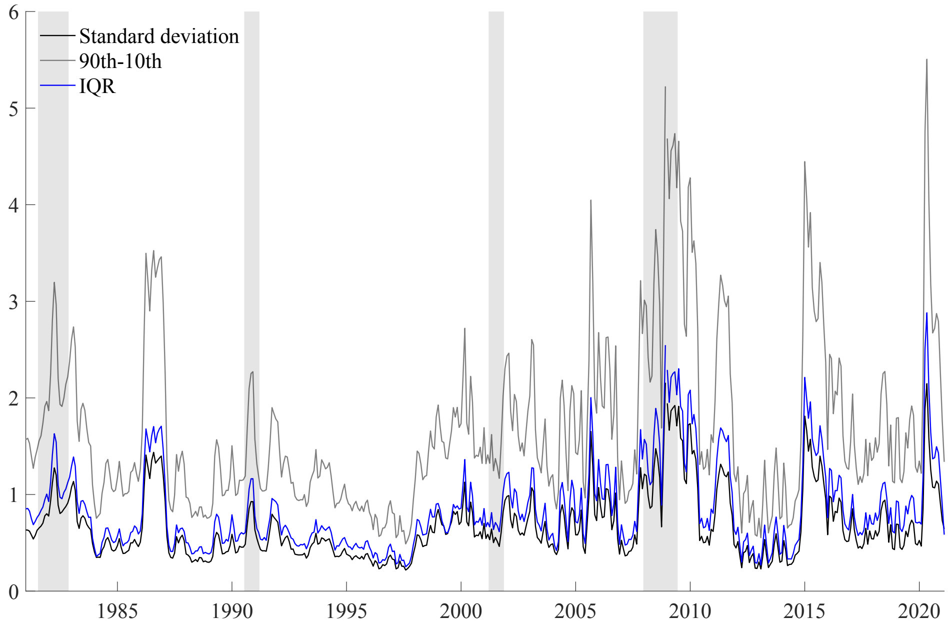
inflation for the "median household" can be considered a quite good approximation of the aggregate economy.

At the same time, the individual inflation rate percentiles in Figure 1.1 reveal how much information is lost when ignoring the heterogeneity across households. Not surprisingly, macroeconomic models have been expanded to include heterogeneity in consumption, wages, asset portfolio composition, and many more. However, most models still abstract from inflation differences and implicitly assume that households are exposed to the same inflation rate. Figure 1.1 strongly rejects this assumption.

1.2.5 Measures of Dispersion

To evaluate how monetary policy shocks affect inflation dispersion in the U.S., we construct three different measures of dispersion: the cross-sectional standard deviation, the difference between the 90th percentile and the 10th percentile (depicted as 90th-10th, henceforth), and the cross-sectional interquartile range (IQR). To avoid the change in the survey composition affecting our results, we calculate the variation in the inflation dispersion measures on the households present in both periods. Therefore, when we calculate the change in the cross-sectional standard deviation from t to $t+1$, we do it only for the households that are present during both periods. Sampling weights are applied throughout the analysis.

Figure 1.2: Historical Series of Inflation Dispersion Measures



Notes: This figure shows the evolution of inflation dispersion measured using the cross-sectional standard deviation, the difference between the 90th and the 10th percentile of the cross-sectional distribution, and the IQR. All the series refer to the period 1981M1:2020M12. The gray shaded areas depict U.S. recessions.

Figure 1.2 shows the historical evolution of the three measures of dispersion, together with U.S. recessions. The three variables are highly correlated, suggesting that a normal distribution approximates the computed individual inflation rates very well. Despite using a different time period and alternative CPI categories, the time series are comparable in magnitude to those found by Johannsen (2014). As one can notice, inflation dispersion tends to increase during U.S. recessions suggesting a sort of correlation with the business cycle in the economy.

1.3 The Effects on Inflation Dispersion

This section presents the results of our empirical analysis. We first study whether and to what extent monetary policy shocks influence aggregate inflation dispersion. We then investigate which expenditure categories drive the main results of our analysis.

1.3.1 Methodology

In the baseline specification, we adopt the Local Projection (LP) method developed by Jorda (2005). As in Cravino et al. (2020), we estimate a series of regressions for the dependent variable over different horizons on the monetary policy shock in period t and controlling for the lags of the shock as well as of the dependent variable:

$$x_{t+h} - x_t = c_h + \beta_h e_t^{RR} + \sum_{j=1}^{J} \theta_{h,j}(x_{t+1-j} - x_{t-j}) + \sum_{i=1}^{I} \gamma_{h,i} e_{t-i} + \epsilon_{t+h}, \tag{1.2}$$

where x is the variable of interest and the monetary policy shocks are denoted by e_t^{RR}. In line with the literature, we include 48 lags of the shocks and 6 lags of the dependent variable as controls. The coefficient β_h for $h = 1, ..., H$ gives the response of the dependent variable at time $t+h$ to a monetary policy shock at time t.[7] The impulse responses are computed over a horizon of 48 months using data from 1980M1 to 2008M12. Standard errors are corrected as in Newey and West (1987). For each impulse response, we present the one and 1.65 standard deviation confidence intervals. Unanticipated changes in the short-term interest rate are identified using the monetary policy shock series devised by Romer and Romer (2004, henceforth called R&R shocks) and extended by Coibion et al. (2017).[8]

The R&R shocks stop before 2009 so the zero lower bound period is excluded. In Appendix 1.D we perform some additional analysis using as an alternative measure of monetary shocks the proxy from Bauer and Swanson (2022) which spans from 1988 to 2019. The main results of the paper hold considering the most recent period as well.

1.3.2 Analysis

We evaluate the overall effects of a contractionary monetary policy shock on inflation dispersion by estimating equation (1.2) using the cross-sectional standard deviation as the baseline measure of inflation dispersion.[9] The results are reported in Figure 1.3. The top panel shows the responses of the annual inflation rate computed by the BLS (blue line) as well as of the median inflation rate across households (black line): following a contractionary shock, the annual rate decreases by approximately 1.5 percentage points, a magnitude in line with the literature. As one might have expected looking at Figure 1.1, the response of the median inflation rate closely matches the response of aggregate inflation.

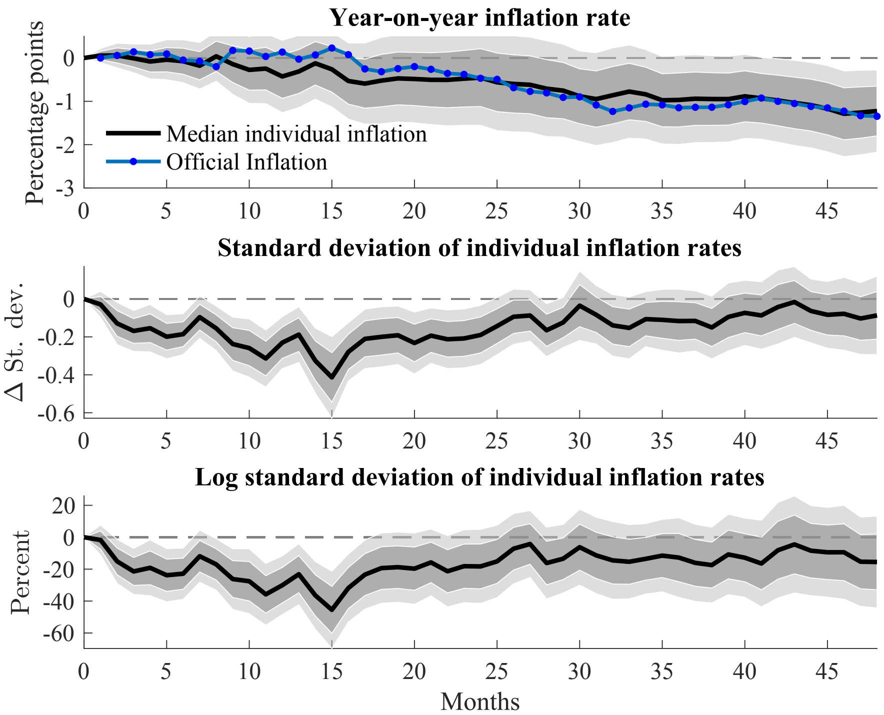
In the middle panel of Figure 1.3, we show the impulse response of our dispersion measure. Inflation dispersion decreases after a contractionary monetary policy shock and remains persistently below zero. Looking at the one and 1.65 standard deviation confidence intervals we can easily reject the null hypothesis that the coefficients are equal to zero for the horizon considered. Therefore, the impulse response strongly suggests that monetary policy shocks lead to a decrease in the inflation dispersion in the economy.

[7] As an alternative specification, we also use the R&R shocks as an instrument for the change in interest rate (IV-LP) instead of directly inserting them in the LP and the results remain basically unchanged.

[8] Coibion (2012) shows how the Romer and Romer (2004) approach might be particularly sensitive to the period in which the Federal Reserve abandoned targeting the federal fund rate between 1979 and 1982. Therefore, in Section 1.6 we redo the analysis starting the sample in 1985, and showing that our results are not driven by these large monetary policy shocks in the early 80s.

[9] The responses for the difference between the 90th and the 10th percentile of the cross-sectional distribution and the IQR are reported in Figure 1.E1. Given the very high correlation among dispersion measures, the IRFs display similar patterns differing mainly in the magnitude of the response.

Figure 1.3: Impulse Responses of the Year-on-Year Inflation Rate as well as the Median and the Standard Deviation of the Individual Inflation Rate Distribution



Notes: The top panel of this figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the official annual inflation rate (black line) and the median inflation rate (blue line) of the individual inflation rate distribution. The middle panel reports the impulse response using as the dependent variable the dispersion in inflation, measured by the cross-sectional standard deviation and the bottom panel the log of the dispersion measure such that it can be interpreted as a percent change relative to the steady state. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

To quantify the magnitude of the decrease in the inflation dispersion, the bottom panel computes the same impulse response but uses the log of the dispersion measure as the dependent variable, such that the magnitude can be interpreted as a percentage change relative to the steady state. Following a contractionary shock, we find that the cross-sectional standard deviation of inflation rates at the household level decreases by around 40% after 15 months and approximately 20% at the end of the horizon considered. The average inflation rate over the same time period is about 3.75% so a decrease of 1.5 percentage points corresponds to a decrease in 60% of the average value.

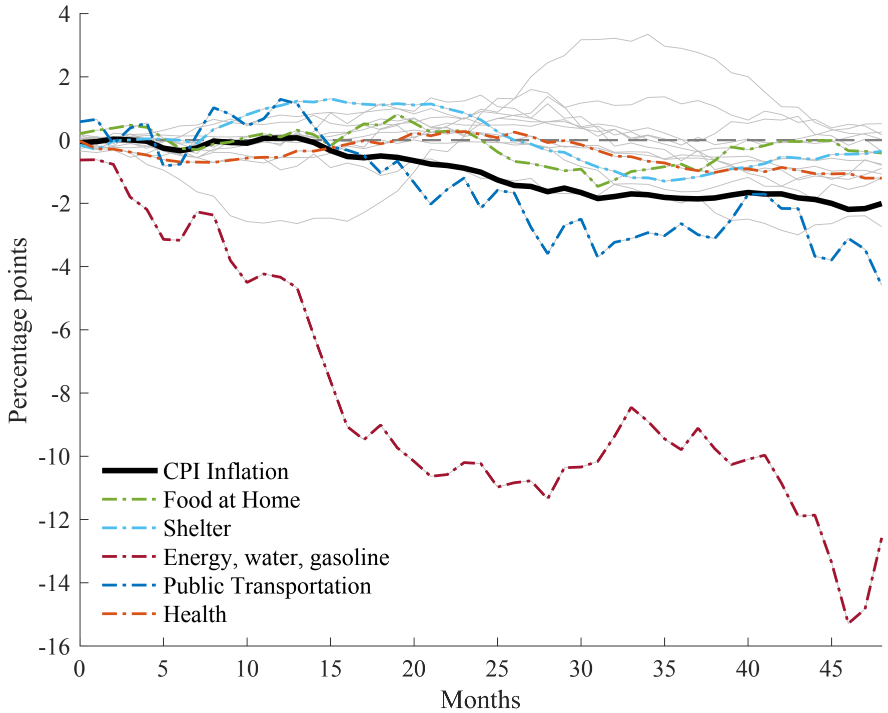
1.3.3 Sectoral Contribution

The individual inflation rates are constructed assuming there is no substitution across categories in response to a monetary policy shock.[10] Therefore, the decrease in inflation dispersion is entirely due to the fact that the inflation of different sectors is heterogeneously sensitive to exogenous changes in the interest rate. To evaluate which sectors are mainly responsible for

[10]This is an assumption which we relaxed in Subsection 1.6.1.

the results documented in the previous sections, we compute the response of several sectoral inflation rates to a contractionary shock. The results are reported in Figure 1.4.

Figure 1.4: Sectoral Inflation Rates Impulse Responses



Notes: This figure shows impulse responses of some of the different sectoral inflation rates that compose the Official CPI inflation (thick black line) to a one percentage point contractionary monetary policy shock. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12

The impact of monetary shocks on the inflation rates is extremely heterogeneous across sectors in line with the empirical evidence from Boivin et al. (2009) and Duarte and Dias (2019). Comparing the sectoral responses to the response of aggregate CPI it emerges that the majority of inflation rates at the sectoral level are only marginally affected by monetary policy shocks. In contrast, the inflation rates of *Public Transportation* and *Energy*, *Water* and *Gasoline* are significantly more responsive.

Energy prices fall after contractionary monetary policy shocks due to their impact on global aggregate demand, which affects the demand for energy (Ider et al., 2023). Given the dominant size of the US economy over the sample period (1980-2008), a strong response of global energy demand to US monetary policy shocks is quite conceivable. Indeed, Miranda-Agrippino and Rey (2020) even document that more generally, US monetary policy has a global impact and is responsible for global financial cycles.

However, these two factors are specific to the position of the US. To see whether our results hold for other countries, it is important to examine the link between monetary policy and energy prices more generally. Indeed, there is a strong link between monetary policy and oil prices outside the US, albeit through a different channel. As oil prices, the dominant component of energy prices over the sample period, are priced in US dollars, there is an additional exchange rate channel, implying that contractionary monetary policy lowers (local) oil prices through an appreciation of the domestic currency (see, e.g., Frankel, 2008). Aliyev and Kočenda (2023) find this to be the dominant channel for the euro area.

Why the price indexes of some categories are more sensitive than others to monetary shocks is beyond the scope of this paper but we can expect it to be related to several factors like the different levels of price stickiness, labor intensity, etc.

The connection between monetary policy and price stickiness goes both ways. On the one hand, given a flexible-price and a sticky-price sector in a simple New Keynesian model, Aoki (2001) shows that monetary policy is optimal when it stabilizes the price level of the sticky-price sector. This result is extended to a model with sticky prices in both sectors by Benigno (2004). In the thesis chapter, this would imply that central banks place more weight on the stabilization of high-income households' inflation rate.

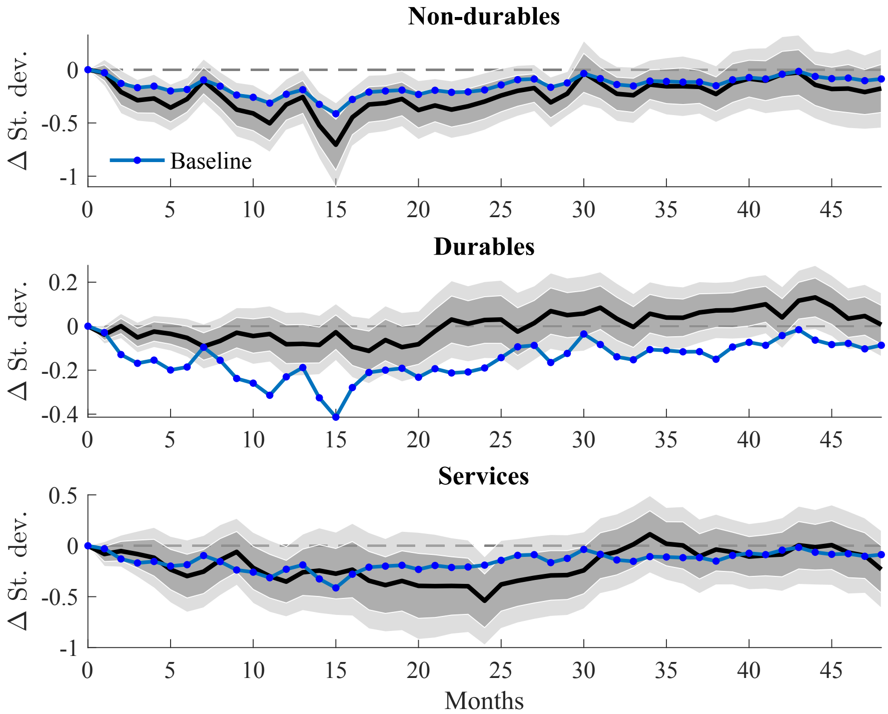
On the other hand, sticky prices by definition react more slowly to macroeconomic shocks. Thus, without this being the objective of the central bank, more flexible prices react more strongly and more quickly to monetary policy shocks. Since we abstract from differences in sectoral prices across households, the different weights of each sector, combined with different levels of price stickiness, imply that inflation rates are different for different households. Distinguishing between high and middle-income households, the middle-income households' price level will be more responsive to monetary policy.

Having shown that the sectoral inflation rates heterogeneously respond to monetary shocks, we now assess the contribution of the different sectors to the decrease in inflation dispersion. We start by computing inflation rates at the household level considering only a subset of the overall consumption basket. In particular, we classify each category into *non-durables*, *durables*, or *services*. As before, we then derive the response of the inflation dispersion across households for these three sub-categories, defined as the cross-sectional standard deviation, to a contractionary monetary shock.

The results are reported in Figure 1.5. The inflation dispersions of the three sub-categories decrease after a contractionary shock. However, they remarkably differ in the magnitude of their responses. The standard deviation of *non-durables* categories is more reactive whether the standard deviations of *durables* and *services* are less responsive to the shock and barely significant. The observed differences in the responses suggest that the main drivers of the decrease in inflation dispersion can be found within the *non-durables* categories.

Therefore, we compute the same cross-sectional standard deviation of individual inflation rates but exclude one important expenditure category at a time. The results of this exercise are shown in Figure 1.6. As one can notice, most expenditure categories like *Housing*, *Health*

Figure 1.5: Impulse Responses of Inflation Dispersion for Different Sub-Categories of Expenditure



Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the dispersion in inflation, measured by the cross-sectional standard deviation. The top panel uses the standard deviation in inflation rates for non-durable categories, the middle panel for durables, and the bottom panel for services. The solid blue line refers to the baseline impulse response obtained using the baseline categories. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

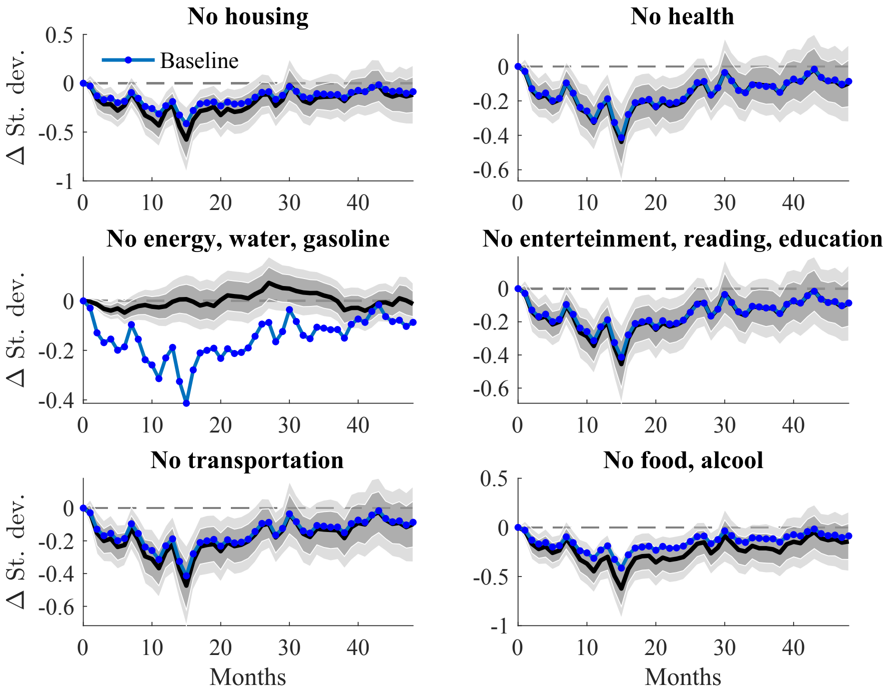
expenditure and *Transportation*[11] have only a marginal effect on our main results despite accounting for a significant share of the household consumption bundles.[12]

The middle left plot reports the inflation dispersion response when we exclude the categories *Energy*, *Water*, and *Gasoline*. This new specification is close to the definition of Core CPI that the Federal Reserve Bank uses to decide which monetary policy to adopt. Not surprisingly given the results shown in Figure 1.4, the omission of these three highly volatile categories leads to a near-complete attenuation of the observed inflation dispersion response. The significance of the *Gasoline* category in influencing the level and evolution over time of inflation inequality has been documented by Hobijn and Lagakos (2005), Cravino et al. (2020), and Orchard (2022). Building upon this prior work, we contribute by demonstrating the substantial role that this particular category plays also in transmitting monetary shocks to individual inflation rates.

[11] *Housing* is defined as the sum of *Rented Dwellings*, *Owned Dwellings* and *Other Lodging*. *Transportation* is equal to the sum of *Public Transportation* and *Other Vehicle Expenses*.

[12] We report the average expenditure weights across different deciles for income, salary, and expenditures in Table 1.A2.

Figure 1.6: Impulse Responses of Inflation Dispersion Excluding Different Categories of Expenditure



Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the dispersion in inflation, measured by the cross-sectional standard deviation. Each panel uses the standard deviation in inflation rates computing excluding expenditure categories from the consumption bundle of the households. The solid blue line refers to the baseline impulse response obtained using the baseline categories. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

To summarize, there is large heterogeneity in the contribution that each sector has to inflation dispersion. Many categories, even though being characterized by large expenditure share, have only a negligible impact. Most of the observed effects are due to the categories *Energy*, *Water*, and *Gasoline*. This empirical evidence suggests that central banks should not neglect the importance of these small and extremely volatile categories in setting their policy rate since most of the variation in inflation dispersion comes actually from them.

1.4 Heterogeneity Across Demographic Groups

Having shown that monetary policy shocks decrease inflation dispersion in the economy, we now evaluate whether the inflation rate of some demographic groups is more sensitive to contractionary shocks relative to other groups and how this affects the cross-sectional inflation dispersion. We focus in particular on three demographic groups: income, salary, and expenditure deciles.

1.4.1 Expenditure Weights

Heterogeneity in inflation rates comes from the fact that households consume different consumption baskets. As in Cravino et al. (2020), we derive the time-varying decile-specific expenditure weights following the procedure used by the BLS to compute the aggregate CPI which we describe in detail in Appendix 1.B.[13] We report in Table 1.A2 the expenditure weights of the first, fifth, and tenth deciles of income, salary, and expenditure deciles for each of the 21 categories for the period 1980-2008.

Several interesting facts can be noticed: First, the pattern across deciles is quite similar for income, salary, and expenditures. This already anticipates that the decile-level inflation rates of these three categories will react in a consistent way to monetary policy shocks. Second, although the weight for most of the categories either decreases or increases from the first to the tenth deciles, some categories display a U-shape pattern, e.g., *Gasoline* and *Medical expenses*. This is consistent with the findings of Cravino et al. (2020) who document that the highest price volatility is experienced by middle-income households.

Third, this implies that different households are subject to substantially different levels of price stickiness in their personal consumption baskets. This is a direct consequence of the fact that a) households consume very different consumption baskets (see Table 2 in the thesis chapter), and b) different sectors have different sectoral frequencies of price adjustment, or price stickiness (as shown by Nakamura and Steinsson, 2008). This finding is the basis of both Cravino et al. (2020), as well as the findings in this thesis chapter. The differences in consumption baskets dominate the potential effects of differences in sector-level prices, as Jaravel (2021) shows. Cravino et al. (2020) show that middle-income households face the most flexible prices, whereas high-income households face more sticky prices. This difference in price stickiness explains the differential effects of monetary policy on inflation across households.

Finally, looking at the differences in weights across deciles, we can already anticipate the inflation rate of which deciles will be more sensitive to monetary shocks. In the previous section, we demonstrate that most of the variation in inflation dispersion comes from *Gasoline* and *Energy* and that low- and middle-income households spend a significantly higher share of their income in these categories compared to high-income households.

1.4.2 Impulse Responses by Demographic Groups

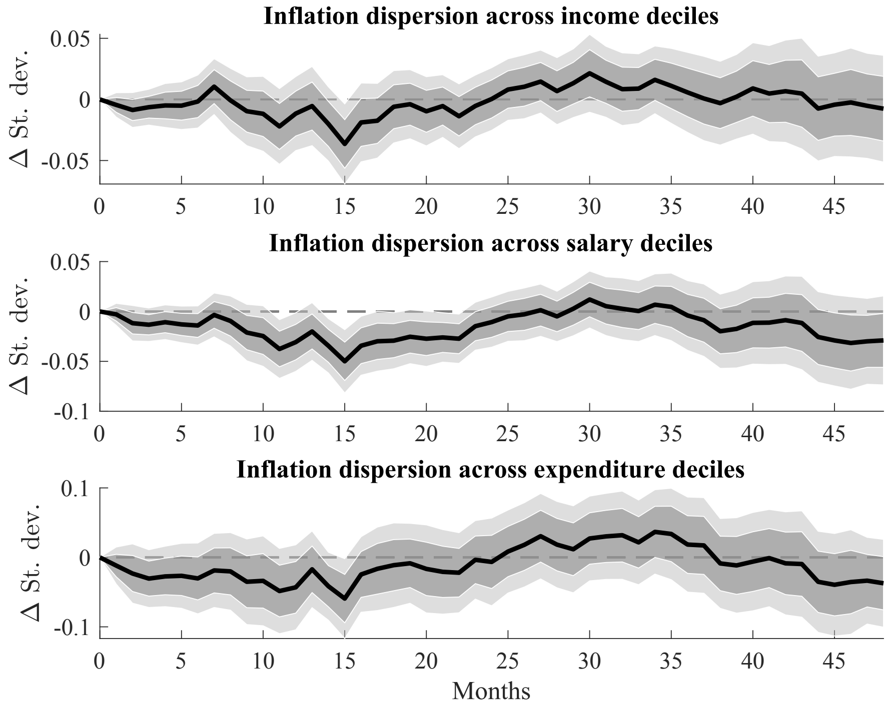
We study how the inflation rates of different demographic groups react to monetary policy shocks. We start by estimating the LP with R&R shocks using as the dependent variable the cross-sectional standard deviation of the decile-specific inflation rates across income, salary, and expenditure deciles which we define as *inflation inequality*.[14] As one can see from

[13] Appendix 1.D shows that the results are not particularly affected by considering the simple median inflation rate for each decile.

[14] Appendix 1.B explains in detail how the median inflation rates are computed following the same approach adopted by the BLS.

Figure 1.7, following a contractionary monetary policy shock inflation inequality for the three groups significantly decreases.

Figure 1.7: Impulse Responses of Inflation Dispersion Across Income, Salary, and Expenditure Deciles

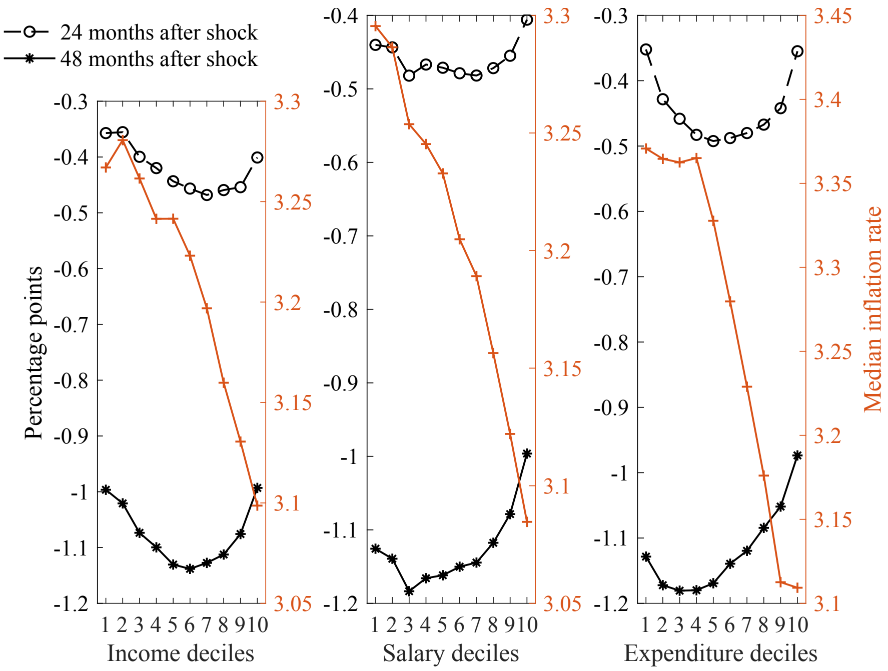


Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for inflation inequality across income (top), salary (middle), and expenditure deciles (bottom). Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

To better understand the main drivers of this result, we compare the median inflation rates of the different income, salary, and expenditure deciles with their impulse responses over time. The black lines in Figure 1.8 report the cross-sectional distribution of the impulse responses for the inflation rate of the different income (left panel), salary (middle panel), and expenditure deciles (right panel) 24 and 48 months after a one-percentage-point contractionary monetary policy shock.

Similar to what Cravino et al. (2020) find for income, the annual inflation rate of the households at the top of the income distribution reacts substantially less to monetary policy shocks than the one of those in the middle. The difference between middle- and high-expenditure households is economically sizable and statistically significant as tested in Appendix 1.C. After 24 months, the annual inflation rate of the households in the top decile responds to around 40% less than the inflation rate of the households in the fifth decile. After 48 months, the difference is still around 25%.

Figure 1.8: Impulse Responses of the Decile-Specific Inflation Rate Across Income, Salary, and Expenditure Deciles



Notes: This figure reports the cross-sectional distribution of the decile-specific inflation rate responses of the different income (left panel), salary (middle panel), and expenditure deciles (right panel) 24 and 48 months after a one-percentage-point contractionary monetary policy shock. The red lines refer to the median inflation rate across deciles (left axis). Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

How does this relate to inflation inequality? We report in the same panels the median inflation rates across deciles relative to the time period considered (red line, left axis).[15] One can notice how the higher the decile the lower the median inflation rate. This result is consistent with the evidence provided by Jaravel (2019) and Kaplan and Schulhofer-Wohl (2017) using the Nielsen scanner data.

On the one hand, given their consumption bundle, high-income households experience a lower median inflation rate than the households on the left side of the distribution. On the other hand, their inflation rate reacts significantly less to monetary policy shocks. These two results combined imply that following a contractionary shock, we observe a convergence of individual inflation rates across the distribution leading to a lower inflation inequality as documented in Figure 1.7. Similar results can be found focusing on salary and expenditure deciles as shown in the middle and right panels of Figure 1.8.

Our empirical analysis strongly suggests that monetary policy shocks can have significant and non-negligible distributional effects on the economy. The median inflation rate of higher-income households is lower relative to low- and middle-income deciles. At the same time,

[15]Plotting the cumulative difference in inflation rates across deciles delivers similar results.

their inflation rate is less reactive to unexpected changes in the interest rate. This results in a decrease in inflation inequality following a contractionary shock.

1.5 Real Expenditure Inequality

Does the identified inflation inequality have any effect on the estimated impact of monetary shocks on real expenditure inequality? To answer this question, we follow Coibion et al. (2017) as closely as possible and compute a broad measure of household expenditure which includes non-durables, durables, and services.[16] Few expenses are excluded since the relative sub-category price index is not easily identifiable, e.g., occupational expenses, mortgage, and property taxes.

To evaluate the role played by inflation inequality, we create two different series for real expenditure. In line with the literature, one is created by deflating each category by the aggregate CPI-U. The other one is obtained by deflating each item group by its relative price index. We then aggregate the expenditures at quarterly levels to reduce sampling error and to avoid having unusual purchases bias the analysis. We also winsorize at the bottom and top 1 percent of the distribution. Expenditure inequality across households is computed as the cross-sectional standard deviation of log levels, the Gini coefficient of levels, and the difference between the 90th percentile and the 10th percentile of log levels. Finally, all series are seasonally adjusted.

Inequality is defined as $Ineq_t^{IH}$ and $Ineq_t^{NoIH}$ respectively for when inflation heterogeneity is taken into account by deflating each category by the relative price index and for when it is neglected. As an example, the standard deviations at time t across households i are equal to $Std(logC_{i,t}^{IH})$ and $Std(logC_{i,t}^{NoIH})$ with:

$$C_{i,t}^{IH} = \sum_{j \in J} \frac{C_{i,j,t}}{P_{j,t}}, \qquad C_{i,t}^{NoIH} = \sum_{j \in J} \frac{C_{i,j,t}}{P_t}, \tag{1.3}$$

where $C_{i,j,t}$ is the nominal consumption of household i relative to category j at time t, $P_{j,t}$ is the price index of the category j at time t and P_t is the aggregate price index.

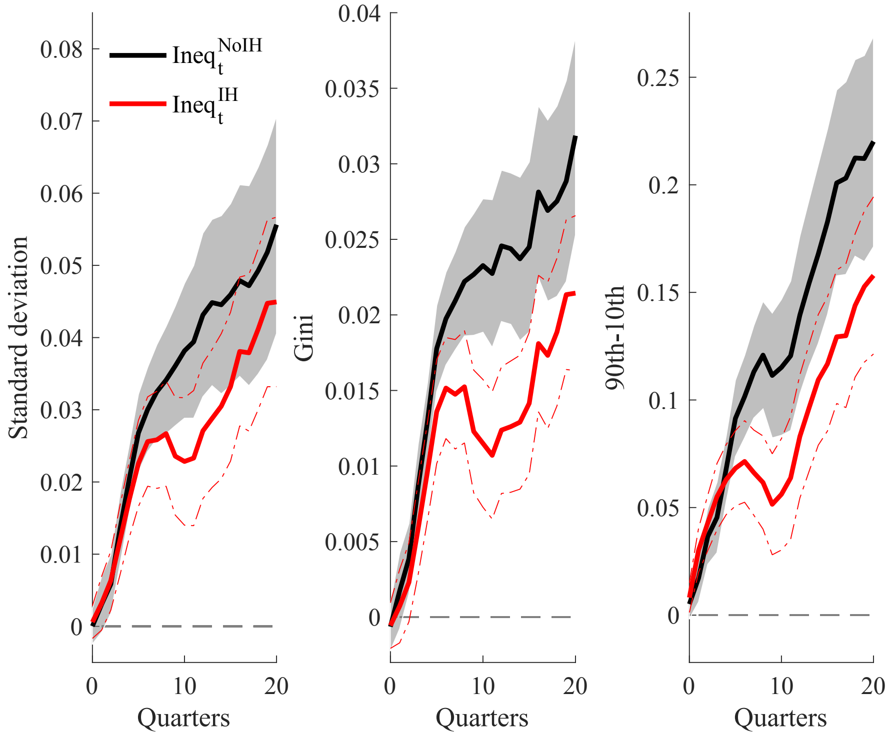
To make our results as comparable as possible, we use the same econometric procedure adopted by Coibion et al. (2017), i.e., local projection with Romer and Romer (2004) shocks at a quarterly frequency, over the same time period, 1980Q1:2008Q4.[17] Since the series is quarterly, we include as controls 20 lags for the shocks and 2 lags for the dependent variable and we compute the impulse responses over 20 quarters.

Figure 1.9 plots the results. The black solid lines report the impulse responses of the three measures of expenditure inequality obtained by deflating the expenditure categories by

[16] In particular, the categories considered are: Food at Home, Food Away, Alcohol at Home, Alcohol Away, Apparel, Gasoline, Personal Care (services and durables), Reading, Tobacco, Household Furnishings and Operations, Energy, Water, Other Lodging, Public Transportation, House expenditures (services and durables), Rental expenditures (services and durables), Rent paid, Heath insurance, Health expenditures (services and durables), Education, Vehicles purchase, Vehicle expenditures (services and durables), Miscellaneous.

[17] Similar results are obtained adopting our empirical.

Figure 1.9: Impulse Responses of Expenditure Inequality



Notes: This figure shows impulse responses to a one percentage point contractionary monetary policy shock, as well as one standard deviation confidence intervals for expenditures inequality. The horizontal axis is in quarters and inequality is measured using the cross-sectional standard deviation (left), Gini coefficient (middle), and the log difference between the 90th and 10th percentiles of the cross-sectional distribution (right). The black solid line and the dark grey shaded areas depict the impulse response obtained by deflating the expenditure categories by the aggregate CPI, the red solid line and the dashed red lines refer to the impulse obtained by deflating each category by their respective price index. Impulse responses are computed at the quarterly frequency using data for the period 1980Q1:2008Q4.

the aggregate CPI. The shape and the magnitude of the responses are very close to those obtained by Coibion et al. (2017). After a contractionary monetary policy shock, expenditure inequality persistently and significantly increases.

However, neglecting inflation heterogeneity across consumption baskets leads to an over-estimation of the overall effect. As shown by the red solid lines which report the responses of the expenditure inequality measures obtained by deflating each category by their respective price index, when the expenditure categories are properly deflated, the estimated effect of monetary policy on inequality is approximately 20% lower for standard deviation and 30% for the Gini coefficient and the 90th-10th percentile difference. It is worth mentioning that the estimated coefficients are still positive and significant which implies that monetary policy still has redistributive effects on the economy.

This result can be explained by combining the new empirical evidence from the previous sections. Along the income distribution, a contractionary monetary shock has heterogeneous effects on nominal consumption. The nominal consumption of low- and middle-income households decreases more than that of high-income households because they are more sensitive to the monetary policy shock, e.g., they are financially constrained, they are more likely to lose their job in an economic downturn, etc. However, at the same time, the cost of their consumption basket decreases more strongly as well. Hence, the overall effect on expenditure is partially offset in real terms. This results in a more muted, but still positive and significant, increase in real expenditure inequality.

1.6 Robustness

To strengthen the validity of our findings in the previous sections, we show that our results are robust across a wide range of alternative specifications. First, we evaluate the importance of substitution effects. Second, we assess the sensitivity of our results to different lag specifications. Third, we perform the same analysis starting our sample in 1985M1 to control for the Volcker disinflation period. More robustness checks can be found in Appendix 1.D. The figures are reported in Appendix 1.E.

1.6.1 Substitution Effects

Throughout the paper, we conduct our analysis under the assumption that differences in inflation dispersion are mainly driven by changes in prices and that variations in expenditure shares play only a marginal role. Both the inflation rate at household-level as well as at the decile level are computed using expenditure weights aggregated over multiple time periods to control for seasonal effects as well as to avoid unusual purchases by the households biasing our results. The weights for the household-level inflation rate rely on the entire time series of expenditure (maximum 12 months) whereas the weights at the decile level are computed following the BLS which updates its expenditure weight reference period approximately every ten years, and since 2002, every two years (more details can be found in Appendix 1.B).

Cravino et al. (2020) tested whether substitution effects are important for the CEX by using the difference between the Laspeyres and Paasche price index as a proxy for the substitution bias from 1987 to 2004. These authors showed that the difference between the two indices is negligible over time demonstrating that the substitution bias must be very small.

Furthermore, using the Nielsen data, Jaravel (2019) evaluates whether the observed inflation heterogeneity along the income distribution stems from the fact that high-income households purchase different goods or whether they pay more for the same goods, for instance, because they buy from different shops. The inflation difference is then decomposed into a *between* and a *within* component. The former corresponds to the inflation difference that we would observe if households differ only in terms of the expenditure shares across categories and if they experience the same within-category inflation. Vice versa, the latter refers to the difference that would arise in case of households experience the same within-category inflation, but have different expenditure shares. The between component accounts for more than 70% of the inflation difference.

Given the importance of the assumption that inflation dispersion is mainly driven by changes in prices rather than in expenditure shares, we also test whether substitution effects are a potential source of bias. We do this through two robustness checks: First, we assess if the granularity of the expenditure categories we choose plays any role. Second, we compute our measures of inflation inequality across deciles by using annual, quarterly, and monthly expenditure shares instead of using multiple years of consumption data like the BLS.

Following the literature, in computing the individual inflation rates we adopt a rather conservative aggregation in the number of categories considered. Not only do we have data for *Food and Beverage*, the most aggregate item category, but also have data for the sub-category *Eggs*, the most disaggregate. In choosing the baseline aggregation, we face a trade-off between using as disaggregate data as possible to fully capture inflation dispersion and the quality of the price index. Many price series started significantly after 1980, especially the most disaggregated goods and services indices.

We show that the main results are basically unaffected by increasing or decreasing the number of categories considered. We compute the household-level inflation dispersion using 14, 31, and 121 expenditure categories.[18] The evolution over time of the dispersion measures is reported in Figure 1.E2.

The number of categories considered significantly affects the overall level of inflation dispersion. Relatively to the baseline inflation dispersion with 21 categories, the magnitude is slightly smaller with 14 categories and is slightly larger with 31. With 121 categories the cross-sectional standard deviation is almost twice as high compared to the baseline. However, the measures of inequality are extremely positively correlated. The correlation with the baseline specification is 0.97, 0.98, and 0.86 for the measures with 14, 31, and 121 categories respectively.

In Figure 1.E3 we compare the response from our baseline specification with 21 categories (blue line) against the three alternative aggregations. When using price indices at a slightly more granular level (middle panel, 31 categories) or an even more conservative number of categories (top panel, 14 categories), the magnitude and the shape of the responses are basically the same as that obtained in our baseline specification. Considering 121 categories the response is still significantly and persistently negative following a contractionary shock. The magnitude of the response is almost twice as much as the one of the baseline response but since the size of the inflation dispersion measure has doubled as well, in percentage terms the results are similar. This suggests that the number of categories considered in computing

[18]For this last specification some of the price indexes were available later than 1980 so it is an unbalanced panel. The 14 categories are Food, Alcohol, Housing, Apparel, Gasoline, Other Vehicle Expenses, Public Transportation, Medical, Entertainment, Personal Care, Reading, Education, Tobacco, and Other Expenses. The 31 categories are Food at Home, Food Away from Home, Alcohol, Rental expenditures (durables), Rental expenditures (services), Rent Paid, Rent Equivalent, House Expenditures (durables), House Expenditures (services), Other House related expenses, Other Lodging, Energy, Water, Phone, Household Furnishings and Operations, Jewelry, Clothing (durables), Clothing (services), Gasoline, Vehicle Expenditure (durables), Vehicle Expenditure (services), Public Transportation, Medical, Entertainment, Personal Care (durables), Personal Care (Services), Reading, Education, Tobacco, and Other Expenses.

individual inflation rates is important for measuring the *level* of inflation inequality but not its *sensitivity* to monetary policy shocks.

As a second test for the role of substitution effects, we compute the expenditure weights for the decile-level inflation rates at annual, quarterly, and monthly frequencies. It is important to notice that by allowing the weights to vary at a much higher frequency than the biannual frequency adopted by the BLS in the last decades, our dispersion measures will not only capture potential adjustments in the consumption bundles due to the shocks but also measurement errors and unusual purchases will account for a larger share.

We report in Figure 1.E4 the response of the cross-sectional standard deviation of the median inflation rates across income deciles as well as the one standard deviation confidence interval (black line and gray area). For comparison, the blue lines refer to the impulse response of the cross-sectional standard deviation as well as the relative confidence interval computed following the BLS methodology as shown in Figure 1.7.

Not surprisingly, moving from annual to quarterly and especially to monthly weights makes the responses more volatile. The responses with time-varying weights are still negative and significant: inflation inequality across expenditure deciles remarkably decreases after a monetary shock. The magnitude is even more negative relative to the baseline. This might suggest that substitution effects move in the same direction as our inflation heterogeneity channel: following a contractionary shock, inflation rates of the expenditure categories purchased by low- and middle-income households decrease more strongly than the other categories so their overall inflation rates react more. Moreover, the same households might even increase their consumption of these categories since they are now relatively cheaper, leading to second-order effects. Similar evidence is found for the dispersions in median inflation across the salary and expenditure deciles whose responses are reported in Figure 1.E5 and Figure 1.E6 respectively.

Since we cannot further disentangle substitution effects from measurement errors in the survey or unrepresentative purchases made by households, we prefer to interpret these results with caution. Overall these findings confirm that substitution effects do not cancel out the impact of contractionary shocks on inflation dispersion and that heterogeneity in prices across, rather than within, expenditure categories is the main driver of our results.

1.6.2 Different Lag Specification

We re-estimate equation (1.2) with an alternative lag specification. In Figure 1.E7 we run the LP regression including 36 and 60 lags for the monetary policy shocks as well as 4 and 8 lags for the cross-sectional standard deviation of the individual inflation. Similar results are also obtained for the other measures of dispersion. Increasing or reducing the number of lags has little to no effect on the impulse responses: after a contractionary monetary policy shock, inflation dispersion significantly decreases.

1.6.3 Volcker Disinflation

Coibion (2012) shows how few episodes in the early 80s can be the main drivers of the impulse responses computed using LP with R&R shocks. Since then, it has been common practice for researchers to test their results excluding the period between 1979 and 1982 in which the Federal Reserve abandoned targeting the federal fund rate. Figure 1.E8 reports the IRFs obtained using the baseline specification but starting the sample in 1985M1. In this case, the results are also robust.

1.7 Conclusion

Central bankers and policymakers are more and more strongly advocating the importance of the conduct of a more inclusive monetary policy where the potential negative spillovers deriving from the monetary authorities' decisions are taken into account. Similarly, macroeconomic research has shifted its focus from the aggregate effects of monetary shocks towards the different channels through which households and firms might be heterogeneously affected by it. Our results suggest that the inflation heterogeneity that arises from the different consumption baskets the agents purchase is of pivotal importance for understanding the distributional consequences of monetary policy.

This paper studies how monetary policy shocks affect the distribution of household-level inflation rates. We rely on individual expenditure data from the CEX and combine it with category-level inflation rates from the BLS to obtain household-level inflation rates. We compute different moments of the individual inflation rates distribution and we evaluate how monetary policy shocks influence the median and the cross-sectional standard deviation of the distribution. Inflation dispersion across households significantly and persistently decreases in response to a contractionary monetary policy shock. *Energy*, *Water* and *Gasoline* are found to explain almost entirely the observed effects despite accounting for a relatively small expenditure share.

We also evaluate how the inflation rate of different demographic groups is heterogeneously affected by monetary policy. We find that the inflation rates of low- and middle-income households are significantly more reactive to monetary shocks than those of high-income households. Since at the same time, they experience a higher median inflation rate, contractionary shocks lead to an overall convergence of inflation inequality across income groups. The same is true for expenditure and salary deciles.

Finally, we demonstrate that assuming that households are exposed to the same inflation rate results in an overestimation of the impact of monetary shocks on expenditure inequality. Following a contractionary shock, low-income households experience a stronger decrease in nominal consumption relative to high-income households. However, the price of their consumption bundles decreases relatively more as well partially offsetting the effect in real terms. Accounting for inflation heterogeneity reduces the estimated response of expenditure inequality to monetary shocks by around 20-30% depending on the measure of inequality considered.

In conclusion, our research provides substantial evidence that designing optimal monetary policies as well as studying their distributional effects cannot abstract from also considering the different inflation rates to which agents are exposed. Indeed, the economic agents experience significantly different inflation rates both in the long run as well as in response to shocks. Inflation heterogeneity in the economy is sizable and related to demographic characteristics. Therefore, focusing only on aggregate inflation or measures of inflation that exclude important components might lead to the implementation of systematically suboptimal policies for specific demographic groups. Finally, taking into account inflation heterogeneity is particularly relevant when it comes to assessing the impact of monetary policy on other forms of inequalities.

Appendix

1.A Data Sources

This section documents in greater detail the data sources used and the properties of the underlying data.

1.A.1 Price Indices

Since individual inflation rates are a weighted average of sectoral price indices, Table 1.A1 displays the CPI subindices used, as well as their respective statistical properties.

Table 1.A1: Item-Level CPI Statistics

CPI series (Item Code)	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Food at Home (SAF11)	3.223	2.176	-2.904	10.524
Food Away from Home (SEFV)	3.598	1.751	1.422	10.675
Alcoholic Beverages (SAF116)	3.388	1.936	0.66	10.961
Rented Dwellings (SEHA)	4.028	1.706	0.694	8.938
Owned Dwellings (SEHC)	3.533	1.067	0.724	6.437
Other Lodging (SE2102-SEHB)	4.876	4.358	-9.313	19.395
Energy (SAH21)	3.744	6.739	-15.168	23.602
Water (SEHG01)	5.442	2.295	0.579	14.217
Phone (SAE2)	-0.812	1.733	-4.611	2.516
Household F&O (SAH3)	1.587	2.051	-2.295	8.545
Apparel (SAA)	1.154	2.46	-4.069	7.378
Gasoline (SETB)	3.531	17.378	-54.864	52.006
Other Vehicle Exp. (SETC-SETD-SETE-SETF)	4.397	2.235	0.208	11.936
Public Transportation (SETG)	4.867	6.313	-12.946	27.742
Medical care (SAM)	5.723	2.347	2.447	11.778
Entertainment (SAR)	2.921	2.048	-0.407	9.391
Personal Care (SAG1)	3.335	1.798	1.028	8.904
Reading (SERG)	3.82	2.682	-0.196	11.825
Education (SAE)	6.929	2.033	4.3	13.126
Tobacco (SEGA)	7.962	6.42	-8.483	33.332
Other Expenses (SEGD)	5.588	2.397	0.972	11.893
CPI-U (SA0)	**3.615**	**2.481**	**-2.119**	**13.764**

Notes: This table displays descriptive statistics about each item-level inflation rate, as measured by year-on-year changes of the respective index. The source of this data is the U.S. Bureau of Labor Statistics.

1.A.2 Consumer Expenditure Survey Data

This section provides further details about the construction of the dataset we use in the empirical analysis. We download the raw data for the period 1980-2005 from the ASCII files available from the Inter-university Consortium for Political and Social Research (ICPSR) whereas from the year 2006 onward we use the data provided by the BLS. For each quarter, the Interview Survey is structured as follows: the expenditure data is recovered from the disaggregated MTAB files, income data is derived from the FMLY files and additional information regarding the households can be found in the MEMB files.

In line with the literature, we aggregate together expenditures about the same month which is reported in different interviews. Then, we drop households that report zero expenditure on food as well as those that report negative expenditure for categories that cannot be negative according to the data codebook, such as expenditure for elderly care. Respondents younger than 25 years and older than 75 are excluded. To correct for sample breaks caused by slight changes in the questionnaire (food at home (1982Q1-88Q1), food away from home (2007Q2), and personal care services (2001Q2)) we regress each expenditure series on a time trend and indicators for the corresponding sample breaks and then subtract the effect of the dummies from the original series. For all these transformations, we rely heavily on Coibion et al. (2017).

Finally, the CEX data started to include the imputed income in 2004. To impute income data before that year, we follow the approach adopted by Fisher et al. (2013) and Coibion et al. (2017): for households recording a bracketed range, we use the median point of the bracket. Furthermore, we estimate the remaining income observations by regressing income on a set of observable characteristics such as age, age squared, the reference person's gender, race, education, number of weeks worked full or part-time in the last 12 months, unadjusted family size, the number of children under 18, the number of people over 64, the number of earners at the annual level and with sampling weights as well as using fixed effects for the income reporting date. To account for the sampling uncertainty, we add residuals drawn randomly with replacement from the sampling distribution to the predicted values. We then trim values above the top-coding threshold at the top coding value.

We then calculate expenditure shares from the cleaned expenditure data, which constitute the weights used to calculate individual inflation rates. We find substantial variation in the weights that can be explained to a large part by either income, salary, or expenditure deciles. Table 1.A2 shows the weights for the 1st, 5th, and 10th deciles.

Table 1.A2: Expenditure Weights for the First, Fifth, and Tenth Decile of Income, Salary, and Expenditure

	Income deciles			Salary deciles			Expenditure deciles		
	1st	5th	9th	1st	5th	9th	1st	5th	9th
Food at Home	14.5	13.0	9.8	13.7	12.8	9.9	22.6	14.7	7.8
Food Away	8.1	8.2	7.7	8.8	8.3	7.7	9.3	8.5	7.2
Alcohol	1.0	1.1	1.2	1.1	1.1	1.2	1.0	1.1	1.0
Rented Dwellings	9.4	8.4	1.9	8.5	8.6	2.0	21.0	7.9	1.4
Owned Dwellings	18.8	17.4	21.4	15.5	16.2	21.5	7.4	19.8	17.7
Other Lodging	0.8	0.6	1.5	1.0	0.6	1.5	0.1	0.1	1.2
Energy	5.3	5.0	3.8	4.9	4.7	3.8	6.8	5.8	2.9
Water	0.8	0.8	0.7	0.8	0.8	0.7	0.9	1.0	0.6
Phone	2.7	2.7	2.0	2.7	2.7	2.0	4.0	3.0	1.5
Household F&O[19]	4.3	4.5	5.1	7.8	4.7	7.0	1.2	3.0	10.6
Apparel	4.1	4.3	5.9	4.6	4.8	6.1	2.6	3.6	6.4
Gasoline	4.1	5.0	4.0	4.7	5.3	4.1	4.8	5.7	3.2
Other Vehicle Expenses	7.9	10.6	11.7	9.5	11.6	12.0	5.6	11.1	10.8
Public Transportation	1.1	1.0	1.8	1.2	1.0	1.8	0.7	0.4	2.8
Medical	5.8	6.6	4.7	5.7	5.2	4.3	4.3	5.6	5.8
Entertainment	4.2	4.8	6.9	4.8	5.3	6.9	2.6	3.9	8.9
Personal Care	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0	0.7
Reading	0.4	0.5	0.6	0.5	0.5	0.6	0.4	0.5	0.4
Education	2.5	1.0	2.7	3.2	1.3	2.8	0.2	0.4	4.3
Tobacco	1.0	1.2	0.5	1.2	1.2	0.5	2.3	1.3	0.4
Other Expenses	1.1	1.2	1.2	1.1	1.1	1.0	0.3	0.6	2.3

Notes: This table displays the first, fifth, and ninth deciles for the weight of income, salary, and expenditure shares. While our methodology uses these shares at a monthly frequency, this table displays the average over the period 1980-2008.

1.A.3 Matching of Expenditure and Inflation Data

We match the expenditure categories with the respective price indices. Following Hobijn and Lagakos (2005), for the category *Other Vehicle Expenses* which does not have a perfect match with the available CPI sub-categories, we create the CPI index by combining the series that match this category (that is, SETC, SETD, SETE, and SETF). As sectoral weights, we use the average over the time period considered of the official weights provided by the BLS, as displayed in the table "Relative Importance in the CPI". Finally, since *Other Lodging* changed the name, we use *Lodging away from home* until 1997 (MUUR0000SE2102) and *Lodging while out of town* (SEHB) until the end of the sample. In all cases, the CPI series we use are the not-seasonally-adjusted *US City Average for all urban consumers* series. Table 1.A3 displays the categories in the CEX, as well as the categories in the CPI data that were used to match the two data sets.

Table 1.A3: Matching Between CEX Expenditure Category and CPI

BLS Expenditure Category	CPI Series (Item Code)
Food at Home	SAF11
Food Away from Home	SEFV
Alcohol	SAF116
Owned Dwellings	SEHC
Rented Dwellings	SEHA
Other Lodging	MUUR0000SE2102-SEHB
Energy	SAH21
Water	SEHG01
Phone	SAE2
Household Furnishings and Operations	SAH3
Apparel	SAA
Gasoline	SETB
Other Vehicle Expenses	SETC-SETD-SETE-SETF
Public Transportation	SETG
Medical	SAM
Entertainment	SAR
Personal Care	SAG1
Reading	SERG
Education	SAE
Tobacco	SEGA
Other Expenses	SEGD

This table displays the expenditure category from the CEX, as well as the respective category code in the CPI index series.

1.B Decile-Level Expenditure Weights

Before computing the decile-level expenditure weights, some adjustments need to be performed. In line with the literature and the BLS procedure, the expenditure weight for the owners' equivalent rent of primary residence is based on the following CEX question: "If someone were to rent your home today, how much do you think it would rent for monthly, unfurnished and without utilities?" The homeowners' answer to this question is stored in the variable RENTEQVX in the characteristics files.

Moreover, as we mention in the main text, vehicle purchases are likely to bias the estimated expenditure shares. Indeed, they are large in size and not representative of the usual household consumption bundle. Therefore, in line with Johannsen (2014), we drop this category when computing household-level inflation rates. Following Cravino et al. (2020), we include expenditures on used cars and trucks when computing the decile-level inflation but we reduce the spending to half to reflect only the dealer value added.

Households are also interviewed a different number of times and for at most four consecutive quarters, which corresponds to twelve months' worth of spending information. However, this does not necessarily match the calendar year. To control for this, we compute the decile-based inflation rate closely following the BLS procedure as in Cravino et al. (2020). First, we sort households into deciles based on their annual income, salary, median, and mean expenditure. We then compute the average expenditure for each item category at every decile in the calendar year. For instance, a respondent interviewed in February will report personal consumption for January, but also for November and December of the previous year. Similar to what the BLS does for the computation of the official CPI, to account for the relative contribution of each household to the decile-mean value of a calendar year, we weight the consumption by the number of months a household reports expenditures during a calendar year (the BLS calls this variable MO_SCOPE).

We can then use the formula below to compute the average expenditure for each category j at each decile d. First, for household i at decile d, we aggregate over all the expenditures on good j during the calendar year. Second, the household total expenditure is weighted by the sampling weights, fwt, provided by BLS to make the survey sample representative of the U.S. population. Then, the weighted household expenditure is summed up at the decile level. Finally, to obtain the monthly average income spent on good j by decile d, we divide the annual weighted household expenditure for category j by the weighted number of months household at decile d reported expenditure during the calendar year. To annualize the average category expenditure at the decile level, it is sufficient to multiply the monthly average expenditure by twelve:

$$X_j^d = \frac{\sum_i fwt_i^d \sum_t c_{i,j,t}^d}{\sum_i fwt_i^d \; MO\_SCOPE_i^d} \times 12, \tag{1.B.1}$$

where fwt_i^d is the frequency weight for household i at decile d, $c_{i,j,t}^d$ refers to the annual consumption on category j by household i at decile d and $MO\_SCOPE_i^d$ identify the number of months per year household i reported its expenditure. The decile-level expenditure weight for category d can then be computed as:

$$w_j^d = \frac{X_j^d}{\sum_j X_j^d}. \tag{1.B.2}$$

1.C Differences in Responses Across Deciles

We evaluate whether the responses of the decile-level median inflation rates to a monetary policy shock are statistically different from each other. To do so, we estimate equation (1.2) using as dependent variable the difference between the inflation rate of the 10th and 1st decile of each group and the inflation rate of the 5th decile. The first column of Figure 1.C1 reports the responses of the difference in median inflation rate for the 10th and the 5th decile, and the second column for the 1st and the 5th decile. The first row shows the responses for the differences across expenditure deciles, the second row for salary deciles, and the last row for income deciles.

As it can be noticed in Figure 1.8, both the median inflation rates of the 10th as well as of the 1st deciles of income, salary, and expenditures react much less to a monetary policy shock than the 5th deciles resulting in a positive and significant response of their differences. The U-shaped response across deciles is in line with what was found by Cravino et al. (2020) who document that the price volatility along the income distribution is hump-shaped with the households at the top of the distribution experiencing the lowest volatility (resulting in the flattest impulse response) and middle-income households being exposed to slightly more price volatility than lower-income households.

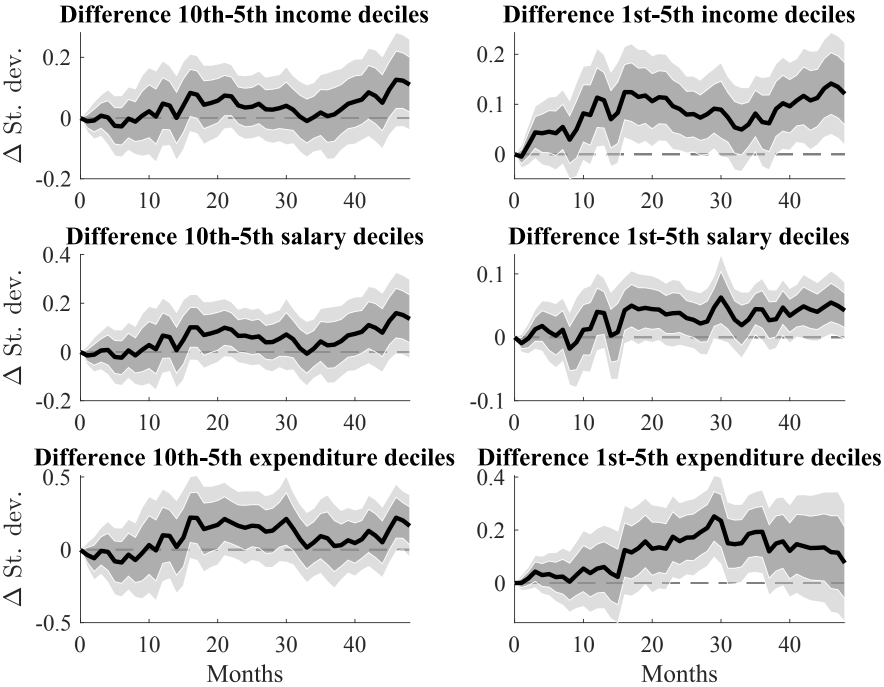
1.D Further Robustness Checks

As a further robustness check, Figure 1.D1 reports the impulse responses excluding all U.S. recession periods from the analysis (1981M07:1982M11, 1990M07:1991M03, 2001M03:2001M11). The results remain qualitatively unchanged with respect to the baseline specification.

As a second set of checks, we assess whether our results are specific to the shock series we chose, i.e., Romer and Romer, 2004. The alternative measure of monetary shocks we use is the high-frequency proxy proposed in Bauer and Swanson (2022). The proxy is computed from changes in future prices in a narrow window around FOMC announcements and orthogonalized with respect to the public information about the economic and inflation outlook. The shock series is available from 1988 to 2019.

The results are presented in Figure 1.D2. The top panel reports the response of the cross-sectional standard deviation to a contractionary shock and the bottom panel shows the response of inflation inequality across expenditure deciles. All the regressions include the

Figure 1.C1: Differences in Impulse Responses Across Deciles



Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the difference in decile-specific inflation rates across deciles of the demographic groups. The first column reports the responses of the difference in inflation rate for the 10th and the 5th decile, and the second column for the 1st and the 5th decile. The first row shows the responses for the difference across expenditure deciles, the second row for salary deciles, and the last row for income deciles. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

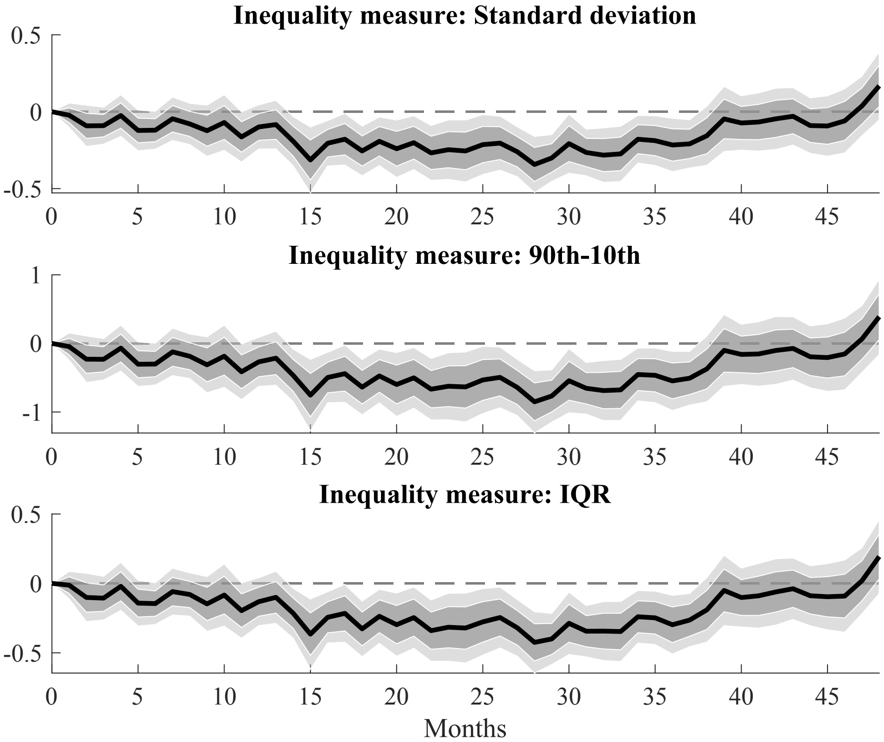
same controls as in the baseline specification. In response to contractionary monetary policy shocks inflation dispersion as well as inequality decrease. Overall, the results from alternative monetary policy shocks confirm our main findings and point towards a distributional role played by monetary policy in terms of inflation dispersion.

Moreover, one might be concerned that part of the inflation heterogeneity we measured is driven by differences in consumption patterns across U.S. states rather than along the income distribution. Since the BLS does not provide price indices at the state level, but only at the division level (Northeast, Midwest, South, and West), we compute the cross-sectional standard deviation of inflation for the four divisions using expenditure weights as well as price indices at division level.[20]

The responses across U.S. divisions are reported in Figure 1.D3. There are some regional differences in the shape of the responses of inflation dispersion to contractionary shocks.

[20]A more limited number of price indices are available at the division level. Therefore, we used the following expenditure categories: Food at Home, Food Away from Home, Alcohol, Rented Dwellings, Owned Dwellings, Household Furnishings and Operations, Utility, Apparel, Private Transportation, Public Transportation, Gasoline, Medical, Education, and Miscellaneous.

Figure 1.D1: Impulse Responses of Inflation Dispersion (Without Recession Periods)



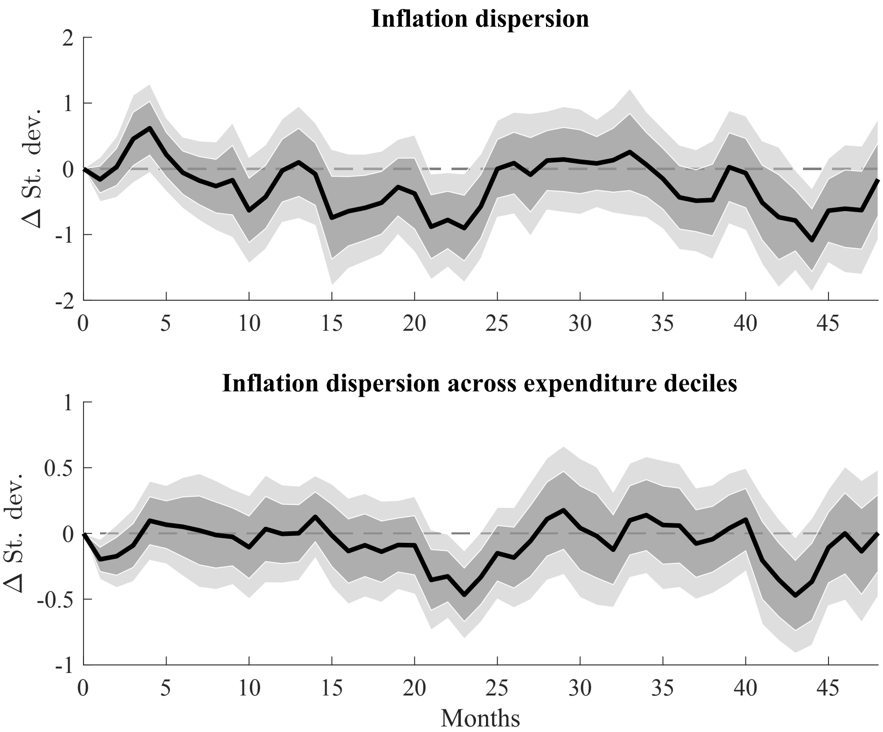
Notes: This figure shows impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentile of the cross-sectional distribution (middle), and the IQR (bottom). Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12

However, the magnitude and significance of the results are comparable to the baseline specification. The decrease is more muted only for the West division.

Finally, in the main analysis, the decile-specific inflation rates are computed following the BLS procedure. The advantage of this approach is that for each decile all the individual expenditure information is combined to form the expenditure weights. In this way, outliers are less likely to bias the analysis. An alternative approach to the BLS methodology would be to simply consider the median of the individual inflation rates within each decile.

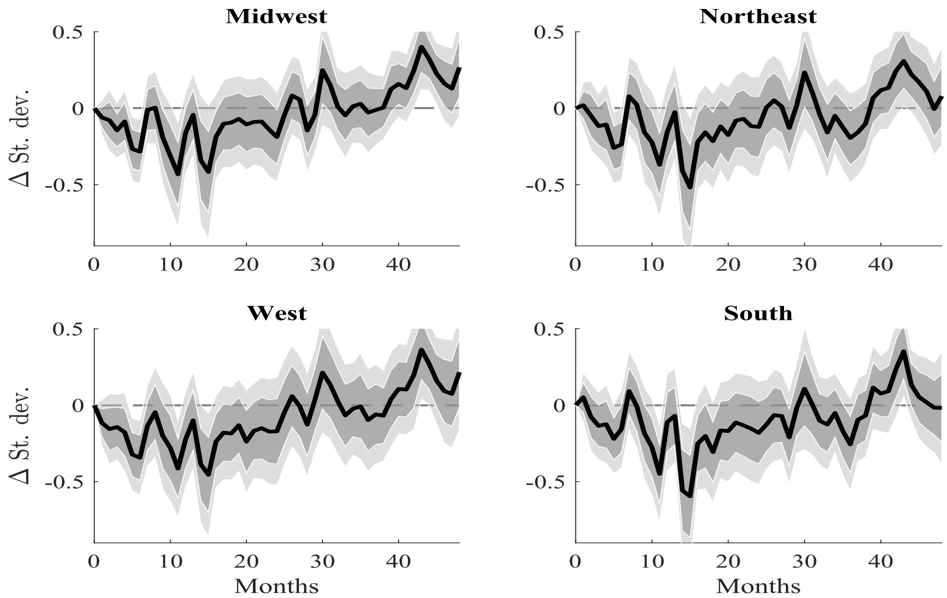
In Figure 1.D4 we report the responses of inflation inequality for income, salary, and expenditures to a contractionary monetary shock. Inflation inequality is measured as the standard deviation of the median inflation rates across deciles. Following a monetary shock the inflation inequality responses are still negative and statistically significant confirming the baseline results.

Figure 1.D2: Impulse Responses of Inflation Dispersion and Inequality, Bauer and Swanson (2022) Monetary Shocks



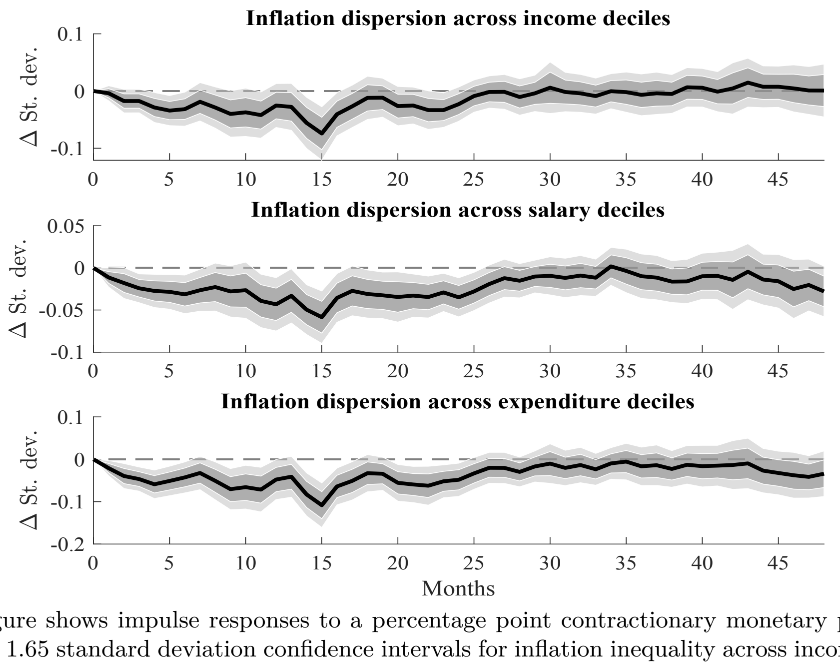
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as the 1.65 standard deviation confidence intervals. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1988M2:2019M12.

Figure 1.D3: Impulse Responses of Inflation Dispersion across U.S. Divisions



Notes: This figure shows impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the inflation dispersion measured as the cross-sectional standard deviation for the four US regions. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12.

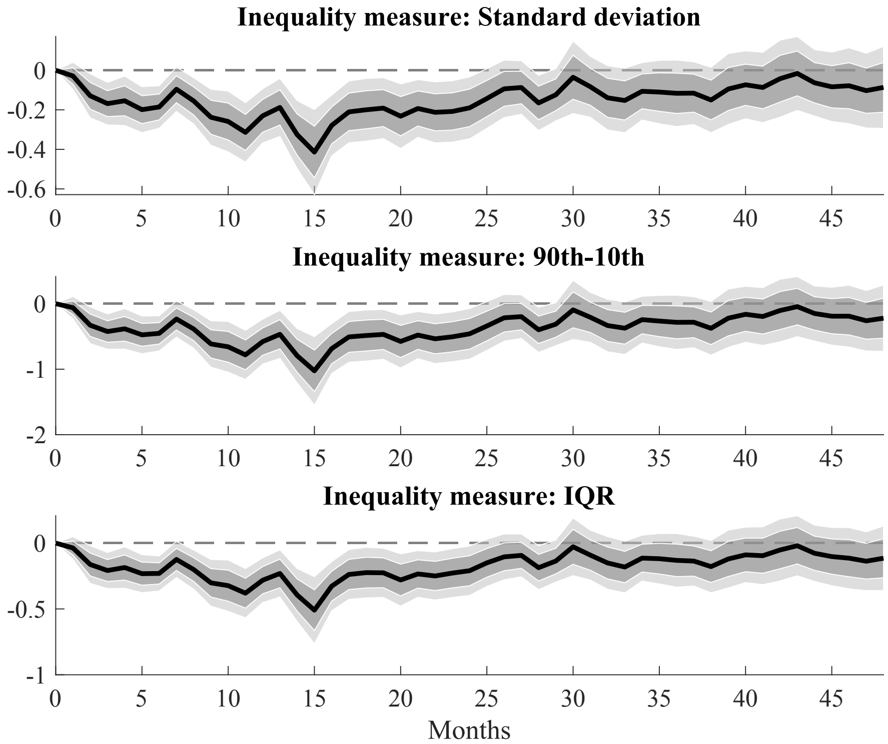
Figure 1.D4: Impulse Responses of the Dispersion across the Median Inflation Rates for Income, Salary, and Expenditure Deciles



Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for inflation inequality across income (top), salary (middle), and expenditure deciles (bottom). Inflation inequality is measured using the cross-sectional standard deviation of the median inflation rate for each decile. The horizontal axis is in months. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

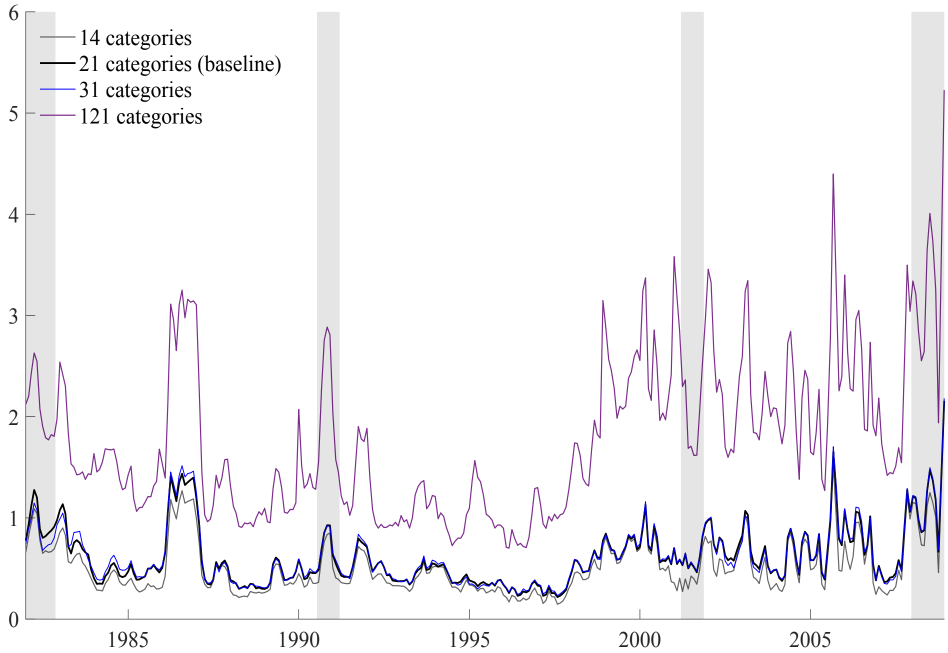
1.E Robustness Plots

Figure 1.E1: Impulse Responses of Inflation Dispersion



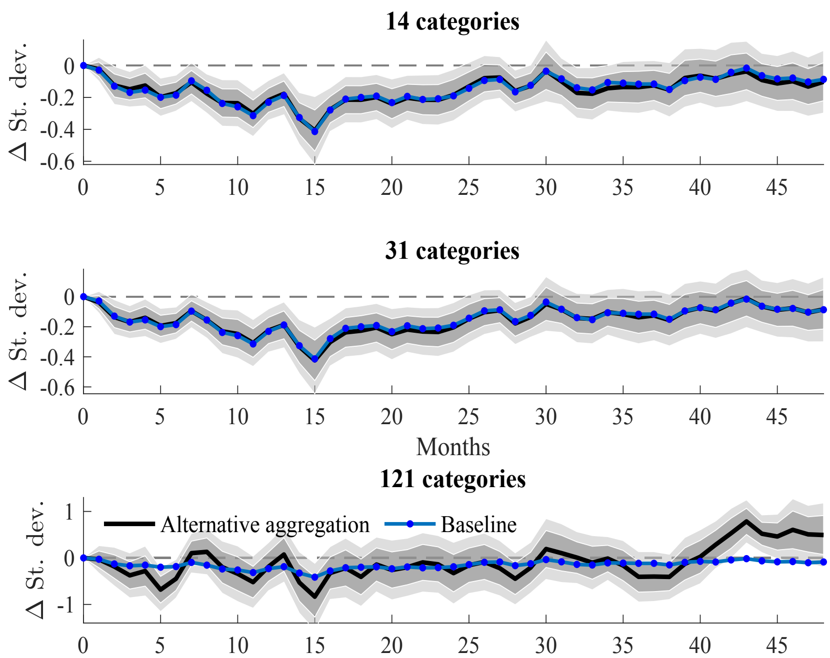
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentile of the cross-sectional distribution (middle), and the IQR (bottom). Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 1.E2: Historical Series of Inflation Dispersion Measures



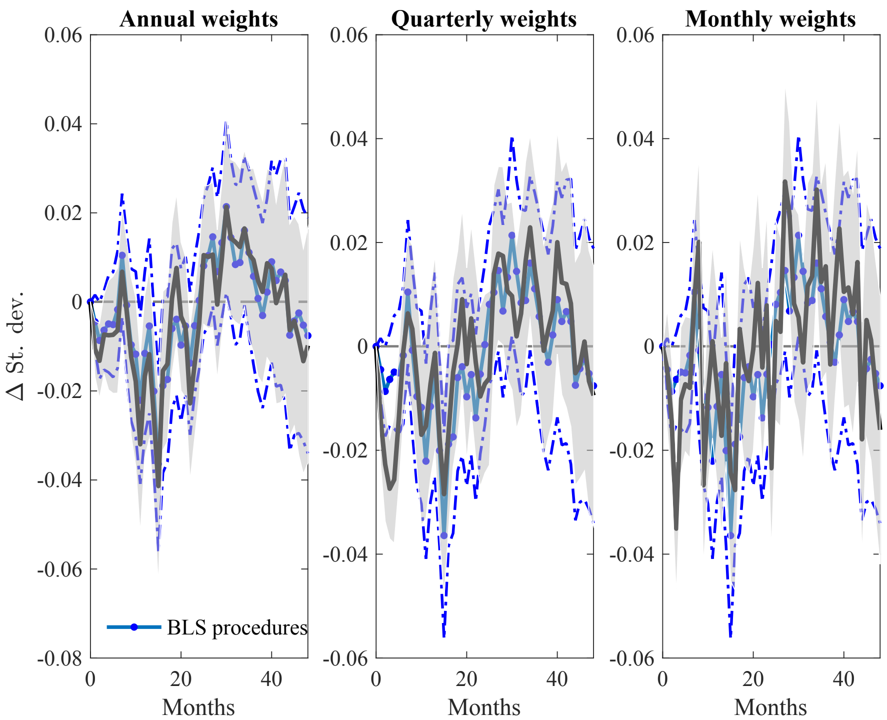
Notes: The plot shows the evolution of inflation dispersion measured using the cross-sectional standard deviation computed using 14, 21, 31, and 121 expenditure categories. All the series refer to the period 1981M1:2009M12. The gray shaded areas depict U.S. recessions.

Figure 1.E3: Impulse Responses of the Cross-Sectional Standard Deviation of Inflation (Alternative Aggregations)



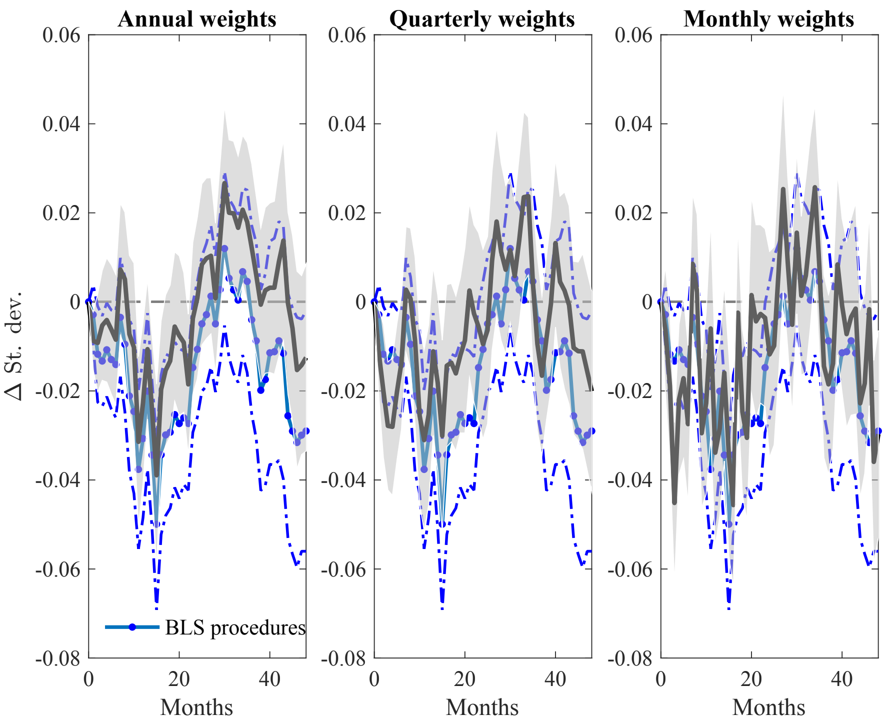
Notes: This figure shows impulse responses of alternatively aggregated inflation rates to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The solid blue line refers to the impulse response obtained using the baseline categories. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12.

Figure 1.E4: Impulse Responses of Inflation Inequality Across Income Deciles with Time-Varying Weights



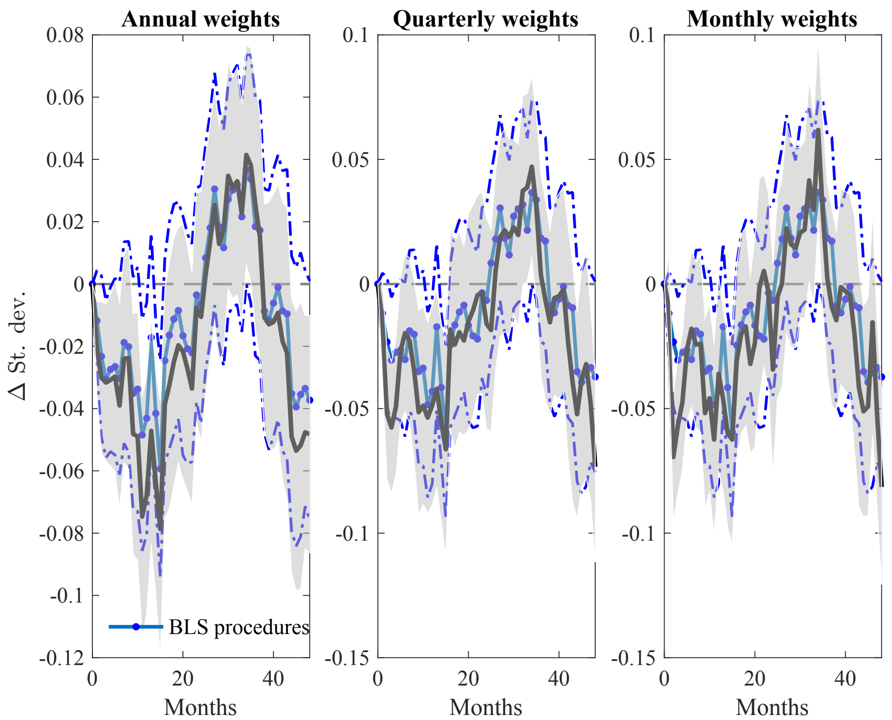
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across income deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights, the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for non-durable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 1.E5: Impulse Responses of Inflation Inequality Across Salary Deciles with Time-Varying Weights



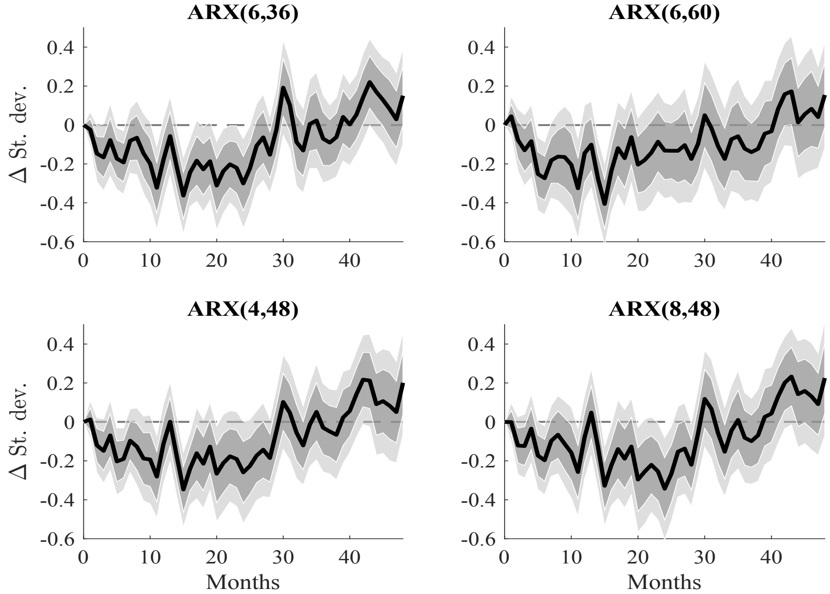
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across salary deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights, the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for non-durable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 1.E6: Impulse Responses of Inflation Inequality Across Expenditure Deciles with Time-Varying Weights



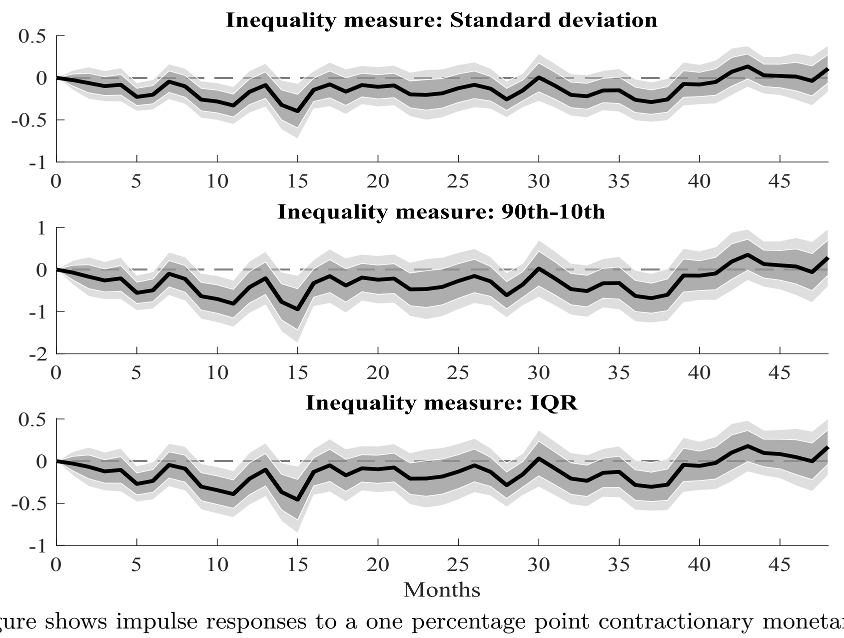
Notes: This figure shows impulse responses to a percentage point contractionary monetary policy shock (black line) as well as one standard deviation confidence interval (gray area) for inflation inequality across expenditure deciles. Inflation inequality is measured using the cross-sectional standard deviation of the decile-specific inflation rates. The expenditure weights are time-varying and computed at annual (left panel), quarterly (middle panel), and monthly (right panel) frequencies. The solid blue line refers to the baseline impulse response obtained following the BLS methodology for the expenditure weights, the blue dashed lines are the one standard deviation confidence interval. The horizontal axis is in months. The top panel uses the standard deviation in inflation rates for non-durable categories, the middle panel for durables, and the bottom panel for services. Impulse responses are computed at a monthly frequency using data for the period 1980M1:2008M12.

Figure 1.E7: Impulse Responses of Inflation Dispersion for Different Lag Specifications



Notes: This figure shows the impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals of the cross-sectional standard deviation. The horizontal axis is in months. In an $ARX(p, r)$-model, we control for p lags of the dependent variable, and for r lags of the shock variable. Impulse responses are computed at a monthly frequency using data relative to the period 1980M1:2008M12.

Figure 1.E8: Impulse Responses of Inflation Dispersion (Without Volcker Period)



Notes: This figure shows impulse responses to a one percentage point contractionary monetary policy shock, as well as one and 1.65 standard deviation confidence intervals for the respective inflation dispersion measures. The horizontal axis is in months. Dispersion is measured using the cross-sectional standard deviation (top), the difference between the 90th and the 10th percentile of the cross-sectional distribution (middle), and the IQR (bottom). Impulse responses are computed at a monthly frequency using data relative to the period 1985M1:2008M12 in order to exclude the Volcker disinflation period.

Chapter 2

Central Bank Information Effects and Exchange Rates

2.1 Introduction

The increasing availability of high-frequency data on financial asset prices has greatly expanded the research frontier on the effects of monetary policy. Observing the response of many financial time series to monetary policy announcements has provided a more detailed view of how central bank decisions and communication affect markets and expectations. These effects are more complex than the implications of conventional monetary policy shocks.

This more refined picture of the immediate effects of monetary policy on financial variables has shed light on puzzles that are difficult to reconcile with conventional monetary theory. For example, it is common for a surprise increase in interest rates to exhibit expansionary effects.[1] While this contradicts our understanding of a conventional monetary policy, it can be explained by central bank information (CBI) effects: if the increase in yields coincides with monetary authorities signaling an improved economic outlook, then an *apparent* monetary tightening may be followed by an expansion.

A recent strand of the literature has identified puzzles regarding the exchange rate effects of monetary policy. Gürkaynak et al. (2021) find that the domestic currency often depreciates after a monetary tightening. This is contrary to standard uncovered interest rate parity (UIP) theory, which suggests that the currency is bound to appreciate in this case. However, Gürkaynak et al. (2021) show that, while inflation or inflation target shocks can theoretically explain the unexpected exchange rate behavior, there remains an identification problem when multiple shocks are used to explain a single covariance in the data. Schmitt-Grohé and Uribe (2022) find that the domestic currency depreciates when the monetary policy shock is permanent, also leading to deviations from UIP. Focusing specifically on CBI shocks, Franz (2020) finds the exchange rate response to be ambiguous and dependent on the currency pair.

[1] see Jarociński and Karadi (2020) or Miranda-Agrippino and Ricco (2021), among many.

This paper aims to examine the effects of monetary policy on the exchange rate, focusing in particular on the informational components of monetary policy. For this, I distinguish between conventional monetary policy shocks and two types of informational monetary policy shocks: The Delphic shock, on the one hand, captures changes in the assessment of future macroeconomic conditions. Similar to a news shock, an unexpected increase in interest rates can serve as a signal of a more optimistic economic outlook, to which the central bank merely reacts. Market participants with imperfect information subsequently revise their expectations. The Odyssean shock, on the other hand, captures changes in the expected future monetary policy stance. Market participants extract signals from central bank communication, in order to learn whether the stance of monetary policy will change in the future. These signals may be unintentional or intentional. They can include inflation target shocks, permanent monetary policy shocks, forward guidance shocks, or changes in central bank preferences.

My analysis has three stages: First, an analytical exchange rate decomposition illustrates how CBI can affect exchange rates through expectations. Starting from a no-arbitrage condition, I show that the exchange rate depends on the path of future interest rate differentials, risk premia, and the long-run inflation differential. This decomposition sheds light on the dependence of the spot exchange rate on expectations of the future path of these variables. As long as a shock affects the expectation of these components, it should affect the current exchange rate as well. Typically, informational monetary policy shocks have a larger effect on long-run expectations—rather than current macroeconomic variables—and are therefore also predicted to affect the current exchange rate.

Second, I extract three types of shocks (Target, Delphic, and Odyssean) from a factor model using high-frequency financial data and analyze their short-run effects on the exchange rate, as well as on other financial data. The construction of these shocks, using data on interest rate futures and inflation-linked swaps, follows Andrade and Ferroni (2021): the Target factor, which captures conventional monetary policy, is the only factor that loads on the short-term interest rate. The Delphic and the Odyssean factors both raise the 5-year interest rate, but they have opposite effects on inflation expectations. While the Delphic factor is inflationary, the Odyssean factor is deflationary. To get a dynamic view of the short-run effects of these shocks, I employ a proxy structural vector autoregression (SVAR) model using daily asset price data. The domestic currency appreciates after both Delphic and Odyssean shocks. The effects of the Delphic factor are particularly persistent, while the effects of the Odyssean factor fade in a 6-month window of daily data.

Third, to assess the longer-term, macroeconomic, effects of the CBI shocks, I construct a monthly proxy SVAR model that goes beyond financial variables to include macroeconomic aggregates as well. The results show that CBI effects have significant effects on macroeconomic variables such as GDP and inflation. Consistent with the daily analysis, the Odyssean shocks are deflationary and the Delphic shocks are inflationary. In both cases, the exchange rate appreciates. For the Delphic shocks, the appreciation is weaker on impact, but more persistent than for the Odyssean shock.

The primary contribution of this paper is to examine the link between CBI shocks and exchange rates in the euro area. In particular, it demonstrates that the exchange rate effects of CBI shocks are consistent with the theoretical predictions from an analytical decomposition, taking into account a wide array of high-frequency data and distinguishing between Delphic and Odyssean shocks. The study therefore also aims to enhance the understanding of the effects of monetary policy more generally. Because the literature on monetary policy and CBI often focuses on closed-economy effects, they forego potentially valuable information inherent in exchange rates, even though the foreign exchange market is highly liquid and forward-looking (King et al., 2012). Also, Rosa (2011) shows that exchange rates are highly sensitive to monetary news, absorbing monetary surprises almost immediately. Hence, the exchange rate may be a valuable source for a more thorough understanding of the nature of monetary policy shocks and CBI, as this paper aims to demonstrate.

The remainder of this paper is organized as follows: Section 2.2 reviews the literature to which this paper relates. Section 2.3 provides an analytical decomposition of the connection between informational monetary policy shocks and exchange rates. Section 2.4 extracts a Target, a Delphic, and an Odyssean factor from high-frequency asset price surprises. Section 2.5 presents the effects of the three factors on exchange rates and the economy in high-frequency data, while Section 2.6 builds a monthly proxy SVAR model to study the long-run effects on exchange rates and the macroeconomy, at a monthly frequency. Section 3.5 concludes.

2.2 Related Literature

In simple open-economy models with floating exchange rates, UIP relates exchange rate changes to the interest rate differential (see, among many, Galí and Monacelli, 2005). Thus, monetary policy is understood as a key determinant of the exchange rate. However, many have documented that UIP is not a good empirical approximation of exchange rates—Fama (1984) being the best-known example of this. Faust and Rogers (2003) show that only a small fraction of the exchange rate variance is explained by monetary policy shocks and that instead, there are large deviations from UIP.

Several strands of the literature have emerged to explain the failure of UIP. Some studies have for instance relaxed the assumption of perfect and rational information about current and future interest rate differentials (see Evans and Lyons (2008) and Bacchetta and Van Wincoop, 2006). An important strand of the literature on the failure of UIP is based on the existence of currency risk premia. Seminal papers in this literature are, Lustig and Verdelhan (2007) and Benigno et al. (2011). Engel (2014) provides an informative overview of this line of research. In particular, the study by Leombroni et al. (2021) is closely related to the present paper, as they show that European Central Bank (ECB) communication has long-run effects on risk premia, as measured by the spread between core and periphery interest rates in the euro area.

My study also relates to the literature on information processing in the foreign exchange market. While Evans and Lyons (2005) show that, due to the microstructure of foreign exchange markets, news is incorporated only gradually (in a few days), Rosa (2011) finds that monetary surprises are incorporated into exchange rates within 30-40 minutes.

The present work also contributes to the study of the effects of monetary policy, as identified with high-frequency asset prices. While studying monetary policy through event-study analysis of unexpected asset price changes goes back to Cook and Hahn (1989) and Kuttner (2001), Gürkaynak et al. (2005a) show, using high-frequency asset price changes, that monetary policy has multiple dimensions. Using a principal component approach, they show that central banks affect the path of future interest rates with a factor that is independent of conventional policy shocks, called the Path factor.[2] Altavilla et al. (2019) apply the approach of Gürkaynak et al. (2005a) to the euro area and extend it by using information from the press release, as well as the press conference of the ECB, deriving forward guidance and quantitative easing shocks.[3] Nevertheless, some studies show that high-frequency shocks may not be exogenous to the economy (see, for example, Ramey (2016), Bauer and Swanson (2023), or Miranda-Agrippino and Ricco, 2021).

Several researchers have suggested a further decomposition of the Path factor. Indeed, an increase in the Path factor could result either from (a) changes in the economic outlook, which market participants learn either from the signals emitted by monetary policy decisions or from the accompanying communication by central bankers, or (b) from (perceived) changes in the intended conduct of monetary policy. While the former mechanism underlies Delphic shocks, the latter defines Odyssean shocks (Andrade and Ferroni, 2021).

Some papers focus more on either the Delphic or the Odyssean component. Papers that focus more on Delphic shocks, are for example Melosi (2017), who shows that higher interest rates can serve as a signal that the economic outlook is more positive than previously expected. Miranda-Agrippino and Ricco (2021) show that information effects can have a confounding effect when assessing the transmission of (conventional) monetary policy to the macroeconomy. Papers focusing on Odyssean shocks include, for example, Gürkaynak et al. (2005b), who relax the assumption of perfectly known long-run equilibria in GDP, inflation, and interest rates. One way to model this is with (permanent) inflation target shocks, as modeled by Ellingsen and Soderstrom (2001) or Lukmanova and Rabitsch (2023). Schmitt-Grohé and Uribe (2022) do a similar exercise, but focus on the open-economy effects of permanent and transitory monetary policy shocks, and find that permanent shocks are contractionary and lead to a depreciation of the domestic currency.

Focusing on CBI effects, Nakamura and Steinsson (2018) find that information effects have an impact on individual expectations, which they proxy with survey data. Bauer and Swanson (2023), however, challenge this interpretation by showing that there is confound-

[2] A promising extension of how monetary policy affects long-term interest rates is provided by Kaminska et al. (2021), who show that effects of monetary policy can be decomposed into three components: the Target factor, the (expected) Path factor, and a factor capturing the uncertainty of the Path factor.

[3] The work of Altavilla et al. (2019) is also key, as they provide, and regularly update the surprises data, on which this paper and many others depend.

ing information between the central bank announcement and the survey date that can also explain the findings. However, this issue does not pertain to the puzzling co-movement between interest rates and other asset prices, as (market-based) expectations are measured at high frequency around monetary policy announcements. Jarociński and Karadi (2020) and Kerssenfischer (2022), among many others, distinguish between conventional monetary policy and CBI shocks via sign restrictions of interest rate and stock price surprises. While both effects move interest rates in the same direction, they have opposite effects on output, and thus on stock prices. Cieslak and Schrimpf (2019) extend this research by additionally identifying growth and risk premia shocks.

Focusing on international effects of CBI shocks, Franz (2020) and Gründler et al. (2023) both employ the interest rate–stock price identification. Franz (2020) examines the effects of the Jarociński and Karadi (2020) shocks (JK shocks, henceforth) on different exchange rates. He finds that the cleaned monetary policy shocks lead to a significant appreciation of the euro. The central bank information (CBI) shocks, however, have heterogeneous exchange rate effects, which are not always significant. This contrasts with the findings of my research, which shows that the effects of informational shocks are strong, immediate and highly significant.

There are a number of important differences between the JK shocks and the shocks derived in this paper. The reasons go beyond the use of inflation-linked swaps instead of stock prices. First, Jarociński and Karadi (2020) use sign restrictions on 1-year interest rates to identify shocks, while I use 5-year OIS rates. In this work, there is substantial evidence that exchange rate changes are more strongly correlated with the long-end of the yield curve, while stock prices are more strongly correlated with short and medium-term interest rates.

Second, macroeconomic theory suggests that Central Bank Information shocks lead to stock price increases and exchange rate appreciations. But neither Franz (2020) nor my work finds this correlation between stock prices and exchange rates. The causality between the two may be more complex and go in both directions. Exchange rates certainly affect the valuation of (international) companies, and thus stock prices. By first identifying shocks with stock price changes and then looking at the effects on exchange rate, there is an implicit assumption that exchange rate changes do not affect stock prices in the same time window, otherwise the identification of shocks would be biased.

In summary, the disentangling of information effects as done by Jarociński and Karadi (2020) focus on more short-term information effects that are not as relevant for the determination of exchange rates as when using longer-maturity asset prices, and should therefore be taken with a grain of salt.

Holtemöller et al. (2020) and Gründler et al. (2023) find that an information shock has a weaker, but more persistent effect on the exchange rate. Pinchetti and Szczepaniak (2021) look at the United States (US) case, and its spillover effects on global economic activity, global risk appetite, and exchange rates, underscoring the global repercussions of US monetary policy. Jarociński (2022) finds that, CBI shocks from ECB policy spill over to the US, but pure policy shocks do not.

Focusing on the high-frequency effects of monetary policy on exchange rates, Gürkaynak et al. (2021) model the informational assumptions behind CBI effects. They find that for a significant fraction of central bank announcements, the domestic currency depreciates for both the US and the euro area. They call this unexpected behavior the *exchange rate puzzle*. I revisit the puzzle, focusing on the 5-year maturity, and discuss it in Subsection 2.5.2.

2.3 Deconstructing Exchange Rate Surprises

This section develops an analytical decomposition of exchange rate changes based on a no-arbitrage condition. Specifically, this decomposition shows how changes in the exchange rate are related to changes in expectations about future interest rate differentials (between the two respective countries and exchange rates), future risk premia, and future inflation differentials. As explained in the introduction, if a shock persistently affects one or several of these components—as will be the case for these shocks, as shown in Sections 2.5 and 2.6—then the analytical decomposition predicts that these shocks should have an impact on contemporaneous changes in the exchange rate.

The derivation builds on Lustig (2021), Stavrakeva and Tang (2015), and Stavrakeva and Tang (2020). The starting point is a representative investor who can freely invest in a domestic or a foreign risk-less bond. The nominal exchange rate serves to equalize the home and foreign bond Euler equation of the investor,

$$E_t\left[M_{t+1}R_t^*\frac{S_t}{S_{t+1}}\right] = E_t[M_{t+1}R_t] = 1, \tag{2.1}$$

where M_{t+1} is the stochastic discount factor, R_t is the nominal return on a risk-free bond, and S_t is the nominal exchange rate, measured in units of foreign currency per unit of domestic currency.[4] This means that an increase in S_t implies a depreciation of the home currency. The exchange rate adjusts to equalize the investor's expected utility gain. Assuming conditional log-normality of exchange rates and interest rates, and taking logs on both sides, I get the following equation:

$$s_t = E_t(s_{t+1}) + d_t + \sigma_t, \tag{2.2}$$

where lowercase letters denote variables in logs and $d_t = i_t - i_t^*$ is the nominal interest rate differential. An asterisk denotes a foreign variable. σ_t is the expected excess return, or foreign exchange risk premia.

Here, σ_t serves as the residual term in (2.2). Thus, the above equation is satisfied by construction.

Iterating (2.2) forward gives

$$s_t = E_t\sum_{j=0}^{\infty}[d_{t+j} + \sigma_{t+j}] + \lim_{k\to\infty} E_t\left[s_{t+k}\right], \tag{2.3}$$

[4] An increase in S_t implies an appreciation of the domestic currency. This is unusual in theoretical papers, but that way, it is consistent with the empirical part in the subsequent chapters.

and, computing the first difference on both sides of the equation gives

$$s_{t+1} - s_t = -d_t - \sigma_t + \sum_{j=1}^{\infty} (E_{t+1} - E_t)\left[d_{t+j} + \sigma_{t+j}\right] + (E_{t+1} - E_t) \lim_{k\to\infty} \left[s_{t+k}\right]. \tag{2.4}$$

Now, I use (2.2) to simplify the equation

$$s_{t+1} - E_t\left[s_{t+1}\right] = -\sum_{j=1}^{\infty} (E_{t+1} - E_t)\left[d_{t+j} + \sigma_{t+j}\right] + (E_{t+1} - E_t) \lim_{k\to\infty} \left[s_{t+k}\right]. \tag{2.5}$$

From here on, I use $\nu_{t+1}(x_{t+h}) = E_{t+1}\left[x_{t+h}\right] - E_t[x_{t+h}]$ to denote the update of conditional expectations for a generic variable x_{t+h}, given the information set at period t and $t+1$. Equation (2.5) is rewritten:

$$\nu_{t+1}(s_{t+1}) = -\sum_{j=0}^{\infty} \nu_{t+1}(d_{t+j+1}) - \sum_{j=0}^{\infty} \nu_{t+1}(\sigma_{t+j+1}) + \nu_{t+1}\left(\lim_{k\to\infty} s_{t+k}\right). \tag{2.6}$$

The previous expression shows that the exchange rate surprise is a function of surprises in the cumulative interest rate differential, the cumulative risk premia, and the surprise in the expected long-run nominal exchange rate.

To get a better understanding of the last term, I follow Stavrakeva and Tang (2015) and assume that long-run purchasing power parity (PPP) holds, meaning that the real exchange rate $q_t = s_t + p_t - p_t^*$ is stationary. First differencing this equation and solving for Δs_{t+1} yields $\Delta s_{t+1} = \Delta q_{t+1} + \pi_{t+1}^* - \pi_{t+1}$, which gives, using (2.6):

$$\begin{aligned}
\nu_{t+1}\left(\lim_{k\to\infty} s_{t+k}\right) &= E_{t+1}\left[\lim_{k\to\infty} s_{t+k}\right] - E_t\left[\lim_{k\to\infty} s_{t+k}\right] \\
&= E_{t+1}\left[\lim_{k\to\infty} s_{t+k} - s_t\right] - E_t\left[\lim_{k\to\infty} s_{t+k} - s_t\right] \\
&= E_{t+1}\left[\lim_{k\to\infty} \sum_{j=1}^{k} \Delta q_{t+j} + \pi_{t+j}^* - \pi_{t+j}\right] - E_t\left[\lim_{k\to\infty} \sum_{j=1}^{k} \Delta q_{t+j} + \pi_{t+j}^* - \pi_{t+j}\right] \\
&= E_{t+1}\left[\lim_{k\to\infty} \sum_{j=1}^{k} \pi_{t+j}^* - \pi_{t+j}\right] - E_t\left[\lim_{k\to\infty} \sum_{j=1}^{k} \pi_{t+j}^* - \pi_{t+j}\right] \\
&= \sum_{j=1}^{\infty} \nu_{t+1}\left(\pi_{t+j}^* - \pi_{t+j}\right).
\end{aligned}$$

Thus, when the real exchange rate $q_t = s_t + p_t^* - p_t$ is stationary, the change in the long-run value of the exchange rate depends entirely on the surprises regarding the difference in the inflation paths for both countries. This implies that, if long-run PPP holds, equation (2.6) can be rewritten as

$$\nu_{t+1}(s_{t+1}) = \sum_{j=0}^{\infty} \nu_{t+1}(d_{t+j+1}) + \sum_{j=0}^{\infty} \nu_{t+1}(\sigma_{t+j+1}) + \sum_{j=0}^{\infty} \nu_{t+1}\left(\pi_{t+j}^* - \pi_{t+j}\right). \tag{2.7}$$

The exchange rate surprise therefore depends on updates in the conditional expectations of the interest rate differential, foreign exchange risk premia, and the inflation differential. Hence, changes in exchange rates depend not only on updates in the expected interest rate differential, but also on risk premia, and importantly, on the inflation differential. In particular, since inflation targeting is the mandated objective of the ECB, actions and communications of the ECB are likely to influence the path of expected inflation rates. The source of this change in expected inflation rates during the monetary policy window could be conventional monetary policy, Delphic, or Odyssean shocks. As informational shocks affect long-run interest rates, which themselves depend on expected average short-term interest rates, one can assume that they have a more meaningful effect on the path of interest rates, when compared to changes in the current short-term interest rate. The following sections show that the Target, the Delphic, and the Odyssean monetary policy shocks do indeed have differentiated dynamic influences on future inflation and interest rates. Accordingly, I can expect these three shocks to also have different effects on exchange rates.

To simplify the analysis and focus on macroeconomic drivers of exchange rates, I will abstract from the risk premium effects. Further, foreign variables could theoretically offset the dynamics in domestic variables, if they are equally affected by the domestic monetary policy shocks. However, to the best of my knowledge, there is no paper in the literature that finds the effects on foreign variables problematic. Therefore, I assume that the dynamics in equation (2.7) are predominantly driven by domestic variables.

Using the previous decomposition, let us try to predict the signs of the effects of positive Odyssean and Delphic shocks on the exchange rate, defining the shock to be positive if it increases domestic interest rates. Following the definition of Andrade and Ferroni (2021)—which I will use below to construct our shocks—an Odyssean shock has effects of opposite signs on the interest rate (i.e., on the d_{t+j}'s) and inflation (the π_{t+j}'s). Therefore, according to (2.7), a positive Odyssean shock should lead to an appreciation of the domestic exchange rate. (Note that the signs in front of the d_{t+j} and the π_{t+j} are opposite in (2.7)) In contrast, a Delphic shock has effects of the same sign on the d_{t+j}'s and the π_{t+j}'s, and the sign of its effect on the exchange rate is therefore ambiguous.[5] The empirical analysis, presented in the following sections, will help to determine this sign.

2.4 Construction of the Shocks

In this section, I derive three monetary policy shocks using a factor model. Namely, a standard monetary policy shock, as captured by the Target factor, is separated from Delphic and Odyssean shocks. In the following sections, these three shocks are then used to explain the response of exchange rates at high and low frequencies. Before turning to the construction

[5]Note, in particular, that the existence of Delphic shock could rationalize the exchange rate puzzle of Gürkaynak et al. (2021) if the inflation effect were to dominate over the exchange rate effect. However, this is not the case, as shown in Subsection 2.5.2.

of the shocks (in Subsection 2.4.2), Subsection 2.4.1 examines whether the magnitude of the observed effects even warrants a separate investigation of information effects in the first place.

2.4.1 The Quantitative Importance of Central Bank Information

To investigate whether informational monetary policy shocks are important for the determination of exchange rates, I exploit the specific structure of ECB announcements. On monetary policy days, the ECB's communication starts with the publication of the press release at 13:45 and continues with a one-hour press conference at 14:30.[6] The press release contains only a brief statement about the interest rate decision. The press conference gives a (carefully crafted) statement explaining the decision. Thus, we have two distinct windows in which to observe the market reaction. I assume that the conventional (short-term) monetary policy shock comes from the press release (RE) window, and the informational shocks stem entirely from the press conference (PC) window. This allows us to obtain preliminary insights into the relative importance of pure monetary policy and informational shocks. It can be understood as a model-free, preliminary analysis of the importance of informational shocks.

In order to assess the asset price dynamics during and shortly after monetary policy meetings, I consider the two signals derived from these meetings: the rate of change in the RE window ($\Delta x_{RE,t}$) and the rate of change in the PC meeting ($\Delta x_{PC,t}$). These signals capture the high-frequency fluctuations in relevant variables, denoted by x.

To assess their impact over different time horizons, I conduct regressions measuring the effects of these signals on subsequent changes in the same variable within slightly longer time windows. Specifically, I define three distinct horizons for these explained changes: the Monetary Event (ME) window ($\Delta x_{ME,t}$), daily changes ($\Delta x_{1d,t}$), and weekly changes ($\Delta x_{7d,t}$).

The ME window encompasses the combined effects of both the RE and PC signals, where $\Delta x_{ME,t} = \Delta x_{RE,t} + \Delta x_{PC,t}$. Daily changes are calculated as the daily difference around monetary policy announcements ($x_{1d,t} = x_{t+1} - x_t$), while weekly changes are computed as ($x_{7d,t} = x_{t+7} - x_t$). Here, t is the date of the monetary policy announcement.

I perform regressions of the form:

$$\Delta x_{h,t} = \beta_0 + \beta_1 \Delta x_{w,t} + \varepsilon_t, \tag{2.8}$$

where $w = RE, PC$ represents the RE and PC windows, and $h = ME, 1d, 7d$ denotes the period over which the asset price change is observed. By regressing each variable on itself with varying window sizes, the aim is to understand the persistence of surprises from the RE and PC windows over a period of up to 7 days.

Table 2.1 presents the adjusted R^2 of these regressions, which indicates the proportion of variance in intra-daily, daily, and weekly changes explained by the dynamics during the monetary policy meetings.

[6] A more detailed description of the monetary policy process of the ECB and the dataset used can be found in Appendix 2.A.

Table 2.1: Explained Variance of the Press Release and Press Conference Surprise (in %)

	RE window			PC window		
	ME	$1d$	$7d$	ME	$1d$	$7d$
OIS 3M	51	8	-	53	46	10
OIS 1Y	21	33	42	85	68	16
OIS 5Y	16	10	-	82	46	28
OIS 10Y	13	6	-	80	24	20
USD/EUR	21	10	3	76	44	10
JPY/EUR	14	20	-	72	23	20
GBP/EUR	24	8	5	73	45	-

Notes: This table shows the adjusted R^2 of each regression in equation (2.8). It shows how intra-daily asset price changes persist over a time period of up to 7 days. The explanatory variable stems from the RE (= press release) window and the PC (= press conference) window, while the explained variable is the same variable for the ME (= monetary event) window (including press release and conference), 1-day difference, and 7-day difference. For regressions that do not reach overall significance (as tested with an F-test at the 1% level), the values are omitted and replaced by "−".

The contributions of RE surprises, which make up the left-hand side of the table, come from the press release and thus from the ECB's interest rate decision. The right-hand side of the table shows the effects of PC surprises. The dynamics stemming from the press conference window are assumed to proxy informational effects. The table shows that, apart from the 3-month OIS rate, changes from the PC window have a significantly greater impact than from the RE window. The price changes of the RE window have no lasting effect on the intra-daily, daily, or weekly rate of change of the respective variable. Interpreting the changes in the two windows as pure policy and CBI effects, respectively, the informational effects strongly dominate the effects of conventional monetary policy.

However, the distinction between the press release and the press conference is not perfect. Since March 2016, the ECB has started to include information about the size of large-scale asset purchases in the press release. Even with these additional shocks in the RE window, the PC window still dominates.

Another indication of the dominance of informational components in exchange rate changes can be found in the correlation of high-frequency asset price surprises around ECB monetary policy announcements. In the 2004-2022 sample period, exchange rate surprises correlate more strongly with changes in long-term interest rates, rather than short-term interest rates. For example, the USD/EUR exchange rate exhibits a 62% correlation with the 5-year OIS rate, but only a 34% correlation with the 3-month OIS rate.[7] This suggests that the long end of the yield curve, (which depicts an average of short-term interest rates), is more closely related to exchange rate changes.

While the findings in this subsection do not provide a rigorous analysis of the importance of CBI effects, they provide a preliminary analysis that suggests that informational monetary policy shocks are quantitatively important—potentially even more important than conven-

[7] A full correlation table of asset price surprises can be found in the appendix, in Table 2.A1.

tional monetary policy shocks—and should therefore be taken into account when analyzing the impact of monetary policy (in the broad sense) on exchange rates.

2.4.2 Factor Model

I build a factor model using data on asset price surprises, in order to derive different monetary policy shocks. Specifically, I use the changes in interest rate, exchange rate, and inflation swaps in a narrow window around ECB announcements. The assumption is that these asset prices are predominantly affected by monetary policy in a narrow window around ECB announcements, and are liquid enough to react immediately to monetary policy. Employing zero and sign restrictions, I derive a Target, a Delphic, and an Odyssean monetary policy factor.[8] The effects of these factors are then analyzed in subsequent sections. For the derivation, I closely follow the methodology of Andrade and Ferroni (2021), as it is well suited to evaluate the effects on exchange rates.

The factor model is of the form

$$Y = F\Omega' + \varepsilon, \tag{2.9}$$

where Y denotes the data matrix. F contains the principal components in its columns and Ω contains the corresponding factor loadings. $\varepsilon \sim N(0, \Sigma)$ denotes the residuals. Y has dimensions $T \times n$, where T is the number of monetary policy meetings, and n is the number of data series included in the model. F is the $T \times k$ matrix of principal components. Ω is the $k \times n$ matrix of factor loadings, whereas k is the number of factors to be included in the model.

The data matrix Y should contain surprises that are related to current and future monetary conditions, are forward-looking, and are liquid enough such that they quickly incorporate news from monetary policy. That way, they are suitable to capture the potentially multidimensional effects of monetary policy. More concretely, I use interest rates across the yield curve, inflation swaps, a stock index, and exchange rates.

For interest rates, I use overnight index swaps (OIS) rates that reflect expected average interest rates, with maturities of 3 and 6 months, as well as 2, 5, and 10 years. For inflation expectations, I use inflation-linked swaps (ILS) with maturities of 2, 5, and 10 years, as well as the 5Y5Y forward inflation rate, which is a common measure of how well inflation expectations are anchored. I combine this data with the euro stoxx50 index, and the USD/EUR, GBP/EUR, and JPY/EUR exchange rates.[9]

The factor model allows us to be agnostic about the number of factors and the asset prices, through which different monetary policy shocks are transmitted. It can also deal well with highly correlated data series, unlike regression-based estimation techniques. However, it would not be advisable to use OIS contracts of all available maturities. In that case, the time

[8]The taxonomy of these shocks is taken from Campbell et al. (2012).

[9]USD/EUR, GBP/EUR, and JPY/EUR denote the euro exchange rate against the US dollar, the British pound, and the Japanese yen, respectively. An increase denotes an appreciation of the euro.

period to maturity between different OIS securities would overlap to a large degree, so prices would correlate rather mechanically than for economic reasons. Instead, the model should capture economically meaningful correlations between the data series.[10] The choice of series takes this caveat into account. To avoid this overlap, it would also be possible to calculate forward interest rates (as Andrade and Ferroni, 2021, do), but this does not significantly change the results. Therefore, I opt for the publicly available data from Altavilla et al. (2019).

The OIS, stock index, and exchange rate data is taken from the euro area Monetary Policy Event-Study Database (EA-MPD).[11] The ILS data is taken from Refinitiv and is of daily frequency. See Appendix 2.A for more details.

I use a sample that covers all monetary policy meetings by the ECB from April 2004 to December 2022. The limiting factor for the sample length is the inflation-linked swaps data, which only starts in 2004. However, as Altavilla et al. (2019) point out, the OIS data before 2002 is very noisy, so the loss in explanatory power may be limited.

Before identifying different monetary policy factors, I determine how many statistically significant factors can be found in the data matrix Y. The Cragg and Donald (1997) test is used for this purpose. The test computes a Wald test statistic testing the null hypothesis that there are $k = k_0$ statistically significant factors. Table 2.2 shows that the hypothesis of two or fewer orthogonal factors is rejected by the test at the 1% level. Therefore, I will aim to identify three orthogonal factors to span the dataset of surprises.

Table 2.2: Cragg and Donald Test

	F-statistic	p-value
$H_0 : k = 0$	60.48	0.000
$H_0 : k = 1$	48.60	0.000
$H_0 : k = 2$	37.65	0.004
$H_0 : k = 3$	27.58	0.121

Notes: This table presents the Wald test statistics of the Cragg and Donald (1997) test, as well as the corresponding p-values. The test is performed under the null hypothesis that the data in matrix Y is driven by k independent factors. $k = 0$ would imply that the dataset contains only independent white noise series.

This is a meaningful result in itself. Considering the dynamics in interest rates, exchange rates, and inflation swaps surprises, the Cragg and Donald (1997) test states that two factors, for example, a Target and a Path factor, would not be sufficient to explain the effects of monetary policy on the set of asset prices.[12] The test implies that three factors are needed

[10] This trade-off is discussed more thoroughly in Swanson (2021).

[11] The EA-MPD is provided by Altavilla et al. (2019) and regularly updated. I use the Monetary Event (ME) window for this analysis, which includes both the press release and the press conference.

[12] The findings of Table 2.2 are independent of any factor rotation. For this reason, this test can be done before identification and factor rotation.

to explain the surprise data. However, the factors need to be rotated to get an economically meaningful identification.[13] This is done in the next subsection.

2.4.3 Identifying Monetary Policy Factors

For the factors to make economic sense, the principal components F in equation (2.9) are rotated using an orthogonal matrix Q. This yields

$$Y = (FQ)(\Omega Q)' + \varepsilon = Z\Lambda' + \varepsilon, \tag{2.10}$$

where $Z = FQ$ represents the rotated factors, and $\Lambda = \Omega Q$ contains the corresponding factor loadings.[14]

In the following, I aim to identify three different monetary policy factors.[15] The Target factor spans the short end of the yield curve. Since the exchange rate effects of the Target factor are very small (see Subsection 2.4.1), the focus of this analysis is not on the short end of the yield curve. However, the Target factor is used to orthogonalize the informational factors from the innovations to the short-term interest rate.

I distinguish between shocks to the expected path of future interest rates, captured by the Odyssean factor, and shocks to the macroeconomic outlook, captured by the Delphic factor.

Odyssean shocks are (perceived) exogenous increases in the future path of interest rates, or monetary policy. Since this implies a more aggressive monetary policy stance in the future, long-term inflation expectations are expected to fall, and long-term interest rates and inflation expectations should co-vary negatively.

Delphic shocks, on the other hand, are assumed to capture changes in the economic outlook, as revealed in the monetary policy announcement. The central bank's decision and communication serve as a signal of the expected path of the business cycle. An unexpected increase in long-term interest rates, interpreted as a positive Delphic shock, thus signals to the public that the expected path of interest rates is higher because the economic outlook is more positive. The central bank is merely reacting to the economic outlook. In this case, positive news leads to an increase in interest rate and inflation expectations, and hence to a positive covariance between the two series.

To achieve identification, I use as a first condition a zero restriction on the informational factors, so they do not load on the short-term interest rate. This condition is sensible because central banks have a high degree of control over the short-term interest rate. As a second condition, I exploit the opposite covariance that Delphic and Odyssean factors have on long-term interest rates and inflation expectations by using sign restrictions to identify the two

[13]The Cragg and Donald (1997) test is invariant to factor rotations, which is why it is done before the factors are rotated.

[14]Each orthogonal matrix Q has the property $QQ' = I_k$, which implies that $F\Omega = (FQ)(\Omega Q)' = Z\Lambda'$ holds for any orthogonal matrix Q.

[15]The identification assumptions are taken from Andrade and Ferroni (2021), as well.

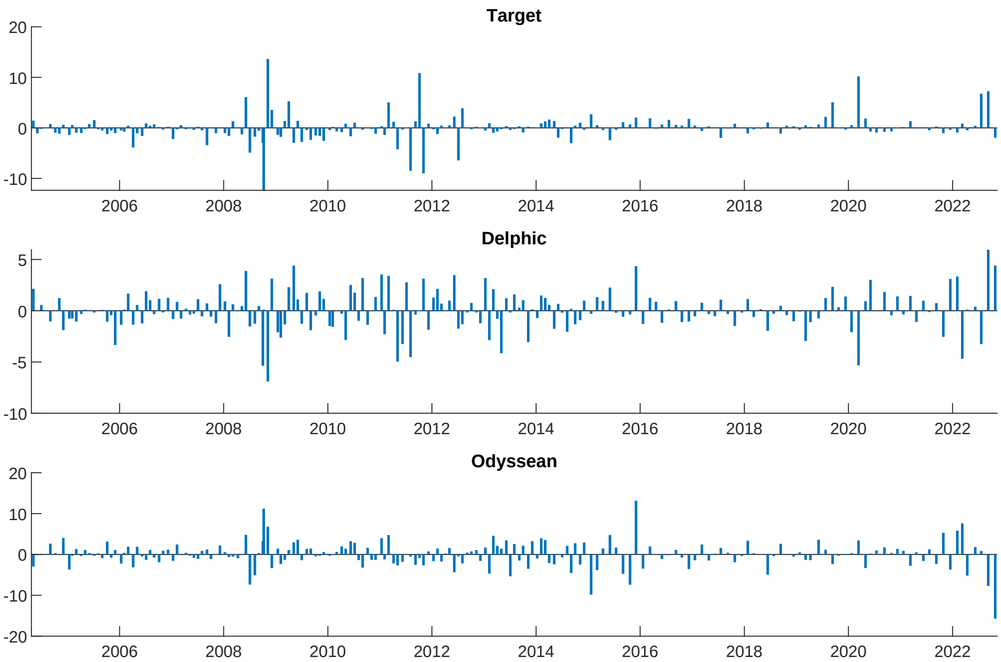
informational factors. Q is selected such that the following restrictions hold:

$$Y_t = \begin{bmatrix} OIS_{3M,t} \\ OIS_{5Y,t} \\ ILS_{5Y,t} \\ \vdots \end{bmatrix} = \begin{bmatrix} * & 0 & 0 \\ * & + & + \\ * & + & - \\ \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} Target_t \\ Delphic_t \\ Odyssean_t \end{bmatrix} + \varepsilon_t,$$

where the first three columns of Y contain the short and long-term interest rates (OIS_{3M} and OIS_{5Y}), and the inflation-linked swap rate (ILS_{5Y}). The equation is consistent with our identification strategy: The Delphic and Odyssean factors do not load on OIS_{3M}. For an Odyssean shock, the interest rate co-moves negatively with inflation expectations, whereas the co-movement is positive for a Delphic shock. Appendix 2.B lays out the methodology to find the rotation matrix Q.

The factors are only identified up to scale and sign. Therefore, in the final step, the Target factor is normalized such that a unit increase implies a one basis point increase in the 3-month OIS rate. The Delphic and Odyssean factors are normalized such that a unit increase implies a one basis point increase in the 5-year OIS rate.

Figure 2.1: Monetary Policy Factors



Notes: This figure shows the calculated factors for the baseline factor model, which is calculated as described in this subsection. All factors are normalized, such that a unit increase in the factor denotes a 1 basis point increase in the 3-month OIS rate for the Target factor, and a 1 basis point increase in the 5-year OIS rate for the Delphic and Odyssean factors.

Figure 2.1 shows the Target, the Delphic, and the Odyssean factor. The Target factor rarely surprises markets. The most significant movement is during crisis periods, such as the Great Financial Crisis or the euro area debt crisis. It is noteworthy that, contrary to a conventional monetary policy shock as captured by Jarociński and Karadi (2020), this Target factor is not constrained to be contractionary. Therefore it partially captures what Jarociński and Karadi (2020) call a CBI shock.

For the Delphic and Odyssean factors, the strong decrease in the variance after 2016 is noteworthy. In this period, 5-year interest rates were close to zero. On the one hand, they can't decrease because of the effective lower bound, and on the other hand, quantitative easing programs prevented the 5-year interest rate from increasing. As a result, the movement of the 5-year interest rate was suppressed, and there was little room for informational monetary policy shocks to materialize, contributing to the muted dynamic of both the Delphic and Odyssean factors.

In the subsequent analysis, the identified shocks are considered exogenous to both economic and financial data, as they arise from asset price changes in a very narrow window around monetary policy announcements. The narrow window ensures that the surprises are not influenced by contemporaneous movements in economic or financial variables. Additionally, the assumption is that all information before the monetary policy announcement is already priced in, such that information from before the announcement does not confound the surprises data. In the rest of this paper, I use the monetary policy factors derived here and evaluate their effects on various asset prices and, most importantly, on exchange rates.

2.5 Exchange Rate Effects at High Frequency

This section focuses on the high-frequency effects of the Target, the Delphic, and the Odyssean shocks. Subsection 2.5.1 depicts the instantaneous impact of the three shocks on asset prices. Before showing dynamic responses (at the daily frequency) in Subsection 2.5.3, Subsection 2.5.2 reexamines the exchange rate puzzle presented by Gürkaynak et al. (2021) in the context of informational monetary policy shocks.

2.5.1 High-Frequency Regressions

To deduce the immediate impact of the Target, the Delphic, and the Odyssean factor on asset prices, I run the following regression:

$$\Delta x_t = \beta_0 + \beta_1 Target_t + \beta_2 Delphic_t + \beta_3 Odyssean_t + \varepsilon_t. \tag{2.11}$$

The three factors are orthogonal by construction. Thus, the results of the regression are identical to three separate simple regressions. In Table 2.3, I have omitted the 3-year and 7-year OIS rates for brevity. The 3-month OIS rate is not displayed, either.[16]

The interest rate response is not the focus of this paper. The regressions confirm, however, that all three factors contribute positively and highly significantly to an interest rate increase

[16] Regressing the 3-month OIS rate on the Target factor gives a coefficient of one, by normalization. For the Delphic, and the Odyssean factors, the coefficient is zero, according to the factor model restrictions.

Table 2.3: Regression of High-Frequency Variables on Monetary Policy Factors

	Target	R^2	Delphic	R^2	Odyssean	R^2
Interest Rates						
OIS 1Y	1.67***	0.55	0.90***	0.44	0.67***	0.16
OIS 2Y	1.61***	0.42	0.98***	0.53	0.90***	0.24
OIS 5Y	1.15***	0.25	1.00***	0.59	1.00***	0.34
OIS 10Y	0.09***	0.09	0.68***	0.56	0.68***	0.33
Inflation-Linked Swaps						
ILS 2Y	−0.56***	0.06	2.18***	0.25	−0.71***	0.19
ILS 5Y	−0.27**	0.03	1.48***	0.34	−0.68***	0.33
ILS 10Y	0.07	0.00	1.05***	0.31	−0.64***	0.46
5Y5Y	0.42**	0.02	0.62***	0.04	−0.60***	0.40
Stock Price						
stoxx50	−0.04*	0.06	0.24	0.09	−0.05***	0.20
Exchange Rates						
USD/EUR	0.04**	0.51	0.16***	0.25	0.19***	0.46
GBP/EUR	0.04***	0.48	0.13***	0.24	0.14***	0.49
JPY/EUR	0.06***	0.59	0.15***	0.22	0.20***	0.51

Notes: This table shows the regression coefficient of simple linear regressions of asset price changes in a 135-minute window around ECB monetary policy announcements, which are regressed on factors from the same time window. The sample period is from April 2004 to December 2022. The units are percentage points for the interest rates and percent for stocks and exchange rates. An increase in the exchange rate denotes an appreciation of the euro. *, **, and *** denote significance of the coefficient at the 10%, 5%, and 1% level, respectively.

across the yield curve. It is important to note that the factors are only defined up to sign and scale. The Target and the informational factors are normalized to have a unit effect on the 3-month and 5-year OIS rates, respectively. Therefore, the magnitude of the factors is not meaningful in and of itself. What may be of interest is that the Delphic shock explains a large fraction of OIS rate changes. At the same time, the explanatory power of the Odyssean shock, while significant, is substantially smaller than that of the Delphic shocks.

The reaction of the stock index is also of secondary importance for this paper. While an Odyssean shock is seen as a contractionary future monetary policy shock, it is expected to decrease stock prices. The Delphic shock, where the central bank merely reacts to a more inflationary economy, does not have a clear effect on stock prices.[17] These properties are confirmed by the stock price response in the above regressions.

The bottom rows of Table 2.3 are more pertinent to the research question. They show that euro exchange rates consistently appreciate after all monetary shocks. However, the main difference between Delphic and Odyssean shocks can be seen by comparing the R^2

[17] If the revealed additional inflation comes from an expected demand shock, the Delphic shock is expansionary. If it comes from an expected supply shock, it is contractionary. Andrade and Ferroni (2021) find that the Delphic shock is expansionary in their analysis. Also, Jarociński and Karadi (2020) show in their appendix that expectational supply shocks have no significant effects.

between the shocks: Delphic shocks explain between 22 and 25% of the variation in exchange rates, while the effect of Odyssean shocks is significantly greater, explaining up to 51% of the variation. Hence, exchange rates are more responsive to Odyssean shocks, at least within high-frequency windows.

2.5.2 The Exchange Rate Puzzle

Before turning to the dynamic responses of asset prices to CBI shocks, I revisit the exchange rate puzzle presented by Gürkaynak et al. (2021) in the context of decomposed monetary policy shocks. This puzzle arises from the observation that the correlation between interest rate surprises and high-frequency exchange rate changes during ECB announcement windows is relatively weak. In particular, a positive interest-rate surprise is accompanied by a depreciation of the euro in many instances. This is unexpected, as the effects in this high-frequency analysis should be less plagued by confounding factors and noise.

This exchange rate puzzle is not directly comparable to Gürkaynak et al. (2021), as they focus on the puzzle in the Target factor. Nevertheless, as discussed in the introduction, the response of exchange rates to monetary policy around monetary policy announcements is not clear and therefore warrants further investigation.

The first step is to quantify the size of the puzzle. Table 2.4 shows the covariation between interest rate surprises and the USD/EUR exchange rate. The first two rows display the percentage of monetary policy meetings, where the covariance between interest rate and exchange rate surprises is puzzling. The bottom two rows show the robust F-statistic and the R^2 from a simple regression on the USD/EUR surprises.

Table 2.4: Covariation of Interest Rate and USD/EUR Surprises

	Interest Rate Surprises					MP Shocks		
	OIS 3M	OIS 1Y	OIS 2Y	OIS 5Y	OIS 10Y	T	D	O
% wrong sign	41	30	28	27	30	29	26	22
% wrong sign (adj.)	36	30	27	26	30	28	27	16
F (robust)	13.4	34.6	33.1	33.8	24.8	7.2	35.8	37.9
R^2 (in %)	14	21	23	31	27	14	22	45

Notes: This table shows the contribution of the 5-year interest rate and the Delphic and Odyssean factors to the exchange rate variance. The contributions are computed by taking the adjusted R^2 of a simple regression on the exchange rate. All variables are asset price changes in a 135-minute window around ECB announcements. The sample period is from April 2004 to December 2022. USD/EUR, JPY/EUR, and GBP/EUR represent the exchange rate of the euro against the US dollar, the Japanese yen, and the British pound, respectively.

The covariance between interest rates and the exchange rate has the wrong sign for all interest rate maturities. Nevertheless, the regression coefficients (not shown in the table) are positive and highly significant, implying no puzzle *on average*. For comparison with the monetary policy shocks derived in this section, the last three columns display the same statistics for the three monetary policy shocks from this article.

To evaluate the exchange rate puzzle with other monetary policy shocks, Table 2.5 calculates the same statistics for well-known monetary policy shocks from the literature.

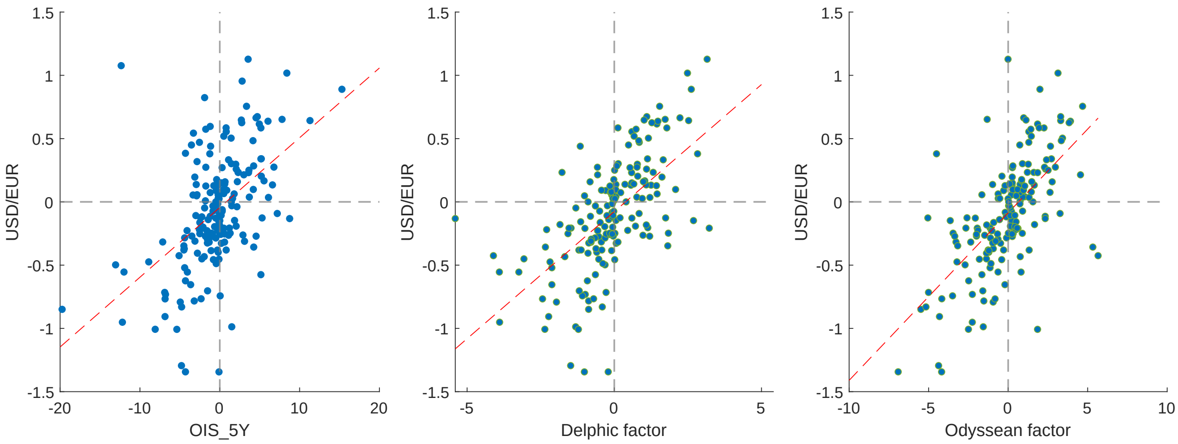
Table 2.5: Covariation of Different MP Shocks and USD/EUR Surprises

	This work			JK20		AF21			ABGMR19	
	T	D	O	MP	CBI	T	D	O	T	FG
% wrong sign	29	26	22	37	47	24	22	22	38	33
% wrong sign (adj)	28	27	16	37	53	30	31	32	46	39
F (robust)	7.2	35.8	37.9	10.5	0.1	6.6	24.5	5.7	5.3	15.5
R^2 (in %)	14	22	45	14	0	12	11	14	4	7

Notes:

The relationship between the 5-year OIS rate and the exchange rate is shown in the leftmost scatter plot of Figure 2.2. The regression line shows that on average, an increase in interest rates leads to a stronger currency. So, on average there is no puzzle. However, there are 30% of ECB announcements in the sample where the covariance between monetary policy and exchange rates is in the "wrong" quadrants, meaning that an unexpected increase in interest rates leads to a depreciation.

Figure 2.2: Exchange Rate Response to ECB Announcements



Notes: This graph depicts the simultaneous change in the OIS 5-year rate and the USD/EUR exchange rate, on the left, and the Delphic and Odyssean factors derived above. The USD/EUR is measured in percentage points, while the OIS 5Y is measured in basis points. The red dashed line depicts the regression line. The sample period is from April 2004 to December 2022.

Looking at the two plots on the right, the exchange rate appreciates more consistently with less noise in the Delphic and Odyssean factor windows. The link between the two factors, which are both normalized to increase the 5-year OIS rate one-to-one, seems stronger than for the 5-year OIS rate. The fact that both factors are strongly positively correlated with the exchange rate, gives some credence to the interpretation of the shocks in section 2.4. Further, given the correlation of the factors to the exchange rate is stronger than for the 5-year OIS rate, this lends some support to identifying informational monetary policy shocks with a factor model and many different asset prices, instead of (implicitly) only looking at one time series to gauge the effects of monetary policy.[18]

2.5.3 Persistence of the Effects on Asset Prices

The results displayed in Table 2.3 (Subsection 2.5.1) are consistent with the factor interpretation. However, the effects underlying this table may be short-lived. Exchange rates, in particular, are known for strong intra-daily dynamics. Thus, it is not clear whether these effects persist beyond an intra-daily time window. To test this, I build a financial SVAR model with the 5-year OIS rate, the 5-year ILS rate, the stoxx50 index, and the USD/EUR exchange rate. The Delphic and the Odyssean factors are used as instruments in a proxy SVAR methodology.[19]

The monetary policy shocks in this paper stem from intra-daily variations in financial variables. Thus, these shocks first materialize in financial markets and are eventually used to explain variations in macroeconomic variables at a monthly frequency. However, moving from intra-daily variation to monthly frequency leaves out a lot of information about variables that are key to identifying different monetary policy shocks. Tracking the dynamics of asset prices at a daily frequency fills this gap. Altavilla et al. (2019) also use a daily VAR model to examine the validity of their monetary policy shocks, which are also derived from a factor model.

Examining a daily proxy VAR model with the same shocks provides important evidence that a) informational monetary policy shocks have important, highly significant, and persistent effects on financial variables, b) Delphic and Odyssean factors do indeed capture shocks with fundamentally different effects, and c) the Delphic shock is more persistent than the Odyssean shock.

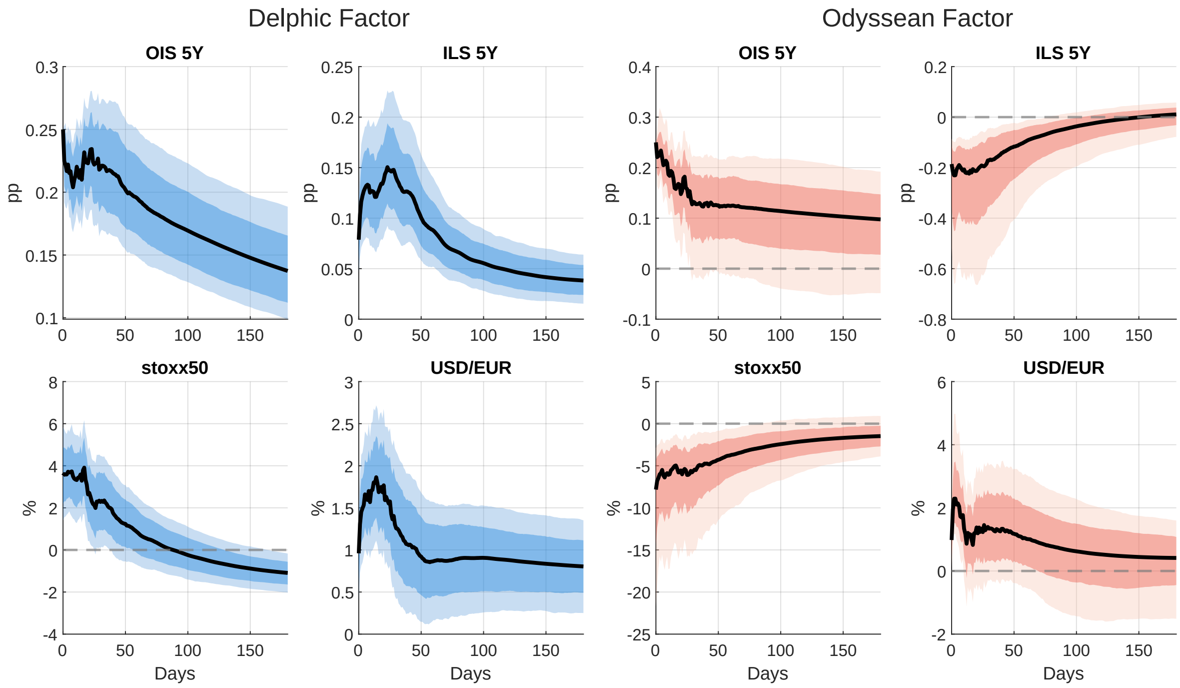
Thus, even though the objective of the paper is to analyze the effects at a monthly frequency, the daily VAR helps to establish that the identification of the shocks is meaningful and that the interpretation of the shocks is consistent with the response of financial markets as seen in the daily VAR model.

Figure 2.3 shows the impact of the two factors for a horizon of 180 working days. Both factors have significant and immediate effects on all variables. A Delphic factor leads to a large increase in inflation expectations (as measured by inflation swaps), and stock prices, as well as to an appreciation of the exchange rate. Interestingly, the stock price effect is the only one that is not persistent. Inflation swaps and the exchange rate remain significantly elevated over the 180-day horizon. The Odyssean factor shows the expected reaction to a monetary policy shock: stock prices and inflation expectations fall, while the currency appreciates. The effects on inflation swaps, stock prices, and the USD/EUR exchange rate

[18] This argument is about the informational aspect of monetary policy. For conventional monetary policy, the link between the 3-month OIS rate and the Target factor is much stronger, due to the central bank's strong control over the short-term interest rates.

[19] The methodology is described in Section 2.6.1, as it is identical to the monthly SVAR model. The data and empirical specification are discussed in Appendix 2.C.2.

Figure 2.3: Financial VAR: Daily Impulse Responses



Notes: This figure shows impulse response functions in a daily proxy SVAR model. The frequency is daily, excluding weekends. An increase in USD/EUR depicts an appreciation of the euro. Both factors are normalized to increase the OIS 5Y rate by 25 basis points. The 68% and 90% confidence intervals are computed by a moving block bootstrap algorithm (Jentsch and Lunsford, 2019). The impulse responses for the Delphic factor, in blue, are on the left-hand side, and the impulse responses for the Odyssean factor, in red, are on the right-hand side of the figure.

are more pronounced for an Odyssean shock when compared to a Delphic shock. The effects are larger, given a normalized 25 basis point increase of the 5-year OIS rate for both shocks. However, the effects of the Odyssean factor are less persistent. The inflation and exchange rate effects go back to zero at the horizon.

2.6 Exchange Rate Effects at Low Frequency

This section aims to quantify the macroeconomic impact of the two informational monetary policy factors. Since macroeconomic variables are not available at high frequency, this section examines the effects at a lower, monthly frequency. To do this, I construct a monthly proxy SVAR model to combine the high-frequency informational monetary policy factors with monthly data.

The proxy SVAR methodology is well suited for this exercise, as the exogeneity assumption is credibly satisfied when using high-frequency data since confounding variables play a negligible role in short windows. Note, however, that the surprise data is only a partial measure of the underlying shock since central banks can also influence the economy outside of this window. By construction, the instrumental variable approach is well-suited for leveraging a partial signal of the true exogenous monetary policy shock.

2.6.1 Setting up a Proxy SVAR Model

The monthly SVAR model mostly follows Stock and Watson (2012) and Mertens and Ravn (2013). It is of the form:

$$Y_t = A_+ X_t + B\varepsilon_t, \tag{2.12}$$

where $X_t = [Y_{t-1}, ..., Y_{t-p}, 1]$, and B is the structural impact matrix. Y_t has dimensions $T \times n$, and X is $T \times (np+1)$. T, n, and p denote the sample length, the number of variables, and the number of lags, respectively. The reduced-form residuals $u_t = B\varepsilon_t$ are collected in a $n \times 1$ vector, with $u_t \sim N(0, \Sigma)$.

By construction, the structural shocks ε_t are orthogonal to each other and have unit variance. Hence, it must be that

$$\Sigma = BB'. \tag{2.13}$$

The vector of structural shocks ε_t is partitioned into $(\varepsilon_{1,t}, \varepsilon_{2:n,t})$. The order is irrelevant, as shocks are not identified with a Cholesky decomposition. The structural shock ε_{1t} is instrumented by Z_t where Z_t denotes different exogenous monetary policy shocks (as derived in Section 2.4). For each monetary policy factor, that is for the Target, the Delphic, and the Odyssean factors, I re-estimate the model separately. For identification, I make the following assumptions, which are typical for an instrumental variable approach:

$$E[\varepsilon_{1,t} Z_t] = \Phi, \tag{2.14}$$

$$E[\varepsilon_{2:n,t} Z_t] = 0, \tag{2.15}$$

where $\Phi \neq 0$. These are the relevance and the exogeneity condition, respectively. With these two assumptions, it is possible to derive B_1, the first column vector of B. First, the SVAR model is estimated by ordinary least squares, yielding the residuals u_t. Then, Assumptions (2.14) and (2.15) allow us to estimate the impact matrix

$$B_{2,1}/B_{1,1} = E\left[u_{2,t} Z_t\right]/E[u_{1,t} Z_t], \tag{2.16}$$

where $u_{1,t}$ and $u_{2,t}$ are the residuals for the instrumented variable, and the other four variables, respectively. The structural impact column B_1 is partitioned such that $B_1 = (B_{1,1},\ B'_{2,1} B_{1,1})'$. As a final step, I set $B_{1,1} = 0.25$, normalizing the effect of the monetary policy factors to have a 25 basis point impact on the domestic interest rate, thereby pinning down the matrix B_1.

2.6.2 Empirical Specification

The sample period runs from January 1999 to December 2022.[20] The model consists of 6 endogenous variables. The main building blocks of UIP are included in the model, namely the European and US 5-year yield, as well as the USD/EUR exchange rate. This allows us to see how the different terms in the UIP equation evolve. To get a clearer picture of the macroeconomic consequences within the euro area, HICP inflation and European industrial production are added to the model. To account for the Great Financial Crisis and the European Debt Crisis, the BBB spread is added to the model as a measure of risk.

The inflation rate and industrial production are linearly detrended, even though this does not significantly change the results. The variables enter the model in log-levels except for the two interest rates and the BBB spread, which are in percentage points. There is a more detailed description of the data in Appendix 2.C

The Delphic and the Odyssean shocks are used as instruments in two separate models, and the European 5-year yield is the instrumented variable.[21] Although the proxy SVAR methodology is valid if Assumptions (2.14) and (2.15) hold, it may still produce unreliable results if the instruments are weak. To test whether the instruments are sufficiently strong, the weak instrument test of Olea and Pflueger (2013) is applied to the first-stage regressions.

Table 2.6: Instrument Strength

	Target	Delphic	Odyssean
F-statistic	42.15	24.52	29.62
F-statistic (robust)	24.76	14.01	24.25
R^2	0.17	0.10	0.13
R^2 adj.	0.17	0.10	0.12
Observations	225	225	

Notes: This table shows different test statistics of the first-stage regressions of the residuals $u_{1,t}$ on the different instruments Z_t The robust F-statistic test is deemed the "weak instrument test". It is robust to heteroskedasticity, serial correlation, and clustering (see Olea and Pflueger, 2013).

Table 2.6 indicates that the Delphic and the Odyssean shocks are sufficiently strong instruments, as the robust F-statistic is above the recommended value of 10. Thus, there is no weak instrument problem in the subsequent analysis.

2.6.3 Impulse Responses

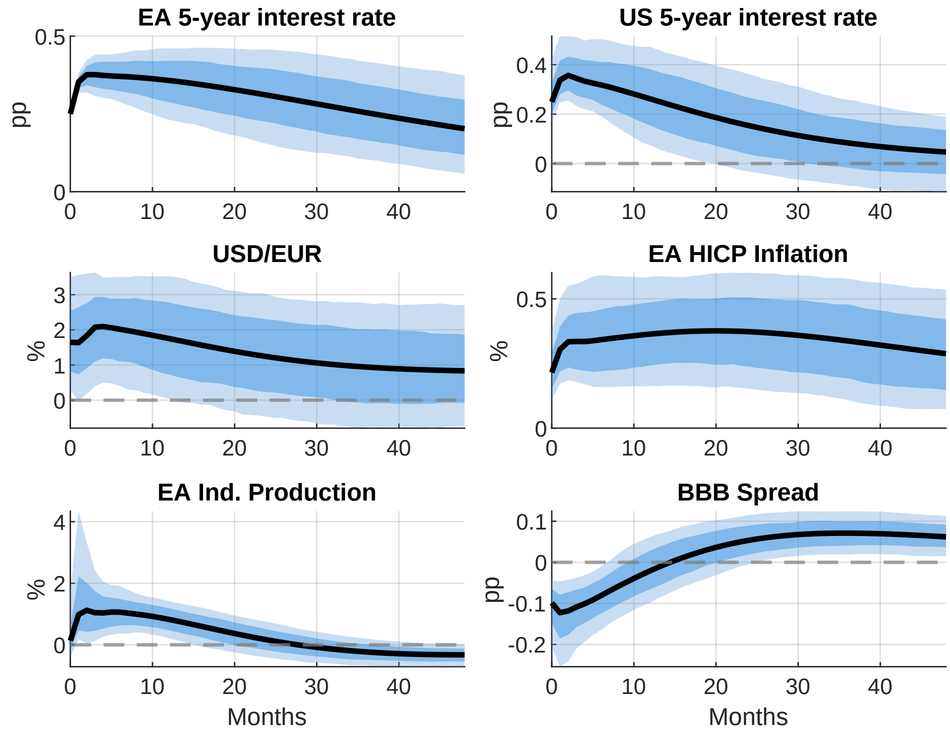
This section shows the impulse responses of the endogenous variables in the SVAR model. Figures 2.4 and 2.5 display the impulse responses, as well as 68% and 90% confidence bands.

[20] Note that the sample length of the proxy SVAR model does not have to coincide with the length of the instrument.

[21] The Target factor captures exogenous changes in the short end of the yield curve, but there is no short-term interest rate in the SVAR model. Therefore, applying the proxy SVAR methodology to the Target factor would not be convincing. In addition, the effects of the Target factor are not the focus of this paper, so I omit the analysis of its effects.

As the factors are only defined up to scale and sign, the response is normalized to a 25 basis point increase in the domestic interest rate.

Figure 2.4: Impulse Response after a Delphic Shock



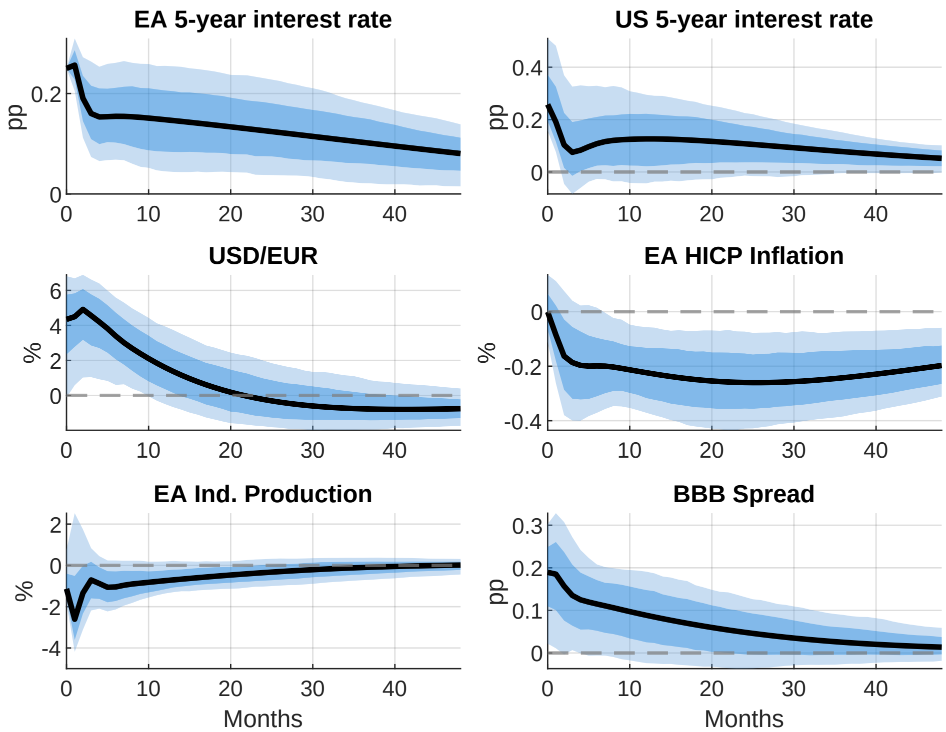
Notes: This figure shows impulse response functions, as well as 68% and 90% confidence intervals computed by a moving block bootstraps algorithm (Jentsch and Lunsford, 2019). EA stands for the euro area and USD/EUR for the bilateral euro-dollar exchange rate. An increase denotes an appreciation of the euro. The shock is normalized to increase the 5-year European yield by 25 basis points.

Consistent with its characterization as an expectational shock on macroeconomic fundamentals (see Subsection 2.4.3), Figure 2.4 shows that a positive Delphic shock is expansionary. Interest rates remain persistently high after an increase in the Delphic factor. The USD/EUR exchange rate, inflation, and industrial production all increase significantly on impact, which is suggestive of an expansionary movement. Besides, the BBB spread decreases, which is also typical for expansions.

These effects are highly persistent. This is in line with Gründler et al. (2023), who note the strong persistence of CBI shocks. Real output, as measured by industrial production, and the BBB spread, are the least persistent, returning to the steady state after 1-2 years. Nominal variables show more persistence, consistent with the classical dichotomy assumption, which states that monetary policy does not affect real variables in the long run.

Consistent with its characterization as an exogenous change in future monetary policy (see Subsection 2.4.3), Figure 2.5 shows that a positive Odyssean shock is contractionary. Moreover, in contrast to the Delphic shock, inflation falls after an Odyssean shock. Given the identifying assumptions of the factors, the inflation decrease may not be surprising. However, the high significance, as well as the strong and persistent disinflationary effects

Figure 2.5: Impulse Response after an Odyssean Shock



Notes: This figure shows impulse response functions, as well as 68% and 90% confidence intervals computed by a moving block bootstraps algorithm(Jentsch and Lunsford, 2019). EA stands for the euro area and USD/EUR for the bilateral euro-dollar exchange rate. An increase denotes an appreciation of the euro. The shock is normalized to increase the 5-year European yield by 25 basis points.

suggest a high explanatory power of the Odyssean factor. The fall in industrial production and the increase in the BBB spread point to the contractionary effects of the shock. The appreciation on impact is almost twice as strong for the same interest rate increase as is the case for the Delphic factor.[22]

The results are also in line with the analytical derivation in Section 2.3, which indicates that Odyssean shocks appreciate the domestic currency not only through interest rates, but also through the inflation differential. However, despite the larger magnitude of the effect on both the USD/EUR exchange rate and industrial production, these effects exhibit less persistence and tend to dissipate more rapidly compared to the effects of the Delphic shock. This is in line with what Gründler et al. (2023) find for the US case.

2.6.4 Decomposing the Exchange Rate Response

The aim of this section is to combine the theoretical decomposition in Equation (2.7) with the empirical results reported in the previous subsection. The objective is to see whether the changes in the exchange rate can be attributed to the cumulative sum of the changes in interest rates and inflation.

[22]Note that both factors are normalized to increase the 5-year OIS rate by 25 basis points.

Equation (2.7), here rewritten for convience, is:

$$\nu_{t+1}(s_{t+1}) = \sum_{j=0}^{\infty} \nu_{t+1}(d_{t+j+1}) + \sum_{j=0}^{\infty} \nu_{t+1}(\sigma_{t+j+1}) + \sum_{j=0}^{\infty} \nu_{t+1}\left(\pi^*_{t+j} - \pi_{t+j}\right).$$

It can be rearranged to be a function of real interest rates:

$$\nu_{t+1}(s_{t+1}) = \sum_{j=0}^{\infty} \nu_{t+1}\left(i_{t+j+1} - \pi_{t+j}\right) - \sum_{j=0}^{\infty} \nu_{t+1}\left(i^*_{t+j+1} - \pi^*_{t+j}\right) + \sum_{j=0}^{\infty} \nu_{t+1}(\sigma_{t+j+1}). \quad (2.17)$$

To get data to quantify this equation, I first extend the VAR model to include U.S. CPI inflation as a seventh variable. This has only a negligible impact on the dynamics of the other variables. Second, I recalculate the impulse responses for 100 months. It can be visually confirmed that all impulse responses are fairly close to zero, and I, therefore, assume that all impulse responses are equal to zero after 100 periods, making it possible to calculate the infinite sums in Equation (2.17).

Abstracting from foreign exchange risk premia, I can compute the theoretical exchange rate response, denoted $\hat{s}_t$ for the three shocks, as displayed in Figure 2.6.

The top two rows show the response of real interest rates in the domestic and foreign economies, represented by the first two right-hand side terms in equation (2.17). The bottom row displays the impulse response of the exchange rate (in blue) and the theoretical response (in orange), abstracting from any changes in the risk premia. The theoretical exchange rate is thus the sum of real interest rate differences.[23]

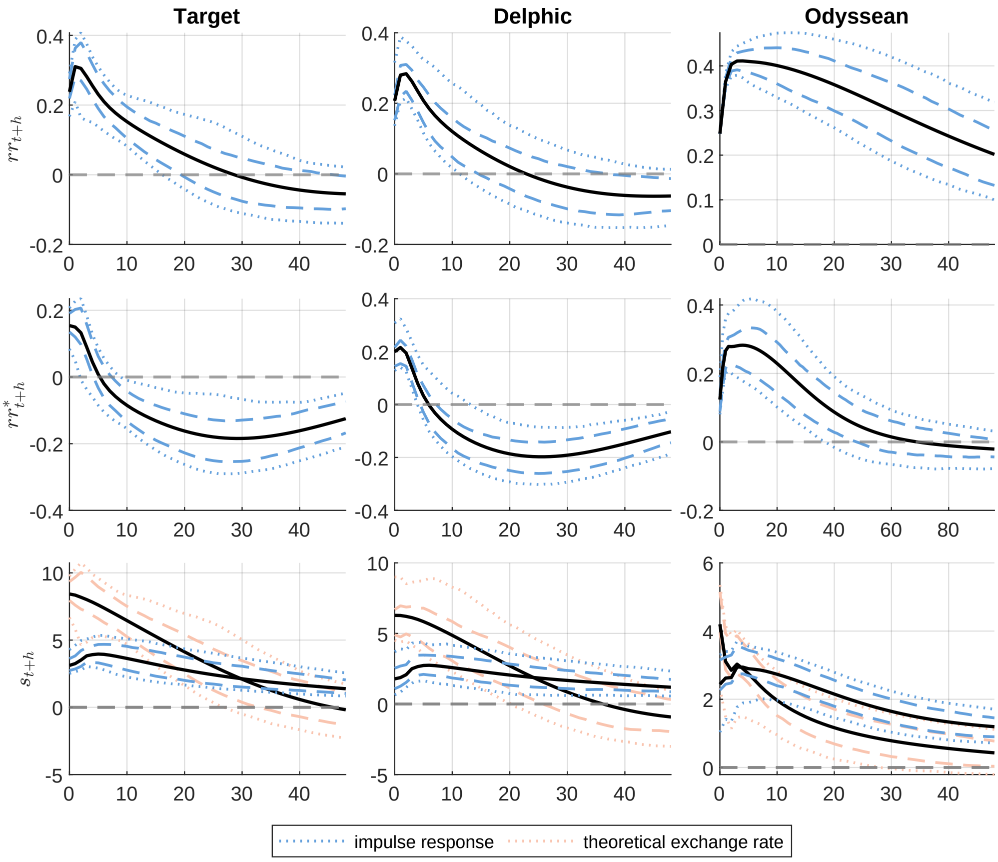
The figure shows that the exchange rate response to a Delphic shock is smaller than the exchange rate implied by the theoretical decomposition. Given all terms in equation (2.17), except for FX risk premia, are determined by the impulse responses, this equation implies that risk premia decrease significantly after a Target or Delphic shock, while this decrease is not significant for the Odyssean shock. It can also be seen that the increased stickiness of the response to a Delphic shock is mainly due to risk premia, while risk premia play a smaller role for the Odyssean shock.

2.7 Conclusion

This paper examines the effects of central bank information (CBI) shocks on exchange rates in the euro area. I evaluate the exchange rate response to different types of informational shocks, namely a Delphic and an Odyssean shock: Delphic shocks capture changes to the economic outlook as revealed by the central bank, and Odyssean shocks capture changes in the expected conduct of monetary policy.

[23]Equation (2.17) comprises the infinite sums of the real interest rates. To be able to calculate these, impulse response functions are computed for 100 periods and assumed to be zero for all periods thereafter.

Figure 2.6: Impulse Response Decomposition



Notes: This figure displays impulse responses (in blue) of the domestic real interest rate, the foreign real interest rate, and the USD/EUR exchange rate in response to a Target, a Delphic, and an Odyssean shock. In orange, the last row displays the theoretical exchange rate, as calculated by Equation (2.17), assuming FX risk premia stay constant. The 68% and 90% confidence intervals are computed using a moving block bootstraps algorithm (Jentsch and Lunsford, 2019), where the calculations described in the main text are computed for each draw.

I find that the effect of the Target factor—an exogenous change in the short-term interest rate—on the exchange rate is small when compared to the two informational factors. This is consistent with the analytical derivation, which shows that changes in the exchange rate depend on the infinite expected path of interest rate differentials. The analytical derivation also shows that there is a direct link between the targeted (long-run) inflation and the current exchange rate.

Using high-frequency regressions and a daily proxy SVAR model, I show that while the effects of the Delphic factor are expansionary, the effects of the Odyssean shock are contractionary. I also find that both factors lead to a significant and immediate appreciation of the currency. While the analytical derivation predicts this in the case of the Odyssean shock, the sign was a priori ambiguous for a Delphic shock. The results also suggest that while the responses to a Delphic shock are long-lived (at the daily frequency), the effects after an Odyssean factor slowly revert back to the mean.

A monthly proxy SVAR model is further used to examine the long-run, macroeconomic effects of the informational monetary policy shocks. The Delphic and Odyssean shocks are shown to have lasting effects over the long term. The Delphic shock is expansionary, leads to an appreciation, and is highly persistent. By contrast, the Odyssean shock is contractionary. It also leads to an appreciation that is stronger in the short run but dissipates more quickly.

These findings underscore the importance of informational monetary policy shocks in shaping exchange rate dynamics and highlight the quantitative importance of new information relative to conventional monetary policy decisions. By examining the nature and transmission of different informational shocks affecting exchange rates, this paper contributes to a deeper understanding of the interplay between monetary policy and exchange rate dynamics.

Appendix

2.A High-Frequency Asset Price Data

This section provides more information on the high-frequency asset price data, known as surprises. This data is used to construct the factor model and also serves as the explained variable in high-frequency regressions. For this reason, it is presented in a separate appendix. I use surprises on interest rates, a stock price index, inflation-linked swaps, and the USD/EUR, JPY/EUR, and GBP/EUR exchange rates. The available sample covers every ECB monetary policy announcement from April 2004 until December 2022.

Interest Rate, Stock, and Exchange Rate Surprises

For the OIS interest rate swaps, the stoxx50 index, and the exchange rates data, I graciously rely on the work of Altavilla et al. (2019), who provide this data and update it regularly.[24] They use underlying tick data from the Thomson Reuters Tick History database.[25] Not all OIS surprises are available from the beginning of the sample. In that case, the series are prepended by the German interest rate swaps series of the same maturity.[26]

This data includes asset price changes in the press release (PR) window, in which the monetary policy decision is being announced, which takes place at 13:45 CET (Central European Time). It also covers the press conference (PC) window that follows the release and starts at 14:30 CET, and that usually takes an hour. The surprise data for the RE window is the difference of each asset price 15 minutes before (median of values from 13:25-13:35), to 20 minutes after the release (median of values from 14:00-14:10). The PC window captures the difference from 10 minutes before the press conference (median of 14:15-14:25) to 15 minutes after the press conference (median of 15:40-15:50). The monetary event window

[24] The dataset which is continually updated can be downloaded under `https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx`.

[25] see Altavilla et al. (2019), as well as their appendix for details on the EA-MPD surprises dataset.

[26] The German OIS series are available for the whole sample period, and its surprises are also provided by Altavilla et al. (2019).

(ME) combines the effects from the RE and the PC windows by capturing the changes from the 13:25-13:35 window (before the press release) and the 15:40-15:50 window (after the press conference).[27]

For the baseline factor model, all data series are from the ME window. Using only the PC window does not significantly change the results, implying that the RE window is of minor importance for information shocks. This is demonstrated in Subsection 2.B.2.

Inflation-Linked Swaps

For the inflation-linked swaps (ILS) data, I use data from Refinitiv, namely the data under the ticker "ICAP EU INFL-LKD SWAP HICP xY" where x is replaced by the maturity of the swap (that is, by the numbers 1 through 10 for the respective maturities). The underlying inflation rate is the official HICP inflation rate excluding tobacco. The series is daily and contains the swap price at 19:00 CET. This is well after the ECB announcements have ended. Thus, I take the difference between the day t (day of the announcement) and day $(t-1)$ to get daily ILS surprise data.

A selection of the surprise data is displayed in Figure 2.A1. Table 2.A1 shows the correlation coefficients between the surprise data series.

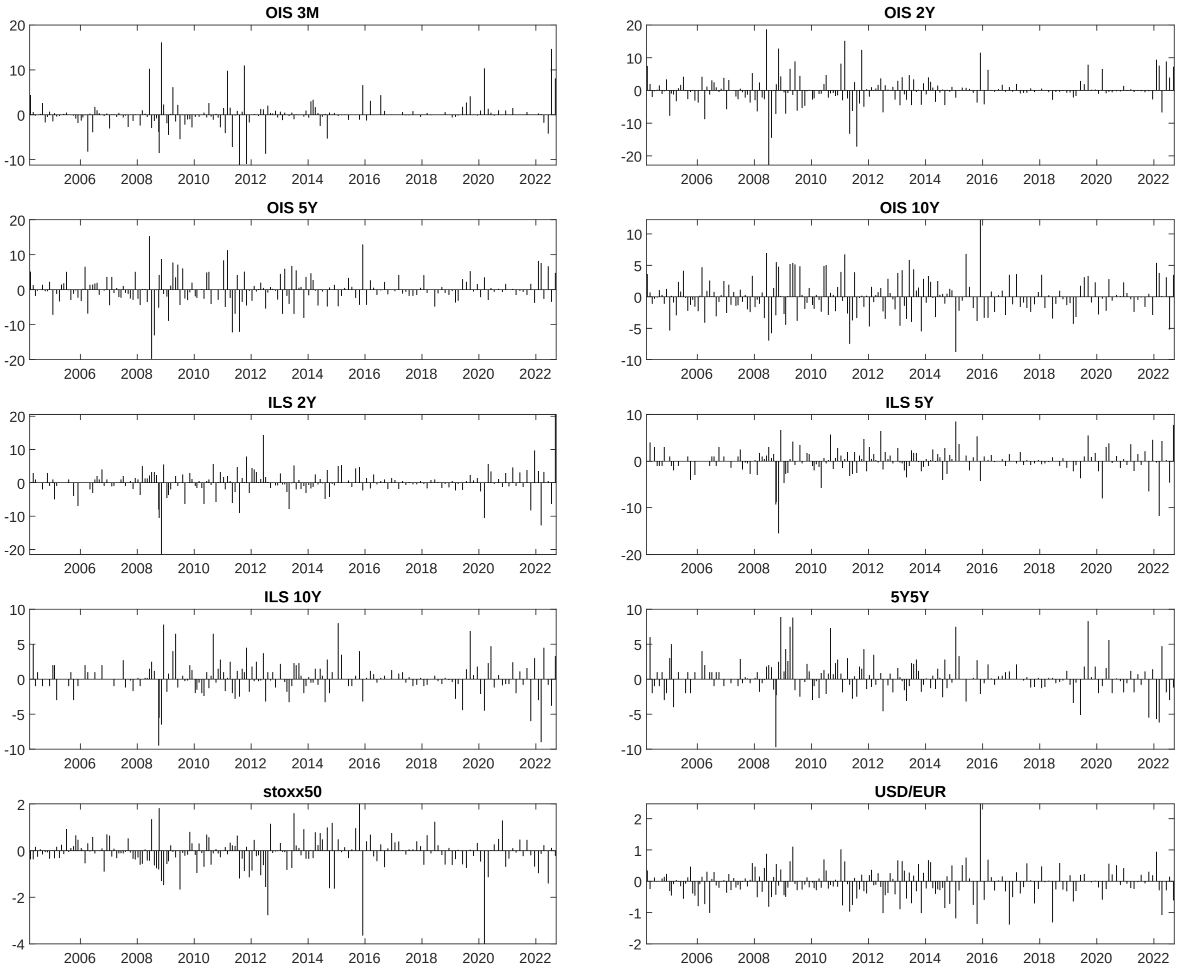
Table 2.A1: Factor Data Correlation Table

	OIS 3M	OIS 1Y	OIS 2Y	OIS 5Y	OIS 10Y	ILS 2Y	ILS 5Y	ILS 10Y	Y5Y5	stoxx50	USD/EUR
OIS 3M	1										
OIS 1Y	0.82	1									
OIS 2Y	0.69	0.96	1								
OIS 5Y	0.53	0.83	0.93	1							
OIS 10Y	0.32	0.59	0.71	0.88	1						
ILS 2Y	-0.06	0.05	0.01	-0.03	-0.01	1					
ILS 5Y	-0.1	-0.03	-0.06	-0.07	-0.04	0.88	1				
ILS 10Y	-0.03	-0.01	-0.04	-0.05	-0.02	0.71	0.9	1			
Y5Y5	0.05	0.02	-0.01	-0.02	0	0.32	0.54	0.86	1		
stoxx50	-0.23	-0.21	-0.22	-0.2	-0.13	0.16	0.21	0.2	0.13	1	
USD/EUR	0.34	0.48	0.53	0.62	0.59	0	-0.04	-0.05	-0.04	-0.3	1

Notes: This table displays Pearson correlation coefficients of high-frequency asset price surprises that comprise the factor model in Section 2.5. They span the Monetary Event window (see Appendix 2.A) for the period April 2004 through December 2022

[27] The timing of the press release and press conference was changed in July 2022, but the window sizes remained the same.

Figure 2.A1: Factor Model Data



Notes: This graph displays all the data points that enter the factor model derived in Section 2.5. An increase in OIS and ILS rates depicts an expected average increase up to the maturity of the swap. An increase in the stoxx50 stock index depicts an increase in its price. An increase in the USD/EUR exchange rate depicts an appreciation of the euro vis-à-vis the dollar.

2.B Deriving a Factor Model

This section gives more information on the factor model, the applied matrix rotation, and the robustness of the results.

2.B.1 Rotating the Factor Matrix

For the factors to be economically meaningful, they have to be rotated. For this, I replicate the methodology of Andrade and Ferroni (2021), employing zero and sign restrictions to rotate the factors. For convenience, I reproduce equations (2.9) and (2.10) from the main text:

$$Y = F\Omega' + \varepsilon, \tag{2.B.1}$$

where Y is the data matrix with the surprises data. F contains the principal components and Ω corresponds to the factor loadings matrix. $\varepsilon \sim N(0, \Sigma)$ denotes the residuals. The matrices F and Ω are rotated by an orthogonal matrix Q such that

$$Y = (FQ)(\Omega Q)' + \varepsilon = Z\Lambda' + \varepsilon, \tag{2.B.2}$$

where $Z = FQ$ and $\Lambda = \Omega Q$ contain the rotated factors, and the corresponding factor loadings, respectively.[28] The objective is to find an orthogonal rotation matrix Q such that the following restrictions are satisfied:

$$Y_t = \begin{bmatrix} OIS_{3M,t} \\ OIS_{5Y,t} \\ ILS_{5Y,t} \\ \vdots \end{bmatrix} = \begin{bmatrix} * & 0 & 0 \\ * & + & + \\ * & + & - \\ \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} Target_t \\ Delphic_t \\ Odyssean_t \end{bmatrix} + \varepsilon_t. \tag{2.B.3}$$

As equation (2.B.3) shows, $\Omega_{3:3}Q$ is subject to both zero and sign restrictions (where $\Omega_{3:3}$ denotes the top 3×3 matrix of Ω). To achieve these restrictions, I let the rotation matrix Q be the product of two orthogonal rotation matrices, i.e. $Q = RS$.[29] To achieve the zero restrictions, I choose R such that $\Omega_{3:3}R$ is lower triangular. For this, I set

$$R = \Omega_{3:3}^{-1} \operatorname{chol}\left(\Omega_{3:3}\Omega_{3:3}'\right).$$

R is orthogonal (since $R'R = I$), and $\Omega_{3:3}R = \operatorname{chol}(\Omega_{3:3}\Omega_{3:3}')$ is lower triangular and therefore assures the zero restrictions in the rotated loadings matrix $\Omega_{3:3}R$.

Then, I rotate the second and third factors. The function $S(\theta_j)$ takes the form

$$S(\theta_j) = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\theta_j & -\sin\theta_j \\ 0 & \sin\theta_j & \cos\theta_j \end{pmatrix},$$

where $\theta_j = \{0, 0.02, 0.04, ..., \pi\}$. This structure ensures that the three factors remain orthogonal, while at the same time spanning all possible rotations of the second and third factors. Let $\Lambda(\theta_j) = \Omega RS(\theta_j)$. Since $S(\theta_j)$ does not rotate the first row of ΩR, the zero restrictions in the first row of ΩR persist. Discard all $S(\theta_j)$ for which $\Lambda(\theta_j)$ does not fulfill the sign restrictions in equation (2.B.3). With the remaining J matrices, I compute

$$S = \frac{1}{J}\sum_{j=1}^{J} S(\theta_j),$$

[28] Any orthogonal matrix Q has the property $QQ' = I_k$, which implies that $F\Omega' = (FQ)(\Omega Q)'$ holds for any orthogonal matrix Q.

[29] This decomposition of the rotation matrix Q is possible because R assures the zero restrictions in the first factor, while S leaves the first factor unchanged and only rotates the other factors.

which is the element-by-element average of the candidate matrices $S(\theta_j)$. Then, $\Lambda' = (\Omega Q)' = (\Omega RS)'$ fulfills the restrictions in equation (2.B.3) and $Z = FQ = FRS$ contains the Target, Delphic, and Odyssean monetary policy factors.

2.B.2 Robustness Checks and Factor Model Statistics

This appendix introduces four factor models that serve as robustness checks and then assesses them and compares them to the Baseline model, which is introduced in the main text. An overview of the robustness check models is given in Table 7.

Table 2.B1: Overview over Robustness Checks Models

Model Name	Description
Baseline	The factor model used in the main text.
PC Model	This model uses data from the PC window, instead of the ME window.
AF Model	This model is as close as possible to Andrade and Ferroni (2021).
GY Model	This model uses German yields for interest rate data, instead of OIS data.
NE Model	This model excludes exchange rate data from the factor model.

All robustness checks keep the same methodology, but use different datasets. The PC model excludes date from the press release (RE) and only focuses on the data from the press conference (PC). The AF model, provides a model that is closer in spirit to the model by Andrade and Ferroni (2021). For this, it includes OIS data from 1-month to 2-years maturities only, thus excluding longer maturities used in the Baseline model. the GY model uses surprisese in German yields instead of OIS data. Finally, the NE model excludes the exchange rates from the model, leaving everything else unchanged.

To summarize the differences in each set of factors by different models, Table 8 shows the correlation between different factors.

Table 2.B2: Correlation of Factors (in %)

	PC Model			**AF Model**			**GY Model**			**NE Model**		
Baseline	T	D	O	T	D	O	T	D	O	T	D	O
Target	89	-11	38	30	-32	-43	98	17	-3	92	-17	-8
Delphic	-22	59	46	2	60	46	-15	92	13	24	95	9
Odyssean	-24	6	74	9	22	57	4	-2	95	-11	4	84

Notes: This table shows the Pearson correlation coefficients between the Baseline Factors (spanning the rows), and the factors from the robustness checks. T=Target Factor, D = Delphic Factor, and O = Odyssean Factor.

A further important property of these factor models is the proportion of the variance that is explained by each factor. This information is given in Table 9:

The factors loadings matrix says by hwo much each factor loads on the input data series in the model. These can be understood as the weights for each series, where the factor is a weighted sum. Table 10 presents the factor loadings (for the Baseline model only):

Table 2.B3: Variance Explained by each Factor (in %)

	Baseline	PC model	AF Model	GY Model	NE Model
Target	42	40	42	39	40
Delphic	21	18	15	18	14
Odyssean	9	11	12	10	13
Total	**72**	**69**	**69**	**67**	**67**

Notes: This table displays the variance explained by the first three principal components of the model. These values are independent of any factor rotation.

Table 2.B4: Factor Loadings in the Baseline Model

	Factors		
	Target	Delphic	Odyssean
OIS 3M	0.34	0	0
OIS 5Y	0.16	0.20	0.20
ILS 5Y	−0.02	0.36	−0.17
OIS 3M	0.35	0.06	0.06
OIS 1Y	0.28	0.16	0.13
OIS 2Y	0.24	0.17	0.16
OIS 10Y	0.07	0.21	0.20
ILS 1Y	−0.01	0.35	−0.14
ILS 2Y	−0.01	0.37	−0.16
5Y5Y	0.06	0.20	−0.11
stoxx50	−0.11	0.040	−0.09
USD/EUR	0.02	0.26	0.19
JPY/EUR	0.04	0.25	0.21
GBP/EUR	0.05	0.25	0.19

Notes: This table shows the factor loadings of the baseline model on the data. The same factor rotations are applied to the loadings matrix as to the factor matrix.

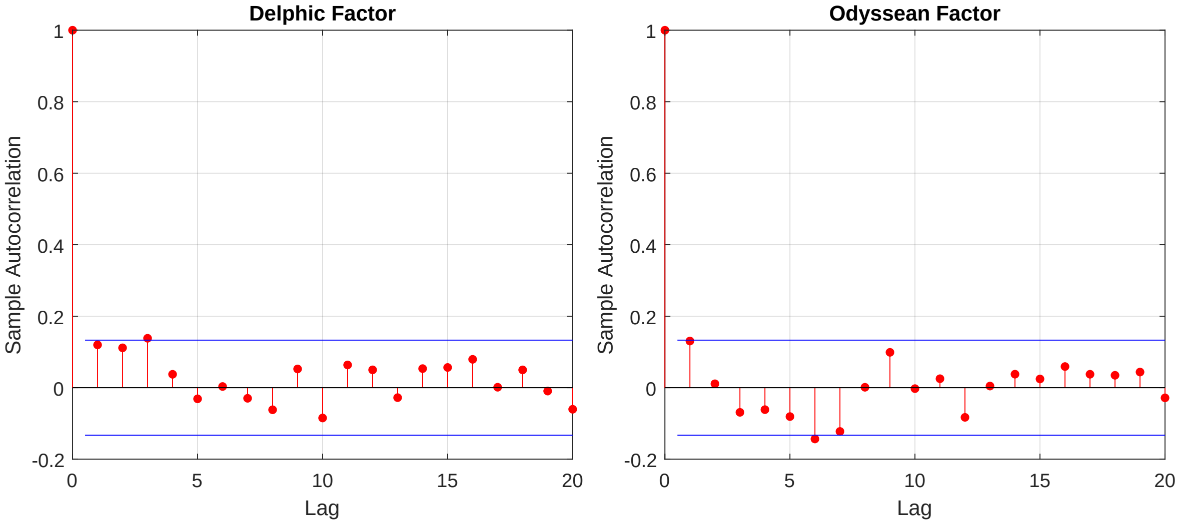
Lastly, it is important that the factors should not be autocorrelated for them to be valid exogenous shocks. Figure 2.B1 shows the sample autocorrelation function of the factors from the baseline model.

In the following, the raw data as well as high-frequency regression results are presented and compared to the Baseline model, for each model separately.

PC Model

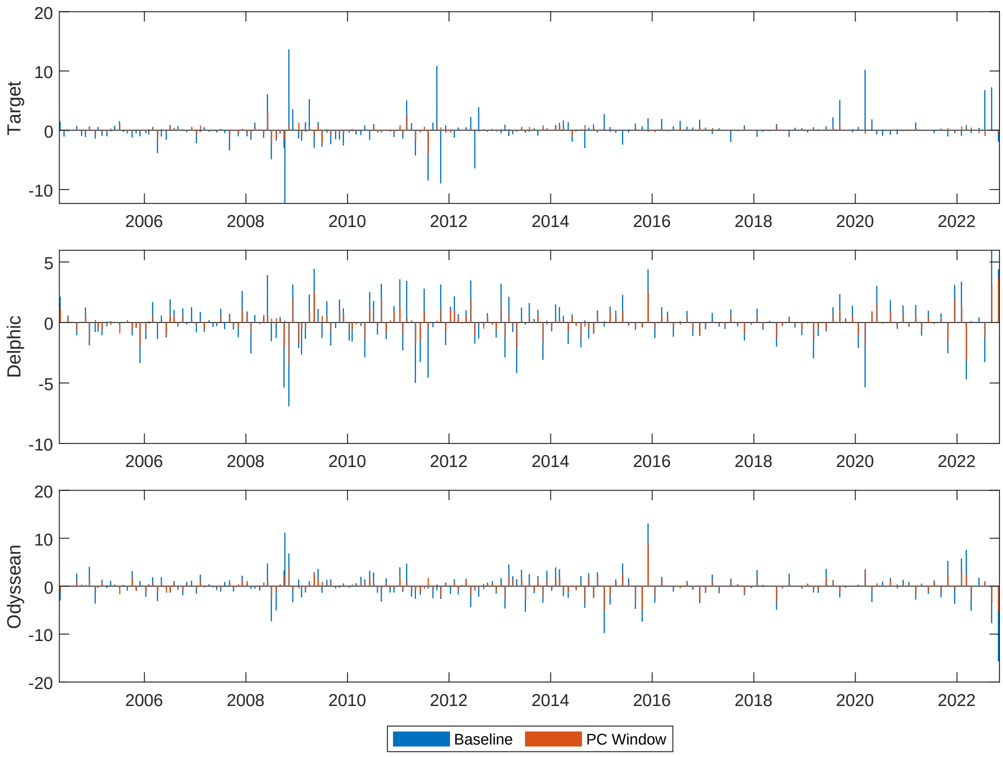
For the PC model, the same data series is used, but the surprise data only comprises price changes from right before to right after the press conference. reactions to price changes stemming from the press release are therefore ignored. As the model is interested in information effects, and since Subsection 4.1 already showed a certain dominance of the PC window, I expect this model to behave simliarly to the baseline model, confirming further the importance of the press conference for informational shocks.

Figure 2.B1: Autocorrelation of Factors (Baseline)



Notes: This figure shows the sample autocorrelation function of the factors at a monthly frequency. The monthly factors are aggregated by summing over each month.

Figure 2.B2: Factor Data Baseline and PC model



Notes: This figure shows the data for the Target, the Delphic, and the Odyssean factors. The correlation between the sets of factors is reported in Table 2.B2.

Table 2.B5: Regression of High-Frequency Variables on Baseline and PC Factors

	Baseline Model				PC Model			
	Delphic	R^2	Odyssean	R^2	Delphic	R^2	Odyssean	R^2
Interest Rates								
OIS 1Y	0.90***	0.44	0.67***	0.16	0.85***	0.05	0.41**	0.03
OIS 2Y	0.98***	0.53	0.90***	0.24	0.95***	0.04	0.73***	0.07
OIS 5Y	1.00***	0.59	1.00***	0.34	1.00***	0.05	1.00***	0.14
OIS 10Y	0.68***	0.56	0.68***	0.33	0.79***	0.07	0.75***	0.16
Inflation-Linked Swaps								
ILS 2Y	2.18***	0.25	−0.71***	0.19	3.31***	0.58	−1.52***	0.30
ILS 5Y	1.48***	0.34	−0.68***	0.33	2.32***	0.56	−1.14***	0.34
ILS 10Y	1.05***	0.31	−0.64***	0.46	1.70***	0.47	−0.86***	0.30
5Y5Y	0.62***	0.04	−0.60***	0.40	1.08***	0.17	−0.59***	0.13
Stock Price								
stoxx50	0.24	0.09	−0.05***	0.20	−0.10**	0.02	−0.19***	0.23
Exchange Rates								
USD/EUR	0.16***	0.25	0.19***	0.46	0.20***	0.20	0.18***	0.38
GBP/EUR	0.13***	0.24	0.14***	0.49	0.15***	0.19	0.13***	0.37
JPY/EUR	0.15***	0.22	0.20***	0.51	0.15***	0.10	0.17***	0.34

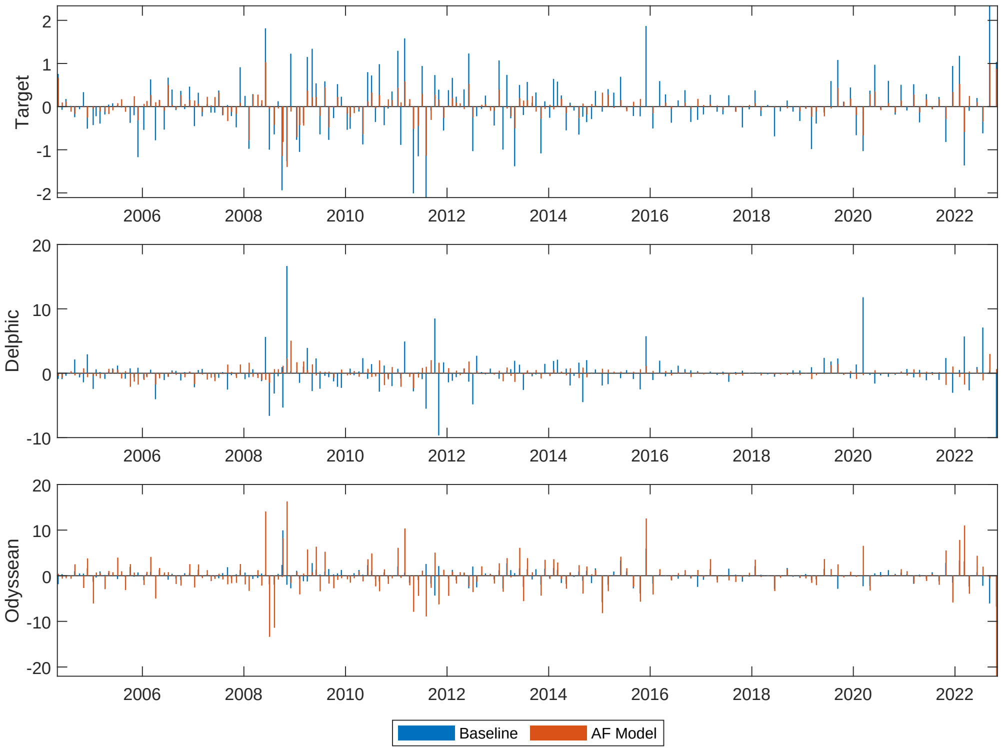
Notes: This table reports the regression coefficient of simple linear regressions of asset price changes on factors from the same time window. An increase in the exchange rate indicates an appreciation of the euro. *, **, and *** indicate the significance of the coefficient at the 10%, 5%, and 1% level, respectively.

The models indeed perform in a very similar manner. Qualitatively the effects of both sets of factors are the same, with the exception that the stock price decreases after a Delphic shock in the PC model, while there was no significant effect in the baseline model. The largest difference in explanatory power can be seen in the OIS rates, where only a small fraction of the OIS movement is explained by the PC model, when comparing to the Baseline model. This indicate that the press release window is important to explain the movement in interest rates. Interestingly, this loss in explanatory power does not affect the explanation of exchange rates at all, further comparing the importance of the PC window for explaining exchange rates.

AF Model

The AF model uses forward rates instead of OIS rates, and also relies on OIS maturities from 1-month to 2-years, whereas the Baseline model uses maturities from 3 months to 10 years. For the ILS rates, the maturities used range from 1 year to 10 year in the PC model, similarly to the Baseline model.

Figure 2.B3: Factor Data Baseline and GY Model



Notes: This figure shows the data for the Target, the Delphic, and the Odyssean factors. The correlation between the sets of factors is reported in Table 2.B2.

Table 2.B6: Regression of High-Frequency Variables on Baseline and AF Factors

	Baseline Model				AF Model			
	Delphic	R^2	Odyssean	R^2	Delphic	R^2	Odyssean	R^2
Interest Rates								
OIS 1Y	0.90***	0.44	0.67***	0.16	0.82**	0.03	0.85***	0.63
OIS 2Y	0.98***	0.53	0.90***	0.24	1.05***	0.04	1.04***	0.75
OIS 5Y	1.00***	0.59	1.00***	0.34	1.00***	0.04	1.00***	0.83
OIS 10Y	0.68***	0.56	0.68***	0.33	0.91***	0.07	0.64***	0.68
Inflation-Linked Swaps								
ILS 2Y	2.18***	0.25	−0.71***	0.19	1.45***	0.10	−0.49***	0.21
ILS 5Y	1.48***	0.34	−0.68***	0.33	1.00***	0.09	−0.38***	0.25
ILS 10Y	1.05***	0.31	−0.64***	0.46	1.04***	0.16	−0.27***	0.19
5Y5Y	0.62***	0.04	−0.60***	0.40	1.08***	0.17	−0.15***	0.05
Stock Price								
stoxx50	0.24	0.09	−0.05***	0.20	−0.12**	0.02	−0.04***	0.05
Exchange Rates								
USD/EUR	0.16***	0.25	0.19***	0.46	0.08**	0.02	0.06***	0.27
GBP/EUR	0.13***	0.24	0.14***	0.49	0.05*	0.01	0.05***	0.30
JPY/EUR	0.15***	0.22	0.20***	0.51	0.09**	0.02	0.07***	0.39

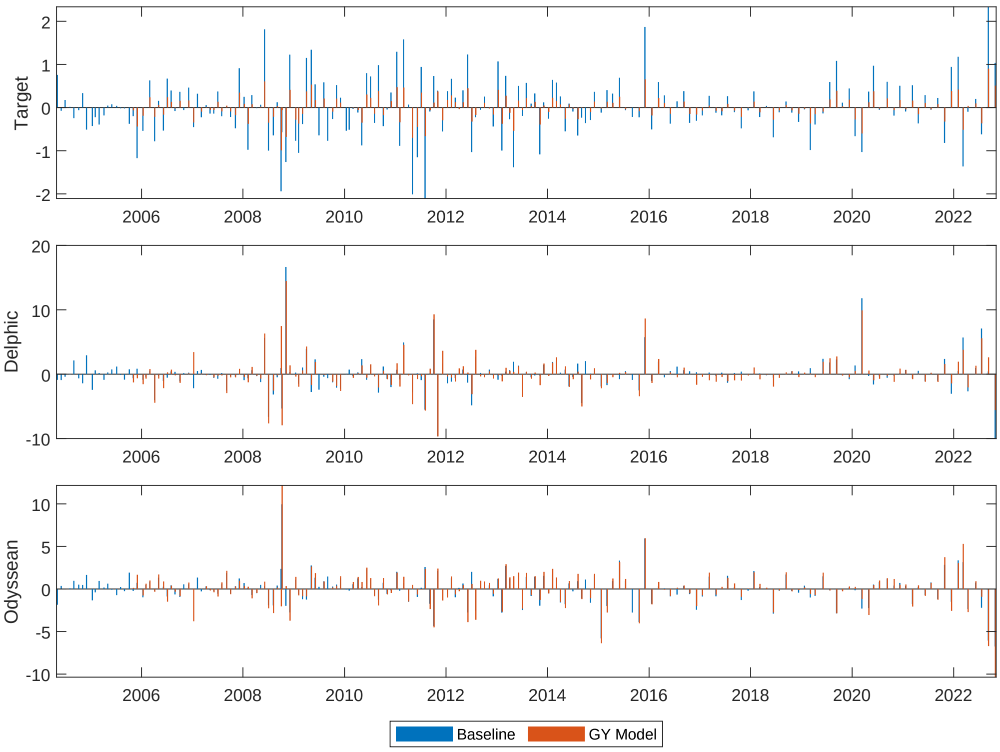
Notes: This table reports the regression coefficient of simple linear regressions of asset price changes on factors from the same time window. An increase in the exchange rate indicates an appreciation of the euro. *, **, and *** indicate the significance of the coefficient at the 10%, 5%, and 1% level, respectively.

The Baseline and the AF model qualitatively have almost identical effects. Focusing on the short-end of the yield curve gives very similar effects on OIS and ILS rates. For exchange rates, however, there is a stark difference. While the Odyssean factor still captures a large, but smaller part of the overall variance in exhcang erate surprises, the Delphic factor explains only a fraction of about 10% of the variance. This, again shows the very different sensitivities of exchange rate and interest rate determination. In order to explain exchange rate surprises well, it is advised to include long-maturity OIS swaps in the factor model.

GY Model

The GY model replaces OIS rates by German Government Bond yields. government bond yields have a different risk structure than OIS rates. Also, they are more liquid than OIS rates, especially at the beginning of the sample. OIS rates, however, became more and more of a benchmark for financial markets.

Figure 2.B4: Factor Data Baseline and GY Model



Notes: This figure shows the data for the Target, the Delphic, and the Odyssean factors. The correlation between the sets of factors is reported in Table 2.B2.

Table 2.B7: Regression of High-Frequency Variables on Baseline and GY Factors

	Baseline Model				GY Model			
	Delphic	R^2	Odyssean	R^2	Delphic	R^2	Odyssean	R^2
Interest Rates								
OIS 1Y	0.90***	0.44	0.67***	0.16	0.80***	0.12	0.68***	0.25
OIS 2Y	0.98***	0.53	0.90***	0.24	0.93***	0.13	0.92***	0.37
OIS 5Y	1.00***	0.59	1.00***	0.34	1.00***	0.18	1.00***	0.52
OIS 10Y	0.68***	0.56	0.68***	0.33	0.72***	0.19	0.69***	0.52
Inflation-Linked Swaps								
ILS 2Y	2.18***	0.25	−0.71***	0.19	1.65***	0.53	−0.82***	0.37
ILS 5Y	1.48***	0.34	−0.68***	0.33	1.15***	0.50	−0.62***	0.42
ILS 10Y	1.05***	0.31	−0.64***	0.46	0.85***	0.44	−0.46***	0.36
5Y5Y	0.62***	0.04	−0.60***	0.40	0.55***	0.18	−0.29***	0.14
Stock Price								
stoxx50	0.24	0.09	−0.05***	0.20	0.03	−0.00	−0.06***	0.08
Exchange Rates								
USD/EUR	0.16***	0.25	0.19***	0.46	0.14***	0.29	0.10***	0.45
GBP/EUR	0.13***	0.24	0.14***	0.49	0.10***	0.25	0.08***	0.44
JPY/EUR	0.15***	0.22	0.20***	0.51	0.12***	0.25	0.11***	0.53

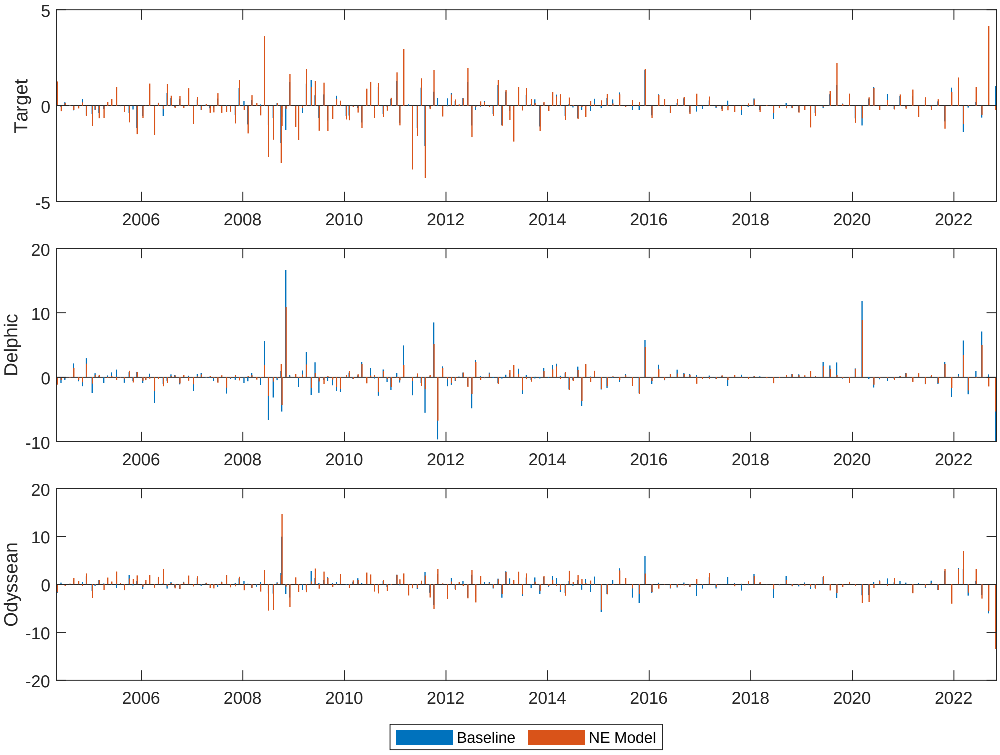
Notes: This table reports the regression coefficient of simple linear regressions of asset price changes on factors from the same time window. An increase in the exchange rate indicates an appreciation of the euro. *, **, and *** indicate the significance of the coefficient at the 10%, 5%, and 1% level, respectively.

The choice of german government bond yields instead of OIS yields does not change the results at all. As Table 8 shows, all three factors are correlated by more than 90%. The differences between german government bond yields and OIS rates are not important in explaining the reaction of asset prices.

NE Model

The NE model excludes the three series of exchange rate surprises from the factor model. While this does not lead to a qualitative change in the effects of the factors, this does decrease the explanatory power of the three factors for exchange rates. However, the effects on exchange rates remain highly significant. Interestingly, this is the only robustness checks where the stock market reacts positively to a Delphic shock. This may be due to the (unexplained) strongly negative correlation between stock prices and exchange rates that can be seen in the surprises data (see Table 6).

Figure 2.B5: Factor Data Baseline and NE Model



Notes: This figure shows the data for the Target, the Delphic, and the Odyssean factors. The correlation between the sets of factors is reported in Table 2.B2.

Table 2.B8: Regression of High-Frequency Variables on Baseline and NE Factors

	Baseline Model				NE Model			
	Delphic	R^2	Odyssean	R^2	Delphic	R^2	Odyssean	R^2
Interest Rates								
OIS 1Y	0.90***	0.44	0.67***	0.16	0.87***	0.19	0.74***	0.36
OIS 2Y	0.98***	0.53	0.90***	0.24	1.02***	0.22	0.98***	0.51
OIS 5Y	1.00***	0.59	1.00***	0.34	1.00***	0.25	1.00***	0.63
OIS 10Y	0.68***	0.56	0.68***	0.33	0.69***	0.24	0.67***	0.59
Inflation-Linked Swaps								
ILS 2Y	2.18***	0.25	−0.71***	0.19	1.37***	0.51	−0.75***	0.38
ILS 5Y	1.48***	0.34	−0.68***	0.33	0.95***	0.47	−0.57***	0.42
ILS 10Y	1.05***	0.31	−0.64***	0.46	0.71***	0.41	−0.42***	0.37
5Y5Y	0.62***	0.04	−0.60***	0.40	0.46***	0.17	−0.28***	0.15
Stock Price								
stoxx50	0.24	0.09	−0.05***	0.20	0.07***	0.04	−0.03**	0.02
Exchange Rates								
USD/EUR	0.16***	0.25	0.19***	0.46	0.07***	0.09	0.06***	0.19
GBP/EUR	0.13***	0.24	0.14***	0.49	0.05***	0.08	0.05***	0.20
JPY/EUR	0.15***	0.22	0.20***	0.51	0.07***	0.12	0.07***	0.30

Notes: This table reports the regression coefficient of simple linear regressions of asset price changes on factors from the same time window. An increase in the exchange rate indicates an appreciation of the euro. *, **, and *** indicate the significance of the coefficient at the 10%, 5%, and 1% level, respectively.

2.C Estimating a Proxy SVAR model

This appendix provides more information on the implementation of the proxy SVAR model. There will be no further information on the methodology, as I exactly follow Gertler and Karadi (2015). The methodology is laid out very clearly in Stock and Watson (2012) and Mertens and Ravn (2013). In the following, I present the data used for the monthly and the daily SVAR model.

2.C.1 Monthly SVAR Model

The sample period runs from January 1999 to December 2022. The lag length is set to 12. The model consists of 6 endogenous variables. The main building blocks of UIP, namely the European and US 5-year yield, as well as the USD/EUR exchange rate, are included. Further, HICP Inflation and European industrial production are added. To account for the Great Financial Crisis and the European debt crisis, I add the BBB spread to the model as a measure of risk.

For the domestic interest rate, I use the euro area 5-year government bond rate,[30] which includes all countries that have a AAA rating (with changing composition). For the US, I choose the 5-year constant maturity treasury yield. Both are daily time series. I transform them to monthly by using the end-of-period value for both. For the USD/EUR exchange rate, I use the end-of-period series of the spot exchange rate. For inflation, I use the HICP overall inflation index which is working-day and seasonally adjusted, as well as the euro area industrial production (excluding construction, fixed composition of 19 countries). For the BBB spread, I use the Option-Adjusted Spread of the ICE BofA Euro High Yield Index which gives the difference between company bonds that are below investment grade (average of Moody's, S&P, and Fitch ratings), and government bonds. The sources for the data series are reported in Table 2.C1.

Table 2.C1: Data Sources of the Monthly SVAR Model

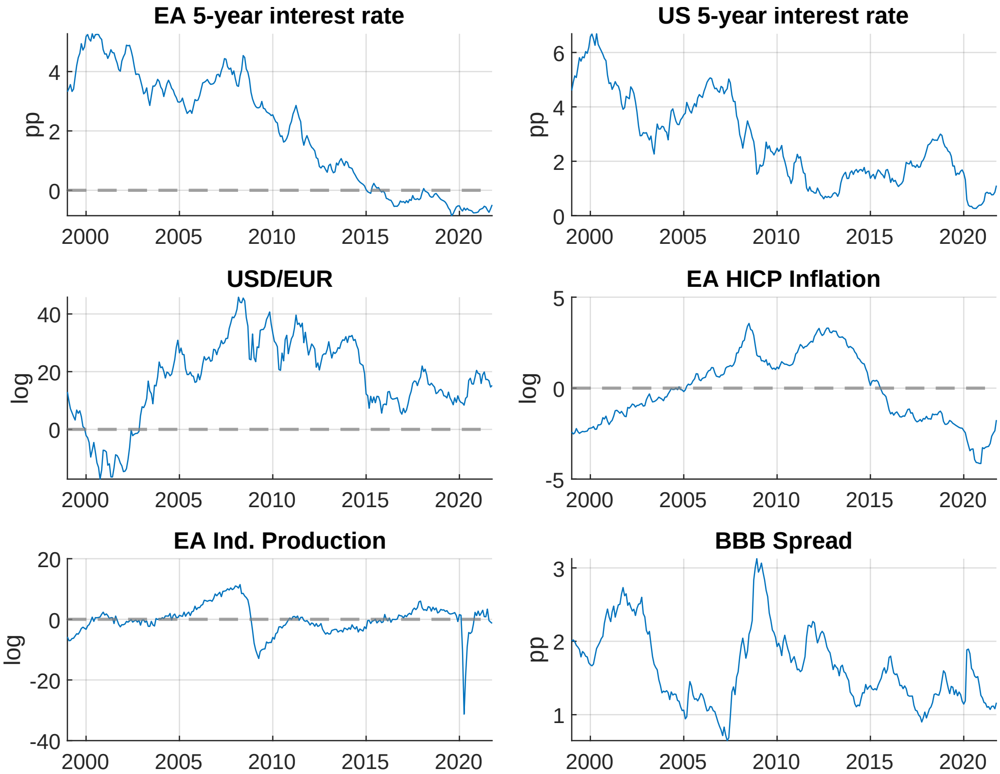
Variable	Transformation	Source	Identifier
5-year EA interest rate	none	sdw.ecb.europa.eu	YC.B.U2.EUR.4F.G_N_A.SV_C_YM.SR_5Y
5-year US interest rate	none	fred.stlouisfed.org	DGS5
USD/EUR	log-levels	fred.stlouisfed.org	CCUSSP01EZM650N
HICP Inflation Index	lin. detrended	sdw.ecb.europa.eu	ICP.M.U2.Y.000000.3.INX
Industrial Production	lin. detrended	sdw.ecb.europa.eu	STS.M.I8.Y.PROD.NS0020.4.000
BBB spread	log-levels	fred.stlouisfed.org	BAMLHE00EHYIOAS

Additional Results

This subsection presents the impulse responses after a Target shock. The shock is normalized to increase the 5-year OIS rate by 25 basis points. It shows a clear and immediate appreciation

[30] This series only goes back to September 2004. It is prepended by the series for 5-year German government bond yields for the period before that (source: data.snb.ch/en/topics/ziredev/chart/rendeidgdtch)

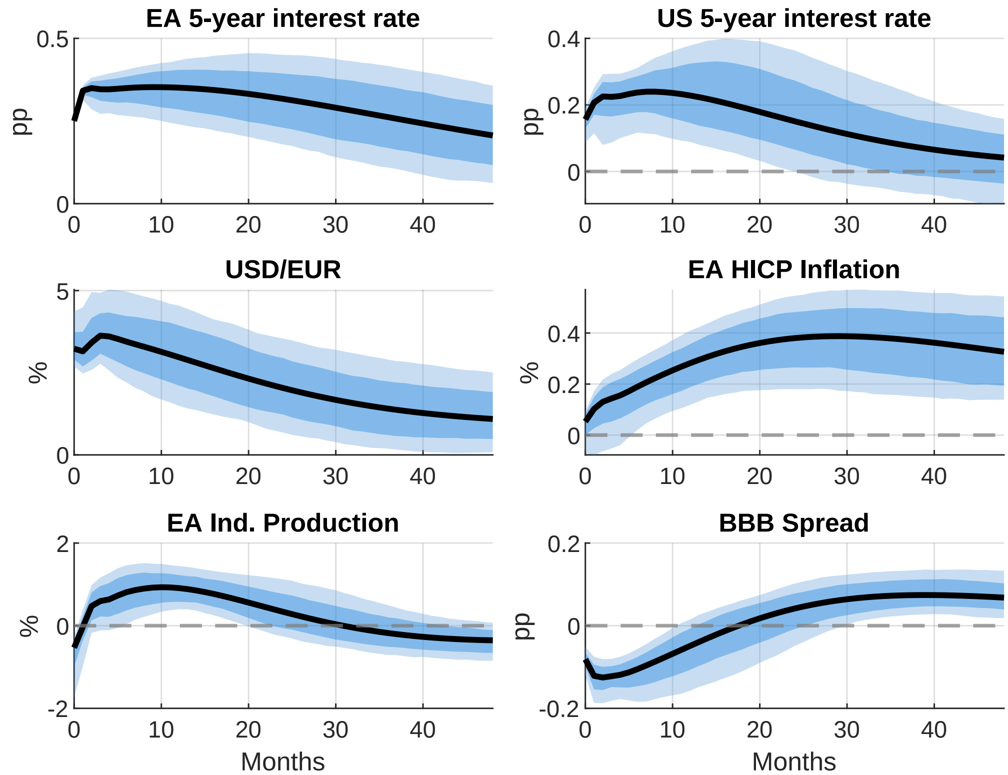
Figure 2.C1: Endogenous Data Series in the Monthly SVAR Model



Notes: This figure displays all endogenous variables in the baseline proxy SVAR model in Section 2.6. The EA and US yields, as well as the BBB spread, are in percentage points. The exchange rate, Inflation, and Industrial Production are transformed by $100 * log(x)$ where x stands for the respective time series. The inflation rate and Industrial Production are linearly detrended, even though this changes the results only marginally. The frequency of the data is monthly.

of the exchange rate, as well as an increase in the foreign 5-year interest rate and a decrease in the BBB spread. Interestingly, the shock does not have a significant immediate impact on GDP and inflation, but slowly builds up an expansionary development over the horizon. This price puzzle that can be seen may be due to information effects that are not controlled for in this paper. The Target factor is simply the unrotated first principle component in the factor model, and there is thus no controlling of potential information effects at shorter horizons. Therefore, these IRFs are subject to the confounding effects shown in Jarociński and Karadi (2020). The Delphic and Odyssean factors in this paper capture information effects at a horizon of 5 years, as those are most relevant for exchange rates.

Figure 2.C2: Impulse Response after a Target Shock

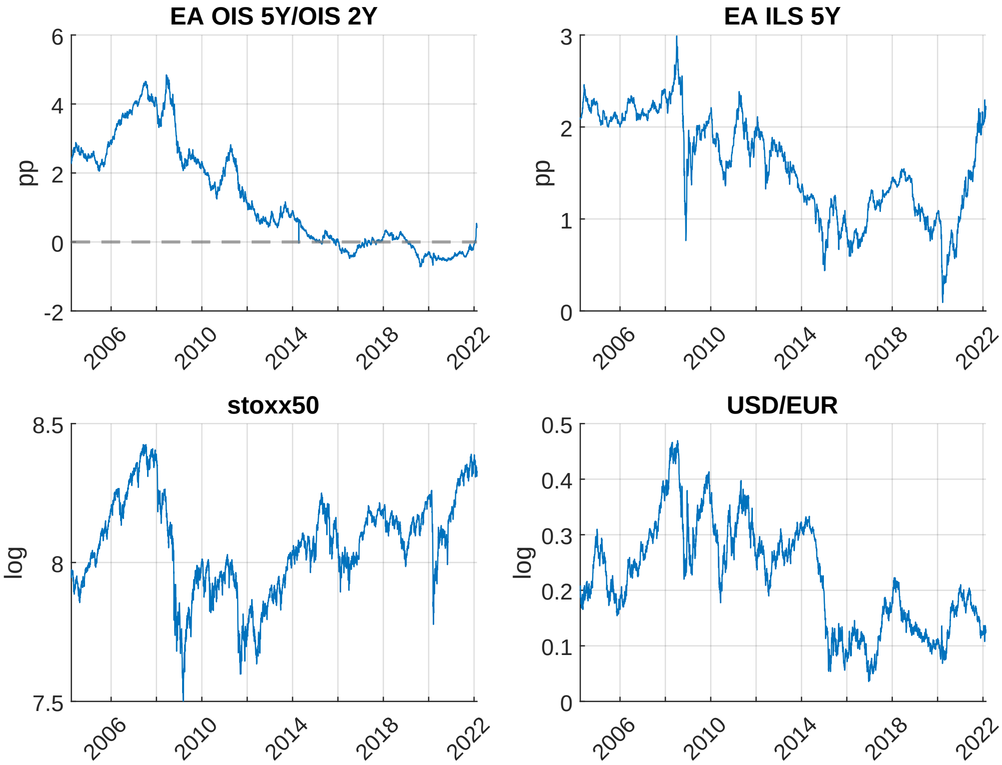


Notes: This figure shows impulse response functions, as well as 68% and 90% confidence intervals computed by a moving block bootstraps algorithm(Jentsch and Lunsford, 2019). EA stands for the euro area and USD/EUR for the bilateral euro-dollar exchange rate. An increase denotes an appreciation of the euro. The shock is normalized to increase the 5-year European yield by 25 basis points.

2.C.2 Daily SVAR Model

This subsection provides more details on the daily proxy SVAR model. The data is at workday frequency. The lag length is chosen to be 30. The sample period runs from April 2004 to December 2022. This gives a sample length of 4054 observations. The model consists of 4 endogenous variables, namely the 5-year OIS interest rate, the 5-year ILS rate, the euroStoxx 50 index, and the USD/EUR exchange rate. The 5-year OIS rate is only available since June 2008, which is why it is prepended by the 2Y OIS rate (the two rates exhibit a correlation of 94%). The data is presented in Figure 2.C3 and the data sources are reported in Table 2.C2.

Figure 2.C3: Endogenous Data Series in the Daily SVAR Model



Notes: This figure displays all endogenous variables in the daily proxy SVAR model in Section 2.5. The stock index and the USD/EUR are used in logs, whereas the OIS and the ILS rates are given in percentage points. The sample period is from April 2004 to December 2022. The 5-year OIS rate starts in June 2008. Before, the series is prepended by the 2-year OIS rate. The frequency of the data is daily (working days).

Table 2.C2: Data Sources of the Daily SVAR Model

Variable	Transformation	Source	Identifier
5-year OIS rate	none	Refinitiv	ICAP EURO 5Y OIS
2-year OIS rate	none	Refinitiv	ICAP EURO 2Y OIS
5-year ILS rate	none	Refinitiv	ICAP EU INFL-LKD SWAP HICP 5Y
stoxx50 index	log-levels	Google finance	SX5E
USD/EUR	log-levels	BIS data portal	D.XM.EUR.A

Additional Results

In the following, additional findings on the daily financial proxy VAR model from subsection 2.5.3 are included. Concretely, Table 2.C3 reports the F-statistics of the weak-instrument-test by Olea and Pflueger (2013).

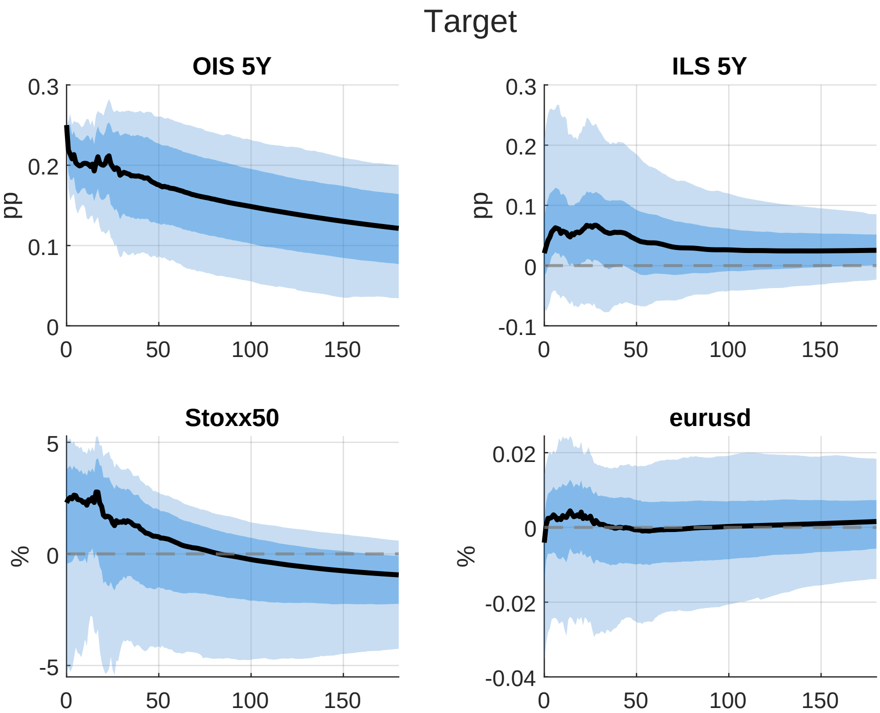
Table 2.C3: Instrument Strength Daily VAR Model

	Target	Delphic	Odyssean
F-statistic	19.01	148.98	39.40
F-statistic (robust)	2.54	97.83	11.49
R^2	0.01	0.05	0.02
R^2 adj.	0.01	0.05	0.01
Observations	225	225	225

Notes: This table shows different test statistics of the first-stage regressions of the residuals $u_{1,t}$ on the different instruments Z_t The robust F-statistic test is deemed the "weak instrument test". It is robust to heteroskedasticity, serial correlation, and clustering (see Olea and Pflueger, 2013).

The impulse responses to the Target factor are displayed in Figure 2.C4. However, the results for the Target factor should be interpreted with a grain of salt. The Target factor is constructed to increase the 3-month OIS rate and is therefore only indirectly related to the 5-year OIS rate, which is instrumented in the daily VAR model. As can be seen in Table 2.C3 the robust F-statistic is quite low for the Target factor, which points to a weak-instrument problem. Its impulse responses are nevertheless reported for completeness. Only the 5-year OIS shows a significant effect. The 5-year ILS and the stock index are slightly positive, which is at odds with our understanding of a conventional monetary policy shock.

Figure 2.C4: Financial VAR: Target Factor Impulse Responses



Notes: This figure shows impulse response functions in a daily proxy SVAR model. The frequency is daily, excluding weekends. An increase in USD/EUR depicts an appreciation of the euro. Both factors are normalized to increase the OIS 5Y rate by 25 basis points. The 68% and 90% confidence intervals are computed by a moving block bootstrap algorithm (Jentsch and Lunsford, 2019). The impulse responses for the Delphic factor, in blue, are on the left-hand side, and the impulse responses for the Odyssean factor, in red, are on the right-hand side of the figure.

Chapter 3

The Importance of Demand and Supply Shocks: Evidence from Professional Forecasters†

3.1 Introduction

Disentangling the effects of demand and supply factors on the economy is at the heart of business cycle research. An economy driven predominantly by supply shocks operates fundamentally differently from one driven by demand shocks. Policymakers must tailor their responses to the specific type of shock. Fiscal stimulus is appropriate for demand-driven issues, while structural reforms or targeted investments are needed to address supply-side constraints.

Traditional macroeconomic models often assume that shock variances are constant over long periods of time. This is however a strong assumption as fundamental changes in technology, politics, and the economy, may affect the relative importance of demand and supply shocks over time. The present paper proposes a measure of such changes. It is defined as the correlation between individual forecasters' GDP and inflation forecasts, as provided by the Survey of Professional Forecasters (SPF). This measure is model-free, based on publicly available data, and computed in real time. Being based on predictions of future GDP and inflation, it is forward-looking by construction and does not rely on realized shocks.

To obtain measures of the relative importance of demand and supply shocks, a standard approach is to compute the rolling correlation between aggregate GDP and inflation. Such a measure has several drawbacks: GDP data is only published with a significant lag, and the measure becomes meaningful only for a certain window size. Unfortunately, the longer the window size, the more backward-looking the measure becomes. Our approach is not subject to these limitations.

†This chapter is co-authored with Adrien Tschopp from the University of Lausanne.

A stylized model with heterogeneous and imperfect information motivates our measure. In the context of our model, the dispersion of GDP and inflation forecasts—across a set of professional forecasters—can be informative about the relative importance of demand and supply shocks in the economy. To grasp the rationale behind this, let's consider an extreme situation where the economy is driven entirely by demand shocks. Specifically, let's assume that both inflation and GDP growth are positively influenced by one persistent factor—a demand factor—and additional volatile, non-persistent shocks. When forecasters are tasked with predicting inflation and GDP, they must first filter out the impact of volatile shocks. With their estimate of the persistent component in hand, they proceed to compute forecasts for GDP and inflation. Since both inflation and GDP positively depend on the latent factor, that is also true for the forecasts they produce. If all forecasters possess identical information, resulting in the same estimation of the latent factor (and assuming they are aware of the model's parameterization), their GDP and inflation forecasts will align. In contrast, if forecasters possess private information about the latent factor, their inferences will lead to divergent GDP and inflation forecasts.

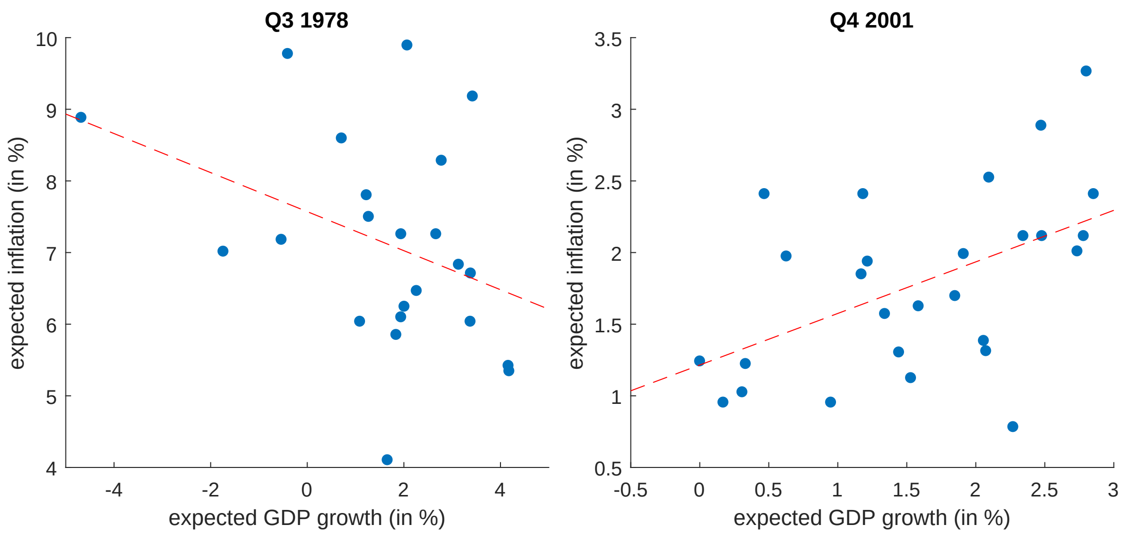
To fix ideas, if a forecaster obtains a particularly high (respectively low) estimate of the latent factor, both her inflation forecast and her GDP forecast will be higher (lower) compared to other forecasters. That is, the correlation of inflation and GDP forecasts—across forecasters—will be positive. Alternatively, it is easy to check that the correlation between inflation and GDP forecasts would be negative in an economy where only a supply factor persistently affects inflation and GDP. As our stylized model illustrates, in intermediate cases, the correlation of inflation and GDP forecasts (across forecasters) depends on the relative importance of demand and supply factors in explaining the joint dynamics of inflation and GDP.

Consistent with this theoretical framework, our measure—which we call the Individual Forecast Slope (IFS) Index or just Slope Index—is computed as the cross-forecaster correlation between expected changes in GDP and inflation. On each date on which it is computed, it aims to capture the relative importance of demand and supply shocks. Figure 3.1 shows two examples of this measure in two different quarters.

The left-hand panel shows 4-quarter-ahead forecasts for GDP and inflation in the third quarter of 1978, just before the second oil price crisis, when heightened political turmoil in Iran, and increased uncertainty about crude oil production and prices dominated the news. The right-hand panel, in contrast, shows Q4 2001. The economy was in a recession due to the dot-com bubble. Also, the terrorist attacks of September 11, 2001, lead to additionally increased uncertainty. This mostly depressed demand, accompanied by a fall in consumption, stock prices, and interest rates. The first episode is a clear example of large uncertainty about supply, while the second one is a typical case of large negative demand shocks.[1] The respective dominance of either supply or demand is reflected in the slope between GDP and inflation forecasts (see Figure 3.1).

[1] Blinder and Rudd (2013) and Blomberg et al. (2004) discuss the two periods and their dominant macroeconomic drivers in great detail.

Figure 3.1: Individual Forecast Correlation for Two Exemplary Dates



Notes: This figure depicts the SPF point forecasts for inflation and GDP growth for all available forecasters at two exemplary dates, along with the regression line. It shows the 4-quarters-ahead forecasts of real GDP and the GDP deflator, respectively. Both variables are in year-on-year growth rates.

The empirical analysis, supported by regression results, demonstrates that the proposed measure effectively captures changes in the realized covariance between GDP and inflation surprises. Moreover, it is informative about the covariance of ex-post mean forecast errors.

Another validation comes from asset prices. It is well-known that term premiums—i.e. risk premiums extracted from bond yields— are negatively correlated with the importance of demand shocks in the economy (e.g., Piazzesi and Schneider, 2007; Rudebusch and Swanson, 2012; Gurkaynak and Wright, 2012; Campbell et al., 2014; Bekaert et al., 2021). In a supply-driven economy, recessions tend to be inflationary. The portfolios of nominal bondholders experience a decline in value during recessions because the real returns of nominal bonds decline with inflation. As the bond returns decline in value during recessions, they exhibit bad hedging properties. Accordingly, bondholders demand an average excess return (called term premium) to carry nominal long-term bonds in this supply-driven economy. Naturally, the logic is reversed in a demand-driven economy, where term premiums tend to be negative. Consistent with these arguments, our measure—which is higher when demand shocks are more important—is negatively correlated with standard term premium measures (namely, those estimated by Adrian et al., 2013).

Our research is also related to several other strands of the literature. First, our study is related to the empirical macroeconomic literature dealing with the differentiation of demand and supply shocks. Some examples of influential early work include Shapiro and Watson (1988), Blanchard and Quah (1989), and Gali (1992). Since then, Structural Vector Auto-Regressive (SVAR) models have been commonly used to identify demand and supply shocks (see Fry and Pagan, 2011, for an overview). Recent contributions on the subject include works by Wolf (2020) and Eickmeier and Hofmann (2022). Specifically, Eickmeier and Hofmann (2022) use a factor model on sector-level data that allows them to extract indicators that suggest varying levels of demand or supply dominance over time. Exploiting the term-premium mechanism described above, researchers have also used asset prices to identify demand and supply factors (e.g. Breach et al., 2020; Bekaert et al., 2022).

Benhima and Poilly (2021) use sign restrictions on inflation and GDP forecasts and compute, aside from demand and supply shock, also a measure of demand and supply noise and point out that demand noise in particular has a negative effect on output and output volatility. This is an important consideration of our work, as we do not control for time-varying demand and supply noise. Finally, Geiger and Scharler (2021) and Bekaert et al. (2020) use survey revisions and higher-order moments to identify demand and supply shocks.

An emerging strand of the literature focuses on inflation and examines the differing effects of policy depending on whether inflation is driven by supply or demand (e.g., Shapiro, 2022; Boissay et al., 2023). It is important to emphasize that the primary objective of the above papers is to estimate demand and supply shocks or factors. In contrast, we aim to measure the time variation in the relative importance of demand and supply shocks, which is a different undertaking to ours.

Second, we contribute to the literature that explores and exploits surveys of professional forecasters (SPFs), which provide valuable insights into expectations and expectation formation. Coibion and Gorodnichenko (2015) use SPFs to study the expectation formation process and to test for informational rigidities. Abel et al. (2016), Aruoba (2016), and Grishchenko et al. (2019) estimate the uncertainty around inflation expectations, relying on the SPF.

Lastly, this paper contributes to the literature that explains univariate or multivariate measures of disagreement in forecasts. Banternghansa and McCracken (2009) and Clements (2022) take into account the covariance between forecasts and produce multivariate disagreement measures to test for forecast efficiency and contrarianism.

Focusing specifically on GDP and inflation forecasts allows us to learn about (expected) demand and supply shocks. Jain (2019) computes measures of inflation persistence implied by professional forecasts, and finds that inflation persistence has decreased since the mid-1990s. Like us, she finds slow-moving changes in the properties of inflation. Supply shocks, that are often deemed to have more persistent effects than demand shocks, have become less important over time, reducing the degree of inflation persistence and increasing the relative importance of demand shocks. This is an alternative explanation to the more common one of a more credible central bank that is more successful in controlling inflation, but one that has high potential for future research.

Patton and Timmermann (2010), similar to this article, examine the drivers behind forecaster disagreement. They find that disagreement increases with the horizon. This is at odds with explanations based on private signals, as these are more important at shorter horizons. Instead, disagreement can be explained by heterogeneity in prior beliefs. Importantly, they also show that the dispersion of forecasts is countercyclical in both GDP and inflation rates. While this does not directly affect our results, it may indicate that recessions have an above-average impact on the Slope Index.

Herbst and Winkler (2021) examine the disagreement between forecasters using a dynamic factor model, and including a large set of professional forecasts. This is highly relevant to our work, as the two most important factors in their work are interpreted as supply and demand disagreement factors. This methodology provides a much finer decomposition of disagreement, without taking a stand on the source of the heterogeneity. In contrast, our paper posits that the relative importance of (fundamental) supply and demand shocks directly affects (and can be measured by) the multivariate disagreement of forecasters.

The paper is structured as follows: Section 3.2 presents a synthetic model that explains the relationship between demand or supply dominance and survey data. Section 3.3 introduces the Slope Index, a forecast-based measure of supply or demand dominance. Then, Section 3.4 examines the implications of the new measure. Finally, Section 3.5 concludes.

3.2 Model

In this section, we propose a stylized model that rationalizes our measure of supply or demand dominance. It describes a situation in which the distribution of expected changes in GDP and inflation (across forecasters) reflects the relative importance of demand versus supply shocks in the economy. It is important to note that, in the context of this stylized homoskedastic model, the relationship between expected changes in GDP and inflation is constant. Our empirical analysis, however, assumes that this relationship is time-varying.[2] One way to reconcile these two observations is to assume that the parameterization of the present model moves over time, but that the agents do not take these changes into account when they compute one-year-ahead forecasts. In other words, we consider the present model to serve as a local approximation of the forecasting process. Having a more realistic modeling approach (that could be brought to the data) would require a model featuring heteroskedastic GDP-inflation dynamics. This is left for further research.

3.2.1 The Model and its Implications

Inflation, GDP and their determinants We denote by $\Delta y_{t-1,t}$ and $\pi_{t-1,t}$ the quarterly GDP growth rate and inflation rate, defined as

$$\pi_{t-1,t} = p_t - p_{t-1}$$
$$\Delta y_{t-1,t} = gdp_t - gdp_{t-1},$$

where $p_t = \log(P_t)$ and $gdp_t = \log(GDP_t)$.

[2] Our measure aims to capture changes in the relative importance of demand and supply shocks.

Without loss of generality, we assume that the long-run mean of both GDP growth and inflation is zero. We also make the hypothesis that the dynamics of quarterly inflation and GDP growth rate are linear combinations of demand and supply factors collected in the 2×1 vector $\xi_t = [d_t, s_t]'$. Importantly, the dynamics of ξ_t is such that its marginal mean is zero. The dynamics of ξ_t can thus be captured by the VAR(1) model

$$\xi_t = F\xi_{t-1} + v_t, \tag{3.1}$$

with

$$F = \begin{bmatrix} \rho_d & 0 \\ 0 & \rho_s \end{bmatrix} \qquad \text{and} \qquad \mathbb{E}(v_t v_t') = Q = \begin{bmatrix} \sigma_d^2 & 0 \\ 0 & \sigma_s^2 \end{bmatrix},$$

and where the eigenvalues of F lie within the unit circle. σ_d^2 and σ_s^2 denote the variance of demand and supply shocks, respectively, and thus determine the relative importance between demand and supply shocks.

Given the dynamics specified above, the joint model for inflation and GDP growth can be expressed as a linear combination of factors plus measurement errors:

$$S_t = \begin{bmatrix} \Delta y_{t-1,t} \\ \pi_{t-1,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ \alpha_d & -\alpha_s \end{bmatrix} \begin{bmatrix} d_t \\ s_t \end{bmatrix} + \begin{bmatrix} \eta_{y,t} \\ \eta_{\pi,t} \end{bmatrix}, \tag{3.2}$$

where $\alpha_d > 0$ and $\alpha_s > 0$ determine the effects of demand and supply factors on inflation. For the sake of simplicity, both parameters are normalized to have a unit effect on GDP.

Private information. While the elements contained in S_t can be considered as a public signal for all forecasters, a given forecaster (i) also has private and imperfect information about the factors d_t and s_t on which she relies to form her forecast. We call these private signals $p_{d,t}^{(i)}$ and $p_{s,t}^{(i)}$, which can be viewed as the demand and supply factors, as perceived by a given forecaster (i):

$$\begin{bmatrix} p_{d,t}^{(i)} \\ p_{s,t}^{(i)} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} d_t \\ s_t \end{bmatrix} + \begin{bmatrix} \eta_{d,t}^{(i)} \\ \eta_{s,t}^{(i)} \end{bmatrix}. \tag{3.3}$$

Combining all elements mentioned above, forecaster (i) observes a total of two public signals, along with two private signals. This results in the following system:

$$Z_t^{(i)} = H'\xi_t + \eta_t^{(i)}, \tag{3.4}$$

where,

$$Z_t^{(i)} = \begin{bmatrix} \Delta y_{t-1,t} \\ \pi_{t-1,t} \\ p_{d,t}^{(i)} \\ p_{s,t}^{(i)} \end{bmatrix}, \quad H' = \begin{bmatrix} 1 & 1 \\ \alpha_d & -\alpha_s \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \xi_t = \begin{bmatrix} d_t \\ s_t \end{bmatrix}, \quad \eta_t^{(i)} = \begin{bmatrix} \eta_{y,t} \\ \eta_{\pi,t} \\ \eta_{d,t}^{(i)} \\ \eta_{s,t}^{(i)} \end{bmatrix},$$

and where the signal variance is given by $\mathbb{E}(\eta_t^{(i)}\eta_t'^{(i)}) = R$.

Kalman algorithm. Assuming that forecasters have a substantial history of observed signals and exhibit consistent behavior, it is reasonable to infer that they employ the Kalman algorithm to formulate their individual conditional expectations, i.e. $\xi_{t|t-1}^{(i)} = \mathbb{E}_{t-1}^{(i)}\Big(\xi_t\Big)$, where $\mathbb{E}_{t-1}^{(i)}\Big(\bullet\Big)$, denotes the expectation conditional on $\underline{Z_{t-1}^{(i)}} = \{Z_{t-1}^{(i)}, Z_{t-2}^{(i)}, \cdots\}$. The Kalman filter allows us to derive these conditional expectations and leads to the following recursive law of motion for $\xi_{t|t}^{(i)}$ (see Appendix 3.A.1 for the derivation):

$$\xi_{t|t}^{(i)} = F\xi_{t-1|t-1}^{(i)} + K\left(Z_t^{(i)} - H'F\xi_{t-1|t-1}^{(i)}\right),$$

where K is the steady-state Kalman gain.

Combining all aspects, we end up with the following VAR representation:[3]

$$X_t^{(i)} = \Phi X_{t-1}^{(i)} + \Sigma\epsilon_t^{(i)}, \tag{3.5}$$

where,

$$X_t^{(i)} = \Big[d_t,\ s_t,\ \Delta y_{t-1,t},\ \pi_{t-1,t},\ p_{d,t}^{(i)},\ p_{s,t}^{(i)},\ d_{t|t}^{(i)},\ s_{t|t}^{(i)}\Big],$$

and $\epsilon_t^{(i)} = \Big[\nu_t, \quad \eta_t^{(i)}\Big]$.

Note that equation (3.5) includes the state variables, observables, as well as the private expectations of the factors, i.e. $\xi_{t|t}^{(i)} = [d_{t|t}^{(i)}, \quad s_{t|t}^{(i)}]'$. In particular, it enables the computation of GDP and inflation expectations for any horizon h:

$$\mathbb{E}_t^{(i)}\begin{bmatrix} \Delta y_{t+h-1,t+h} \\ \pi_{t+h-1,t+h} \end{bmatrix} = H_{[1:2,1:2]}F^h\xi_{t|t}^{(i)} = H_{[1:2,1:2]}F^h\Pi X_t^{(i)},$$

where $\Pi X_t^{(i)} = \xi_{t|t}^{(i)}$, and Π is a selection matrix.

Joint Distribution between forecasters. This model contains the whole information set of forecaster (i). Since there are variations in the private signals $p_{d,t}^{(i)}$ and $p_{s,t}^{(i)}$, there will also be variations in individual expectations between forecasters. The unconditional distribution of $X_t^{(i)}$ is

$$X_{\mathrm{t}}^{(i)} \sim N\left(0, \Sigma_X\right), \tag{3.6}$$

[3]See Appendix 3.A.2 for the derivation of the VAR representation.

where $\Sigma_X = (I_8 - \Phi)^{-1} \left(\Sigma \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix} \Sigma' \right) (I_8 - \Phi)'^{-1}$.

Finally, We can derive the forecaster's expected changes[4] in GDP growth and inflation, which can be expressed as a function of $X_t^{(i)}$ (see Appendix 3.A.3 for more details):

$$\Gamma_{t,h}^{(i)} = \mathbb{E}_t^{(i)} \begin{bmatrix} \Delta y_{t+h-1,t+h} - \Delta y_{t-1,t} \\ \pi_{t+h-1,t+h} - \pi_{t-1,t} \end{bmatrix} = \Lambda_h X_t^{(i)}, \tag{3.7}$$

where

$$\Lambda_h = \begin{bmatrix} 0_2 & -I_2 & 0_2 & H'_{[1:2,1:2]} F^h \end{bmatrix}.$$

Since we know the (Gaussian) distribution of $X_t^{(i)}$, we can compute the conditional distribution of $\Gamma_{t,h}^{(i)} | \xi_t$:

$$\Gamma_{t,h}^{(i)} \mid \xi_t \sim N\left(\widetilde{\Lambda_h} \Sigma_{X_{21}} \Sigma_{X_{11}}^{-1} \xi_t \ , \ \widetilde{\Lambda_h} \left(\Sigma_{X_{22}} - \Sigma_{X_{21}} \Sigma_{X_{11}}^{-1} \Sigma_{X_{12}} \right) \widetilde{\Lambda_h}' \right), \tag{3.8}$$

with $\widetilde{\Lambda_h} = \begin{bmatrix} -I_2 \ , \ 0_2 \ , \ H'_{[1:2,1:2]} F^h \end{bmatrix}$ and $\Sigma_{X_{11}}$, $\Sigma_{X_{12}}$, $\Sigma_{X_{21}}$, $\Sigma_{X_{22}}$ are sub-matrices of Σ_X, such that,

$$\Sigma_X = \begin{bmatrix} \Sigma_{X_{11}} & \Sigma_{X_{12}} \\ \Sigma_{X_{21}} & \Sigma_{X_{22}} \end{bmatrix}.$$

Equation (3.8) shows the joint distribution of expected changes in GDP and inflation across forecasters. Figure 3.1 is its empirical counterpart. It is important to note that while the expected value of the distribution in equation (3.8) depends on ξ_t, the variance-covariance matrix does not. Thus, in the context of this simple model, the distribution (across forecasters) of expected changes in inflation and GDP moves over time only because the coordinates of the "center" of the distribution depend on ξ_t. In particular, in this model, the slope of the regression line in the regression of expected changes in GDP on expected changes in inflation (which relate to our measure) is not time-varying.[5] However, this is not the case in the data (as illustrated by Figure 3.1). To reconcile the present model with the data, one can think of the model as a "local" approximation of reality. A model that accounts for changes in the regression line—which could then be amenable to the data—would require heteroskedastic demand and supply shocks (i.e., a time-varying Σ_X). However, this is beyond the scope of the present paper.

[4]For the sake of simplicity, we use the difference between the expectations and current values of inflation and GDP. We focus on the forecaster's expected changes, as they exhibit a mean of zero. In addition, we focus on the slope of the scatter plot, as shown in Figure 3.1, which is contingent on the second-order moment of the distribution. Notably, this slope remains unaffected by the aforementioned change.

[5]Note that this is the case in the population (of forecasters). That is, this is only if an infinite number of forecasts were included in the regression (and under the model assumptions) that we would have a constant regression slope.

3.2.2 Demand and Supply-Dominant Economies

As mentioned above, the model developed in the last subsection lacks dynamic changes in the relative importance of demand and supply, since σ_d^2 and σ_s^2 remain constant over time. Nevertheless, this model is useful for elucidating the relationship between the distribution of expected changes in inflation and GDP growth (across forecasters) and the relative importance of demand and supply shocks in the economy, which can be measured by σ_d/σ_s.

For this purpose, we consider three calibrations of the model that differ substantially with respect to σ_d/σ_s. The first scenario is a "balanced" economy with two shocks of equal magnitude, i.e., $\sigma_d = \sigma_s$. The second scenario represents a demand-dominant economy where $\sigma_d = 10\sigma_s$. The third scenario corresponds to a supply-dominant economy, where $\sigma_s = 10\sigma_d$. Appendix 3.A.4 presents the model calibration.

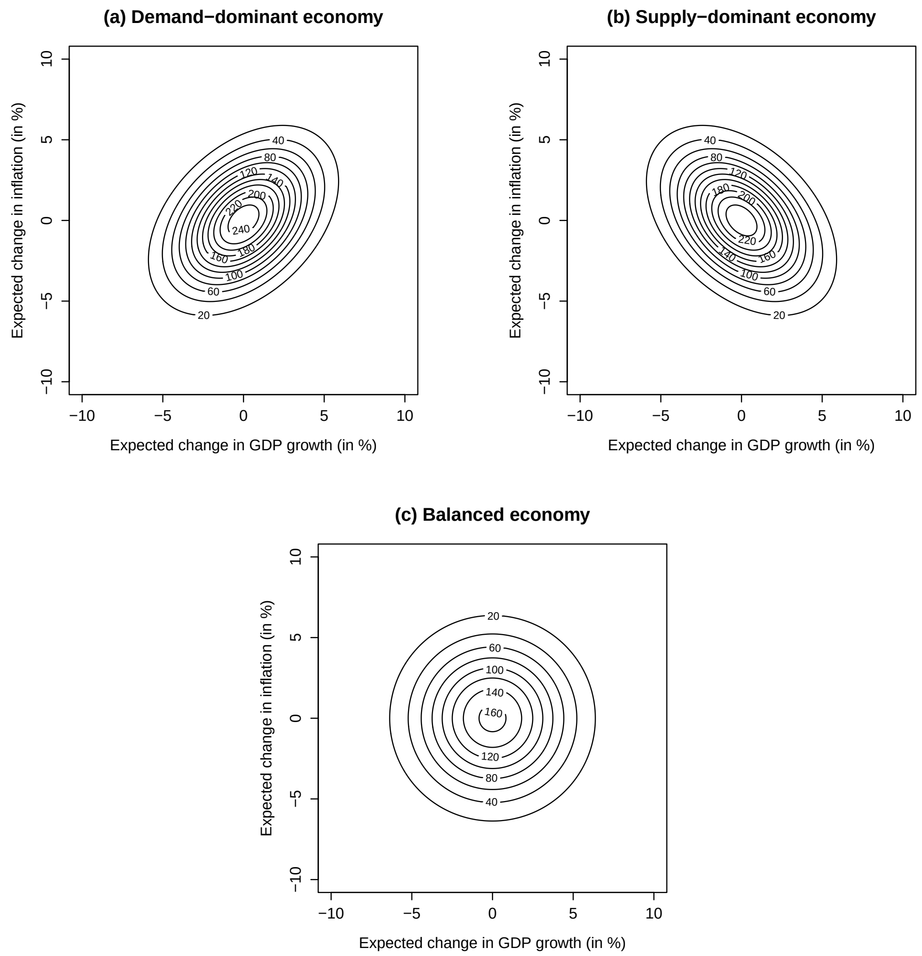
Figure 3.2 shows the joint distributions—across forecasters—of expected changes in inflation and GDP growth for the three different scenarios: demand-dominant economy (top left chart), supply-dominant economy (top right chart), and balanced economy (bottom chart). As shown in (3.8), these distributions depend on the value of ξ_t. For simplicity, we consider the case where ξ_t equals zero (its long-run mean), such that the distribution is centered around zero as well. This is without loss of generality since the second-order moments of the distribution—in which we are primarily interested—do not depend on ξ_t.

For the demand-dominant economy, the contour plot reveals elongated ellipses. The positive correlation across forecasters between inflation and GDP growth is evident as the ellipses are stretched in one direction—from northeast to southwest. Conversely, the supply-dominant economy exhibits a negative correlation. For the balanced economy, we see no correlation between the expected changes in inflation and GDP growth. This is consistent with Figure 3.1, which shows different types of slopes depending on the type of shock prevailing in the economy.

The previous results suggest that the shape of the joint distribution of expected changes in GDP and inflation is informative about the relative importance of demand shocks in the economy. This is further illustrated by Figure 3.3, where the black line plots the correlation of expected changes in GDP and inflation as a function of the relative importance of demand shocks.[6]

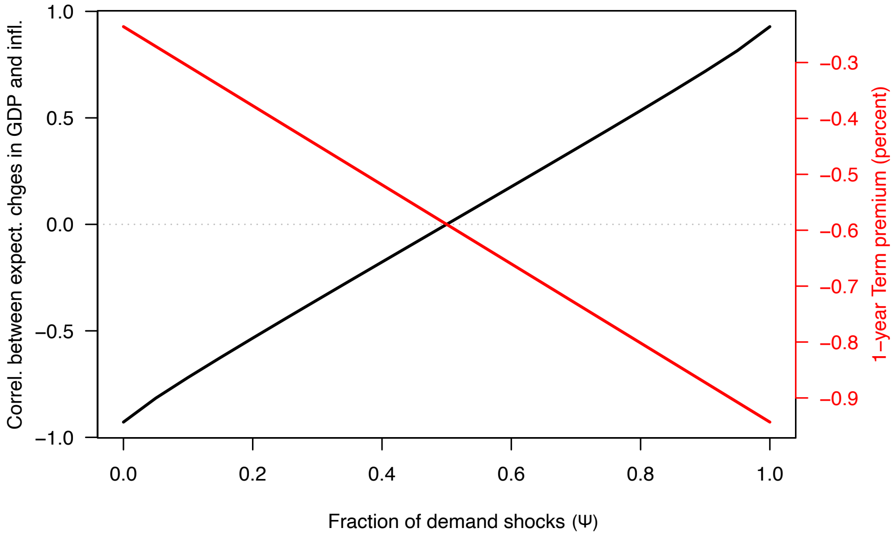
[6]This section focuses on the correlation between the expected changes in GDP and inflation (black line). The relationship with the term premium (red line) is discussed in Section 3.4.3.

Figure 3.2: Demand versus Supply-Dominant Economy



Notes: This figure shows joint distributions of expected change in inflation and GDP growth (across forecasters) under three distinct scenarios: one characterized by the dominance of demand shocks (upper left chart with $(\sigma_d, \sigma_s) = (0.5\%, 0.05\%)$), another by the prevalence of supply shocks (upper right chart with $(\sigma_d, \sigma_s) = (0.05\%, 0.5\%)$), and the last representing the balanced situation (bottom center chart with $(\sigma_d, \sigma_s) = (0.5\%, 0.5\%)$). The calibration of other coefficients is symmetric and outlined in Appendix 3.A.4.

Figure 3.3: Term Premium and the Relative Importance of Demand Shocks



Notes: This figure illustrates the evolution of the correlation between expected changes in GDP and inflation on the left y-axis, and the evolution of the term premium on the right y-axis, as the fraction of demand shocks varies. See Section 3.4.3 for details regarding the term premium. σ_d^2 and σ_s^2 are set depending on the fraction of demand shocks ψ. The specifications are such that the total variance in the model remains constant when ψ varies. See Appendix 3.A.4 for details on the model calibration.

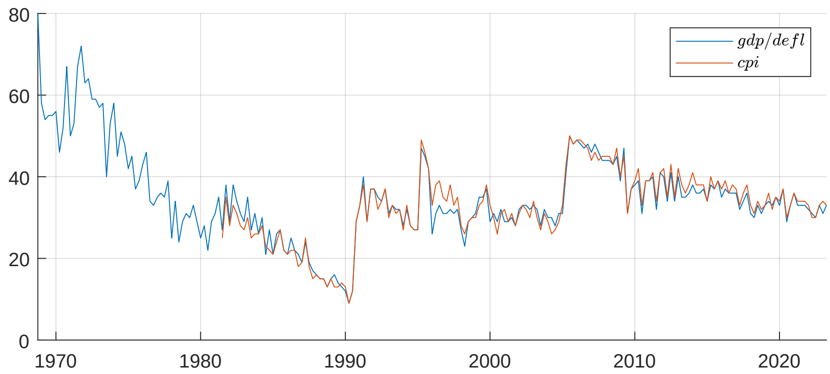
3.3 Construction of the Indicator

This section presents the data and the computation of the Individual Forecaster Slope Index.

3.3.1 Data

The Survey of Professional Forecasters (SPF) is a quarterly survey of forecasts from financial and research institutions. It provides forecasts for a multitude of variables and horizons. We make use of quarterly point forecasts of real GDP, the implicit GDP deflator, and CPI inflation, covering all forecasts with horizons from current-quarter to four quarters ahead. Participating institutions also provide forecasts for calendar years with a changing forecast horizon each quarter [7]. The fixed-horizon forecasts (from current-quarter to 4 quarters ahead) are more homogeneous, comparable, and thus better suited for our purposes.[8]

Figure 3.4: Number of Forecasts per Quarter



Notes: This figure depicts the number of forecasts for each quarter. The blue line depicts both the number of observations for GDP and the GDP deflator, as the two numbers are equal for every quarter. The red line depicts forecasts for CPI inflation, which starts in 1981Q3, only. The smallest number of observations is 9 forecasts, which is recorded for 1990Q2.

All variables are expressed as year-on-year percentage changes, henceforth referred to as growth rates for GDP and inflation rates for the GDP deflator and the CPI. The sample period starts in 1968Q4 for GDP and the GDP deflator forecasts, and in 1981Q3 for CPI forecasts. The last observation is in 2023Q3.[9]

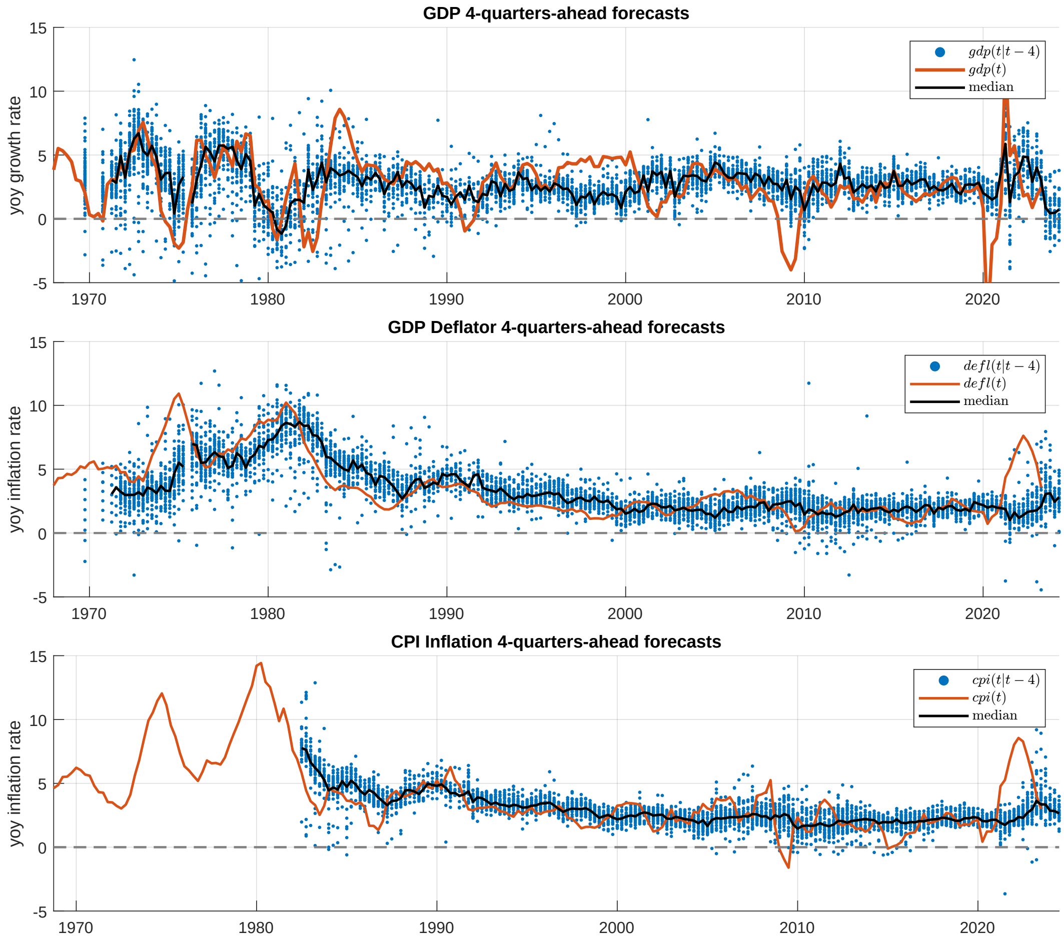
Each forecaster has a unique identification number that allows them to be tracked over time. However, it is important to note that ID numbers are not always unique, as there are instances where the IDs of leaving institutions have been reassigned to new entrants. Due to this, and because of constant changes in the composition of forecasters, we do not exploit the time series dimension of individual forecasters. In the cross-section, the number of forecasters per quarter was quite volatile before 1990, when the Federal Reserve Bank of Philadelphia

[7] e.g. every quarter in 2022, forecasters make forecasts for the calendar years 2022, 2023, and 2024

[8] Notably, forecasts are sampled mid-quarter, prior to the release of official GDP and GDP deflator figures, giving rise to current-quarter forecasts.

[9] For more information on the SPF, and the construction and transformation of the forecast data, see Appendix 3.C.

Figure 3.5: Individual 4-Quarter-Ahead Forecasts and Realizations



Notes: This figure shows individual 4-quarter-ahead forecasts for year-on-year growth rates of GDP, the GDP deflator, and the CPI. The red line denotes the last vintage of official data for the three series. The black line denotes the median forecast and the blue dots denote the individual forecasts. Forecasts are displayed at the date which is targeted by the forecast, not the date when the forecast was made.

took over the survey from the National Bureau of Economic Research. The average number of respondents in the sample is about 36, and the minimum is 9 observations in 1990Q1 (see Figure 3.4).

Table 3.1 reports descriptive statistics. The statistics are presented for the three variables of interest and for three horizons: $h = \{0, 1, 4\}$.[10] Both the forecast error variance, as well as the disagreement increase with the length of the horizon. The statistics shown in Table 3.1 average over both the time and forecaster dimensions. Figure 3.6, however, shows that mean forecast errors and disagreement vary over time, with both variables increasing in periods of distress (e.g., during the great financial crisis or during the COVID period). The same statistics for forecasts of shorter horizons ($h = 0$ and $h = 1$) are available in Appendix 3.C.

[10] Note that the forecasts for the current quarter $h = 0$ (or nowcasts) are submitted before any official figures are published. This is with the exception of CPI inflation, which is partially known (see Appendix 3.C for details).

Table 3.1: Descriptive Statistics SPF

Mean Forecast Errors: $MFE_t = \mu_t\left(x_t - x^{(i)}_{t\|t-h}\right)$, where $x_t = \{gdp_t, defl_t, cpi_t\}$									
	gdp_t			$defl_t$			cpi_t		
	$h=0$	$h=1$	$h=4$	$h=0$	$h=1$	$h=4$	$h=0$	$h=1$	$h=4$
$\mu(MFE_t)$	0.17	0.17	-0.01	0.11	0.14	0.19	0.06	0.05	-0.09
$\sigma(MFE_t)$	0.62	1.27	2.19	0.32	0.60	1.68	0.33	0.72	1.56
$\rho(MFE_t)$	0.02	0.19	0.78	0.60	0.79	0.96	0.15	0.49	0.84
Disagreement: $D_t = \sigma_t\left(x^{(i)}_{t\|t-h}\right)$, where $x_t = \{gdp_t, defl_t, cpi_t\}$									
$\mu(D_t)$	0.37	0.59	1.16	0.28	0.44	0.93	0.23	0.37	0.64
$\sigma(D_t)$	0.28	0.42	0.76	0.16	0.25	0.59	0.13	0.21	0.34
$corr(MFE_t, D_t)$	0.62	0.41	0.34	0.62	0.50	0.46	0.75	0.60	0.41

Notes: This table reports common descriptive statistics for the SPF data from 1968 - 2023. μ_t and σ_t denote the cross-sectional mean and standard deviation across forecasters, whereas μ and σ depict the mean and standard deviation across time. $\rho(MFE_t)$ depicts the sample autoregressive coefficient of MFE_t for $lag = 1$, and $corr(MFE_t, D_t)$ stands for the correlation coefficient between mean forecast errors and disagreement. x_t stands for the respective variable $x_t = \{gdp_t, defl_t, cpi_t\}$, which is transformed into year-on-year growth rates.

3.3.2 Constructing the Individual Forecast Slope Index

Our Slope Index is based on individual SPF forecasts. This data being available at the forecaster level, we can exploit it to operationalize the insights of Section 3.2, according to which the correlation (across forecasters) of expected changes in GDP and inflation is informative about the relative importance of demand shocks in the economy. Importantly, this correlation can be computed on each date when SPFs are released (at the quarterly frequency).

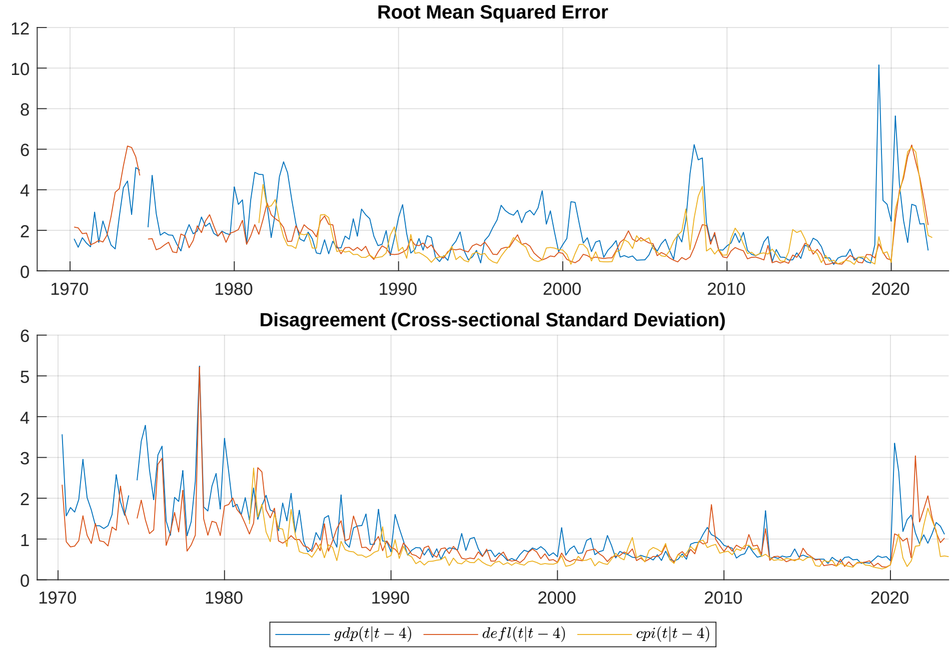
There are roughly 36 forecasts submitted, on average, per date. Given this relatively small number, and taking into account the fact that in our methodology, a single forecaster can significantly change the Slope Index, we proceed in three steps to construct the indicators:

- Taking all forecasts for horizons $h \in \{0, 1, ..., 4\}$, we winsorize the data at the 95th percentile.
- We calculate the Pearson correlation coefficient for each horizon separately:

$$Corr^{gdp,\pi}_{t,t+h} = corr(y^{(i)}_{t,t+h}, \pi^{(i)}_{t,t+h}), \tag{3.9}$$

  with horizons $h \in \{0, 1, ..., 4\}$ and $\pi \in \{defl, cpi\}$ indicating the price index used to compute inflation.
- We collect the Slope Indices for each horizon by extracting the first principal component. Depending on the measure for inflation, this yields three different *Individual Forecast Slope* (IFS) indices, or just Slope Indices, in short.

Figure 3.6: Accuracy and Disagreement for Horizon $h = 4$



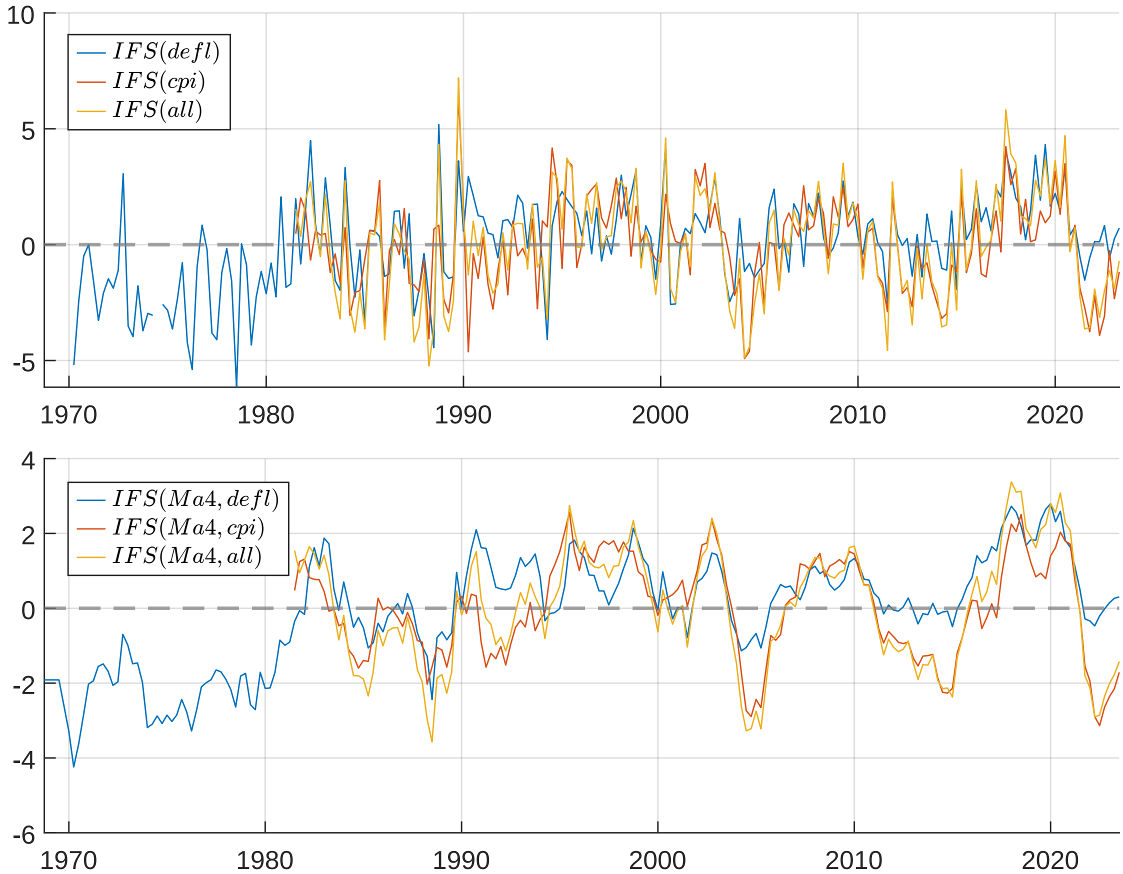
Notes: The top figure depicts the root mean squared error (RMSE) of point forecasts for each date t, namely $rmse_{t,h} = x_t - x_{t|t-h}$, with $x_t = \{gdp_t, defl_t, cpi_t\}$. The bottom figure displays the disagreement between forecasts, which means the dispersion between point forecasts. It is measured by the cross-sectional standard deviation. The horizon for both plots is $h = 4$. For other horizons, the same plots can be found in Appendix 3.C.

In graphs and tables, $IFS_t(defl), IFS_t(cpi)$, and $IFS_t(all)$ denote the three Slope Indices for the rest of the paper. The first two use the respective inflation measure to construct the Slope Index, and the last index combines the Slope Indices of both inflation measures. Thus, for $IFS_t(defl)$ and $IFS_t(cpi)$ we use 5 data series ($Corr^{gdp,defl}_{t,t+h}$ or $Corr^{gdp,cpi}_{t,t+h}$, respectively, for all h), while for $IFS_t(all)$ we have 10 series ($Corr^{gdp,defl}_{t,t+h}$ and $Corr^{gdp,cpi}_{t,t+h}$, combined, for all h) that are used to draw the principal component.

Because the three IFS (top graph in Figure 3.7) are quite noisy, and since we view the Slope Index as a measure that captures slow-moving changes in demand or supply dominance in the economy, we apply a 4-quarter moving average filter to the three IFS. These smoothed indices are denoted $IFS_t(Ma4, defl), IFS_t(Ma4, cpi)$, and $IFS_t(Ma4, all)$, respectively. Our outputs (tables and figures) report the results for the original Slope Indices and for the smoothed versions. Let us reiterate that the *cpi* forecasts are only available starting in 1981. Table 3.2 reports the correlation between different Slope Indices.

Because it is based on SPF data, our Slope Index is a forward-looking measure, in the sense that it is based on how forecasters see the future dynamics of GDP and inflation. It is model-free, and available in real time, even if the $Ma4$ versions are based only on forecast data published over the last four quarters. These properties are not shared by alternative approaches. In particular, those approaches relying on rolling windows to compute time-varying correlations between GDP and inflation are backward-looking; to produce a

Figure 3.7: Original and Smoothed Slope Indices



Notes: This figure depicts the 3 principal components, as derived from the Slope Indices from the three inflation measures (always combined with *gdp*). The top plot depicts the original series, and the bottom plot the smoothed series (smoothed by a 4-quarter moving-average filter).

reasonable correlation estimate, they must rely on windows longer than one year. However, they can provide good *ex-post* measures of the GDP-inflation correlation.

The Slope Index is strongly negative in the first period of the sample, from 1968 to the early 1980s. A period in which supply shocks were clearly dominant and very strong. This raises the concern that our results are based solely on the events of the 1970s and therefore have no external validity beyond this specific period.

The $IFS(Defl)$ index, which goes back to 1968, may suffer from weak identification problems, as the supply-dominant period is mostly at the beginning of the sample. However, this is not the case for $IFS(Cpi)$ and $IFS(All)$, which both start in 1980. First, analyzing the raw Slope Index data (see Figure 7), the $IFS(Defl)$ is very rarely negative in the second part of the sample. 71% of the sample points after 1990 are positive. The $IFS(Cpi)$ and $IFS(All)$, on the other hand, are evenly split between supply dominant and demand-dominant periods, with 43% and 49%, respectively, having a negative Slope Index. It should be noted that these differences are not due to different sample periods, as the calculations are based purely on cross-sectional correlations.

Table 3.2: Correlations between Slope Indices

	IFS_{defl}	IFS_{cpi}	IFS_{all}	IFS_{defl}^{Ma4}	IFS_{cpi}^{Ma4}	IFS_{all}^{Ma4}
$IFS(defl)$	1.00					
$IFS(cpi)$	0.42	1.00				
$IFS(all)$	0.84	0.85	1.00			
$IFS(Ma4, defl)$	0.69	0.40	0.55	1.00		
$IFS(Ma4, cpi)$	0.37	0.65	0.60	0.63	1.00	
$IFS(Ma4, all)$	0.50	0.60	0.65	0.87	0.92	1.00

Notes: This table reports the Pearson correlation coefficient between the six different Slope Indices. They are calculated using the maximum sample size per pair of data series, which is 169 observations when CPI data is used, and 220 observations otherwise.

In the next subsection, we examine the relationship between our Slope Indices and such *ex-post* correlation measures.

3.4 Regression Analysis

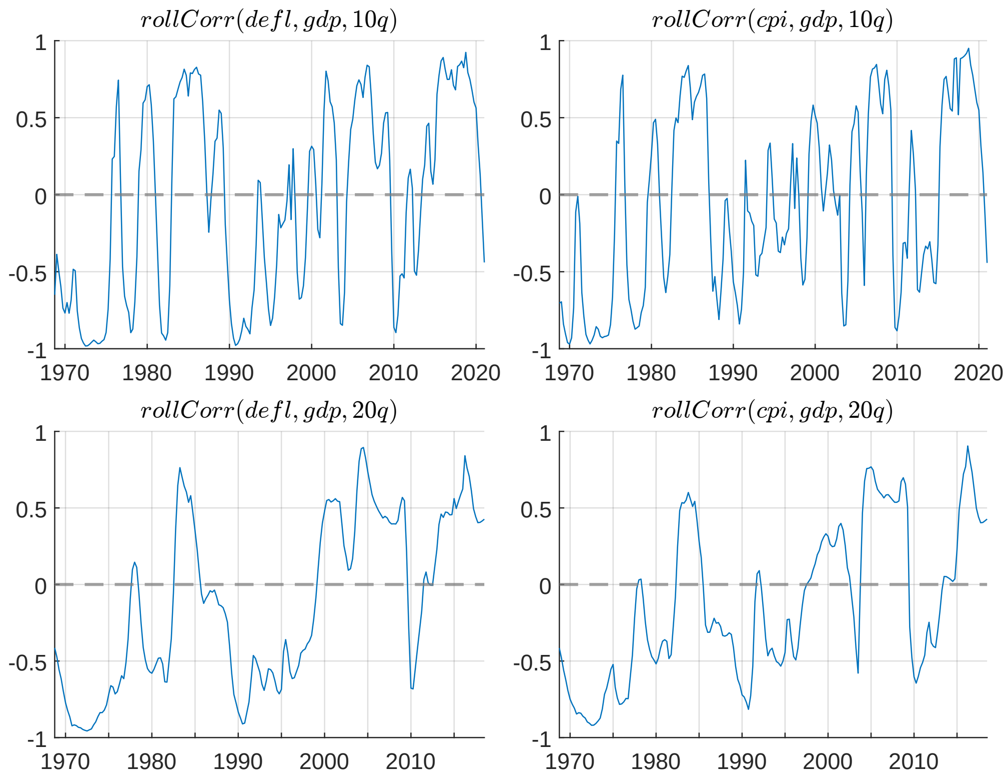
3.4.1 Slope Index and Aggregate Correlations

We consider rolling correlations between real GDP and inflation, using a sliding window of 10 and 20 quarters, and call them aggregate correlations, where aggregate refers to official and realized macroeconomic variables, as opposed to the survey-based correlations underlying the Slope Index.

These rolling correlations are displayed in Figure 3.8 using both the GDP deflator ($defl$) and CPI inflation (cpi) as the inflation measure. The results indicate considerable co-movement between GDP and Inflation. While there are some fast-moving changes in these series, there is also a slow-moving part that drives the series. This simple measure is roughly in line with the dominant economic forces in the U.S. economic development since 1968: In the 1970s and 1990s, inflation and GDP co-moved negatively in the vast majority of quarters, suggesting a larger role for supply shocks. The 1970s are known as a stagflationary period, where high inflation coincided with low growth rates. The 1990s were characterized by accelerating globalization and deregulation; two changes that directly influence supply.

On the other hand, the 1980s were characterized by Reagonomics, i.e. a strong expansion due to fiscal policy (through tax cuts and expenditure increases) and a more active monetary policy. Both affect aggregate demand. The 2000s and 2010s were characterized by the Great Moderation. Impulses came mainly from expansionary monetary policy. Supply factors played a smaller role. These historical findings are consistent with other research on the importance of demand and supply, see e.g. Eickmeier and Hofmann (2022). At the same time, the Slope Indices (Figure 3.7), as well as the ex-post correlations (Figure 3.8) fit these observations reasonably well.

Figure 3.8: Rolling Correlation of GDP and Inflation



Notes: This figure shows the evolution of the rolling correlation coefficient across time. The left column uses the GDP deflator ($defl$) as an inflation measure, the right column uses CPI (cpi). The top row uses a 10-quarter ($10q$), the bottom row a 20-quarter ($20q$) rolling window to calculate correlations. The X-axis denotes the first observation of the rolling window, i.e. for the bottom row (20 quarters the value at $t = 2018Q1$ uses observations from $2018Q1$ to $2022Q4$.

We now examine whether professional forecasters capture the changes in the correlation structure of GDP and inflation in real time. To do this, we use the Slope Index, as derived in Subsection 3.3.2, and we set up the following regression:

$$rollCorr_{t,q}(gdp, \pi) = \beta_0 + \beta_1 IFS_t(i) + \varepsilon_t, \tag{3.10}$$

where $\pi = \{defl, cpi\}$ depicts the aggregate inflation measure, $i = \{defl, cpi, all\}$ denotes the Slope Index used. $rollCorr_{t,q}(gdp, \pi)$ denotes the *ex-post* rolling correlation coefficient between GDP and inflation measure π for the time window $(t : t + q - 1)$. For the following regressions, we set $q = 10$ and $q = 20$.

The results are displayed in Table 3.D4. They portray a positive relationship between the Slope Index and the rolling correlation, providing evidence in support of the hypothesis that a positive Slope Index at time t (indicating a demand-dominant economy) coincides with a positive correlation between aggregate GDP and inflation in the 10 or 20 quarters following period t. More generally, the observed positive relationship substantiates the claim

Table 3.3: Rolling Correlation Regressions

	$rollCorr_{t,10}(gdp, defl)$			$rollCorr_{t,20}(gdp, defl)$		
$IFS(defl)$	0.065^{*}			0.058^{**}		
	(0.033)			(0.027)		
$IFS(cpi)$		0.019			-0.035	
		(0.032)			(0.031)	
$IFS(all)$			0.013			-0.032
			(0.026)			(0.023)
Observations	205	159	159	195	149	149
R^2	0.046	0.004	0.003	0.046	0.017	0.021
F-test (robust)	3.831^{*}	0.345	0.261	4.476^{**}	1.274	1.914
	$rollCorr_{t,10}(gdp, cpi)$			$rollCorr_{t,20}(gdp, cpi)$		
$IFS(defl)$	0.085^{***}			0.077^{***}		
	(0.029)			(0.023)		
$IFS(cpi)$		0.053^{**}			0.001	
		(0.027)			(0.025)	
$IFS(all)$			0.041^{*}			0.006
			(0.025)			(0.020)
Observations	205	159	159	195	149	149
R^2	0.094	0.037	0.033	0.101	0.000	0.001
F-test (robust)	8.710^{***}	4.005^{**}	2.778^{*}	11.567^{***}	0.003	0.085

Notes: This table reports simple regressions of the rolling correlation coefficient on different Slope Indices. The dependent variable is a measure of rolling correlations between aggregate output and GDP. Top regressions: GDP deflator used as the inflation measure. Bottom regressions: CPI is used as the measure of inflation. First three columns: the rolling window spans 10 quarters. Last three columns: The rolling window spans 20 quarters. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parentheses. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

that GDP and inflation are not forecast in isolation and that we can derive information on the underlying shock structure.

The additional results in Appendix 3.D confirm the robustness of these findings across various subsamples, including the earliest and most recent periods. However, significance diminishes for the intermediate period (1986-2008), possibly due to fewer observations or challenges in disentangling demand and supply shocks amidst low inflation rates.

3.4.2 Regressing Mean Forecast Errors

This subsection presents the results of a related regression exercise based on a simpler measure of GDP and inflation covariance. Let $MFE^{v}_{t,t+h}$ denote the aggregate forecast error made by forecasters for variable v between dates t and $t+h$, that is $MFE^{v}_{t,t+h} = v_{t+h} - \mathbb{E}_t(v_{t+h})$. Considering GDP and inflation as v variables, we can compute the ex-post forecast errors using SPF data. By definition, we have

$$\mathbb{E}_t(MFE^{gdp}_{t,t+h} \times MFE^{\pi}_{t,t+h}) = \mathbb{C}ov_t(\Delta y_{t,t+h}, \pi_{t,t+h}),$$

which implies

$$MFE^{gdp}_{t,t+h} \times MFE^{\pi}_{t,t+h} = \mathbb{C}ov_t(\Delta y_{t,t+h}, \pi_{t,t+h}) + \varepsilon_{t+h},$$

where $\mathbb{E}_t(\varepsilon_{t+h}) = 0$. By the law of iterated expectations, we also have $\mathbb{E}(\varepsilon_{t+h}) = 0$. Since the Slope Index can be seen as a proxy for $\mathbb{C}ov_t(\Delta y_{t,t+h}, \pi_{t,t+h})$, what precedes suggests that the regression of $MFE^{gdp}_{t,t+h} \times MFE^{\pi}_{t,t+h}$ on the date-t Slope Index should result in a positive coefficient. To test for the potential forward-looking nature of the Slope Index, we include the rolling covariance between GDP and inflation over the past 10 quarters ($rollCov_t(gdp, \pi)$, say) as a control in some of the regressions.[11] Formally, our regressions are as follows:

$$MFE^{gdp}_{t,t+h} \times MFE^{\pi}_{t,t+h} = \beta_0 + \beta_1 IFS_t(i) + \beta_2 rollCov_t(gdp, \pi) + \varepsilon_t, \tag{3.11}$$

where $i = \{defl, cpi, all\}$, $\pi = \{defl, cpi\}$, and $h = \{0, 1, 4\}$. Tables 3.4 and 3.5 show the regression results for $h = 4$.[12] This shows the relationship between the Slope Index and the product of the one-year-ahead mean forecast errors, which confirms the ability of our measure to capture changes in the relative importance of demand shocks in real time.

Table 3.4: MFE Product (*gdp-defl*) Regressions, for $h = 4$

	$MFE^{GDP}_{t,t+h} \times MFE^{defl}_{t,t+h}$					
$IFS(Ma4, defl)$	1.078^{*}			0.689		
	(0.597)			(0.611)		
$IFS(Ma4, cpi)$		0.844^{*}			0.466	
		(0.455)			(0.658)	
$IFS(Ma4, all)$			0.749^{**}			0.435
			(0.334)			(0.677)
$rollCov(gdp, defl)$				0.588	0.904^{*}	0.776^{**}
				(0.550)	(0.483)	(0.356)
Observations	210	168	168	208	168	168
R^2	0.094	0.077	0.085	0.173	0.115	0.119
F-test (robust)	3.263^{*}	3.433^{*}	5.037^{**}	2.097	4.026^{**}	4.961^{***}

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$.

[11] It is important to note that $rollCov_t(gdp, \pi)$ is backward-looking (as opposed to $rollCorr_{t,q}(gdp, \pi)$ in Subsection 3.4.1, which is forward-looking.)

[12] We get very similar results for $h = 1$ and $h = 0$ (see Appendix 3.D.2).

Table 3.5: MFE Product (*gdp-cpi*) Regressions, for $h = 4$

	$MFE^{GDP}_{t,t+h} \times MFE^{cpi}_{t,t+h}$					
$IFS(Ma4, defl)$	0.798**			0.254		
	(0.400)			(0.723)		
$IFS(Ma4, cpi)$		0.930*			0.335	
		(0.485)			(0.651)	
$IFS(Ma4, all)$			0.716**			0.297
			(0.351)			(0.675)
$rollCov(gdp, defl)$				0.797*	0.976*	0.737**
				(0.411)	(0.502)	(0.363)
Observations	164	164	164	164	164	164
R^2	0.025	0.065	0.054	0.033	0.079	0.065
F-test (robust)	3.976**	3.680*	4.167**	2.538*	2.685*	2.979*

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

3.4.3 Relationship with the Term Premium

In this subsection, we study the relationship between our Slope Index and term premium measures. The latter are deviations from the expectation hypothesis (EH). More specifically, they are the difference between the interest paid on a long-term bond and the expected return associated with the strategy that consists of rolling over a portfolio by investing the entire portfolio, at each period, in short-term bonds. (Under the EH, the yield-to-maturity of a long-term bond would be equal to the expected average of future short-term rates until the maturity of the bond.) As discussed in the introduction, the theory predicts that supply shocks pose a greater risk to holders of long-term bonds than demand shocks which implies that term premiums are higher in an economy driven by supply shocks (e.g., Piazzesi and Schneider, 2007; Gurkaynak and Wright, 2012).

This can be illustrated in the context of the model presented in Section 3.2. Appendix 3.B extends this model by introducing a representative investor who consumes the output and features time-separable power-utility preferences. In that context, one can derive the term premiums in closed form. Figure 3.3 shows how, in this framework, term premiums depend on the relative importance of demand shocks. In contrast to the correlation between expected changes in inflation and GDP (in black), term premiums depend negatively on the importance of demand shocks.

We now turn to the empirical evaluation of this model prediction. Since the Slope Index increases with demand dominance, we expect a negative relationship with the term premium.

To test this hypothesis, we run the following linear regressions:

$$TP_{k,t} = \beta_0 + \beta_1 IFS_t(i) + \varepsilon_t, \tag{3.12}$$

where $i = \{defl, cpi, all\}$, and $k = \{10Y, 2Y\}$. As a positive Slope Index coincides with a demand-dominant economy, we expect term premiums to be lower in this case. Therefore, we expect the regression coefficients to be negative.

Table 3.6: Term Premium Regressions (10Y TP)

	ACM Term Premia 10 years					
	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(defl)$	−0.052			−0.015***		
	(0.032)			(0.006)		
$IFS(cpi)$		−0.026			−0.000	
		(0.041)			(0.007)	
$IFS(all)$			−0.050			−0.010*
			(0.035)			(0.005)
Observations	214	168	168	210	167	167
R^2	0.028	0.005	0.028	0.029	0.000	0.020
F-test (robust)	2.649	0.392	1.996	7.390***	0.001	3.895*
	ACM Term Premia 10 years					
	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(Ma4, defl)$	−0.089			−0.078***		
	(0.058)			(0.021)		
$IFS(Ma4, cpi)$		−0.037			0.009	
		(0.081)			(0.029)	
$IFS(Ma4, all)$			−0.083			−0.052**
			(0.073)			(0.021)
Observations	220	169	169	219	168	168
R^2	0.042	0.005	0.035	0.035	0.001	0.032
F-test (robust)	2.388	0.202	1.319	13.321***	0.096	6.322**

Notes: This figure shows regressions of the 10-year term premiums on the different measures of the Slope Index. The term premiums data is from Adrian et al. (2013). In the top half of the table, we use the unchanged Slope Indices, and in the bottom half, we use the 4-quarter moving average filtered Slope Indices. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

For this empirical exercise, we use the term premiums derived from the Adrian et al. (2013) term structure model. Their estimates go back to 1961 and are continuously updated by the Federal Reserve Bank of New York.[13]

[13]The term premium data, as calculated by Adrian et al. (2013), is plotted in Figure 3.D1 in the appendix.

Table 3.7: Term Premium Regressions (Different Time Periods)

	ACM Term Premia 10y			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(defl)$	-0.110	0.276^{***}	-0.079	-0.218^{**}
	(0.068)	(0.057)	(0.059)	(0.103)
Observations	214	64	89	62
R^2	0.027	0.244	0.022	0.076
F-test (robust)	2.638	23.142^{***}	1.771	4.456^{**}
	ACM Term Premia 10y			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(cpi)$	-0.059	-0.030	-0.119^{**}	-0.008
	(0.091)	(0.064)	(0.055)	(0.125)
Observations	168	18	89	62
R^2	0.006	0.019	0.067	0.000
F-test (robust)	0.418	0.220	4.738^{**}	0.004
	ACM Term Premia 10y			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(all)$	-0.106	-0.047^{**}	-0.100^{**}	-0.070
	(0.077)	(0.021)	(0.046)	(0.089)
Observations	168	18	89	62
R^2	0.027	0.102	0.063	0.021
F-test (robust)	1.929	5.074^{**}	4.779^{**}	0.620

Notes: This figure shows regressions of the 10-year term premiums on the different measures of the Slope Index. In the top half of the table, we use the unchanged Slope Indices, and in the bottom half, we use the 4-quarter moving average filtered Slope Indices. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

As there is a slight linear trend in the regressor and regressand, we want to make sure that our results are not driven by spurious correlation. For this, we include regressions of first differences. The first three columns of Table 3.D10 contain the standard regression, while the last three columns contain the regression in first differences. Consistent with the theory, the table shows that term premiums are negatively related to the Slope Index. While all coefficients are negative, only a third are statistically significant. Results for the 2-year maturity, shown in Appendix 3.D, are qualitatively equivalent.

Table 3.7 reports the results of the same regressions run on three subperiods. It shows that the negative correlation between the different periods does not come from any particular subset of the sample. Rather, it holds for both low and high-inflation environments, and for periods where demand dominates, as well as for periods where supply shocks are dominant.

3.5 Concluding Remarks

This article focuses on the time variation in the relative importance of demand and supply shocks in the U.S. economy. To do so, it proposes a simple metric that is computed each quarter, namely the correlation between GDP and inflation forecasts across individual forecasts in the Survey of Professional Forecasters. We call this metric Slope Index, as it resembles a regression of expected changes in GDP and inflation (for each date, across forecasters). Unlike standard measures based on rolling correlations between realized GDP and inflation data, our measure is forward-looking and available in real time. This can be particularly useful in periods of rapid changes and uncertainties, such as the COVID era, when capturing the nature of the underlying shocks was crucial for devising suitable policy responses.

Building a synthetic model in which forecasters use imperfectly correlated private information about demand and supply, we show that the relationship between expected changes in GDP and inflation across forecasters is informative about the relative importance of demand over supply shocks. We find that when the model is calibrated such that demand shocks dominate, the correlation of GDP and inflation expectations across forecasters is more positive and term premiums are lower when compared to a calibration where supply shocks dominate.

Several empirical exercises suggest that our Slope Index is able to track, ex ante, part of the co-movement between GDP and inflation (as measured ex post). We also find a negative relationship between the Slope Index and bond term premiums, consistent with the latter, in theory, being negatively related to the importance of demand shocks in the economy.

To summarize, this paper shows that the importance of demand and supply varies over time and provides a novel way to track these changes. Further research is needed to uncover the drivers and the repercussions of these changes.

Appendix

3.A Model Derivations

The derivations in this appendix complement the model in Section 3.2.

3.A.1 Kalman algorithm

Given equations (3.1) and (3.4), we take expectations of ξ_t conditional on forecaster (i)'s information set, which yields:

$$\mathbb{E}_{t-1}^{(i)}\Big(\xi_t\Big) = \xi_{t|t-1}^{(i)} = F\xi_{t-1|t-1}^{(i)}$$

and

$$\mathbb{E}_{t-1}^{(i)}\Big(Z_t^{(i)}\Big) = Z_{t|t-1}^{(i)} = H'\xi_{t|t-1}^{(i)}$$

, where $\mathbb{E}_{t-1}^{(i)}\Big(\bullet\Big)$, denote the expectation conditional on $\underline{Z_{t-1}^{(i)}} = \{Z_{t-1}^{(i)}, Z_{t-2}^{(i)}, \cdots\}$. To simplify notation, we denote $X_{t|t-1}^{(i)} = \mathbb{E}_{t-1}^{(i)}(X_t)$ for a generic variable $X_t^{(i)}$.
This derivation closely follows Hamilton (1994). We denote the mean squared error matrix $P_{t|t-1} = \mathbb{E}_{t-1}\Big[(\xi_t - \xi_{t|t-1})(\xi_t - \xi_{t|t-1})'\Big]$. The Kalman Filter is given by:

$$K_t = P_{t|t-1}H\Big[H'P_{t|t-1}H + R\Big]^{-1} \tag{3.A.1}$$

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q \tag{3.A.2}$$

and hence

$$\xi_{t|t}^{(i)} = \xi_{t|t-1}^{(i)} + K_t\left(Z_t^{(i)} - Z_{t|t-1}^{(i)}\right) \tag{3.A.3}$$

$$P_{t|t} = P_{t|t-1} - K_tH'P_{t|t-1}. \tag{3.A.4}$$

As the sample size increases, $P_{t|t-1}$ and K_t converge to its steady-state values P and K, respectively.[14] Equations (3.A.1) and (3.A.2) become:

$$P = F\Big(P - PH(H'PH + R)^{-1}H'P\Big)F' + Q$$
$$K = PH\left[H'PH + R\right]^{-1}.$$

Hence, equation (3.A.3) can be rewritten as

$$\xi_{t|t}^{(i)} = F\xi_{t-1|t-1}^{(i)} + K\left(Z_t^{(i)} - H'F\xi_{t-1|t-1}^{(i)}\right).$$

[14]Proposition 13.1 in Hamilton (1994) shows that $P_{t|t-1}$ and K_t converge under the given assumptions.

To simplify the reading, we rename $\xi_{t|t}^{(i)}$ by $U_t^{(i)}$, i.e. the signal reflecting the demand and supply shocks captured by the forecaster (i) and taking into account all the information available (public and private) at time t:

$$U_t^{(i)} = -KA + KZ_t^{(i)} + (I_2 - KH')FU_{t-1}^{(i)}. \tag{3.A.5}$$

3.A.2 Towards a VAR model

Combining equations (3.1), (3.4), and (3.A.5), we get the following VAR(1) representation:

$$\widetilde{A_0}X_t^{(i)} = \widetilde{\Phi}X_{t-1}^{(i)} + \widetilde{\Sigma}\epsilon_t^{(i)}, \tag{3.A.6}$$

where,

$$X_t^{(i)} = \begin{bmatrix} \xi_t \\ Z_t^{(i)} \\ U_t^{(i)} \end{bmatrix}, \quad \widetilde{A_0} = \begin{bmatrix} I_2 & 0 & 0 \\ -H' & I_4 & 0 \\ 0 & -K & I_2 \end{bmatrix}, \quad \widetilde{\Phi} = \begin{bmatrix} F & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & (I_2 - KH')F \end{bmatrix}$$

and

$$\widetilde{\Sigma} = \begin{bmatrix} I_2 & 0 \\ 0 & I_4 \\ 0 & 0 \end{bmatrix}, \quad \epsilon_t^{(i)} = \begin{bmatrix} v_t \\ \eta_t^{(i)} \end{bmatrix}.$$

This equation can be transformed to:

$$X_t^{(i)} = \Phi X_{t-1}^{(i)} + \Sigma\epsilon_t^{(i)}, \tag{3.A.7}$$

where,

$$\Phi = \widetilde{A_0}^{-1}\widetilde{\Phi} \quad \text{and} \quad \Sigma = \widetilde{A_0}^{-1}\widetilde{\Sigma},$$

with,

$$\widetilde{A_0}^{-1} = \begin{bmatrix} I_2 & 0 & 0 \\ H' & I_4 & 0 \\ KH' & K & I_2 \end{bmatrix}, \quad \Phi = \begin{bmatrix} F & 0 & 0 \\ H'F & 0 & 0 \\ KH'F & 0 & (I_2 - KH')F \end{bmatrix}, \quad \Sigma = \begin{bmatrix} I_2 & 0 \\ H' & I_4 \\ KH' & K \end{bmatrix}.$$

Given the assumption of normally distributed innovations, the unconditional distribution of $X_t^{(i)}$ is:

$$X_{\mathrm{t}}^{(i)} \sim N\left(0, \Sigma_X\right), \tag{3.A.8}$$

where $\Sigma_X = (I_8 - \Phi)^{-1} \left(\Sigma \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix} \Sigma' \right) (I_8 - \Phi)'^{-1}$ denotes the long-run variance of the model.

3.A.3 Forecasting Inflation and GDP

Given the dynamics of ξ_t in (3.1), the best forecast of period h for forecaster (i) is $\xi^{(i)}_{t+h|t} = F^h \xi^{(i)}_{t|t}$. Combined with the observation equations (3.2), we get the forecast for inflation and GDP at time $t+h$ with the information set at time t:

$$S^{(i)}_{t+h|t} = \mathrm{E}^{(i)}_{\mathrm{t}} \left(S_{t+h} \right) = H'_{[1:2,1:2]} F^h \xi^{(i)}_{t|t}, \tag{3.A.9}$$

where $H_{[1:2,1:2]}$ denotes the top left $2x2$ matrix of H'.

Of particular interest, especially given its zero mean, is the difference between the expected and current, realized values of inflation and GDP. These measures are referred to as the expected change in GDP growth and the expected change in inflation, expressed by the following formula:

$$\Gamma^{(i)}_{t,h} = S^{(i)}_{t+h|t} - S_t = \Lambda_h X^{(i)}_t, \tag{3.A.10}$$

where,

$$\Lambda_h = \begin{bmatrix} 0_2 & -I_2 & 0_2 & H'_{[1:2,1:2]} F^h \end{bmatrix}.$$

Another notable aspect is the distribution of $\Gamma^{(i)}_{t,h}$ given ξ_t. This distribution serves as the basis for drawing the individual perceptions of forecasters, as shown in Figure 3.1. To construct this distribution, we start by formulating the joint distribution of $W^{(i)}_t$ and ξ_t, where $W^{(i)}_t = \left[Z^{(i)}_t, U^{(i)}_t \right]'$. To do this, we need to rewrite equation (3.A.9) as:

$$\Gamma^{(i)}_{t,h} = \widetilde{\Lambda_h} W^{(i)}_t,$$

where

$$\widetilde{\Lambda_h} = \begin{bmatrix} -I_2 & 0_2 & H'_{[1:2,1:2]} F^h \end{bmatrix}.$$

The joint distribution of $W^{(i)}_t$ and ξ_t is therefore:

$$\begin{bmatrix} \xi_t \\ W^{(i)}_t \end{bmatrix} \sim N \left(\begin{bmatrix} 0_2 \\ 0_6 \end{bmatrix}, \begin{bmatrix} \Sigma_{X_{11}} & \Sigma_{X_{12}} \\ \Sigma_{X_{21}} & \Sigma_{X_{22}} \end{bmatrix} \right), \tag{3.A.11}$$

with $\Sigma_{X_{11}}$ refering to the upper-left 2×2 submatrix of Σ_X, $\Sigma_{X_{22}}$ representing the lower-right 6×6 submatrix of Σ_X, while $\Sigma_{X_{12}}$ and $\Sigma'_{X_{21}}$ both denote the upper-left 2×6 submatrix of Σ_X. Hence, the conditional distribution of $W^{(i)}_t$ given ξ_t, can be written as:

$$W^{(i)}_t \mid \xi_t \sim N \left(\Sigma_{X_{21}} \Sigma^{-1}_{X_{11}} \xi_t \ , \ \Sigma_{X_{22}} - \Sigma_{X_{21}} \Sigma^{-1}_{X_{11}} \Sigma_{X_{12}} \right).$$

The conditional distribution of $\Gamma_{t,h}^{(i)}$ given ξ_t is hence given by:

$$\Gamma_{t,h}^{(i)} \mid \xi_t \sim N\left(\widetilde{\Lambda_h}\Sigma_{X_{21}}\Sigma_{X_{11}}^{-1}\xi_t \ , \ \widetilde{\Lambda_h}\left(\Sigma_{X_{22}} - \Sigma_{X_{21}}\Sigma_{X_{11}}^{-1}\Sigma_{X_{12}}\right)\widetilde{\Lambda_h}'\right). \tag{3.A.12}$$

3.A.4 Baseline Calibration

In this subsection, we provide a simple calibration to illustrate the properties of the model. The goal, as already emphasized in the main text, is not to bring the model to the data. Rather, the guiding principle of this calibration, as well, is to keep the model as simple as possible. This calibration is used in Sections 3.2.2 and 3.4.3.

The coefficient matrices are

$$F = \begin{bmatrix} \rho_d & 0 \\ 0 & \rho_s \end{bmatrix} = \begin{bmatrix} 0.8 & 0 \\ 0 & 0.8 \end{bmatrix}, \ H' = \begin{bmatrix} 1 & 1 \\ \alpha_d & -\alpha_s \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix},$$

and the covariance of the measurement equations are

$$R = \mathbb{E}(\eta_t^{(i)}\eta_t'^{(i)}) = \begin{bmatrix} 0.02^2 & 0 & 0 & 0 \\ 0 & 0.02^2 & 0 & 0 \\ 0 & 0 & 0.02^2 & 0 \\ 0 & 0 & 0 & 0.02^2 \end{bmatrix}.$$

These values remain the same for all calibrations. What changes is the covariance matrix of the demand and supply factors, given by

$$Q = \mathbb{E}(v_t v_t') = \begin{bmatrix} \sigma_d^2 & 0 \\ 0 & \sigma_s^2 \end{bmatrix}.$$

For the different economies, we set it to

$$Q_{bal} = \begin{bmatrix} 0.005^2 & 0 \\ 0 & 0.005^2 \end{bmatrix}, \ Q_{dem} = \begin{bmatrix} 0.05^2 & 0 \\ 0 & 0.005^2 \end{bmatrix}, \text{and } Q_{sup} = \begin{bmatrix} 0.005^2 & 0 \\ 0 & 0.05^2 \end{bmatrix},$$

where Q_{bal}, Q_{dem}, and Q_{sup} depict the balanced, the demand-dominant, and the supply-dominant economy, respectively. Finally we choose $\gamma = 3$, and $\beta = 0.99$ in the calculation of the term premium.

The fraction of demand shocks spans the interval $\psi = (0, 1)$. It is used for calculating Figure 3.3. The demand and supply shock variances then equal

$$\begin{aligned} \sigma_d^2 &= \psi\left(\sigma_{d,bal}^2 + \sigma_{s,bal}^2\right) \\ \sigma_s^2 &= (1-\psi)\left(\sigma_{d,bal}^2 + \sigma_{s,bal}^2\right), \end{aligned}$$

where $\sigma^2_{d,bal} + \sigma^2_{s,bal}$ is the sum of the variances in the balanced model. This way, the total variance in the model remains constant independently of ψ.

3.B Term Premium - Derivation

3.B.1 Fundamental Asset Pricing Equation

The structural model outlined here is based on a simplified version of the representative agent models of asset returns developed by Breeden (1979) and Lucas (1978). For the sake of clarity, we assume an economy without frictions, characterized by a singular representative household. We consider a discrete-time model with an infinite horizon so that the representative investor has a utility function of the form:

$$U_t = \mathbb{E}_t \left[\sum_{h=0}^{\infty} \beta^h u(c_{t+h}) \right], \tag{3.B.1}$$

where c_t represents the consumption of period t, $u(c_t)$ an increasing, continuously differentiable concave utility function, β the time discount factor and $\mathbb{E}_t()$ the expectation operator conditional on information available at time t.
The utility function is of the constant relative risk aversion class. This preference function is scale-invariant and independent of the initial distribution of endowments.

$$u(c_{t+h}) = \frac{c_{t+h}^{1-\gamma}}{1-\gamma} \qquad \text{(CRRA)},$$

where the parameter γ is positive for risk-averse agents and measures the curvature of the utility function. The elasticity of intertemporal substitution is the inverse of the coefficient of relative risk aversion.
The first-order condition for maximizing the utility function under the resource constraint requires that the price, in real terms, of a one-period zero-coupon bond be:

$$P_{t,1} = \exp(-i_{t,1}) = \mathbb{E}_t \left[\beta \left(\frac{c_{t+1}}{c_t} \right)^{-\gamma} \cdot \exp(-\pi_{t,t+1}) \cdot \underbrace{1}_{=P_{t+1,0}} \right], \tag{3.B.2}$$

where $\pi_{t,t+1}$ denotes the inflation rate between t and $t+1$ and $i_{t,1}$ the nominal yield of a zero coupon bond. This finally gives us:

$$\begin{aligned} P_{t,1} &= \beta \mathbb{E}_t \left\{ \exp \left[-\gamma \ln \left(\frac{c_{t+1}}{c_t} \right) \right] \cdot \exp(-\pi_{t,t+1}) \right\} \\ &= \mathbb{E}_t \left\{ \beta \exp \left[-\gamma \Delta c_{t,t+1} - \pi_{t,t+1} \right] \right\} = \mathbb{E}_t(M_{t,t+1}), \end{aligned}$$

where $\Delta c_{t,t+1} = \ln\left(\frac{c_{t+1}}{c_t}\right)$[15] and $M_{t,t+1} = \beta \exp\left[-\gamma \Delta c_{t,t+1} - \pi_{t,t+1}\right]$ is the Representative Agent's Stochastic Discount Factor (SDF, henceforth) in nominal terms.

Knowing the SDF allows us to relate current prices to those of the following period. In particular, if we denote by $P_{t,h}$ the price of a nominal zero-coupon bond with residual maturity h, we obtain:

$$P_{t,h} = \exp(-i_{t,h} \cdot h) = \mathbb{E}_t\left[M_{t,t+1} \cdot P_{t+1,h-1}\right]. \tag{3.B.3}$$

This outcome is recognized as the fundamental asset pricing equation. Its validity extends to all bonds, which inherently prevents arbitrage opportunities across maturities.

3.B.2 Bond Prices as a Function of State Vector

In the interest of streamlining our model and aligning with its structure, where the GDP growth rate is a component of the state vector $X_t^{(i)}$, we adopt the GDP growth rate as a proxy for the consumption growth rate. Moreover, in our model, the equation governing the term premium is not affected by $X_t^{(i)}$, rendering individual components irrelevant. As a result, we omit the (i) index for the remaining portion of the derivation. This implies that the SDF can be rewritten as:

$$M_{t,t+1} = \beta \exp\left[-\gamma \Delta y_{t,t+1} - \pi_{t,t+1}\right] = \beta \exp\left[G' X_{t+1}\right], \tag{3.B.4}$$

where $G = [0, \;\; 0, \;\; -\gamma, \;\; -1, \;\; 0, \;\; \cdots, \;\; 0]$.

Hence, the fundamental pricing equation given by equation (3.B.3) for $h = 1$ can be rewritten as:

$$\begin{aligned} P_{t,1} &= \mathbb{E}_t\left[\beta \exp\left(G' X_{t+1}\right)\right] = \mathbb{E}_t\left[\beta \exp\left(G'(B + \Phi X_t + \Sigma \epsilon_t)\right)\right] \\ &= \beta \exp\left(G'B + G'\Phi X_t + \frac{G'\Sigma \mathbb{V}(\epsilon_t)\Sigma' G}{2}\right) = \exp\left(A_1 + B_1 X_t\right), \end{aligned} \tag{3.B.5}$$

where $A_1 = \log(\beta) + G'B + \frac{G'\Sigma\mathbb{V}(\epsilon_t)\Sigma'G}{2}$ and $B_1 = \Phi' G$.
Since the nominal yield of maturity h is given by $-1/h \log P_{t,h}$, we get the one-period zero-coupon interest rate:

$$i_{t,1} = \overline{A_1} + \overline{B_1'} X_t, \tag{3.B.6}$$

with $\overline{A_1} = -A_1$ and $\overline{B_1} = -B_1$.
Considering equation (3.B.3) and assuming $P_{t,h-1} = \exp(A_{h-1} + B_{h-1}' X_t)$, the price of h-

[15] $\Delta c_{t,t+1}$ can also be thought of as the growth rate of consumption in period $t+1$ when $g_{c_{t+1}}$ is small.

period zero-coupon bond can be rewritten as:

$$
\begin{aligned}
P_{t,h} &= \mathbb{E}_t\left[\beta \exp\left(G' X_{t+1}\right) \cdot \exp(A_{h-1} + B'_{h-1} X_{t+1})\right] \\
&= \mathbb{E}_t\left[\beta \exp\left(A_{h-1} + (G + B_{h-1})' X_{t+1}\right)\right] \\
&= E_t\left[\beta \exp\left(A_{h-1} + (G + B_{h-1})'(B + \Phi X_t + \Sigma \epsilon_t)\right)\right] \\
&= \beta \exp\left[A_{h-1} + (G + B_{h-1})' B + (G + B_{h-1})' \Phi X_t + \frac{(G + B_{h-1})' \Sigma \mathbb{V}(\epsilon_t) \Sigma' (G + B_{h-1})}{2}\right] \\
&= \exp(A_h + B'_h X_t), \qquad (3.B.7)
\end{aligned}
$$

where the coefficients are:

$$
\begin{cases}
A_h = \log(\beta) + A_{h-1} + (G + B_{h-1})' B + \frac{(G+B_{h-1})' \Sigma \mathbb{V}(\epsilon_t) \Sigma' (G+B_{h-1})}{2} \\
B_h = \Phi'(G + B_{h-1}).
\end{cases}
$$

We have therefore shown that $P_{t,h} = \exp(A_h + B'_h X_t)$ for all maturities h. Denoting by $i_{t,h}$ the nominal zero-coupon bond of maturity h, we have:

$$
i_{t,h} = -\frac{\log(P_{t,h})}{h} = \overline{A_h} + \overline{B'_h} X_t, \qquad (3.B.8)
$$

where $\overline{A_h} = -\frac{A_h}{h}$ and $\overline{B'_h} = -\frac{B_h}{h}$.

3.B.3 Derivation of the Term Premium

By definition:

$$
\text{Term Premium} = i_{t,h} - \frac{1}{h} \mathbb{E}_t(i_{t,1} + i_{t+1,1} + \cdots + i_{t+h-1,1}). \qquad (3.B.9)
$$

Considering equations (3.B.6) and (3.B.8), we obtain the expression for the term premium for maturity h:

$$
\begin{aligned}
TP_{t,h} &= \overline{A_h} + \overline{B'_h} X_t - \frac{1}{h} \mathbb{E}_t\left(\overline{A_1} + \overline{B'_1} X_t + \overline{A_1} + \overline{B'_1} X_{t+1} + \cdots + \overline{A_1} + \overline{B'_1} X_{t+h}\right) \\
&= \overline{A_h} + \overline{B'_h} X_t - \overline{A_1} - \frac{1}{h} \overline{B'_1} \mathbb{E}_t\left(X_t + X_{t+1} + \cdots + X_{t+h}\right) \\
&= \overline{A_h} + \overline{B'_h} X_t - A_1 - \frac{1}{h} \overline{B'_1} \Big((h-1)B + (h-2)\Phi B + \cdots + 2\Phi^{h-3} B + \Phi^{h-2} B \\
&\quad + (I + \Phi + \cdots + \Phi^{h-1}) X_t\Big).
\end{aligned}
$$

It is then easy to show that B_h can also be written as:

$$
B_h = \Phi'(G + B_{h-1}) = (I + \Phi' + \cdots + \Phi'^{(h-1)}) B_1.
$$

Hence, as stated above, the term premium for maturity h is independent of X_t:

$$
TP_{t,h} = \overline{A_h} - \overline{A_1} - \frac{1}{h} \overline{B'_1} \Big((h-1)B + (h-2)\Phi B + \cdots + 2\Phi^{h-3} B + \Phi^{h-2} B\Big),
$$

that we can simplify as :

$$TP_{t,h} = \overline{A_h} - \overline{A_1} - \frac{1}{h}\overline{B_1'}\widetilde{A}_h, \tag{3.B.10}$$

where $\widetilde{A}_h = \Phi\widetilde{A}_{h-1} + (h-1)B$. Therefore, our model indicates that the term premium varies with respect to h, but remains constant over time.

3.C Survey of Professional Forecasters

The Survey of Professional Forecasters (SPF) is conducted quarterly, with a deadline for forecasters in the middle of February, May, August, and November. This deadline for the survey precedes the release of the official GDP and GDP deflator data, allowing a forecast for the current quarter to be made before the official data is released. GDP and the GDP deflator are forecast in levels. They are seasonally adjusted, with different base years, which is irrelevant, since we convert these variables to year-on-year growth rates.

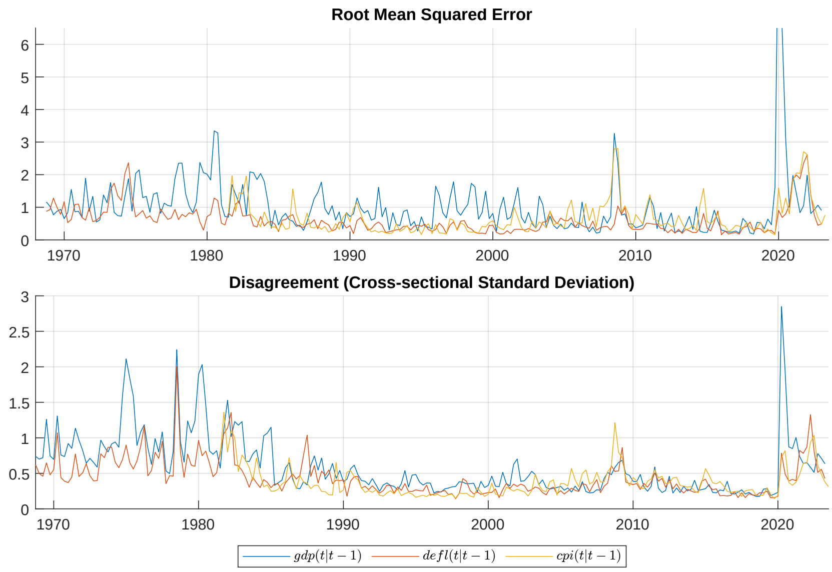
Prior to 1992Q1, forecasters targeted GNP and the GNP deflator. After that date, they switched to fixed-weight GDP data, and later to chain-weighted GDP data. For analytical consistency, and because the series are very similar, no distinction is made between the slightly different variables and they are treated as equivalent.

Official CPI data is monthly. The quarterly CPI forecasts in the SPF aim to predict the average of the three monthly CPI releases published each quarter. These releases typically occur around the middle of each month. In most quarters (though not always), the CPI release precedes the SPF deadline. In fact, forecasters typically have data from two of the three monthly CPI releases for the current quarter when they submit their forecasts. Forecasters provide quarter-on-quarter growth rates, which are seasonally adjusted annual rates. We then convert these forecasts to year-on-year growth rates (i.e., in the case of CPI forecasts, year-on-year inflation rates). The median and the 10th and 90th percentiles of the forecasts are displayed for each date in Figure 3.C1.

Figure 3.C1: Median, 1st and 9th Decile of 4-Quarter-Ahead Forecasts

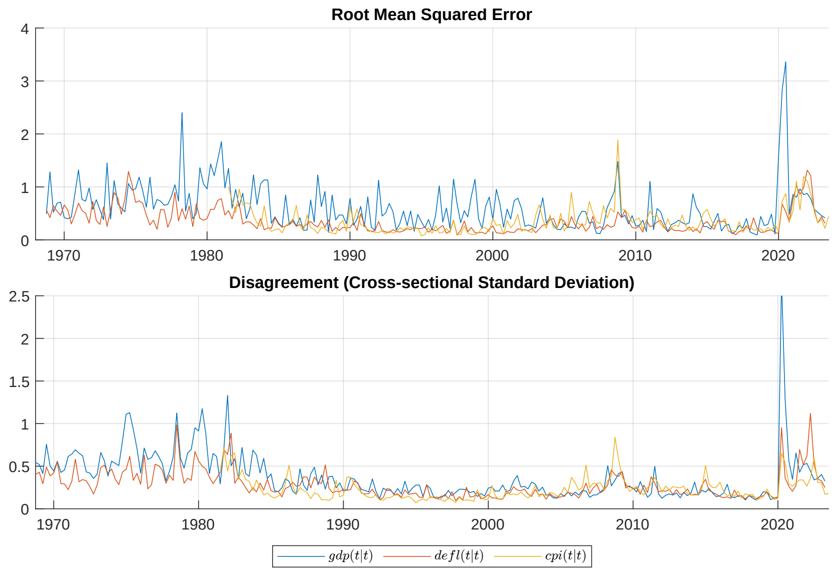
Notes: This figure shows scatter plots of individual 4-quarter-ahead forecasts for year-on-year growth rates of GDP, the GDP deflator, and CPI. The red line indicates the most recent vintage of official data for the three series. Forecasts are displayed on the date which is targeted by the forecast, not the date when the forecast was made.

Figure 3.C2: Accuracy and Disagreement for Horizon $h = 1$



Notes: The top figure depicts the root mean squared error (RMSE) of point forecasts for each date t, namely $rmse_{t,h} = x_t - x_{t|t-h}$, with $x = \{gdp, defl, cpi\}$. The bottom figure displays the disagreement between forecasts, meaning the cross-sectional standard deviation between point forecasts.

Figure 3.C3: Accuracy and Disagreement for Horizon $h = 0$



Notes: The top figure depicts the root mean squared error (RMSE) of point forecasts for each date t, namely $rmse_{t,h} = x_t - x_{t|t-h}$, with $x = \{gdp, defl, cpi\}$. The bottom figure displays the disagreement between forecasts, meaning the cross-sectional standard deviation between point forecasts.

3.D Further Empirical Results

In this section, we present further regression results that include the Slope Index and its relation with the measures presented in Section 3.3.

3.D.1 Rolling Correlation

In subsection 3.4.1, we display that there is a significant co-movement between the Slope Index and the rolling correlation between aggregate GDP and inflation. In this part of the appendix, we show that the results do not depend on a specific time period. it is positive and significant for the period before 1985, and also highly significant after 2008. Table 3.D1 corresponds to Table 3.D4 in the main text, with the regressors here being the smoothed version of the Slope Index (smoothed with a 4 quarter moving average filter).

Table 3.D1: Rolling Correlation Regressions (MA-filtered Slope Indices)

	$rollCorr_{t,10}(gdp, defl)$			$rollCorr_{t,20}(gdp, defl)$		
$IFS(Ma4, defl)$	0.102*			0.146***		
	(0.056)			(0.044)		
$IFS(Ma4, cpi)$		−0.049			−0.094	
		(0.064)			(0.058)	
$IFS(Ma4, all)$			−0.048			−0.081
			(0.053)			(0.050)
Observations	210	159	159	200	149	149
R^2	0.059	0.010	0.015	0.146	0.051	0.053
F-test (robust)	3.348*	0.571	0.800	11.071***	2.642	2.666
	$rollCorr_{t,10}(gdp, cpi)$			$rollCorr_{t,20}(gdp, cpi)$		
$IFS(Ma4, defl)$	0.151***			0.164***		
	(0.048)			(0.037)		
$IFS(Ma4, cpi)$		0.041			−0.034	
		(0.059)			(0.053)	
$IFS(Ma4, all)$			0.036			−0.019
			(0.052)			(0.048)
Observations	210	159	159	200	149	149
R^2	0.150	0.009	0.011	0.222	0.008	0.004
F-test (robust)	9.888***	0.482	0.487	19.635***	0.413	0.152

Notes: This table reports simple regressions of the rolling correlation coefficient on different Slope Indices. The dependent variable is a measure of rolling correlations between aggregate output and GDP. Top Regressions: The GDP deflator is used as the inflation measure. Bottom Regressions: CPI is used as the measure for inflation. First three columns: the rolling window spans 10 quarters. Last three columns: The rolling window spans 20 quarters. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$.

Next, we want to make sure that the results are valid for different time periods independently. For this, we repeat the same regressions for different subsamples. We also show the

Table 3.D2: Rolling Correlation Regressions (Different Time Periods)

	rollCorr gdp - defl (10q)			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(defl)$	0.065^{*}	0.048	-0.030	0.160^{***}
	(0.033)	(0.050)	(0.037)	(0.037)
Observations	205	64	89	53
R^2	0.046	0.023	0.009	0.203
F-test (robust)	3.831^{*}	0.932	0.645	19.150^{***}

	rollCorr gdp - cpi (10q)			
time period:	(68 - 22)	(68 - 85)	(86 - 08)	(08 - 22)
$IFS(defl)$	0.085^{***}	0.090^{**}	-0.005	0.195^{***}
	(0.029)	(0.041)	(0.037)	(0.037)
Observations	205	64	89	53
R^2	0.094	0.096	0.000	0.240
F-test (robust)	8.710^{***}	4.950^{**}	0.019	27.829^{***}

Notes: This table reports simple regressions of the rolling correlation coefficient on different Slope Indices. The dependent variable is a measure for rolling correlation between aggregate output and GDP. Top regression: GDP deflator used as inflation measure. Bottom regressions: CPI is used as a measure of inflation. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

same regressions, using the smoothed Slope Indices. While these results are less significant than for the original Slope Indices, they are qualitatively similar.

Table 3.D3: Rolling Correlation Regressions: starting 1990 vs whole sample

1990 - 2023	$rollCorr_{t,10}(gdp, defl)$			$rollCorr_{t,20}(gdp, defl)$		
$IFS(defl)$	0.069*			−0.048		
	(0.041)			(0.040)		
$IFS(cpi)$		0.063			−0.031	
		(0.038)			(0.041)	
$IFS(all)$			0.063**			−0.036
			(0.032)			(0.031)
Observations	125	125	125	115	115	115
R^2	0.032	0.040	0.053	0.019	0.012	0.021
F-test (robust)	2.872*	2.736	3.974**	1.462	0.554	1.354

	$rollCorr_{t,10}(gdp, defl)$			$rollCorr_{t,20}(gdp, defl)$		
$IFS(defl)$	0.065*			0.058**		
	(0.033)			(0.027)		
$IFS(cpi)$		0.019			−0.035	
		(0.032)			(0.031)	
$IFS(all)$			0.013			−0.032
			(0.026)			(0.023)
Observations	205	159	159	195	149	149
R^2	0.046	0.004	0.003	0.046	0.017	0.021
F-test (robust)	3.831*	0.345	0.261	4.476**	1.274	1.914

Notes: This table reports simple regressions of the rolling correlation coefficient on different Slope Indices. The top half displays results from a sample starting in 1990, whereas the bottom half displays the original results from the main text. The dependent variable is a measure of rolling correlations between aggregate output and GDP. Top regressions: GDP deflator used as the inflation measure. Bottom regressions: CPI is used as the measure of inflation. First three columns: the rolling window spans 10 quarters. Last three columns: The rolling window spans 20 quarters. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 3.D4: Rolling Correlation Regressions: starting 1990 vs whole sample

1990 - 2023	$rollCorr_{t,10}(gdp, cpi)$			$rollCorr_{t,20}(gdp, cpi)$		
$IFS(defl)$	0.062			0.011		
	(0.040)			(0.034)		
$IFS(cpi)$		0.084^{***}			0.010	
		(0.028)			(0.033)	
$IFS(all)$			0.072^{***}			0.010
			(0.026)			(0.026)
Observations	125	125	125	115	115	115
R^2	0.033	0.089	0.086	0.001	0.002	0.002
F-test (robust)	2.382	9.299^{***}	7.603^{***}	0.104	0.088	0.164

	$rollCorr_{t,10}(gdp, cpi)$			$rollCorr_{t,20}(gdp, cpi)$		
$IFS(defl)$	0.085^{***}			0.077^{***}		
	(0.029)			(0.023)		
$IFS(cpi)$		0.053^{**}			0.001	
		(0.027)			(0.025)	
$IFS(all)$			0.041^{*}			0.006
			(0.025)			(0.020)
Observations	205	159	159	195	149	149
R^2	0.094	0.037	0.033	0.101	0.000	0.001
F-test (robust)	8.710^{***}	4.005^{**}	2.778^{*}	11.567^{***}	0.003	0.085

Notes: This table reports simple regressions of the rolling correlation coefficient on different Slope Indices. The top half displays results from a sample starting in 1990, whereas the bottom half displays the original results from the main text. The dependent variable is a measure of rolling correlations between aggregate output and GDP. Top regressions: GDP deflator used as the inflation measure. Bottom regressions: CPI is used as the measure of inflation. First three columns: the rolling window spans 10 quarters. Last three columns: The rolling window spans 20 quarters. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parentheses. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

3.D.2 Mean Forecast Errors

In the following, we do the same regressions as in the main text, but using the unchanged Slope Indices as regressors.

Table 3.D5: MFE Regressions ($h = 4$)

	$MFE^{GDP}_{t,t+h} \times MFE^{defl}_{t,t+h}$					
$IFS(defl)$	0.400			0.707		
	(0.289)			(0.568)		
$IFS(cpi)$		0.160			0.435	
		(0.242)			(0.741)	
$IFS(all)$			0.177			0.423
			(0.183)			(0.755)
$rollCov(gdp, defl)$				0.190	0.219	0.207
				(0.192)	(0.189)	(0.149)
Observations	209	168	168	207	168	168
R^2	0.030	0.006	0.011	0.135	0.039	0.043
F-test (robust)	1.909	0.440	0.937	1.464	1.766	1.758

	$MFE^{GDP}_{t,t+h} \times MFE^{cpi}_{t,t+h}$					
$IFS(defl)$	0.187			0.258		
	(0.220)			(0.755)		
$IFS(cpi)$		0.270			0.312	
		(0.267)			(0.723)	
$IFS(all)$			0.213			0.289
			(0.211)			(0.739)
$rollCov(gdp, defl)$				0.192	0.313	0.236
				(0.210)	(0.227)	(0.187)
Observations	164	164	164	164	164	164
R^2	0.004	0.012	0.011	0.013	0.024	0.021
F-test (robust)	0.719	1.018	1.019	0.489	1.412	1.047

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$.

In the main text, we only display the results for $h = 4$ with the goal of being concise. Here, we display the same results for $h = 1$ and $h = 0$, meaning for 1-quarter-ahead forecast errors and for nowcasts.[16]

[16] We define nowcasts to be all forecasts with horizon $h = 0$.

Table 3.D6: MFE Regressions ($h = 1$)

	$MFE^{GDP}_{t,t+h} \times MFE^{defl}_{t,t+h}$					
$IFS(Ma4, defl)$	0.099			−0.044		
	(0.074)			(0.078)		
$IFS(Ma4, cpi)$		0.185*			−0.060	
		(0.100)			(0.100)	
$IFS(Ma4, all)$			0.170*			−0.065
			(0.091)			(0.099)
$rollCov(gdp, defl)$				0.141	0.177*	0.166*
				(0.100)	(0.096)	(0.089)
Observations	218	168	168	210	168	168
R^2	0.020	0.059	0.070	0.029	0.069	0.082
F-test (robust)	1.789	3.377*	3.477*	1.002	2.069	2.196
	$MFE^{GDP}_{t,t+h} \times MFE^{cpi}_{t,t+h}$					
$IFS(Ma4, defl)$	0.322			−0.075		
	(0.227)			(0.115)		
$IFS(Ma4, cpi)$		0.280**			−0.053	
		(0.142)			(0.108)	
$IFS(Ma4, all)$			0.243*			−0.062
			(0.133)			(0.106)
$rollCov(gdp, defl)$				0.322	0.273*	0.240*
				(0.228)	(0.145)	(0.134)
Observations	167	167	167	167	167	167
R^2	0.032	0.047	0.049	0.037	0.050	0.053
F-test (robust)	2.020	3.900**	3.371*	1.705	2.700*	2.613*

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\, p < 0.1$; $^{**}\, p < 0.05$; $^{***}\, p < 0.01$.

Table 3.D7: MFE Regressions ($h = 0$)

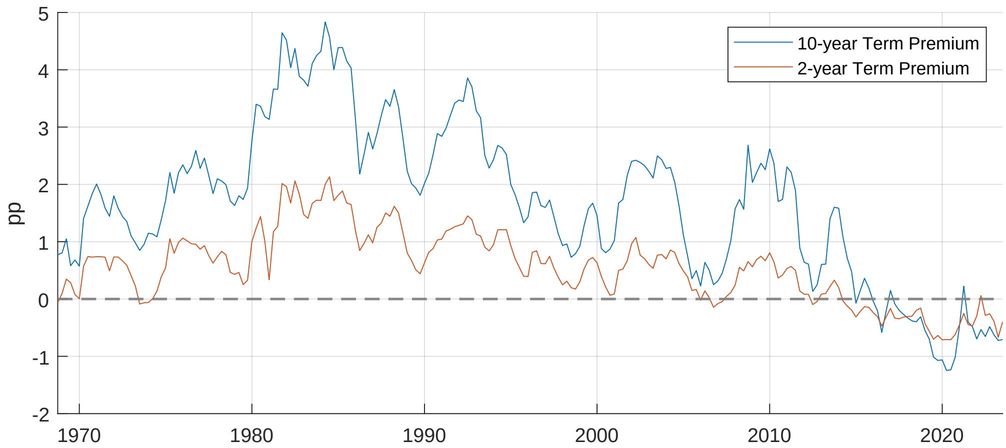
	$MFE^{GDP}_{t,t+h} \times MFE^{defl}_{t,t+h}$					
$IFS(Ma4, defl)$	−0.001			−0.016		
	(0.013)			(0.013)		
$IFS(Ma4, cpi)$		0.026			−0.013	
		(0.017)			(0.018)	
$IFS(Ma4, all)$			0.026*			−0.014
			(0.015)			(0.018)
$rollCov(gdp, defl)$				0.009	0.024	0.026*
				(0.017)	(0.016)	(0.014)
Observations	219	168	168	210	168	168
R^2	0.000	0.025	0.037	0.014	0.035	0.048
F-test (robust)	0.002	2.338	3.288*	0.748	1.459	1.985
	$MFE^{GDP}_{t,t+h} \times MFE^{cpi}_{t,t+h}$					
$IFS(Ma4, defl)$	0.040			−0.006		
	(0.029)			(0.016)		
$IFS(Ma4, cpi)$		0.035*			−0.003	
		(0.020)			(0.015)	
$IFS(Ma4, all)$			0.037**			−0.004
			(0.018)			(0.014)
$rollCov(gdp, defl)$				0.040	0.035*	0.036**
				(0.030)	(0.020)	(0.018)
Observations	168	168	168	168	168	168
R^2	0.014	0.021	0.031	0.015	0.021	0.031
F-test (robust)	1.867	3.140*	4.176**	1.180	1.768	2.420*

Notes: This table reports simple regressions of the product of ex-post mean forecast errors on different Slope Indices. *rollCov* is a backward-looking measure of covariance between GDP and inflation. An intercept is included in the regression, but not displayed. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$.

3.D.3 Term Premiums

For term premiums, we use the data from Adrian et al. (2013). They derive term premiums from a model based on Treasury yields for maturities from one to ten years. We choose to work with their set of term premiums because of the large sample length, which goes from 1961 to today. Figure 3.D1 shows the term premium data that is used in the regressions in the main text and this appendix.

Figure 3.D1: Term Premium over Time



Notes: This figure denotes the term premium data, as it is calculated by Adrian et al. (2013). It is quarterly, and continuously updated by the Federal Reserve Bank of New York.

We present additional regression results on term premiums. In the main text, we presented the results for 10-year term premiums. In the following, we display the same regressions for 2-year term premiums.

The results between the 2-year and the 10-year term premium regressions are very similar. While the significance of the original slope Index is slightly higher for the 10-year term premiums, the 2-year term premiums have a slightly stronger relationship with the smoothed Slope Indices. However, the differences are very small.

Table 3.D8: Term Premium Regressions (2Y TP)

	ACM Term Premia 2 years					
$IFS(defl)$	-0.110			-0.017^{*}		
	(0.068)			(0.009)		
$IFS(cpi)$		-0.059			0.004	
		(0.091)			(0.013)	
$IFS(all)$			-0.106			-0.011
			(0.077)			(0.010)
Observations	214	168	168	210	167	167
R^2	0.027	0.006	0.027	0.013	0.001	0.007
F-test (robust)	2.638	0.418	1.929	3.722^{*}	0.104	1.169

	ACM Term Premia 2 years					
$IFS(Ma4, defl)$	-0.186			-0.094^{***}		
	(0.127)			(0.032)		
$IFS(Ma4, cpi)$		-0.065			0.031	
		(0.187)			(0.044)	
$IFS(Ma4, all)$			-0.163			-0.055
			(0.165)			(0.035)
Observations	220	169	169	219	168	168
R^2	0.039	0.003	0.028	0.019	0.002	0.010
F-test (robust)	2.132	0.120	0.979	8.403^{***}	0.480	2.492

We regress term premiums on the different measures of the Slope Index. The term premiums data is from Adrian et al. (2013). In the top half of the table, we use the unchanged Slope Indices, and in the bottom half, we use the 4-quarter moving average filtered Slope Indices. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

Table 3.D9: Term Premium Regressions starting 1990 vs. whole sample (10Y TP)

	ACM Term Premia 10 years					
1990 - 2023	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(defl)$	-0.057			-0.013^{*}		
	(0.043)			(0.007)		
$IFS(cpi)$		0.001			-0.001	
		(0.041)			(0.006)	
$IFS(all)$			-0.021			-0.007
			(0.036)			(0.005)
Observations	134	134	134	133	133	133
R^2	0.025	0.000	0.007	0.024	0.000	0.011
F-test (robust)	1.760	0.001	0.360	3.893^{*}	0.024	1.752
	ACM Term Premia 10 years					
	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(defl)$	-0.052			-0.015^{***}		
	(0.032)			(0.006)		
$IFS(cpi)$		-0.026			-0.000	
		(0.041)			(0.007)	
$IFS(all)$			-0.050			-0.010^{*}
			(0.035)			(0.005)
Observations	214	168	168	210	167	167
R^2	0.028	0.005	0.028	0.029	0.000	0.020
F-test (robust)	2.649	0.392	1.996	7.390^{***}	0.001	3.895^{*}

Notes: This figure shows regressions of the 10-year term premiums on the different measures of the Slope Index. The top half displays results from a sample starting in 1990, whereas the bottom half displays the original results from the main text. The term premiums data is from Adrian et al. (2013). In the top half of the table, we use the unchanged Slope Indices, and in the bottom half, we use the 4-quarter moving average filtered Slope Indices. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 3.D10: Term Premium Regressions starting 1990 vs. whole sample (10Y TP)

	ACM Term Premia 10 years					
1990 - 2023	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(Ma4, defl)$	−0.135			−0.061*		
	(0.101)			(0.035)		
$IFS(Ma4, cpi)$		0.015			0.005	
		(0.066)			(0.025)	
$IFS(Ma4, all)$			−0.027			−0.021
			(0.062)			(0.022)
Observations	135	135	135	134	134	134
R^2	0.047	0.001	0.006	0.026	0.000	0.007
F-test (robust)	1.792	0.052	0.194	3.007*	0.040	0.948

	ACM Term Premia 10 years					
	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(Ma4, defl)$	−0.089			−0.078***		
	(0.058)			(0.021)		
$IFS(Ma4, cpi)$		−0.037			0.009	
		(0.081)			(0.029)	
$IFS(Ma4, all)$			−0.083			−0.052**
			(0.073)			(0.021)
Observations	220	169	169	219	168	168
R^2	0.042	0.005	0.035	0.035	0.001	0.032
F-test (robust)	2.388	0.202	1.319	13.321***	0.096	6.322**

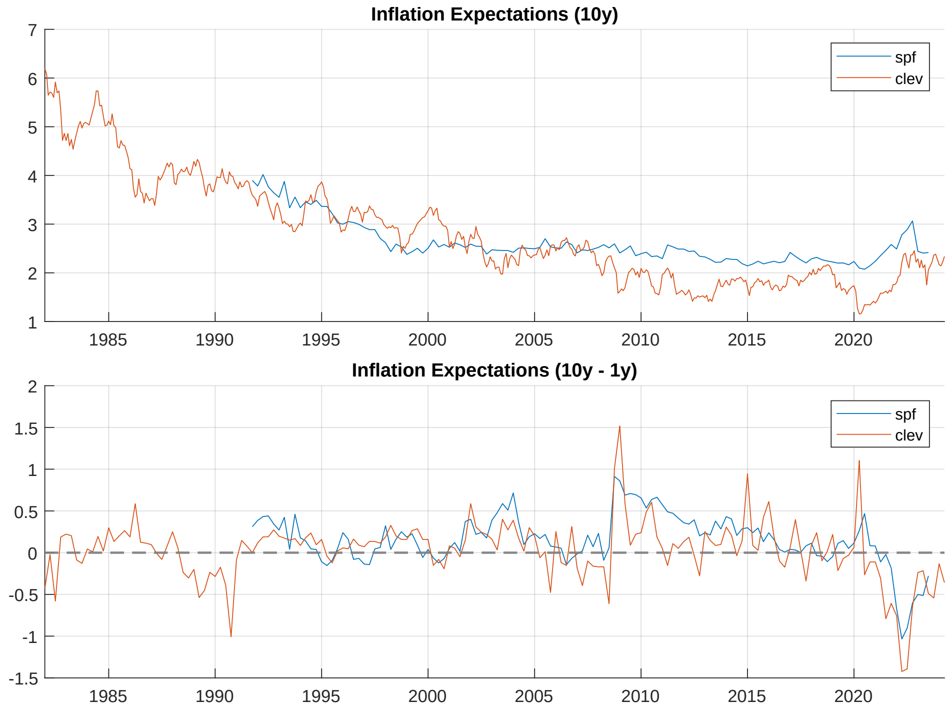
Notes: This figure shows regressions of the 10-year term premiums on the different measures of the Slope Index. The top half displays results from a sample starting in 1990, whereas the bottom half displays the original results from the main text. The term premiums data is from Adrian et al. (2013). In the top half of the table, we use the unchanged Slope Indices, and in the bottom half, we use the 4-quarter moving average filtered Slope Indices. An intercept is included in the regression, but not displayed. HAC-robust standard errors are reported in parenthesis. $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

3.D.4 The Slope Index And Long-Term Inflation Expectations

Supply Shock Dominance and Long-Term Inflation Expectations

As discussed in the introduction, an economy that is dominated by supply shocks may be very different from an economy that is dominated by supply shocks. Monetary Policy is significantly less effective after supply shocks (Boissay et al., 2023). Also, inflation is more persistent after supply shocks (Jain, 2019). Therefore, periods where supply shocks are very important compared to demand shocks, (as measured by a negative Slope Index) may therefore have strong effects on long-term inflation expectations. We test this hypothesis by regressing the Slope Index on measures of inflation expectations.

Figure 3.D2: Long-Term Inflation Expectations



Notes: This figure displays long-term inflation expectations from the Survey of Professional Forecasters and from the Inflation Expectations Model of the Federal Reserve Bank of Cleveland (Haubrich et al., 2011). The top panel displays the average inflation expectation over ten years, and the bottom panel displays 10-year minus 1-year inflation expectations.

Figure 3.D2 shows the data for long-term inflation expectations in the SPF only goes back to 1992. We therefore added another measure of inflation expectations, which stems from the Inflation Expectations Model of the Federal Reserve Bank of Cleveland (Haubrich et al., 2011, denoted *clev* in the table and figure). This data goes back to 1982 Table 3.D11 displays the results of these regressions of the Sloep Index on Long-Term inflation expectations.

Clearly, these results are barely significant. The only positive results (at the 10% level) are using the SPF, and taking first differences on the "slope" of inflation expectations. As the regressions on the 10-year do not yield significant results, these results are likely driven by the 1-year rate and hence do not point to movements in long-term inflation expectations. There

Table 3.D11: Regressing Long-Term Inflation Expectations on the Slope Index

	SPF (Levels)						SPF (First Differences)					
	10y-1y	10y-1y	10y-1y	10y	10y	10y	10y-1y	10y-1y	10y-1y	10y	10y	10y
IFS(defl)	0.001			−0.015			0.015**			−0.006		
	(0.017)			(0.027)			(0.007)			(0.006)		
IFS(cpi)		0.015			0.009			0.015*			−0.009	
		(0.030)			(0.025)			(0.009)			(0.006)	
IFS(all)			0.008			−0.001			0.014**			−0.007
			(0.021)			(0.020)			(0.006)			(0.005)
Observations	127	127	127	127	127	127	126	126	126	126	126	126
R^2	0.000	0.008	0.003	0.003	0.002	0.000	0.019	0.029	0.032	0.006	0.020	0.016
F-test (robust)	0.002	0.238	0.146	0.326	0.122	0.004	4.247**	2.759*	5.821**	1.007	2.433	2.210
	CLEV (Levels)						CLEV (First Differences)					
	10y-1y	10y-1y	10y-1y	10y	10y	10y	10y-1y	10y-1y	10y-1y	10y	10y	10y
IFS(defl)	0.001			−0.071			−0.017			−0.014		
	(0.013)			(0.069)			(0.014)			(0.009)		
IFS(cpi)		0.037			−0.030			0.001			−0.012	
		(0.024)			(0.057)			(0.011)			(0.007)	
IFS(all)			0.019			−0.045			−0.007			−0.012*
			(0.016)			(0.053)			(0.010)			(0.006)
Observations	166	166	166	166	166	166	165	165	165	165	165	165
R^2	0.000	0.042	0.016	0.012	0.003	0.010	0.008	0.000	0.002	0.016	0.014	0.022
F-test (robust)	0.011	2.374	1.338	1.078	0.283	0.724	1.554	0.005	0.483	2.643	2.715	3.697*

Notes: This table shows regression results of different measures of long-term inflation expectations on the different Slope Indices. The top table takes expectations from the SPF, whereas the bottom table uses the ones from the Inflation Expectations Model of the Reserve Bank of Cleveland (CLEV). The right half displays results on first differences, whereas the left half uses levels of inflation expectations. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

is also some evidence of increased long-term inflation expectations for a supply-dominant economy from the right-most column in the Cleveland table. However, given the very weak overall significance of these regressions, this should not be taken as constituting a correlation between the Slope Index and long-term inflation expectations.

Including Long-Term Inflation Expectations in the Slope Index

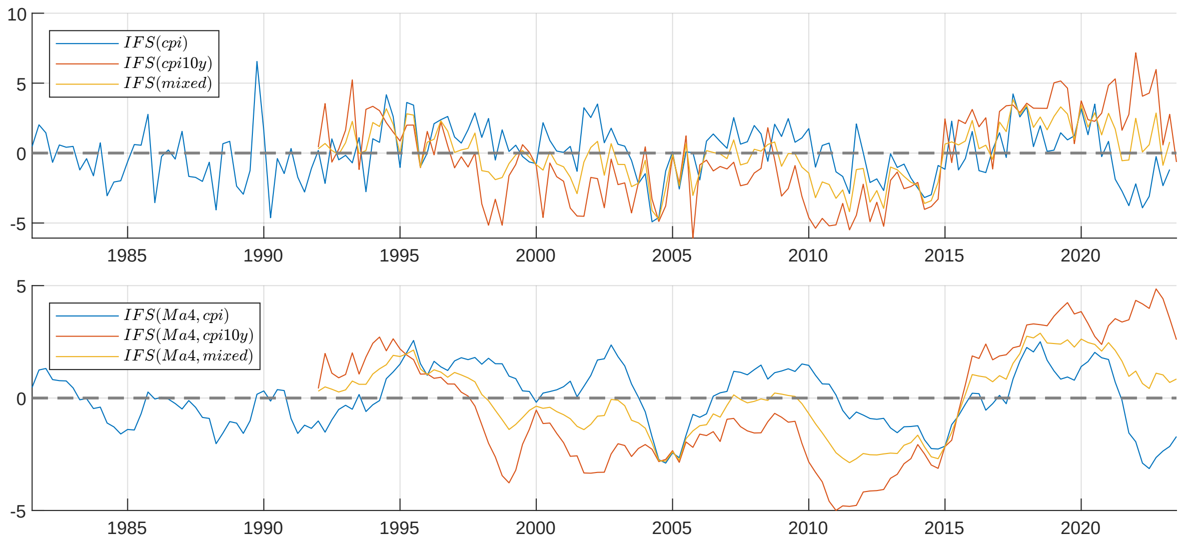
Given the interdependencies between Long-Term Inflation Expectations and supply shock dominance, it might make sense to directly add longer-horizon forecasts into the Slope Index.

Given our sample period (1968 – 2023), however, there is not a large amount of data for longer-horizon expectations in the Survey of Professional Forecasters. Apart from the quarterly forecasts used in the chapter, there are yearly average growth rates for the current calendar year, and 1-3 years ahead. The current and next calendar year do not add new information to the model, and have the problem of changing forecast horizons every quarter. The forecasts for 2-3 years ahead are only available starting in 2005 or 2009. This leaves $CPI10$ and $RGDP10$, as measures of the average inflation or GDP growth rates, which start in 1991 and 1992, respectively.

This scarcity of longer-horizon forecasts has the effect that, using the same methodology and adding the longer-horizon series, results in a virtually identical slope index. This is because a) there are 5 short-term correlation series in the dataset and only 1 long-term series, and b) the short-term series are strongly correlated, whereas the long-term series is only weakly correlated. The principal component methodology then puts barely any weight on the series that is different from all other series. As a result, the new Slope Index is 99.6 % correlated with the origin one, and all results are identical.

As an alternative measure, we combine the original Slope Index and combine it with the long-run correlation measure, and give each measure equal weights. The original Slope Index, the one only based on a 10-year horizon, and the combined Slope Index (with weights of 50% each) is displayed in Figure 3.D3.

Figure 3.D3: Alternative Slope Indices with Long-Term Inflation Expectations



Notes: This figure displays three Slope Indices: $IFS(cpi)$ is the baseline index, as it is calculated in the main text; $IFS(cpi10y)$ relies solely on the 10-year inflation and GDP forecasts, and $IFS(mixed)$ denotes the average of the two other indices. The bottom panel displays the 4-quarter moving average of the Slope Indices in the top panel.

Like in the last subsection, we apply these alternative Slope Indices to the same variables as before. First, we compute the regressions for the ex post measure of rolling correlations:

Finally, we compute the regression coefficients for the Term Premiums:

These results suggest that augmenting the Slope Index with the correlation of long-term inflation and GDP forecasts does not lead to significant or convincing results. Given that the longer-horizon GDP and inflation forecasts show a significantly different path from the shorter-horizon forecasts, it is possible that it does not capture supply or demand dominance, and that it cancels out effects that can be captured by the original slope index. Further, the fact that the results are not significant might also be due to the fact that supply or demand dominance is present at a shorter horizon but mostly cancels out when taking a horizon of 10 years.

Table 3.D12: Regressing Alternative Slope Indices on Rolling Correlations

	$rollCorr_{t,10}(gdp, defl)$			$rollCorr_{t,20}(gdp, defl)$		
IFS(cpi)	0.019			−0.035		
	(0.032)			(0.031)		
IFS(cpi10y)		0.045			−0.018	
		(0.030)			(0.035)	
IFS(mixed)			0.070			−0.052
			(0.044)			(0.048)
Observations	159	117	117	149	107	107
R^2	0.004	0.057	0.058	0.017	0.010	0.038
F-test (robust)	0.345	2.233	2.524	1.274	0.264	1.184

Notes: This table displays regressions of the same measures of rolling regressions as in the main text on alternative Slope Indices. $IFS(cpi)$ denotes the original measure, as used in the main text, $IFS(cpi10y)$ only consists of the long-run cross-sectional correlations between GDP and CPI inflation, and $IFS(mixed)$ combines the two measures with equal weights. The significance levels are $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

Table 3.D13: Regressing Alternative Slope Indices on Rolling Correlations (Ma4)

	$rollCorr_{t,10}(gdp, defl)$			$rollCorr_{t,20}(gdp, defl)$		
IFS(Ma4, cpi)	−0.049			−0.094		
	(0.064)			(0.058)		
IFS(Ma4, cpi10y)		0.045			−0.051	
		(0.040)			(0.049)	
IFS(Ma4, mixed)			0.043			-0.118^{*}
			(0.060)			(0.067)
Observations	159	117	117	149	107	107
R^2	0.010	0.040	0.016	0.051	0.053	0.121
F-test (robust)	0.571	1.271	0.526	2.642	1.092	3.108^{*}

Notes: This table displays regressions of the same measures of rolling regressions as in the main text on alternative Slope Indices. $IFS(cpi)$ denotes the original measure, as used in the main text, $IFS(cpi10y)$ only consists of the long-run cross-sectional correlations between GDP and CPI inflation, and $IFS(mixed)$ combines the two measures with equal weights. The significance levels are $^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$.

Table 3.D14: Regressing Alternative Slope Indices on Term Premiums

	ACM Term Premia 10 years					
	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(cpi)$	-0.026			0.005		
	(0.041)			(0.007)		
$IFS(cpi10y)$		-0.054^{**}			0.000	
		(0.025)			(0.005)	
$IFS(mixed)$			-0.061			0.005
			(0.044)			(0.006)
Observations	168	127	126	168	127	126
R^2	0.005	0.098	0.049	0.003	0.000	0.003
F-test (robust)	0.392	4.700^{**}	1.944	0.548	0.010	0.508

Notes: This table displays regressions of the same term premium measures as in the main text on alternative Slope Indices. $IFS(cpi)$ denotes the original measure, as used in the main text, $IFS(cpi10y)$ only consists of the long-run cross-sectional correlations between GDP and CPI inflation, and $IFS(mixed)$ combines the two measures with equal weights. The significance levels are $^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$.

Table 3.D15: Regressing Alternative Slope Indices on Term Premiums (Ma4)

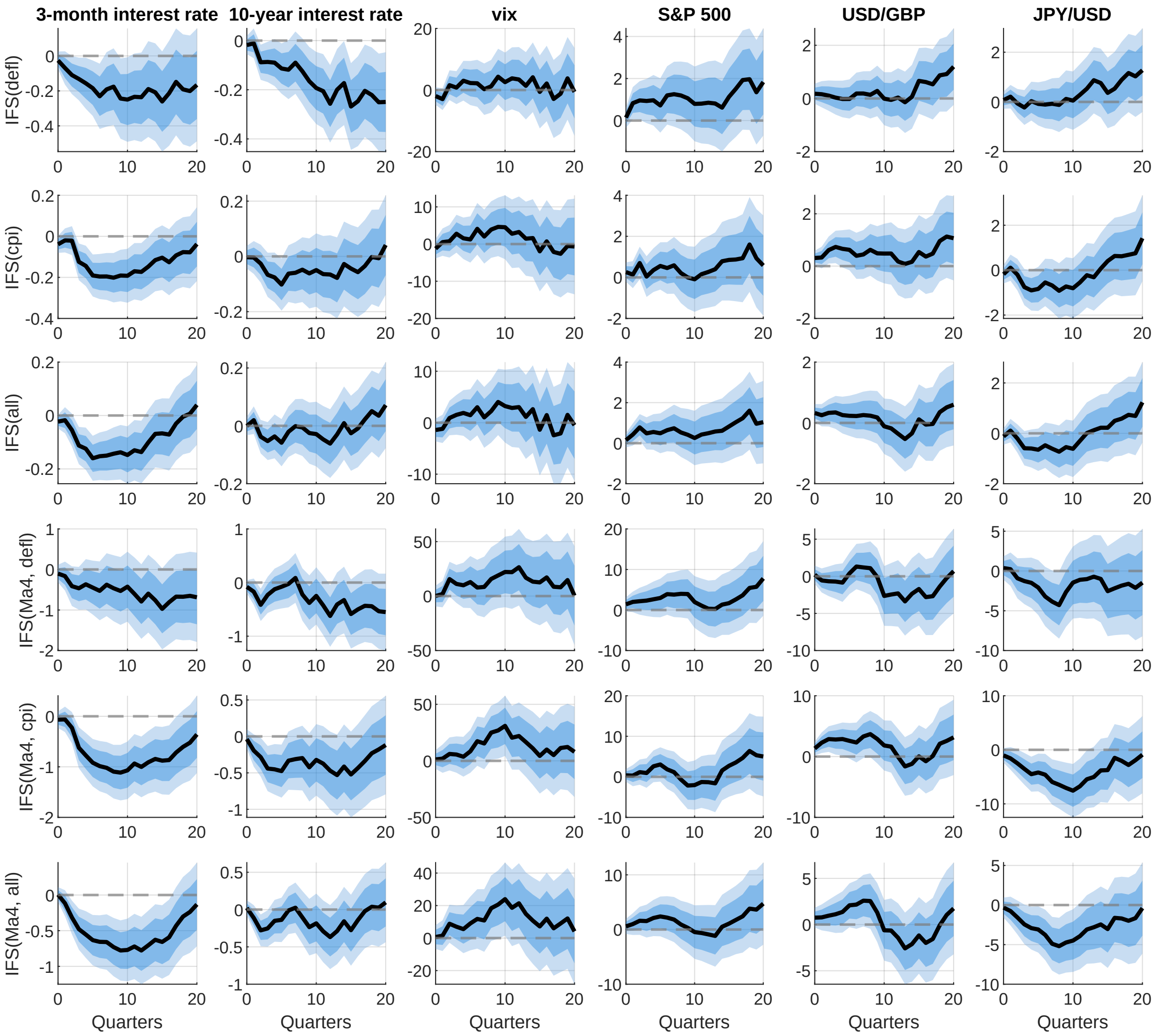
	ACM Term Premia 10 years					
	TP on Slope Index			Δ TP on Δ Slope Index		
$IFS(Ma4, cpi)$	-0.037			0.013		
	(0.081)			(0.010)		
$IFS(Ma4, cpi10y)$		-0.067^{**}			-0.001	
		(0.033)			(0.005)	
$IFS(Ma4, mixed)$			-0.080			0.004
			(0.059)			(0.009)
Observations	169	127	127	169	127	127
R^2	0.005	0.116	0.056	0.008	0.000	0.001
F-test (robust)	0.202	4.181^{**}	1.799	1.500	0.025	0.157

Notes: This table displays regressions of the same term premium measures as in the main text on alternative Slope Indices. $IFS(cpi)$ denotes the original measure, as used in the main text, $IFS(cpi10y)$ only consists of the long-run cross-sectional correlations between GDP and CPI inflation, and $IFS(mixed)$ combines the two measures with equal weights. The significance levels are $^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$.

3.D.5 Predictive Power of the Slope Index

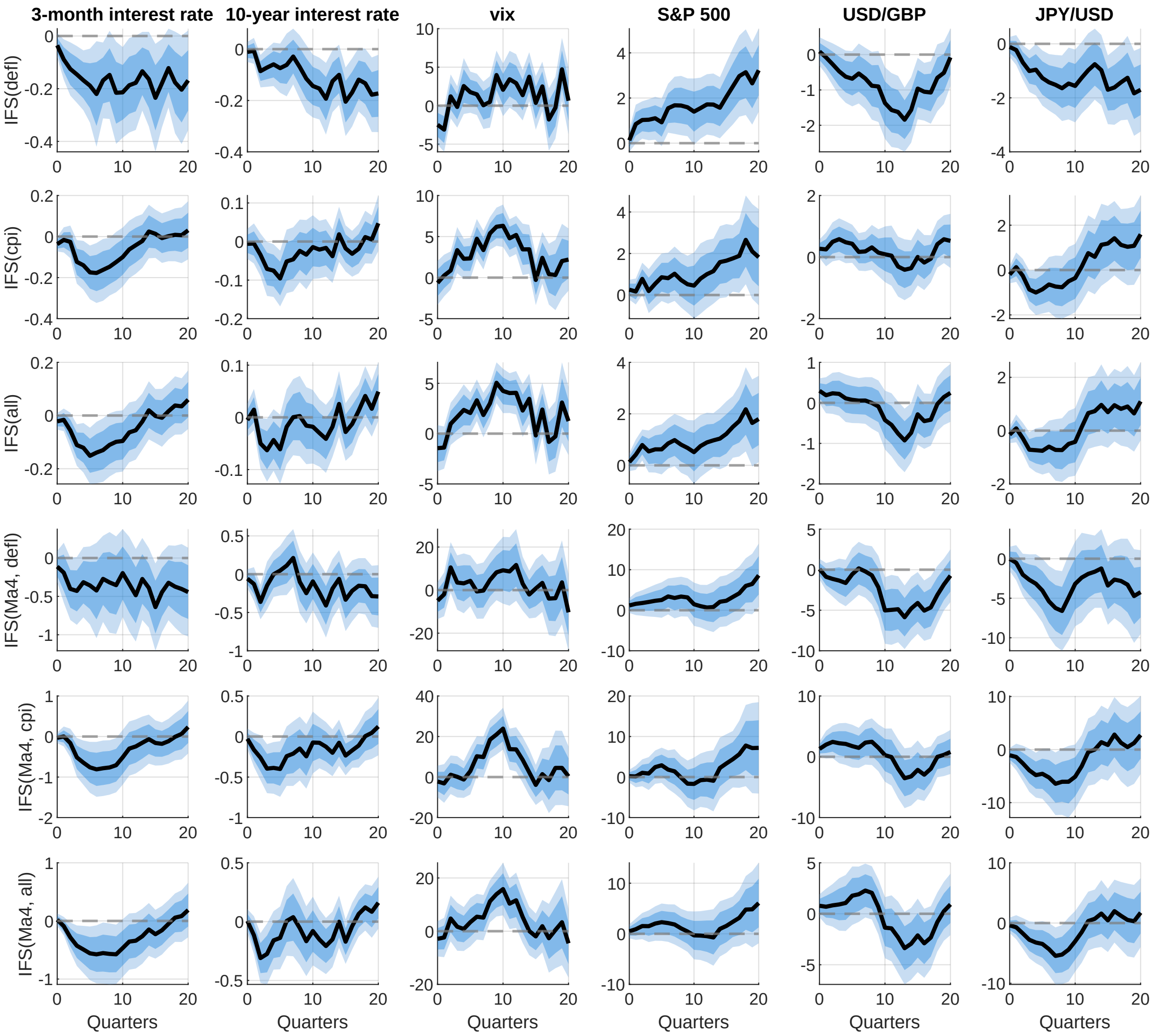
This subsection aims to provide more information on the empirical properties of the Slope Indices. For this, we compute Local Projections for various asset prices, to establish the potential predictive power of the Slope Indices (see, e.g. Jorda, 2005). For this, we include one lag of both the asset price and one lag of the Slope Index and calculate the dynamic effects. Figure 3.D4 computes the coefficients using first differences as the dependent variable and then sums up the coefficients (compare, e.g. Coibion et al., 2017). Figure 3.D5 detrends all asset prices, and then uses levels to compute the impulse responses.

Figure 3.D4: Impulse Responses of Asset Prices (First Differences)



Notes: This figure displays local projections for the 3-month and 10-year treasury rates, the vix volatility index, the S&P 500 stock price index, and the USD/GDP and JPY/USD exchange rates. All data is from fred.stlouisfed.org/. The interest rates enter in first differences, and all other variables in log differences (multiplied by 100). One lag for both the asset price and the Slope Index are included in the model. The 90% and 68% confidence bands are computed using Driscoll-Kraay standard errors.

Figure 3.D5: Impulse Responses of Asset Prices (Detrended Variables)



Notes: This figure displays local projections for the 3-month and 10-year treasury rates, the vix volatility index, the *S&P 500* stock price index, and the USD/GDP and JPY/USD exchange rates. All data is from fred.stlouisfed.org/. The interest rates enter in first differences, and all other variables in log differences (multiplied by 100). One lag for both the asset price and the Slope Index are included in the model. The 90% and 68% confidence bands are computed using Driscoll-Kraay standard errors.

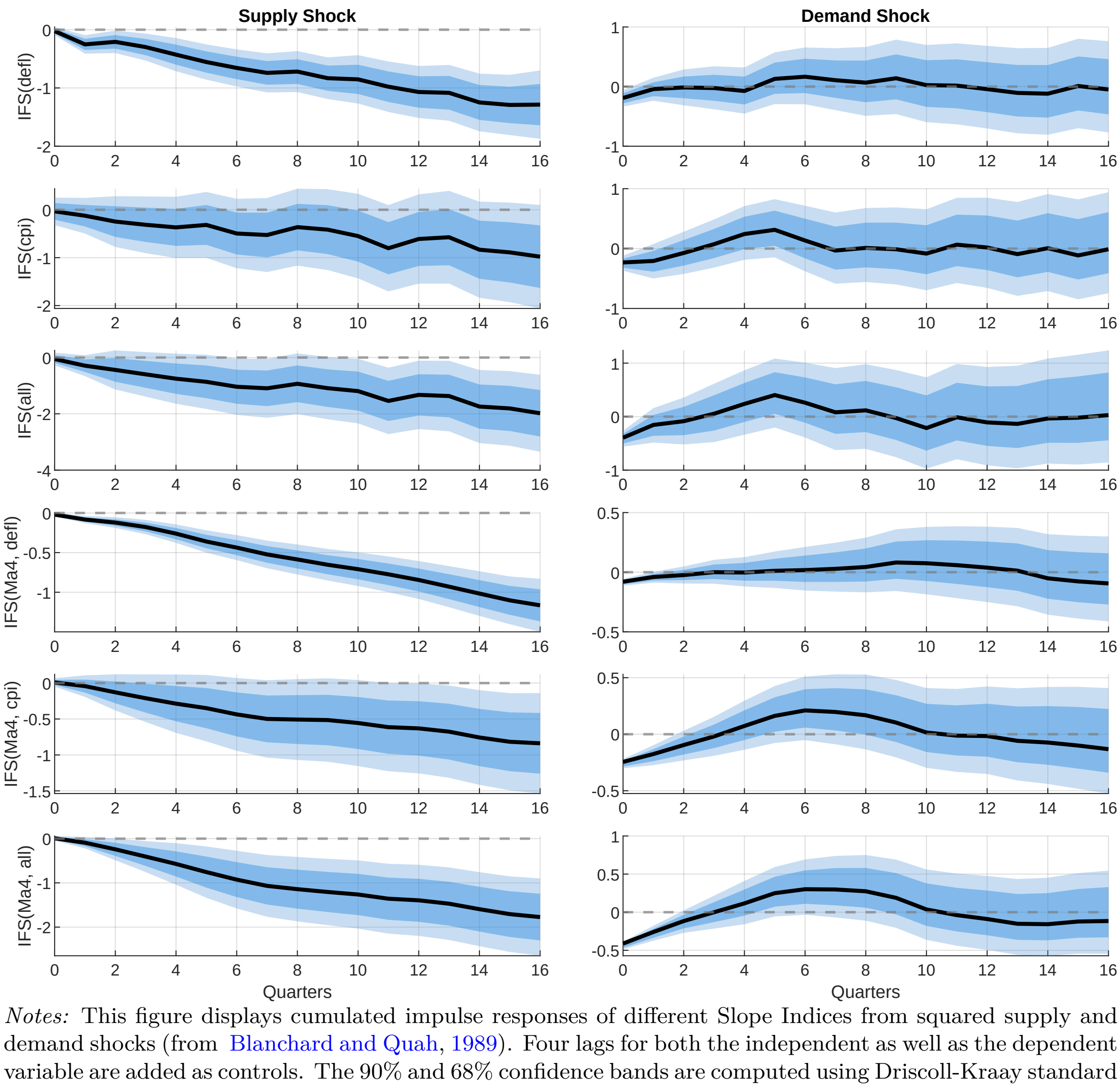
An increase in the Slope Index leads to a decrease in both the short and the long end of the yield curve. This is consistent with the expected decrease in the term premium. It may also be a signal that monetary policy is more expansionary in a demand-dominant world, as monetary policy is better suited to combat potential inflation risks, it can choose a more expansionary policy. Both the *vix* and the *S&P 500* show some slight increases, but these cannot be deemed significant. However, an increase in both variables would be expected, given the arguments in the main text. The uncertainty around stock returns decreases with a demand-dominant economy, and investing in stocks therefore becomes more lucrative. Given the diminished risks, investors may choose more risky stocks, leading to an increase in the *vix*.

For the exchange rates, the response to an increase in the Slope Index seems inconclusive, with some evidence that the US Dollar depreciates slightly in a more demand-dominant economy.

3.D.6 Effects of Structural Shocks on the Slope Index

This section evaluates whether the Slope Index responds to common measures of supply and demand shocks. For this purpose, we replicate the work of Blanchard and Quah (1989), and apply the same methodology to an extended dataset that goes until Q42019.[17] As the Slope Index does not distinguish between positive and negative supply (or demand) shocks, we apply Local Projections to find the effects of the square of the Blanchard and Quah (1989) shocks on different measures of the Slope Index. The results are displayed in Figure 3.D6.

Figure 3.D6: Cumulated Responses of the Slope Index to Squared Supply and Demand Shocks)



Notes: This figure displays cumulated impulse responses of different Slope Indices from squared supply and demand shocks (from Blanchard and Quah, 1989). Four lags for both the independent as well as the dependent variable are added as controls. The 90% and 68% confidence bands are computed using Driscoll-Kraay standard errors.

[17]The date of Q42019 is selected such that the COVID period is excluded, which would contain very large outliers.

It can be seen that the presence of supply shocks indeed leads to a slow-moving decrease in the Slope Index, and hence to a more supply-dominant economy. The same is not true for demand shock. An increase in the variance of demand shocks does not lead to a significant increase in the Slope Index. There is an immediate and unexplained reduction in the slope index after a demand shock. Then, the index returns to the steady state before the demand shock (and, for some indices, even leads to a small increase), but the overall effect is not significant.

This asymmetry between the effects of supply and demand shocks is not explained by the present work, and warrants further research into the sources and drivers of demand and supply-shock dominance.

Bibliography

Abel, J., Rich, R., Song, J., and Tracy, J. (2016). The measurement and behavior of uncertainty: Evidence from the ecb survey of professional forecasters. *Journal of Applied Econometrics*, 31(3):533–550.

Adrian, T., Crump, R. K., and Moench, E. (2013). Pricing the term structure with linear regressions. *Journal of Financial Economics*, 110(1):110–138.

Aliyev, S. and Kočenda, E. (2023). ECB monetary policy and commodity prices. *Review of International Economics*, 31(1):274–304.

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., and Ragusa, G. (2019). Measuring Euro Area Monetary Policy. *Journal of Monetary Economics*, 108:162–179.

Andrade, P. and Ferroni, F. (2021). Delphic and Odyssean Monetary Policy Shocks: Evidence from the Euro Area. *Journal of Monetary Economics*, 117:816–832.

Aoki, K. (2001). "Optimal monetary policy responses to relative-price changes". *Journal of Monetary Economics, Volume 48, Issue 1, Pages 55-80.*

Argente, D. and Lee, M. (2021). "Cost of Living Inequality during the Great Recession". *Journal of European Economic Association.*

Aruoba, S. B. (2016). Term structures of inflation expectations and real interest rates. *SSRN Working Paper.*

Bacchetta, P. and Van Wincoop, E. (2006). Can Information Heterogeneity Explain the Exchange Rate Determination Puzzle? *American Economic Review*, 96(3):552–576.

Banternghansa, C. and McCracken, M. W. (2009). Forecast disagreement among FOMC members. Working Papers 2009-059, Federal Reserve Bank of St. Louis.

Bauer, M. D. and Swanson, E. T. (2022). "A Reassessment of Monetary Policy Surprises and High-Frequency Identification". *NBER Working Papers 29939, National Bureau of Economic Research.*

Bauer, M. D. and Swanson, E. T. (2023). An Alternative Explanation for the 'Fed Information Effect'. *American Economic Review*, 113(3):664–700.

Bee, A., Meyer, B., and Sullivan, J. (2013). "The Validity of Consumption Data: Are the Consumer Expenditure Interview and Diary Surveys Informative?". In *Improving the Measurement of Consumer Expenditures*, NBER Chapters, pages 204–240. National Bureau of Economic Research, Inc.

Bekaert, G., Engstrom, E., and Ermolov, A. (2020). Aggregate Demand and Aggregate Supply Effects of COVID-19: A Real-time Analysis. Finance and Economics Discussion Series 2020-049, Board of Governors of the Federal Reserve System (U.S.).

Bekaert, G., Engstrom, E., and Ermolov, A. (2021). Macro risks and the term structure of interest rates. *Journal of Financial Economics*, 141(2):479–504.

Bekaert, G., Engstrom, E., and Ermolov, A. (2022). Identifying aggregate demand and supply shocks using sign restrictions and higher-order moments. *SSRN Working Paper*.

Benhima, K. and Poilly, C. (2021). Does demand noise matter? Identification and implications. *Journal of Monetary Economics*, 117(C):278–295.

Benigno, G., Benigno, P., and Nisticò, S. (2011). Risk, Monetary Policy and the Exchange Rate. In *NBER Macroeconomics Annual 2011, Volume 26*, NBER Chapters, pages 247–309. National Bureau of Economic Research, Inc.

Benigno, P. (2004). "Optimal monetary policy in a currency area". *Journal of International Economics 63(2), 293–320.*

Blanchard, O. J. and Quah, D. (1989). The Dynamic Effects of Aggregate Demand and Supply Disturbances. *American Economic Review*, 79(4):655–673.

Blinder, A. and Rudd, J. B. (2013). The supply-shock explanation of the great stagflation revisited. In *The Great Inflation: The Rebirth of Modern Central Banking*, pages 119–175. National Bureau of Economic Research, Inc.

Blomberg, S., Hess, G. D., and Orphanides, A. (2004). The macroeconomic consequences of terrorism. *Journal of Monetary Economics*, 51(5):1007–1032.

Boissay, F., Collard, F., Manea, C., and Shapiro, A. (2023). Monetary tightening, inflation drivers and financial stress. BIS Working Papers 1155, Bank for International Settlements.

Boivin, J., Giannoni, M., and Mihov, I. (2009). "Sticky Prices and Monetary Policy: Evidence from Disaggregated US Data". *American Economic Review, March 2009, 99 (1), 350–84.*

Breach, T., D'Amico, S., and Orphanides, A. (2020). The Term Structure and Inflation Uncertainty. *Journal of Financial Economics*, 138(2):388–414.

Breeden, D. T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, 7(3):265–296.

Campbell, J., Evans, C., Fisher, J., and Justiniano, A. (2012). Macroeconomic Effects of Federal Reserve Forward Guidance. *Brookings Papers on Economic Activity*, 43(1 (Spring)):1–80.

Campbell, J., Pflueger, C. E., and Viceira, L. M. (2014). Macroeconomic drivers of bond and equity risks. *Journal of Political Economy*, 128:3148 – 3185.

Cieslak, A. and Schrimpf, A. (2019). Non-Monetary News in Central Bank Communication. *Journal of International Economics*, 118:293–315.

Clements, M. P. (2022). Forecaster efficiency, accuracy, and disagreement: Evidence using individual-level survey data. *Journal of Money, Credit and Banking*, 54(2-3):537–568.

Coibion, O. (2012). "Are the Effects of Monetary Policy Shocks Big or Small?". *American Economic Journal: Macroeconomics 2012, 4(2): 1–32*.

Coibion, O. and Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, 105(8):2644–78.

Coibion, O., Gorodnichenko, Y., Kueng, L., and Silvia, J. (2017). Innocent bystanders? monetary policy and inequality. *Journal of Monetary Economics*, 88:70–89.

Colciago, A., Samarina, A., and de Haan, J. (2019). "Central bank policies and income and wealth inequality: A survey". *Journal of Economic Surveys, 33(4), 1199– 1231.*

Cook, T. and Hahn, T. (1989). The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics*, 24(3):331–351.

Cragg, J. G. and Donald, S. (1997). Inferring the Rank of a Matrix. *Journal of Econometrics*, 76(1-2):223–250.

Cravino, J., Lan, T., and Levchenko, A. (2020). "Price Stickiness Along the Income Distribution and the Effects of Monetary Policy". *Journal of Monetary Economics, 110:19-32.*

Duarte, J. B. and Dias, D. A. (2019). "Monetary Policy, Housing Rents, and Inflation Dynamics". *Journal of Applied Econometrics.*

Eickmeier, S. and Hofmann, B. (2022). What drives inflation? Disentangling demand and supply factors. Discussion Papers 46/2022, Deutsche Bundesbank.

Ellingsen, T. and Soderstrom, U. (2001). Monetary Policy and Market Interest Rates. *American Economic Review*, 91(5):1594–1607.

Engel, C. (2014). Exchange Rates and Interest Parity. In Gopinath, G., Helpman, E., and Rogoff, K., editors, *Handbook of International Economics*, volume 4 of *Handbook of International Economics*, pages 453–522. Elsevier.

Evans, M. D. and Lyons, R. K. (2005). Do Currency Markets Absorb News Quickly? *Journal of International Money and Finance*, 24(2):197–217.

Evans, M. D. and Lyons, R. K. (2008). How Is Macro News Transmitted to Exchange Rates? *Journal of Financial Economics*, 88(1):26–50.

Fama, E. F. (1984). Forward and Spot Exchange Rates. *Journal of Monetary Economics*, 14(3):319–338.

Faust, J. and Rogers, J. H. (2003). Monetary Policy's Role in Exchange Rate Behavior. *Journal of Monetary Economics*, 50(7):1403–1424.

Fisher, D. J., Johnson, S. D., and Smeeding, M. T. (2013). "Measuring the Trends in Inequality of Individuals and Families: Income and Consumption". *American Economic Review 103(3), 184-88*.

Frankel, J. A. (2008). The Effect of Monetary Policy on Real Commodity Prices. In *Asset Prices and Monetary Policy*, NBER Chapters, pages 291–333. National Bureau of Economic Research, Inc.

Franz, T. (2020). Central Bank Information Shocks and Exchange Rates. Discussion Papers 13/2020, Deutsche Bundesbank.

Fry, R. and Pagan, A. (2011). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature*, 49(4):938–60.

Furceri, D., Loungani, P., and Zdzienicka, A. (2018). "The effects of monetary policy shocks on inequality". *Journal of International Money and Finance, Volume 85, July 2018, Pages 168-186.*

Gali, J. (1992). How Well Does The IS-LM Model Fit Postwar U. S. Data? *The Quarterly Journal of Economics*, 107(2):709–738.

Galí, J. and Monacelli, T. (2005). Monetary Policy and Exchange Rate Volatility in a Small Open Economy. *Review of Economic Studies*, 72(3):707–734.

Geiger, M. and Scharler, J. (2021). How do people interpret macroeconomic shocks? evidence from u.s. survey data. *Journal of Money, Credit and Banking*, 53(4):813–843.

Gertler, M. and Karadi, P. (2015). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Grishchenko, O., Mouabbi, S., and Renne, J.-P. (2019). Measuring Inflation Anchoring and Uncertainty: A U.S. and Euro Area Comparison. *Journal of Money, Credit and Banking*, 51(5):1053–1096.

Gründler, D., Mayer, E., and Scharler, J. (2023). Monetary Policy Announcements, Information Shocks, and Exchange Rate Dynamics. *Open Economies Review*, 34(2):341–369.

Guerello, C. (2018). "Conventional and unconventional monetary policy vs. households income distribution: An empirical analysis for the Euro Area". *Journal of International Money and Finance, 2018, vol. 85, issue C, 187-214.*

Gurkaynak, R. S. and Wright, J. H. (2012). Macroeconomics and the term structure. *Journal of Economic Literature*, 50(2):331–67.

Gürkaynak, R. S., Kara, A. H., Kısacıkoğlu, B., and Lee, S. S. (2021). Monetary Policy Surprises and Exchange Rate Behavior. *Journal of International Economics*, 130:103443.

Gürkaynak, R. S., Sack, B., and Swanson, E. (2005a). Do Actions Speak Louder than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking*, 1(1).

Gürkaynak, R. S., Sack, B., and Swanson, E. (2005b). The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models. *American Economic Review*, 95(1):425–436.

Hamilton, J. D. (1994). *Time Series Analysis.* Princeton University Press.

Haubrich, J. G., Pennacchi, G., and Ritchken, P. H. (2011). Inflation expectations, real rates, and risk premia: evidence from inflation swaps. Working Papers (Old Series) 1107, Federal Reserve Bank of Cleveland.

Herbst, E. P. and Winkler, F. (2021). The Factor Structure of Disagreement. Finance and Economics Discussion Series 2021-046, Board of Governors of the Federal Reserve System (U.S.).

Hobijn, B. and Lagakos, D. (2005). "Inflation inequality in the United States". *Review of Income and Wealth.*

Holtemöller, O., Kriwoluzky, A., and Kwak, B. (2020). Exchange Rates and the Information Channel of Monetary Policy. IWH Discussion Papers 17/2020, Halle Institute for Economic Research (IWH).

Ider, G., Kriwoluzky, A., Kurcz, F., and Schumann, B. (2023). "The Energy-Price Channel of (European) Monetary Policy". *DIW Berlin Discussion Paper No. 2033.*

Jain, M. (2019). Perceived inflation persistence. *Journal of Business & Economic Statistics*, 37(1):110–120.

Jaravel, X. (2019). "The unequal gains from product innovations: evidence from the U.S. retail sector". *The Quarterly Journal of Economics, Volume 134, Issue 2, Pages 715-783.*

Jaravel, X. (2021). Inflation inequality: Measurement, causes, and policy implications. *Annual Review of Economics*, 13:599–629.

Jarociński, M. (2022). Central bank information effects and transatlantic spillovers. *Journal of International Economics*, 139:103683.

Jarociński, M. and Karadi, P. (2020). Deconstructing Monetary Policy Surprises — The Role of Information Shocks. *American Economic Journal: Macroeconomics*, 12(2):1–43.

Jentsch, C. and Lunsford, K. G. (2019). The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States: Comment. *The American Economic Review*, 109(7):2655–2678.

Johannsen, B. K. (2014). "Inflation Experience and Inflation Expectations: Dispersion and Disagreement Within Demographic Groups". *FEDS Working Paper No. 2014-89.*

Jorda, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Kaminska, I., Mumtaz, H., and Šustek, R. (2021). Monetary Policy Surprises and Their Transmission Through Term Premia and Expected Interest Rates. *Journal of Monetary Economics*, 124:48–65.

Kaplan, G. and Schulhofer-Wohl, S. (2017). "Inflation at the household level". *Journal of Monetary Economics 91, 19-38.*

Kerssenfischer, M. (2022). Information Effects of Euro Area Monetary Policy. *Economics Letters*, 216:110570.

King, M. R., Osler, C., and Rime, D. (2012). Foreign exchange market structure, players, and evolution. In James, J., Marsh, I. W., and Sarno, L., editors, *Handbook of Exchange Rates*, chapter 1, pages 1–44. John Wiley & Sons, Ltd.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of Monetary Economics*, 47(3):523–544.

Leombroni, M., Vedolin, A., Venter, G., and Whelan, P. (2021). Central Bank Communication and the Yield Curve. *Journal of Financial Economics*, 141(3):860–880.

Leslie, M. and Paulson, A. (2006). "Constructing the Chicago Fed Income Based Economic Index–Consumer Price Index: Inflation Experiences by Demographic Group: 1983–2005". *Federal Reserve Bank of Chicago Working Paper, 2006.*

Lucas, R. E. (1978). Asset prices in an exchange economy. *Econometrica*, 46(6):1429–1445.

Lukmanova, E. and Rabitsch, K. (2023). Evidence on Monetary Transmission and the Role of Imperfect Information: Interest Rate versus Inflation Target Shocks. *European Economic Review*, 158(C).

Lustig, H. (2021). Asset-Pricing View of Exchange Rates. Unpublished working paper, Stanford University.

Lustig, H. and Verdelhan, A. (2007). The Cross Section of Foreign Currency Risk Premia and Consumption Growth Risk. *American Economic Review*, 97(1):89–117.

Melosi, L. (2017). Signalling Effects of Monetary Policy. *The Review of Economic Studies*, 84(2 (299)):853–884.

Mertens, K. and Ravn, M. O. (2013). The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States. *American Economic Review*, 103(4):1212–47.

Miranda-Agrippino, S. and Rey, H. (2020). U.S. Monetary Policy and the Global Financial Cycle. *Review of Economic Studies*, 87(6):2754–2776.

Miranda-Agrippino, S. and Ricco, G. (2021). The Transmission of Monetary Policy Shocks. *American Economic Journal: Macroeconomics*, 13(3):74–107.

Mumtaz, H. and Theophilopoulou, A. (2017). "The impact of monetary policy on inequality in the UK. An empirical analysis". *European Economic Review, Volume 98, Pages 410-423.*

Nakamura, E. and Steinsson, J. (2008). Five Facts about Prices: A Reevaluation of Menu Cost Models*. *The Quarterly Journal of Economics*, 123(4):1415–1464.

Nakamura, E. and Steinsson, J. (2018). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect. *The Quarterly Journal of Economics*, 133(3):1283–1330.

Newey, W. and West, K. (1987). "A Simple, Positive-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix". *Econometrica 55:703–708.*

Olea, J. L. M. and Pflueger, C. (2013). A Robust Test for Weak Instruments. *Journal of Business & Economic Statistics*, 31(3):358–369.

Orchard, J. (2022). "Cyclical Demand Shifts and Cost of Living Inequality". *Working paper.*

Patton, A. J. and Timmermann, A. (2010). Why do forecasters disagree? lessons from the term structure of cross-sectional dispersion. *Journal of Monetary Economics*, 57(7):803–820.

Piazzesi, M. and Schneider, M. (2007). Equilibrium yield curves. In *NBER Macroeconomics Annual 2006, Volume 21*, pages 389–472. National Bureau of Economic Research, Inc.

Pinchetti, M. and Szczepaniak, A. (2021). Global Spillovers of the Fed Information Effect. Bank of England working papers 952, Bank of England.

Ramey, V. (2016). Macroeconomic Shocks and Their Propagation. volume 2 of *Handbook of Macroeconomics*, chapter 2, pages 71–162. Elsevier.

Romer, C. D. and Romer, D. H. (2004). "A new measure of monetary shocks: Derivation and implications". *American Economic Review 94(4), 1055-84.*

Rosa, C. (2011). The High-Frequency Response of Exchange Rates to Monetary Policy Actions and Statements. *Journal of Banking & Finance*, 35(2):478–489.

Rudebusch, G. D. and Swanson, E. T. (2012). The bond premium in a dsge model with long-run real and nominal risks. *American Economic Journal: Macroeconomics*, 4(1):105–43.

Samarina, A. and Nguyen, A. (2023). "Does monetary policy affect income inequality in the euro area?". *Journal of Money, Credit and Banking.*

Schmitt-Grohé, S. and Uribe, M. (2022). The Effects of Permanent Monetary Shocks on Exchange Rates and Uncovered Interest Rate Differentials. *Journal of International Economics*, 135:103560.

Shapiro, A. (2022). Decomposing supply and demand driven inflation. Working Paper Series 2022-18, Federal Reserve Bank of San Francisco.

Shapiro, M. D. and Watson, M. W. (1988). Sources of Business Cycle Fluctuations. In *NBER Macroeconomics Annual 1988, Volume 3*, NBER Chapters, pages 111–156. National Bureau of Economic Research, Inc.

Stavrakeva, V. and Tang, J. (2015). Exchange Rates and Monetary Policy. FRB Working Papers 15-16, Federal Reserve Bank of Boston.

Stavrakeva, V. and Tang, J. (2020). A Fundamental Connection: Exchange Rates and Macroeconomic Expectations. FRB Working Papers 20-20, Federal Reserve Bank of Boston.

Stock, J. H. and Watson, M. (2012). Disentangling the Channels of the 2007-09 Recession. *Brookings Papers on Economic Activity*, 43(1 (Spring)):81–156.

Swanson, E. T. (2021). Measuring the Effects of Federal Reserve Forward Guidance and Asset Purchases on Financial Markets. *Journal of Monetary Economics*, 118:32–53.

Thesia, G. I., David, J. S., and Kokoski, M. F. (1996). "An Experimental Consumer Price Index for the Poor". *Monthly Labor Review, 119 (1996), 32.*

Wolf, C. K. (2020). Svar (mis)identification and the real effects of monetary policy shocks. *American Economic Journal: Macroeconomics*, 12(4):1–32.