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The macroeconomic effects of inflation uncertainty

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Non-technical summary

Research Question

Buoyant consumer demand combined with supply-side constraints and geopolitical tensions have paved the way for an inflationary recovery of the U.S. economy from the COVID-19 recession, with prices soaring for a broad range of goods and services. A public debate has emerged on whether inflation is transitory or here to stay, reflecting uncertainty about inflation dynamics. Several empirical measures indicate a recent increase in inflation uncertainty. Volatility estimates show that particularly the uncertainty of core inflation has increased during and after the pandemic to the same order of magnitude as during the oil crises of the 1970s and the Volcker disinflation of the early 1980s. Against this background, we study the macroeconomic consequences of inflation uncertainty.

Contribution

Existing studies are ambiguous about the relationship between inflation uncertainty and economic activity, both from a theoretical and an empirical perspective. Existing empirical studies predominantly focus on correlations between measures of inflation uncertainty and economic activity. The novelty of our study is to investigate the macroeconomic impact of shocks to inflation uncertainty in a vector autoregressive framework.

Results

We find that, after controlling for movements in macroeconomic and financial uncertainty, an unexpected rise in the uncertainty of headline inflation has hardly any effects on the economy. Thus, shocks to headline inflation uncertainty seem to propagate through the same transmission channels as macroeconomic and financial uncertainty shocks. By contrast, an unexpected rise in the uncertainty of core inflation has inflationary effects that resemble a positive aggregate demand shock. One possible reason why this occurs is that households significantly and quite persistently raise their near-term inflation expectations when faced with more volatile core consumer prices. By contrast, households do not persistently revise their inflation expectations after a shock to the uncertainty of headline inflation, suggesting that they regard the volatility of cyclically sensitive food and energy prices – an important component of headline inflation uncertainty – as mostly transient.

Nichttechnische Zusammenfassung

Forschungsfrage

Eine starke Verbrauchernachfrage, Lieferkettenengpässe und geopolitische Spannungen haben den Weg für eine inflationäre Erholung der US-Wirtschaft von der COVID-19-Rezession geebnet, wobei die Preise für eine breite Palette von Waren und Dienstleistungen in die Höhe schnellten. Es ist eine öffentliche Debatte darüber entstanden, ob die Inflation vorübergehend ist oder anhalten wird, was die Unsicherheit über die Inflationsdynamik widerspiegelt. Mehrere empirische Maße deuten auf einen jüngsten Anstieg der Inflationsunsicherheit hin. Volatilitätsschätzungen zeigen, dass insbesondere die Unsicherheit der Kerninflation während und nach der Pandemie auf die gleiche Größenordnung gestiegen ist wie während der Ölkrisen der 1970er Jahre und der Volcker-Desinflation Anfang der 1980er Jahre. Vor diesem Hintergrund untersuchen wir die makroökonomischen Folgen der Inflationsunsicherheit.

Beitrag

Der Zusammenhang zwischen Inflationsunsicherheit und Wirtschaftsaktivität ist in der Literatur sowohl aus theoretischer als auch aus empirischer Sicht umstritten. Bestehende empirische Studien konzentrieren sich überwiegend auf Korrelationen zwischen Maßen der Inflationsunsicherheit und der Wirtschaftsaktivität. Der Beitrag unserer Studie besteht darin, die makroökonomischen Auswirkungen von Schocks auf die Inflationsunsicherheit in einem vektorautoregressiven Rahmen zu untersuchen.

Ergebnisse

Unsere Schätzungen zeigen, dass ein unerwarteter Anstieg der Unsicherheit der Gesamtinflation nach Berücksichtigung der Bewegungen der makroökonomischen und finanziellen Unsicherheit kaum Auswirkungen auf die Wirtschaft hat. Somit scheinen sich Schocks der Gesamtinflationsunsicherheit über dieselben Übertragungskanäle auszubreiten wie makroökonomische und finanzielle Unsicherheitsschocks. Im Gegensatz dazu hat ein unerwarteter Anstieg der Unsicherheit der Kerninflation inflationäre Auswirkungen, die einem positiven Gesamtnachfrageschock ähneln. Ein möglicher Grund dafür ist, dass die privaten Haushalte ihre kurzfristigen Inflationserwartungen angesichts volatilerer Kernverbraucherpreise deutlich und ziemlich kontinuierlich erhöhen. Im Gegensatz dazu korrigieren die Haushalte ihre Inflationserwartungen nach einem Schock der Unsicherheit der Gesamtinflation nicht dauerhaft, was darauf hindeutet, dass sie die Volatilität der konjunkturabhängigen Lebensmittel- und Energiepreise – einen wichtigen Bestandteil der Unsicherheit der Gesamtinflation – als überwiegend vorübergehend betrachten.

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The macroeconomic effects of inflation uncertainty*

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Abstract

The uncertainty of U.S. core inflation, measured by the stochastic volatility of forecast errors, has soared to a level not seen in nearly five decades since the COVID-19 pandemic hit the global economy. Prices, consumption, and production increase after a positive shock to core inflation uncertainty in a vector autoregression. Endogenous changes in household inflation expectations help to understand the transmission mechanism through which an inflation uncertainty shock generates positive demand effects. Households expect significantly higher inflation when confronted with a surprise increase in the uncertainty of core consumer prices. In turn, they consume more, which boosts aggregate demand.

JEL classification: E31, E32

Keywords: Household Expectations; Inflation; Uncertainty; Stochastic Volatility; Structural VAR

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1 Introduction

The inflation landscape has changed dramatically in the United States since the COVID-19 pandemic hit the global economy in March 2020. Prices have soared for a broad range of goods and services in the aftermath of the pandemic. For instance, the annual change in the core personal consumption expenditures (PCE) price index, which excludes volatile food and energy prices, rose to a 29-year high of 5.4% in February 2022, well above the Federal Reserve's 2% inflation target. Pent-up demand, supply-chain disruptions, and geopolitical events are among the likely causes of the post-pandemic surge in prices (e.g., Reis, 2022). A public debate has emerged on whether inflation is transitory or here to stay, reflecting uncertainty about inflation dynamics. Several empirical measures indicate a recent increase in inflation uncertainty (see Figure 1). Against this background, the question arises: What are the macroeconomic consequences of inflation uncertainty?

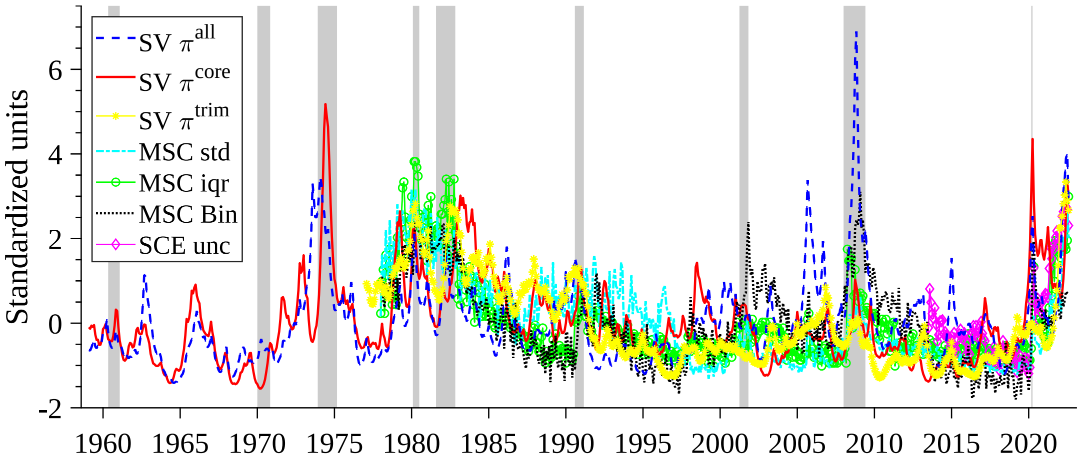

Figure 1: **Measures of U.S. inflation uncertainty**

Note: The figure shows the following time-series measures of U.S. inflation uncertainty, estimated using an unobserved components stochastic volatility model with moving-average errors (Chan, 2013): the stochastic volatility of the all-items PCE inflation rate (SV π^{all}), estimated over the period 1959:M2-2022:M8; the stochastic volatility of the core PCE inflation rate (SV π^{core}), estimated over the period 1959:M2-2022:M8; and the stochastic volatility of the trimmed-mean PCE inflation rate (SV π^{trim}), estimated over the period 1977:M3-2022:M8. The figure also shows the following survey-based measures of U.S. households' inflation uncertainty: the standard deviation and the interquartile range (75th-25th percentile) of expected price changes from the Michigan Survey of Consumers (respectively, MSC std and MSC iqr), available from 1978:M1 onward; the share of households who are relatively uncertain about their inflation expectations in the Michigan Survey (MSC Bin), estimated by Binder (2017) from 1978:M1 onward; and median one-year ahead inflation uncertainty from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE unc), available from 2013:M6 onward. Gray shaded areas denote U.S. recessions dated by the National Bureau of Economic Research (NBER). All series are standardized with zero mean and unit standard deviation.

In this paper, we investigate the macroeconomic impact of shocks to inflation uncertainty (IU) in a structural vector autoregression (VAR). We measure uncertainty by the stochastic volatility of forecast errors, as proposed by Jurado et al. (2015).[1] In the baseline, we focus on the uncertainty of core inflation, derived from the core PCE price index. This inflation gauge is closely watched by the Federal Reserve as it conducts monetary policy because it sets apart underlying inflation from temporary or idiosyncratic factors. In order to capture variation in the purely unforecastable component of core inflation, we estimate IU using an unobserved-components stochastic volatility (UCSV) model with moving-average errors, which has been shown to outperform a host of competing models in forecasting post-World War II U.S. inflation (see Chan, 2013). We add IU to a Bayesian VAR for the U.S. economy, estimated from January 1978 to June 2022. Confounding movements in general economic uncertainty present a challenge when attempting to identify IU shocks. Therefore, we cleanse IU of the measures of macroeconomic uncertainty (MU) and financial uncertainty (FU) proposed by Jurado et al. (2015) before including it in the VAR. Identification of IU shocks then proceeds according to a recursive scheme with IU ordered first.[2] To prevent the COVID-19 pandemic from contaminating the VAR estimates, we drop the March-June 2020 observations, as suggested by Schorfheide and Song (2021).[3]

We make three main contributions to the macroeconomic literature. First, we show that an unexpected rise in the uncertainty of core inflation has *inflationary* effects that resemble a *positive* aggregate demand shock: Industrial production, consumption, and consumer prices significantly increase after the shock, and the short-term interest rate rises to counteract an overheating economy. A natural follow-up question then to ask is: Through what mechanism do positive demand effects arise?

As a second contribution, we highlight a potential transmission channel via households' inflation expectations. When households are confronted with an unexpected increase in the volatility of core consumer prices, they become wary of higher future inflation and raise their inflation expectations. The IU shock leads to an increase in the median inflation rate expected over the next year, and the distribution of expected infla-

[1]The conditional volatility of forecast errors is sometimes referred to as "objective" uncertainty (e.g., Bachmann et al., 2021), as opposed to the "subjective" uncertainty perceived by economic agents, as captured, for instance, by survey expectations (e.g., De Bruin et al., 2011; Binder, 2017; Ryngaert, 2022). Other measures of uncertainty include proxies for implied volatility such as the VIX index (e.g., Bloom, 2009) and indices that measure how often newspapers contain certain words expressing uncertainty (e.g., Baker et al., 2016). For an overview, see Cascaldi-Garcia et al. (forthcoming).

[2]Similar two-step approaches to controlling for confounding factors have been adopted by, e.g., Romer and Romer (2004), Cloyne and Hürtgen (2016), Gilchrist and Zakrajsek (2012), Basset et al. (2014), and Metiu (2021). A recursive identification of uncertainty shocks with uncertainty measures ordered above macroeconomic aggregates also constitutes a common approach in the literature (see, e.g., Bloom, 2009; Carriere-Swallow and Cespedes, 2013; Jurado et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017).

[3]Other approaches to account for the large shock volatility in the early months of the pandemic have been proposed by Lenza and Primiceri (2022) and Carriero et al. (2022).

tion becomes more dispersed and right-skewed after the shock. In turn, higher expected inflation goes along with a rise in consumption and less saving, consistent with standard New Keynesian models and survey evidence on the positive relationship between inflation expectations and the willingness to consume (e.g., Duca-Radu et al., 2021; Dräger and Nghiem, 2021; Andrade et al., 2021). Thus, households bring forward their consumption to shield themselves from the risk of higher future inflation. Stronger consumer demand stimulates industrial activity and creates inflationary pressures. The monetary authority reacts by tightening the policy stance, which dampens inflation expectations and cools down the economy.

We show that the transmission mechanism described above does not come into play after a shock to the uncertainty of headline inflation, which is our third contribution. An unexpected rise in the uncertainty of headline inflation, measured by either headline PCE or a survey-based measure of households' IU proposed by Binder (2017), leads to a significant drop in prices, production, and consumption. These effects are reminiscent of a negative aggregate demand shock. The negative demand effects vanish once we control for fluctuations in MU and FU. Most remarkably, the shock has hardly any effects on expected inflation when factoring out these fluctuations. This suggests that the shock propagates through the same transmission channels as MU and FU shocks, which is likely due to cyclically sensitive food and energy prices being an important component of headline inflation. Households seem to attribute the volatility of food and energy prices to mostly transitory factors. As a result, they do not persistently change their inflation expectations and consumption behavior when the volatility of overall inflation unexpectedly rises.

Our main results are not sensitive to the identifying assumptions in the VAR. We obtain nearly identical results when imposing alternative recursive structures, including those that contain MU and FU directly in the VAR. Recursive identification schemes rule out simultaneous feedback between uncertainty and macroeconomic aggregates. Ludvigson et al. (2021) address this potential shortcoming by proposing an identification strategy that imposes "event constraints" on the sign and the magnitude of the structural shocks during special episodes of history for which the events of the time would suggest a certain behavior of the shocks. We extend this approach to the identification of IU shocks by imposing the event constraints that positive and large IU shocks occurred at the time of the Iranian Revolution in February 1979 and when the American Rescue Plan Act was signed into law in March 2021, as suggested by the data. The results obtained with these identifying restrictions are fully in line with the effects of an IU shock estimated using recursive zero restrictions.

We additionally conduct an extensive sensitivity analysis. Our investigation shows that the main results are not driven by the COVID-19 pandemic. We obtain robust estimates in a sample that ends in February 2020. Moreover, the baseline estimates are qualitatively identical and quantitatively very similar to those obtained with the time-varying parameter VAR proposed by Lenza and Primiceri (2022), which has time-varying errors during the pandemic. Hence, the simple approach of dropping the extreme data points from the sample is acceptable for the purpose of estimation. Our results are also robust to estimating the uncertainty of core PCE inflation using an SV model with autoregressive conditional mean dynamics or a GARCH model, and when measuring core inflation using the trimmed-mean PCE or the core CPI instead of the core PCE. In addition, the results are not sensitive to using a sample that starts in 1985, purging IU of lags of MU and FU, adding different interest rate and price measures to the VAR, and using more lags in the reduced-form system. Finally, we find that long-run inflation expectations remain more anchored than short-run expectations after an IU shock.

Existing studies are ambiguous about the relationship between IU and economic activity. In theory, Friedman (1977) conjectures that rising IU should depress real economic activity. By contrast, Dotsey and Sarte (2000) show that higher IU raises growth through precautionary savings in a neoclassical growth model. The empirical evidence on reduced-form correlations between IU and economic activity is inconclusive: some papers find a negative association (e.g., Evans and Wachtel, 1993; Judson and Orphanides, 1999; Grier and Perry, 2000; Elder, 2004), while others find a positive or negligible relationship (e.g., Froyen and Waud, 1987; Clark, 1997; Bredin and Fountas, 2009). A few recent studies elicit IU from household surveys. For instance, Ryngaert (2022) finds that a larger interquartile range of household inflation expectations in the New York Fed's Survey of Consumer Expectations is associated with higher expected consumption growth. Binder (2017) finds that consumers who are relatively uncertain about their inflation expectations in the Michigan Survey of Consumers are less likely to say that now is a good time to buy durable goods, cars, and homes. This could be consistent with planning to spend less now and more in the future, implying higher expected consumption growth, in line with the findings of Ryngaert (2022). The novelty of our study is to examine the effects of exogenous shocks to IU in a structural VAR framework.

Our empirical results are important for the uncertainty literature because they provide novel insight into how uncertainty affects the economy. On the one hand, our finding that IU shocks generate positive demand effects contrast with existing evidence that bouts of macroeconomic and financial uncertainty affect the economy in a way reminiscent of negative aggregate demand shocks (e.g., Bloom, 2009; Jurado et al., 2015; Basu and Bundick, 2017; Gorodnichenko and Ng, 2017). Negative demand effects have been explained with the real option value of investment (e.g., Bernanke, 1983; Bloom, 2009, 2014), financial frictions (e.g., Christiano et al., 2014; Alessandri and Mumtaz, 2019), or a combination of labor search frictions and nominal rigidities (Leduc and Liu, 2016). On the other hand, our results are consistent with recent evidence by Ludvigson et al. (2021), who find that a positive MU shock leads to an increase in real activity, which they rationalize with "growth options" theories. For instance, using a model of irreversible investment with time to build, Bar-Ilan and Strange (1996) demonstrate theoretically that an increase in price uncertainty may encourage rather than delay investment. A potential transmission mechanism through household inflation expectations is novel to the literature.

Our empirical results also provide valuable insight for the recent literature on household inflation expectations (see Coibion et al., 2020, for an overview). For instance, using data from the Michigan Survey, Gorodnichenko and Sergeyev (2021) show that inflation expectations are asymmetric: while households often expect relatively high inflation even when actual inflation is low and stable, they do not expect deflation even when persistent deflation is a strong possibility. In a similar vein, Baqaee (2020) documents that inflation expectations in the Michigan Survey are more responsive to inflationary shocks than to disinflationary shocks and proposes a general equilibrium model with ambiguity averse households, which provides microfoundations for this asymmetry. Households who try to minimize worst-case losses are more sensitive to inflationary news than to disinflationary news in the model because, with fixed nominal wages, higher inflation lowers their purchasing power while lower inflation raises it. We contribute to this strand of the literature by empirically documenting a positive link between shocks to the second moment of inflation and household inflation expectations.

The remainder of the paper is structured as follows. Section 2 discusses the measurement and time series properties of inflation uncertainty. Section 3 presents our main results on the macroeconomic effects of inflation uncertainty. Finally, section 4 concludes.

2 Measuring inflation uncertainty

We measure inflation uncertainty as the time-varying stochastic volatility of the unforecastable component of the inflation rate. This approach follows Jurado et al. (2015), who suggest modelling uncertainty using stochastic volatility because it permits the construction of a shock to the second moment that is independent of innovations to the level, which is consistent with the theoretical literature on uncertainty (e.g., Bloom, 2009).

Let π_t^{core} denote the annualized log difference of the monthly U.S. core PCE price index, computed as $\pi_t^{core} = 1200\log(PCE_t^{core}/PCE_{t-1}^{core})$ (henceforth we drop the superscript *core* to simplify notation).[4] We employ the following UCSV model for π_t, introduced by Chan (2013):

$$\pi_t = \mu_t + \epsilon_t^\pi, \tag{1}$$

where the conditional mean (or time-varying trend component) of inflation, $\mu_t \equiv \tau_t$, evolves according to:

$$\tau_t = \tau_{t-1} + \epsilon_t^\tau, \quad \epsilon_t^\tau \sim \mathcal{N}(0, \sigma_\tau^2), \tag{2}$$

the inflation forecast error ϵ_t^π has a first-order moving-average (MA(1)) representation:

$$\epsilon_t^\pi = u_t + \psi_1 u_{t-1}, \quad u_t \sim \mathcal{N}(0, e^{h_t}), \tag{3}$$

and the process for the log-volatility h_t is specified as a first-order autoregressive (AR(1)) stochastic volatility model:

$$h_t = \mu_h + \phi_h(h_{t-1} - \mu_h) + \epsilon_t^h, \quad \epsilon_t^h \sim \mathcal{N}(0, \sigma_h^2), \tag{4}$$

where we assume stationarity such that $|\phi_h| < 1$. The errors u_t and ϵ_t^h are independent of each other for all leads and lags, and it is assumed that $u_0 = u_{-1} = 0$.

Our approach to estimation and inference follows closely that of Chan (2013). In particular, we estimate the model given by Equations (1)-(4) using Bayesian methods with an efficient Markov chain Monte Carlo (MCMC) sampler developed by Chan (2013) for this class of models. We choose relatively non-informative priors for the parameters.[5] Our estimation sample spans the period from February 1959 to August 2022 (we lose the January 1959 observation due to taking first differences).

[4] The terrorist attacks that occurred on September 11, 2001 produced the single largest drop in core PCE inflation of -6.81 percent per annum. Luciani and Trezzi (2019) provide some background information on this data point: "The 2001 swing in the PCE price index excluding food and energy was driven by the price index for life insurance, which plunged 55 percent in September 2001 and jumped 121 percent in October 2001 as a result of the 9/11 terrorist attacks" (see footnote 6 in Luciani and Trezzi, 2019). This peculiar event would produce a large spike in the SV estimate, which is out of scope of the data generating process. Therefore, we replace the 9/11 observation of the core PCE price index with the mean for the six months preceding and succeeding September 2001. This procedure essentially removes the 9/11 outlier from the sample.

[5] The priors are chosen as in Chan (2013). Specifically, we assume the truncated normal prior for the MA coefficient $\psi_1 \sim \mathcal{N}(\psi_0, V_\psi)\mathbb{1}(|\psi_1| < 1)$, so that the MA process is invertible. We set $\psi_0 = 0$ and $V_\psi = 1$. We further assume the following independent inverse-gamma priors for σ_τ^2 and σ_h^2: $\sigma_\tau^2 \sim \mathcal{IG}(\nu_\tau, S_\tau)$ and $\sigma_h^2 \sim \mathcal{IG}(\nu_h, S_h)$, with relatively uninformative values for the degrees of freedom parameters $\nu_\tau = \nu_h = 10$. We set the scale parameters $S_\tau = 0.18$ and $S_h = 3.24$. These values imply $\mathbb{E}(\sigma_\tau^2) = 0.141^2$ and $\mathbb{E}(\sigma_h^2) = 0.6^2$. This latter hyperparameter is analogous to that of Chan (2013), adapted to the monthly frequency of our data. Finally, for μ_h and ϕ_h, we assume the following normal and truncated normal priors, respectively: $\mu_h \sim \mathcal{N}(\mu_{h0}, V_{\mu_h})$ and $\phi_h \sim \mathcal{N}(\phi_{h0}, V_{\phi_h})\mathbb{1}(|\phi_h| < 1)$, with $\mu_{h0} = 0$, $V_{\mu_h} = 5$, $\phi_{h0} = 0.9$ and $V_{\phi_h} = 1$.

Chan (2013) shows that the UCSV model with MA(1) errors presented here provides a better out-of-sample forecast of post-war U.S. inflation than a battery of competing models. Among others, it outperforms SV models in which the process for the conditional mean μ_t is specified as an AR model (with or without MA errors), as well as the UCSV model proposed by Stock and Watson (2007), which has stochastic volatility in both the trend component and the forecast errors (again, with or without MA errors). Hence, the model we opt for constitutes a useful benchmark for modeling inflation and estimating its time-varying uncertainty. Nevertheless, we assess the robustness of our estimates using alternative models.

Figure 2 depicts the core PCE inflation rate together with its estimated time-varying trend $\hat{\tau}_t$ and stochastic volatility $e^{\hat{h}_t/2}$ (i.e., our IU measure). The trend component of core inflation rose from the mid-1960s until the early 1980s, consistent with existing evidence (e.g., Chan, 2013; Mertens, 2016). During this period, we also find three episodes of elevated IU that coincide with the oil crises of the 1970s and the Volcker disinflation in the early 1980s. From the mid-1980s onward, the U.S. economy saw the onset of the Great Moderation, which was characterized by a large drop in the cyclical volatility of economic activity (e.g., Stock and Watson, 2002). In line with this reduction in volatility, both the trend and the uncertainty of core inflation fell quickly by the mid-1980s and reached historically low levels in the two decades before the outbreak of the COVID-19 pandemic. IU remained low even during significant events like the early 1990s recession, the financial market turmoils of the late 1990s, and the 2008-2009 Great Recession. During the COVID-19 pandemic, the core inflation rate has trended upwards and its stochastic volatility has risen to levels last seen in the 1970s.

When correlating IU with various time series, several interesting stylized facts arise. First, IU is weakly counter-cyclical: its correlation coefficient with the year-on-year growth rate of U.S. industrial production over the period between February 1959 and August 2022 is equal to $\rho = -0.14$. Second, IU co-varies with assets that are often considered as hedges against inflation. In particular, there is a positive, albeit rather low, correlation between IU and the real price of gold ($\rho = 0.20$).[6] Gold is a key safe-haven asset that may offer protection against inflation, particularly in uncertain times. Moreover, variation in the real price of gold has been used to inform the identification of uncertainty shocks (e.g., Piffer and Podstawski, 2018; Ludvigson et al., 2021). Another inflation hedge are Treasury Inflation-Protected Securities (TIPS), and IU bears a

[6]We measure the real price of gold as the gold fixing price in U.S. dollars from the auctions organised at 3:00 p.m. by the London Bullion Market, deflated by the U.S. CPI. The gold price is observed between 1968:M4-2021:M10.

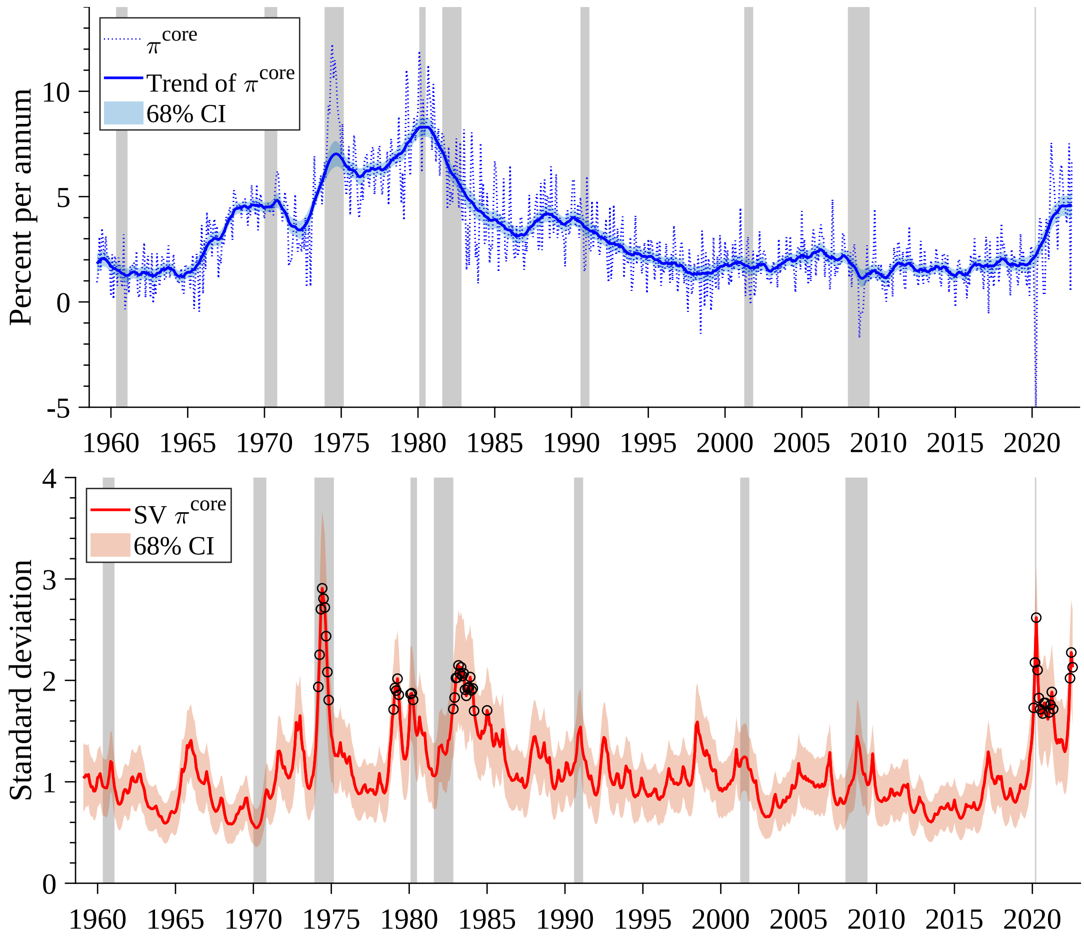

Figure 2: **Time-varying trend and uncertainty of U.S. core PCE inflation**

Note: The figure shows estimates from an UCSV model with MA(1) errors (Chan, 2013). Top panel: Monthly log-difference of the core PCE price index π^{core} (blue dotted line), and its estimated time-varying trend $\hat{\tau}_t$ (blue solid line), with the 68% credible interval shaded. Bottom panel: The estimated stochastic volatility $e^{\hat{h}_t/2}$ of core inflation forecast errors (red solid line), with the 68% credible interval shaded. Black circles denote observations that lie at least 1.65 standard deviations above the mean, capturing large spikes in inflation uncertainty. Gray shaded areas denote U.S. recessions dated by the NBER. Sample: 1959:M2-2022:M8.

moderate negative relationship with TIPS yields (ρ =-0.22).[7] Third, there is a positive association between IU and Google queries for the term "inflation" (ρ =0.50), which is consistent with individuals seeking more information about inflation in turbulent periods.[8] The term has indeed never been googled as often in the past two decades as during the pandemic.

Fourth, there is a positive correlation between IU and survey-based measures of uncertainty about future inflation perceived by households. In particular, IU is positively

[7]We measure TIPS yields using the average yield for all inflation-indexed U.S. Treasury bonds with remaining terms to maturity of more than 10 years, observed between January 2000 and August 2022.

[8]Using Google Trends, we measure the frequency of Google searches in the U.S. for the term "inflation" in the category Finance since January 2004.

correlated with the dispersion of households' inflation expectations as measured by either the standard deviation (ρ =0.53) or the interquartile range (ρ =0.54) of expected price changes from the Michigan Survey of Consumers. IU is also positively correlated with an uncertainty measure proposed by Binder (2017), which quantifies the share of households that are relatively uncertain about their inflation expectations in the Michigan Survey (ρ =0.41).[9] There is, furthermore, a positive association between IU and households' subjective uncertainty about one-year ahead inflation derived from the Federal Reserve Bank of New York's Survey of Consumer Expectations (ρ =0.58).[10] It is worthwhile to note that the survey-based IU measures are for overall inflation and, therefore, likely largely depend on food and energy prices, which might explain why the correlations with our core IU measure are not higher.

Finally, a fifth set of stylized facts concerns the relation to other measures of uncertainty. In particular, IU is positively correlated with the composite MU index proposed by Jurado et al. (2015). This is the average of the estimated time-varying stochastic volatility of the forecast error of each series in a large panel of macroeconomic variables. Since the panel also contains various price indices (e.g., sub-aggregates of the PPI, the CPI, and the PCE deflator), the positive correlation coefficient of ρ =0.52 with this variable is not surprising. In addition, IU also has a moderate positive correlation with the composite FU index proposed by Jurado et al. (2015) (ρ =0.31) and the news-based indices of U.S. economic policy uncertainty (ρ =0.38) and monetary policy uncertainty (ρ =0.22) proposed by Baker et al. (2016).[11]

3 Macroeconomic effects of inflation uncertainty

Armed with a new measure of IU, we now investigate the dynamic responses of key macroeconomic variables and households' inflation expectations to IU shocks. In this section, we first describe our econometric approach and then present the main empirical results and various sensitivity checks.

[9] Data from the Michigan Survey are available from January 1978 to August 2022. We thank Carola Binder for providing us the updated time series of the measure proposed by Binder (2017).

[10] This measure is based on De Bruin et al. (2011), who estimate households' inflation uncertainty from survey respondents' subjective probability distribution of one-year ahead inflation outcomes. The data are available between June 2013 and August 2022.

[11] The Jurado et al. (2015) measures of MU and FU are available between July 1960 and June 2022. The Baker et al. (2016) measures of economic policy uncertainty and monetary policy uncertainty are available from January 1985 onward.

3.1 Econometric approach

Existing evidence shows that uncertainty shocks significantly affect economic activity (e.g., Jurado et al., 2015; Basu and Bundick, 2017). Thus, confounding movements in general economic uncertainty may pose an identification challenge when attempting to estimate the macroeconomic impact of inflation uncertainty shocks. To tackle this issue, we first regress IU on potential confounding factors and then use the residuals as a measure of "idiosyncratic" IU in a VAR. This two-step approach to controlling for potential confounders is widespread in macroeconomics.[12] It is a shorthand method to ordering confounding variables above IU in a recursive VAR identified using a Cholesky decomposition, with the advantage of controlling for the contemporaneous effect of confounders while maintaining a parsimonious VAR specification. As a robustness check, we include potential confounding factors directly in the VAR.

3.1.1 First-stage regression

We regress IU on the contemporaneous values of the MU and FU measures proposed by Jurado et al. (2015). Table 1 reports the OLS estimates. We employ the method proposed by Dumont et al. (2005) to correct the standard errors of the coefficient estimates to account for the additional variance due to the estimation uncertainty surrounding the stochastic volatility estimate. When individually included, both MU and FU are significantly positively associated with IU (columns 1 and 2, respectively). When included jointly, only MU retains a statistically significant positive relationship with IU (column 3). These outcomes are robust to adding lags of MU and FU to the model specification (not reported here).

Figure 3 depicts IU together with the OLS regression residual from the specification in column (3), which isolates movements in IU that are unrelated to contemporaneous movements in MU and FU. The residual can be seen as a measure of idiosyncratic IU. Even though IU strongly co-moves with the residual series, fluctuations in MU and FU have shaped movements in IU particularly in the early 1980s, during the Great Recession, and in the recent pandemic.

[12]For instance, Romer and Romer (2004) and Cloyne and Hürtgen (2016) have used this approach to estimate monetary policy shocks, Gilchrist and Zakrajsek (2012) and Basset et al. (2014) have used it to identify credit shocks, and Metiu (2021) has taken this route to identify trade policy shocks.

	Dependent variable: stochastic volatility of core PCE in period t		
	(1)	(2)	(3)
MU_t	1.717***		1.726***
	(0.116)		(0.116)
	[0.222]		[0.296]
FU_t		0.655***	-0.010
		(0.084)	(0.081)
		[0.132]	[0.174]
Observations	744	744	744
Adjusted R^2	0.27	0.10	0.27

Table 1: **Regression of IU on macroeconomic and financial uncertainty**

Note: The table reports OLS regression coefficients. The dependent variable is the stochastic volatility of the core PCE inflation rate in period t. The regressors are the contemporaneous values of the macroeconomic uncertainty (MU_t) and financial uncertainty (FU_t) measures proposed by Jurado et al. (2015). White standard errors appear in parentheses below the coefficients (White, 1980). Standard errors corrected to account for the estimation uncertainty of stochastic volatility are given in square brackets (Dumont et al., 2005). The model includes a constant term whose estimate is suppressed. *** denote significance at the one percent level. The sample period is 1960:M7-2022:M6.

3.1.2 VAR model

We study the impact of IU shocks in a Bayesian VAR model for the U.S. economy. Consider the following VAR in reduced form:

$$y_t = C + B_1 y_{t-1} + \dots B_p y_{t-p} + u_t, \tag{5}$$

where y_t is an $n \times 1$ vector of endogenous variables observed in month t, $B_1, \dots, B_p$ are $n \times n$ coefficient matrices, and the reduced-form errors are $u_t \sim N(0, \Sigma_u)$. In this framework, we identify uncertainty shocks using recursive timing restrictions, consistent with existing studies (e.g., Bloom, 2009; Carriere-Swallow and Cespedes, 2013; Jurado et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017). Our main identifying assumption is that a shock to inflation uncertainty instantaneously affects the level of macroeconomic variables, while first-moment shocks affect inflation uncertainty with a delay of at least one month. We impose this assumption through a recursive (Cholesky) scheme with IU ordered first in the VAR. We thus partition the vector of endogenous variables as $y_t = [IU_t, z_t']'$, where IU_t is our measure of inflation uncertainty (either IU or idiosyncratic IU), and z_t is an $(n-1) \times 1$ vector of macroeconomic variables. Basu and Bundick (2017) show that this recursive identification of uncertainty shocks is supported by a New Keynesian model with time-varying demand uncertainty. First-moment technology

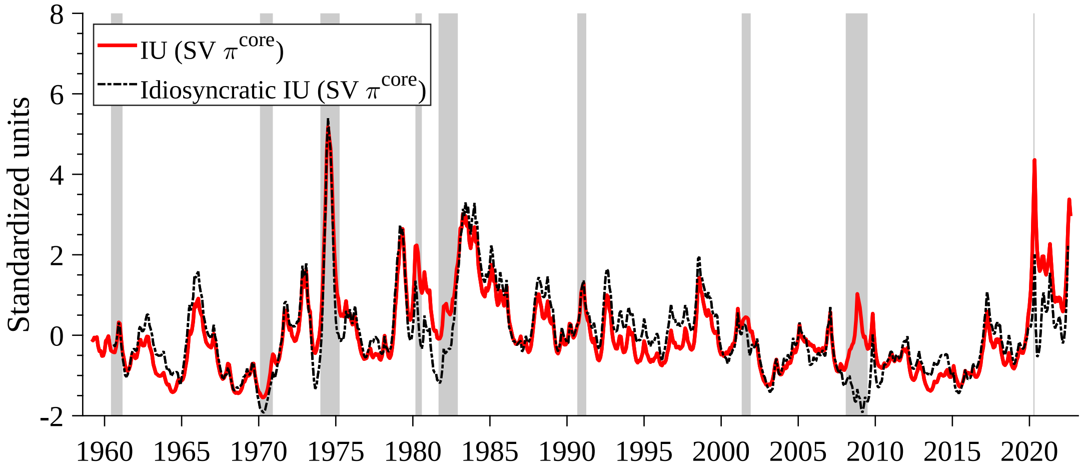

Figure 3: **Inflation uncertainty cleansed of macro and financial uncertainty**

Note: Inflation uncertainty measured by the stochastic volatility of the core PCE inflation rate (red solid line), and idiosyncratic IU measured by the residual of a regression of IU on the contemporaneous values of macroeconomic and financial uncertainty (black dashed line). Variables are standardized to have zero mean and unit standard deviation. Shaded areas represent U.S. recessions dated by the NBER. Sample: 1959:M2-2022:M8 (IU) and 1959:M2-2022:M6 (idiosyncratic IU).

or demand shocks have almost no effect on uncertainty in their model. For the sake of robustness, we use alternative recursive restrictions that allow for an immediate reaction of IU to first-moment macroeconomic shocks; in addition, we lift all recursive zero restrictions and instead impose shock-based restrictions as proposed by Ludvigson et al. (2021).

As a benchmark, we consider a parsimonious VAR specification, in which the vector z_t contains the following five variables: The log of U.S. industrial production, the log of real personal consumption expenditures, the log of the core PCE price index, the 1-year Treasury bond yield, and households' inflation expectations. The 1-year Treasury yield can be seen as an indicator of monetary policy that is less affected by the zero lower bound (see also Gertler and Karadi, 2015; Jarocinki and Karadi, 2020). We measure inflation expectations by the median of households' expected price changes over the next 12 months from the Michigan Survey. We add a host of other variables one-at-a-time to the benchmark VAR in order to gain more insight into the transmission mechanism, such as additional measures of inflation expectations from the Michigan Survey, consumption sub-aggregates, and the personal saving rate. Moreover, we include prices for food, energy, and oil, as well as the headline price index, which might have important feedback with core inflation and household inflation expectations.

We estimate the VAR model using a Bayesian approach with a standard Minnesota prior, whose tightness is chosen as in Giannone et al. (2015).[13] The baseline model is estimated for the period between January 1978 and June 2022, using $p = 6$ lags.[14] The massive shifts in macroeconomic variables during the outbreak of the COVID-19 pandemic may call into question our assumptions of a stationary and linear model. Several recent studies discuss how to address the econometric issues that arise when estimating a VAR with a sequence of extreme observations. Schorfheide and Song (2021) recommend excluding the observations from March to June 2020 from the sample, but including the subsequent data points. Lenza and Primiceri (2022) also conclude that this simple strategy provides an acceptable way to prevent the pandemic from contaminating the parameter estimates. We thus follow their lead and drop the observations between March and June 2020. More sophisticated approaches to account for COVID-19 have been proposed by Lenza and Primiceri (2022) and Carriero et al. (2022). We assess alternative ways to handle the pandemic in a robustness exercise.

3.2 Macroeconomic effects of core inflation uncertainty

Figure 4 depicts the impulse response functions (IRFs) to a one-standard-deviation exogenous increase in the uncertainty of core inflation.[15] The IU shock leads to a statistically significant increase in industrial production and consumption. The real effects are more pronounced when factoring out movements in MU and FU. Production displays a hump-shaped reaction, reaching a peak of around 2% after about a year and a half, before gradually returning to its baseline level. Consumption rises more persistently, reaching a maximum of around 1% one year after the shock. There is also a significant and long-lasting increase in consumer prices. Their level (stripped of food and energy prices) is about 0.5% higher two years after the shock.

At this point, it is worth comparing our estimates with the existing evidence on the real effects of MU and FU shocks. A central finding in the literature is that an unexpected increase in uncertainty leads to a significant reduction in economic activity and prices, which is reminiscent of a *negative* aggregate demand shock (e.g., Bloom, 2009; Jurado

[13]Specifically, we impose a gamma density with mode equal to 0.2 and standard deviation equal to 0.4 as a hyperprior on the tightness parameter of the Minnesota prior.

[14]The sample period is determined by data availability. Data on inflation expectations start in January 1978. The Jurado et al. (2015) MU and FU measures used to cleanse IU of confounding factors are only available until June 2022.

[15]Note that the stochastic volatility of core inflation is estimated with uncertainty. However, we treat it as observed in the VAR analysis, which is a common assumption in the related literature (e.g. Gilchrist and Zakrajsek, 2012; Basset et al., 2014; Jurado et al., 2015; Metiu, 2021). Consequently, our inference on IRFs is likely to understate the true estimation uncertainty and should be interpreted with some caution.

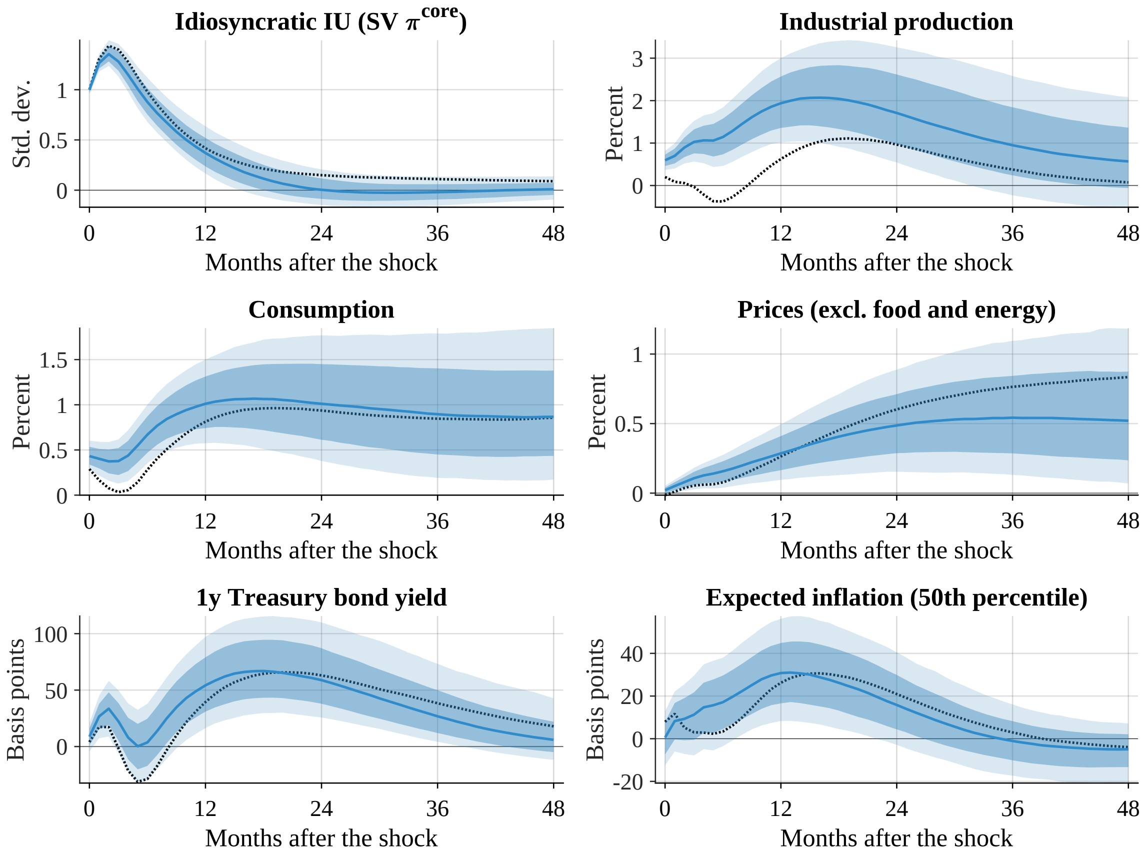

Figure 4: **Effects of an exogenous increase in core inflation uncertainty**

Note: The figure depicts the impulse responses to a one-standard-deviation positive shock to U.S. core inflation uncertainty (IU), identified using recursive zero restrictions with IU ordered first. Posterior median (blue solid lines) with 68% (dark blue) and 90% (light blue) credible regions. IU is measured by the stochastic volatility of the core PCE inflation rate (SV π^{core}), purged of the composite indices of macroeconomic and financial uncertainty proposed by Jurado et al. (2015) in a first-stage regression. The figure also shows the posterior median of the impulse responses to a one-standard-deviation positive shock to IU before cleansing it of macroeconomic and financial uncertainty (black dotted lines). Figure A.1 in the Online Appendix reports the responses with 68% and 90% credible regions.

et al., 2015; Basu and Bundick, 2017).[16] One explanation for negative demand effects is that the real option value of investment rises when uncertainty is high, making it worthwhile to delay investment projects until uncertainty is resolved (e.g., Bernanke, 1983; Bloom, 2009, 2014). Other explanations place financial frictions or the interplay between labor search frictions and nominal rigidities at the center of the transmission mechanism (e.g., Christiano et al., 2014; Leduc and Liu, 2016; Alessandri and Mumtaz, 2019). Our results instead resemble a *positive* aggregate demand shock: economic activity

[16] Jurado et al. (2015) find that an increase in their measure of uncertainty reduces industrial production by around 2% in the first month after the shock. Bloom (2009) uses stock market volatility to measure uncertainty and finds that higher uncertainty reduces industrial production by around 1% within the first five months after the shock. Using the same uncertainty measure, Basu and Bundick (2017) find that GDP drops by around 0.2% within a year after the shock and that prices decline as well.

and prices increase after an unexpected rise in core inflation uncertainty. This finding is in line with the results in Ludvigson et al. (2021), who find that a positive MU shock leads to an increase in real activity, which they rationalize with "growth options" theories (e.g., Bar-Ilan and Strange, 1996).

Endogenous movements in the inflation expectations of households are a potential channel through which positive demand effects arise. Our estimates indicate that households expect significantly higher inflation over the subsequent year after a positive shock to the uncertainty of core inflation (Figure 4, bottom right). The impact on one-year-ahead inflation expectations is stronger and more long-lasting when IU is purged of MU and FU. Households raise their expectations regarding the near-term inflation rate for a year after the shock, until expectations reach a peak at around 30 basis points above their baseline level. Inflation expectations then return gradually to the baseline.

A closer look at the impact on survey expectations beyond the central tendency underscores that inflation expectations become less anchored after a positive IU shock. In particular, the shock leads to a significant increase in not only the median but also the the lower tail (25th percentile) and the upper tail (75th percentile) of inflation expectations (see Figure 5). Initially, the lower tail increases more than the median and the upper tail, leading to an initial drop in the dispersion of expectations, as measured by the interquartile range (75th-25th percentile) of expected price changes. Hence, a higher inflation uncertainty first raises the inflation expectations of those households that expect relatively low inflation over the next year. After three months, however, the interquartile range tends to rise as the upper tail of inflation expectations starts to increase more strongly. As a result, the distribution of expected inflation becomes right-skewed, indicating that a growing number of households expects a marked increase in inflation. Another way to capture the shift in inflation expectations is by studying changes in the share of households expecting a drop or an increase in prices. The share of households who expect prices to fall over the next year tends to drop after the shock. Instead significantly more households expect prices to go up over the next 12 months. Households initially expect a moderate price increase of between 1-5%. Inflation expectations then pick up more strongly, as captured by a significant rise in the share of households who expect an increase in prices by 6% or more. Reis (2022) documents a comparable shift in the distribution of inflation expectations toward higher expected inflation during the 2021-2022 period, taking this as evidence for a de-anchoring of expectations.

The rise in inflation expectations rationalizes the positive consumption response to an IU shock. Macroeconomic models predict that higher expected inflation coupled with a sticky nominal interest rate induce households to consume more and save less for the future (e.g., Smets and Wouters, 2007). We study the consumption and saving response

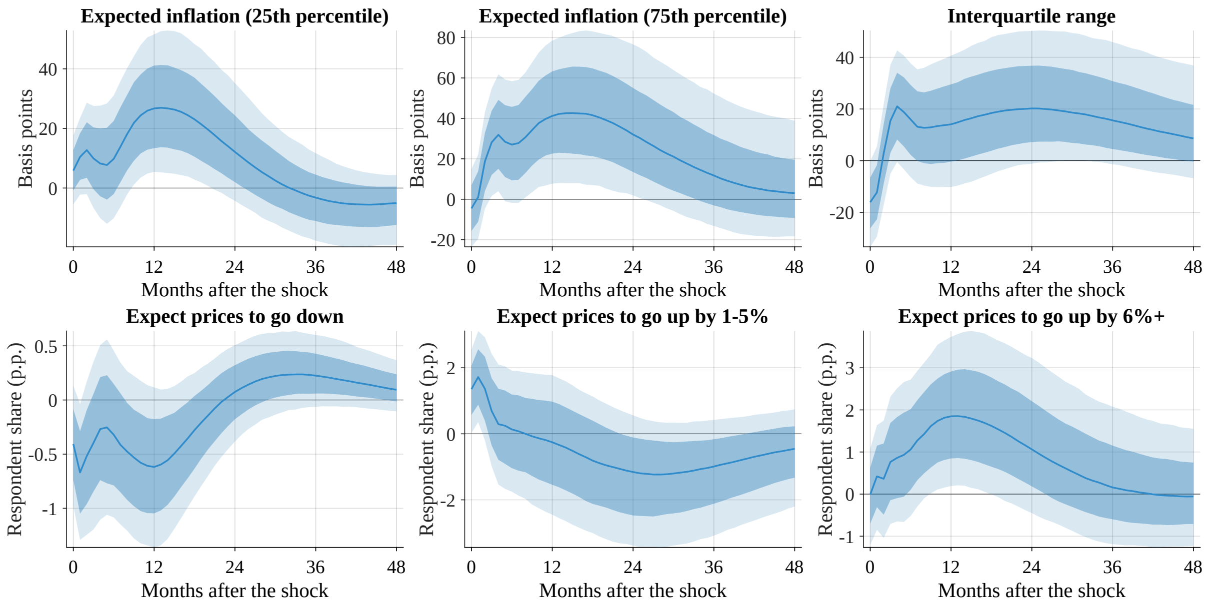

Figure 5: **Effects of an exogenous increase in core inflation uncertainty: Responses of selected variables from the Michigan Survey of Consumers**

Note: Impulse responses of selected variables from the Michigan Survey of Consumers to a one-standard-deviation positive IU shock, identified using recursive zero restrictions with IU ordered first. Posterior median (blue solid lines) with 68% (dark blue) and 90% (light blue) credible regions. Variables whose response is shown here are added one-at-a-time to the baseline VAR model specification. Figures A.2 to A.7 in the Online Appendix show the full set of responses for each model specification.

in more depth by replacing total consumption in the baseline model one-at-a-time with the following variables: the log of real PCE for durable goods; the log of real PCE for nondurable goods; the log of real PCE for services; the log of real PCE excluding food and energy; and personal saving as a percentage of disposable personal income. Figure 6 depicts the estimated IRFs. A positive shock to IU is followed by a significant increase in the consumption of durables, nondurables, services, and core consumer items. Moreover, the personal saving rate tends to fall after the shock. These findings are consistent with the standard consumption Euler equation and with recent survey evidence on a positive relationship between inflation expectations and consumer demand (e.g., Duca-Radu et al., 2021; Dräger and Nghiem, 2021; Andrade et al., 2021).[17] Durable consumption responds particularly strongly to an IU shock, in line with existing evidence that the durable goods sector is largely sensitive to demand-type shocks (e.g., Erceg and Levin, 2006). It is then plausible that stronger demand boosts industrial activity and puts upward pressure on the aggregate price level. Monetary policy reacts to the inflationary shock by tightening the policy stance, as indicated by a delayed but relatively strong increase in one-year Treasury yields up to around 75 basis points (Figure 4, bottom left). This, in turn,

[17]Earlier survey evidence, however, indicates that the impact of higher inflation expectations on the willingness to consume is insignificant or even negative (e.g., Bachmann et al., 2015).

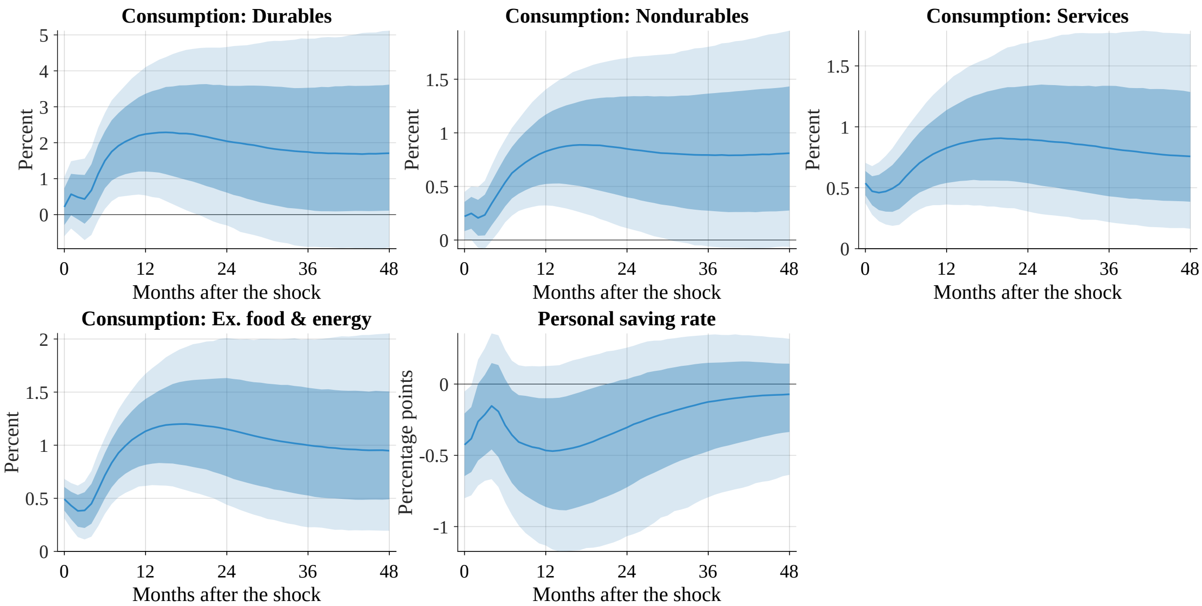

Figure 6: **Effects of an exogenous increase in core inflation uncertainty: Responses of consumption and saving**

Note: Impulse responses of selected consumption sub-aggregates and the personal saving rate to a one-standard-deviation positive IU shock, identified using recursive zero restrictions with IU ordered first. Posterior median (blue solid lines) with 68% (dark blue) and 90% (light blue) credible regions. Variables whose response is shown here are added one-at-a-time instead of total consumption to the baseline VAR model specification. Figures A.8 to A.12 in the Online Appendix show the full set of responses for each model specification.

dampens inflation expectations and cools down the economy.

3.3 Macroeconomic effects of headline inflation uncertainty

Having established that a shock to the uncertainty of core inflation generates positive aggregate demand effects, the question arises whether a shock to the uncertainty of overall, or headline, inflation has similar macroeconomic consequences. While core inflation is closely watched by Fed policymakers, the headline (all-items) PCE price index is the Fed's preferred measure of overall inflation. Hence, we estimate the uncertainty of headline inflation as the stochastic volatility of all-items PCE using the UCSV model with MA(1) errors proposed by Chan (2013). In addition, we use a measure of households' inflation uncertainty developed by Binder (2017). She quantifies the share of households who are relatively uncertain about their one-year-ahead inflation expectations using an insight from research on cognition, linguistics, and communication, which shows that individuals have a tendency to report round numbers (e.g., multiples of 10) when they are relatively more uncertain about quantitative estimates. To derive her uncertainty estimate, Binder (2017) relies on the following question in the Michigan Survey: "By about what percent do you expect prices to go up, on the average, during the next 12 months?". More uncertain respondents are more likely to answer this question with a round number. Since this survey question refers to overall price changes, Binder (2017)'s measure can be seen as a metric for headline inflation uncertainty.

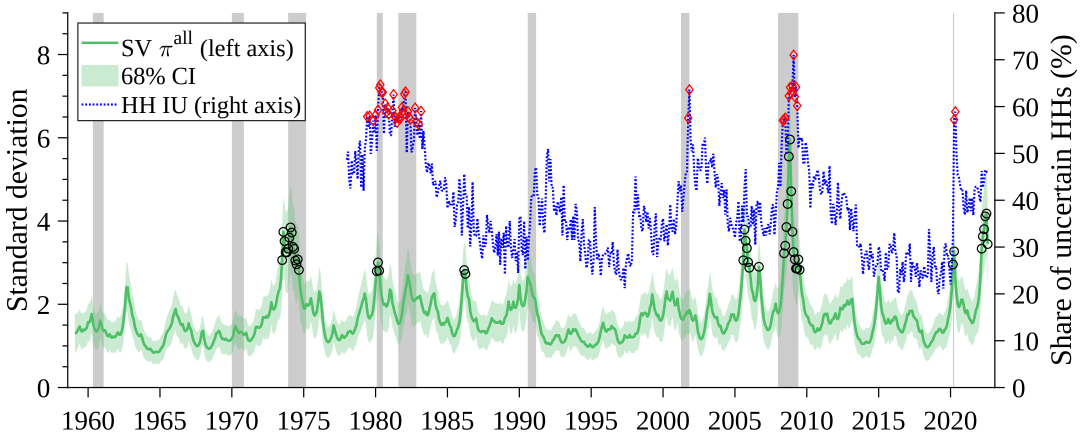

Figure 7: **Time-varying uncertainty of headline inflation**

Note: The figure shows the stochastic volatility of the forecast errors of all-items PCE inflation π^{all} (green solid line) with the 68% credible interval shaded (measured on the left axis in standard deviations). The estimates are obtained using an UCSV model with MA(1) errors (Chan, 2013). Black circles denote observations that lie at least 1.65 standard deviations above the mean. The figure also shows the share of households (HHs) that are relatively uncertain about their inflation expectations (blue dotted line), as estimated by Binder (2017) using data from the Michigan Survey of Consumers (measured on the right axis in percent). Red diamonds denote observations that lie at least 1.65 standard deviations above the mean. Gray shaded areas denote U.S. recessions dated by the NBER. Sample: 1959:M2-2022:M8.

Figure 7 depicts the stochastic volatility of headline PCE inflation, together with Binder (2017)'s uncertainty measure. Both of them indicate an elevated uncertainty of headline inflation during the recessions of the mid-1970s and early 1980s, and in the recent pandemic. Household IU also spiked briefly in the early 2000s recession. Remarkably, the highest readings in both measures occur during the 2008-2009 global recession. This contrasts with a subdued uncertainty of core inflation and, at the same time, mirrors large increases in the Jurado et al. (2015) measures of MU and FU during the Great Recession. A factor behind the large inflation volatility is a nearly 70% drop in the price of Brent crude oil from mid-2008 to the turn of 2009. Over the whole sample, the stochastic volatility of headline and core inflation correlate positively, although this correlation is far from perfect ($\rho = 0.49$). Not surprisingly, the former correlates somewhat more strongly with Binder (2017)'s uncertainty measure than the latter ($\rho = 0.45$ vs. $\rho = 0.40$). At the same time, the PCE-based and the survey-based measures of headline IU have a higher correlation with MU ($\rho = 0.68$ and $\rho = 0.65$, respectively) and with FU ($\rho = 0.48$ and $\rho = 0.39$, respectively), and they are more counter-cyclical ($\rho = -0.35$ and $\rho = -0.39$, respectively) than the uncertainty of core inflation.

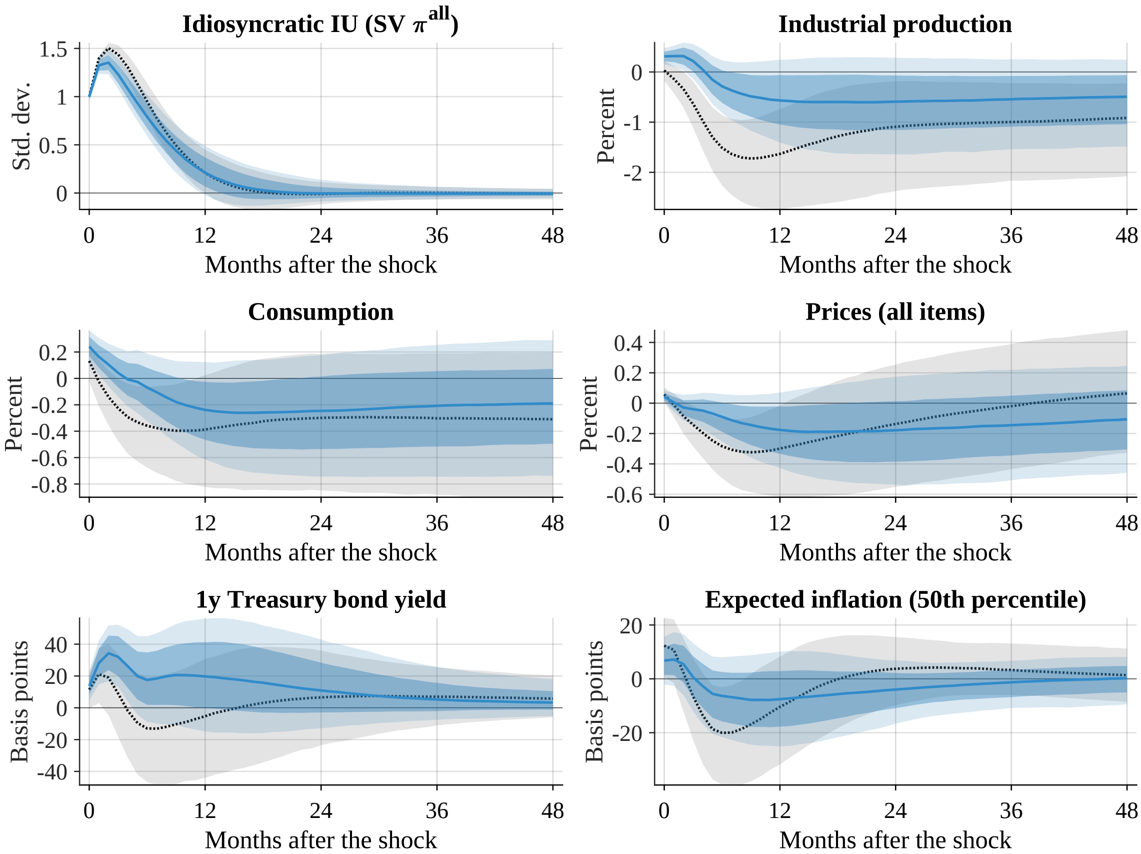

Figure 8: **Effects of an exogenous increase in headline inflation uncertainty**

Note: Impulse responses to a one-standard-deviation positive shock to the uncertainty of headline inflation, identified using recursive zero restrictions with inflation uncertainty ordered first. Posterior median (blue solid line) with 68% (dark blue) and 90% (light blue) credible regions. Headline inflation uncertainty is measured by the stochastic volatility of the all-items PCE price index (SV π^{all}), purged of macroeconomic and financial uncertainty in a first-stage regression. Black dotted lines denote the posterior median of the responses computed without purging inflation uncertainty of macroeconomic and financial uncertainty, with 90% credible regions shaded in gray.

Figure 8 shows the IRFs to a one-standard-deviation positive shock to the stochastic volatility of headline PCE inflation. We report the results with and without removing fluctuations in MU and FU.[18] Before removing these fluctuations, we find that production, consumption, and prices drop significantly after an unexpected rise in the uncertainty of headline inflation. This resonates with evidence from studies on MU and FU, which find that positive shocks to uncertainty affect the economy in a way reminiscent of negative aggregate demand shocks (e.g., Bloom, 2009; Jurado et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017; Gorodnichenko and Ng, 2017). The estimated effects are more subdued when factoring out movements in MU and FU. In fact, most of the effects are

[18]We use a first-stage OLS regression to remove the contemporaneous fluctuations in MU and FU from the stochastic volatility of headline PCE inflation (see Table A.1 in the Appendix).

not or only briefly statistically significant. We obtain similar results when measuring headline inflation uncertainty using Binder (2017)'s measure (see Figure A.13). Before purging this measure of MU and FU, we again find evidence for negative demand-side effects, with a significant drop in production, consumption, and prices. The effects vanish once we leave aside movements in MU and FU.[19]

Thus, shocks to headline inflation uncertainty seem to propagate through the same transmission channels as MU and FU shocks. Once we control for contemporaneous movements in MU and FU, households' inflation expectations do not react significantly to an unexpected increase in headline inflation uncertainty. This suggests that households regard the volatility of cyclically sensitive food and energy prices – an important component of headline inflation uncertainty – as mostly transient. Hence, they do not persistently revise their inflation expectations after a headline IU shock, and the transmission mechanism described above for core IU shocks does not become active.

3.4 Sensitivity analysis

We conduct an extensive sensitivity analysis summarized in what follows.

3.4.1 Robustness to identifying assumptions

We begin by assessing how sensitive the results are to the identifying assumptions in the structural VAR. First, we simply reverse the order of the variables in the VAR and perform a Cholesky decomposition for the alternative order. Second, instead of purging IU of MU and FU in a regression, we account for these potentially omitted variables by ordering them above IU in a recursive VAR. Third, we replace the Cholesky scheme with shock-based restrictions as proposed by Ludvigson et al. (2021).

Reversing the recursive order. We order IU below all endogenous variables in a recursive VAR. This identifying assumption implies that IU reacts contemporaneously to all shocks in the VAR, whereas macroeconomic variables respond to IU shocks with a lag of at least one month. This identification scheme provides a lower bound on the estimated effects of an IU shock in a recursive framework. We obtain robust results when using this alternative ordering scheme (see Figure A.14).

Including confounders in the VAR. Our econometric approach consists of first regressing IU on MU and FU, and then using the residuals in a VAR. Notice that this approach does not eliminate feedback between the uncertainty measures that occurs with a delay of at least one month and, therefore, does not rule out the possibility that an

[19] We remove the contemporaneous fluctuations in MU and FU from Binder (2017)'s uncertainty measure in a first-stage OLS regression (see Table A.2 in the Appendix).

IU shock has adverse macroeconomic effects. At the same time, the question may still arise whether MU and FU are omitted variables. We thus include them in the VAR as a robustness check. We estimate an eight-variate recursive VAR with MU ordered first, FU second, and IU third (unpurged), followed by all other endogenous variables from the baseline model specification. The effects of an IU shock in this specification are nearly identical to those obtained when purging IU in a first-stage regression (see Figure A.15). We find that MU significantly increases after an IU shock, while FU briefly drops.

Shock-based restrictions. Recursive identification schemes explicitly rule out simultaneous feedback between uncertainty and macroeconomic aggregates in the VAR. Ludvigson et al. (2021) address this potential drawback by proposing an identification strategy that imposes "event constraints" on the structural shocks. These are inequality constraints that put restrictions on the sign and the magnitude of the structural shocks during special episodes of history. We estimate the same eight-variate reduced-form VAR as in the previous robustness exercise, and we use event constraints to simultaneously identify MU, FU, and IU shocks in this model.

The identification approach proceeds as follows. First, we generate 5000 draws from the posterior distribution of the VAR parameters and discard the first 2500. For each of the remaining draws, we then take the lower triangular Cholesky factor of the reduced-form variance-covariance matrix Σ_u and rotate it by 100,000 random orthogonal matrices Q, obtained using the QR decomposition, where Q is a square matrix such that $Q'Q = QQ' = I_n$. This method produces a vast number of candidate shocks with varying impulse responses. The candidate shocks are discarded if the MU, FU, and IU shock series do not satisfy a set of event constraints, and we keep those candidates that satisfy all constraints.

To identify MU and FU shocks, we adopt the following event constraints from Ludvigson et al. (2021): The FU shock found in October 1987 (Black Monday) is positive and exceeds the 75^{th} percentile of the distribution of all potential candidate shocks obtained from different rotations in that month; the MU and FU shocks found in September 2008 (Lehman bankruptcy) are positive and exceed the 75^{th} percentile of the distribution of all candidate MU and FU shocks in that month, respectively; and the MU and FU shocks found in October 1979, July 2011, and August 2011 are non-negative.

We extend the procedure in Ludvigson et al. (2021) to the identification of IU shocks. Searching over a million rotations, we find two dates in our sample with the most maxima in the candidate shock series for IU shocks – these are February 1979 and March 2021.[20] Both correspond to episodes of history for which the events of the time would suggest large IU shocks. February 1979 marks the Islamic Revolution and the collapse of the monarchy

[20]We also find maxima in September and October 2008 as well as in July 2020 but we exclude them because they are not plausibly independent from the financial crisis and the COVID-19 crisis.

in Iran, which sparked the 1979 oil crisis. Oil prices more than doubled throughout 1979 and early 1980, which has been attributed to a sharp increase in precautionary demand (Kilian, 2009). On a year-over-year basis, the U.S. core PCE inflation rate nearly doubled between February 1979 and its peak of nearly 10% in November 1980. To stem runaway inflation, Paul Volcker was appointed as Fed chairman in August 1979. A large IU shock is also consistent with a historical reading of the events in March 2021. President Biden signed the American Rescue Plan Act into law on March 11, 2021. A public debate emerged shortly thereafter on whether the post-pandemic inflation is transitory or persistent.[21] For instance, it has been argued that the US$1.9 trillion stimulus package may "set off inflationary pressures of a kind we have not seen in a generation".[22] Thus, we impose the event constraints that the IU shocks found in February 1979 and March 2021 are positive and exceed the k^{th} percentile of the distribution of all candidate IU shocks obtained from different rotations in those two months.

The IRFs estimated using shock-based identifying restrictions closely resemble those estimated using recursive zero restrictions. We estimate the responses for two potential parameterizations, by setting k equal to either the 75^{th} percentile of the shock distribution (see Figure A.16) or the 90^{th} percentile, for which we obtain more clear-cut results (see Figure A.17).[23] A one-standard-deviation positive IU shock, identified using event constraints, leads to a significant and relatively persistent increase in prices and consumption. Industrial production also increases, with the 68% credible interval excluding zero for the first few months after the shock. Inflation expectations increase strongly and significantly on impact and remain significantly above the baseline level for about two years after the shock. Treasury bond yields significantly rise with a delay of about a year.

[21]For instance, Federal Reserve chair Jerome H. Powell argued in favor of transitory effects at an FOMC press conference, stating: "Over the next few months, 12-month measures of inflation will move up as the very low readings from March and April of last year fall out of the calculation. Beyond these base effects, we could also see upward pressure on prices if spending rebounds quickly as the economy continues to reopen [...]. However, these one-time increases in prices are likely to have *only transient effects on inflation*." (emphasis added) – See page 3 of the Transcript of Chair Powell's Press Conference on March 17, 2021.

[22]See the opinion piece by Lawrence H. Summers in the Washington Post from February 4, 2021, titled: "The Biden stimulus is admirably ambitious. But it brings some big risks, too", retrieved from: https://www.washingtonpost.com/opinions/2021/02/04/larry-summers-biden-covid-stimulus/.

[23]Out of the two billion five hundred million potential candidates, we find 8247 models that satisfy all event constraints when k is set to the 75^{th} percentile and 428 models that fulfil the event constraints when k is set to the 90^{th} percentile of the IU shock distribution in February 1979 and March 2021. In addition to event constraints, Ludvigson et al. (2021) also impose "external variable constraints" that require the identified uncertainty shocks to exhibit a positive correlation with the log change in the real price of gold and a negative correlation with stock market returns. We do not impose these constraints because they restrict *ex ante* the set of identified shocks to those that have features of an *adverse* uncertainty shock. *Ex post* we find that 95% of the identified IU shocks correlate positively with the change in the real gold price and 93% are positively correlated with real returns on the S&P 500 composite index. These correlations are consistent with the view that gold and common stocks hedge against inflation (e.g., Boons et al., 2020).

Finally, MU rises significantly after a year and a half, while FU does not materially respond to the shock. In sum, allowing for simultaneous feedback between the endogenous variables does not materially affect the results.

3.4.2 Accounting for the COVID-19 pandemic

One might wonder how sensitive our results are to how we account for macroeconomic dynamics during the COVID-19 pandemic. Our baseline estimates are obtained by simply omitting the data points between March and June 2020 from the sample, as suggested by Schorfheide and Song (2021). One may also drop all observations after February 2020. Lenza and Primiceri (2022) propose a more sophisticated econometric approach that introduces heteroscedasticity in the errors during the pandemic. In particular, consider the following VAR:

$$y_t = C + B_1 y_{t-1} + \dots B_p y_{t-p} + s_t u_t, \tag{6}$$

where, y_t, $B_1, \dots, B_p$, and u_t are defined as before, and additionally s_t is a scaling factor that is set equal to 1 up to February 2020, denoted as t^*, and it takes distinct values $\bar{s}_0$, $\bar{s}_1$, and $\bar{s}_2$ in March, April, and May 2020. It decays exponentially at a rate ρ after that, i.e., $\bar{s}_{t^*+j} = 1 + (\bar{s}_2 - 1)\rho^{j-2}$, where $\theta \equiv [\bar{s}_0, \bar{s}_1, \bar{s}_2, \rho]$ is a vector of unknown parameters. We estimate the model using a Bayesian approach with the Minnesota prior as before, and we set the priors on the parameters in θ as in Lenza and Primiceri (2022).[24]

The IRFs estimated on the pre-pandemic sample are broadly in line with the baseline estimates, although the magnitude of the effects is somewhat smaller, especially for prices and inflation expectations (see Figure A.18). Yet the estimates are overall consistent with a demand-side shock. In addition, the IRFs estimated with the model proposed by Lenza and Primiceri (2022) and those obtained from the baseline VAR are qualitatively identical and quantitatively very similar (see Figure A.18). Taken together, we conclude that the results are not driven by how we account for the pandemic period.

3.4.3 Alternative models of core inflation uncertainty

We estimate core inflation uncertainty using two alternatives to the UCSV model with MA errors employed in the baseline. First, we use a stochastic volatility model without MA errors, and in which the process for the conditional mean μ_t in Equation (1) is specified as an AR(l) model:

$$\mu_t = \phi_0 + \phi_1 \mu_{t-1} + \dots + \phi_l \mu_{t-l}. \tag{7}$$

[24]Specifically, we use a Pareto distribution with scale and shape equal to one as a prior for $\bar{s}_0$, $\bar{s}_1$, and $\bar{s}_2$, and we impose a a Beta prior for ρ with mode equal to 0.8 and standard deviation equal to 0.2.

We model the process for the log-volatility h_t of the errors ϵ_t^π in Equation (1) using a first-order stochastic volatility model of the form given by Equation (4). The ARSV model given by Equations (1), (4), and (7) is closer in spirit to the one used by Jurado et al. (2015) to estimate the uncertainty of forecast errors of the individual series that enter their composite index of uncertainty. We estimate this ARSV model using a Bayesian approach with $l = 6$ lags and priors chosen as in Chan and Grant (2016).

In the baseline, we use an SV model to estimate uncertainty following Jurado et al. (2015) because, unlike models from the generalized autoregressive conditionally heteroscadastic (GARCH) family, it permits the construction of a shock to the second moment of inflation that is independent of innovations to its level, which is consistent with the theoretical literature on uncertainty. Nevertheless, numerous studies have estimated IU using the conditional residual standard deviation obtained with GARCH-type models (e.g., Engle, 1982; Bollerslev, 1986; Grier and Perry, 1996, 1998, 2000; Bredin and Fountas, 2009). Hence, as a second alternative, we fit an AR model with GARCH errors to the core PCE inflation rate. That is, we model π_t using Equation (1), specifying an AR(l) model given by Equation (7) for the conditional mean, and assuming that the inflation forecast errors ϵ_t^π are normally distributed and conditionally heteroscedastic, $\epsilon_t^\pi \sim \mathcal{N}(0, \sigma_t^2)$, with the following GARCH model specified for the conditional variance process:

$$\sigma_t^2 = \xi + \gamma(L)(\epsilon_{t-1}^\pi)^2 + \kappa(L)\sigma_{t-1}^2. \tag{8}$$

We set the lag length in Equation (7) to $l = 6$ months, consistent with the Bayesian information criterion, and we assume that the lag polynomials $\gamma(L)$ and $\kappa(L)$ are of order one. The AR(6)-GARCH(1,1) model is estimated using maximum likelihood (ML). We obtain the following ML estimates of the parameters in the conditional variance equation:

$$\sigma_t^2 = \underset{(0.025)}{0.065} + \underset{(0.022)}{0.106}(\epsilon_{t-1}^\pi)^2 + \underset{(0.032)}{0.857}\sigma_{t-1}^2,$$

with a log-likelihood $= -1214.60$. The estimated ARCH and GARCH parameters in the variance equation are highly significant as can be seen by the respective standard errors in parentheses. The process for the conditional variance is stable, as the coefficients sum to less than one. In fact, the coefficients are close to those obtained by Bollerslev (1986) and Grier and Perry (1998) for earlier sample periods.

We obtain very similar estimates of IU from the baseline UCSV model and the two alternative models (depicted in Figure A.19). The contemporaneous sample correlation of the baseline estimate is equal to $\rho = 0.95$ with the ARSV estimate and to $\rho = 0.75$

with the GARCH estimate.[25] Our main results are not sensitive to how we model the uncertainty of core inflation: A positive IU shock unequivocally leads to a significant increase in industrial production, consumption, prices, the short-term interest rate, and one-year-ahead inflation expectations (see Figure A.20).

3.4.4 Alternative measures of core inflation

There are at least two alternatives to the core PCE price index when it comes to measuring the core inflation rate. The first one is the trimmed-mean PCE inflation rate, calculated by staff at the Dallas Fed.[26] This measure omits extreme price movements by dropping the items with the largest or smallest price changes in a given month from the PCE index. The second measure is the core CPI for all urban consumers less food and energy items.

The model by Chan (2013) yields broadly similar estimates for the stochastic volatility of the core PCE, the trimmed-mean PCE, and the core CPI (see Figure A.21). The correlation between the uncertainty of core PCE inflation and trimmed-mean PCE inflation is relatively high at $\rho = 0.65$. The correlation between the uncertainty of core PCE inflation and core CPI inflation is also positive but somewhat lower at $\rho = 0.48$. All three measures point to high uncertainty during the oil crises of the 1970s and the recessions of the early 1980s, as well as during the COVID-19 pandemic, and they indicate subdued uncertainty during the Great Moderation and the Great Recession. The IRFs to a positive IU shock are qualitatively identical across all measures of core inflation, in spite of some quantitative differences (see Figure A.22).

3.4.5 Additional price variables

Our benchmark VAR specification omits some price variables that might have important feedback with core inflation and household inflation expectations. Therefore, we add to the VAR the following prices: the log of the PCE price index for food; the log of the PCE price index for energy goods and services; the headline PCE price index; and the spot price of crude oil (West Texas Intermediate), deflated by the U.S. CPI index. A positive IU shock leads to a significant and persistent increase in not only prices for core consumer items but also the overall PCE price index (see Figure A.23). Food prices react more strongly and significantly to the shock than energy prices and oil prices, which tend to

[25]There is a lead-lag relationship between the SV and GARCH estimates: The correlation of the one-month lag of the baseline SV estimate with the GARCH estimate is equal to $\rho = 0.83$. One potential explanation is that, when there is a large inflation forecast error, the contemporaneous volatility under SV becomes large as h_t is essentially a measurement for the latent volatility. In contrast, a large forecast error only affects the conditional variance in the GARCH model at time $t + 1$ via Equation (8). We thank Joshua Chan for suggesting us this interpretation.

[26]See: https://www.dallasfed.org/research/pce.

rise but not in a statistically significant manner. The IRFs for macroeconomic variables and inflation expectations are robust to the inclusion of additional price variables.

3.4.6 Additional robustness checks

We carry out four additional robustness checks. First, we drop the observations for the 1970s and early 1980s from our sample and estimate the VAR from January 1985 onward since the beginning of the Great Moderation. This allows us to study the extent to which the episodes of elevated IU during the 1970s oil crises and the Volcker disinflation drive our results. Second, we use more controls in the first-stage regression by including six lagged values of MU and FU. Third, we replace the 1-year Treasury yield in the baseline VAR with the federal funds rate spliced with the Wu and Xia (2016) shadow short rate between December 2008 and March 2022, which accounts for the expansionary stance of monetary policy during the zero lower bound period (see Basu and Bundick, 2017). Finally, we estimate the VAR with 12 lags of the endogenous variables. In all four cases, we obtain impulse responses that closely resemble the baseline IRFs (see Figure A.24).

3.4.7 Long-run inflation expectations

In the baseline model specification, we focus on one-year-ahead inflation expectations. How an IU shock affects inflation expectations over longer horizons may also be of interest. To address this question, we estimate the VAR from April 1990 to June 2022 using five-year-ahead inflation expectations from the Michigan Survey, as the long-run expectations data have large gaps before the 1990s. Five-year-ahead inflation expectations only increase marginally after a positive IU shock, and the increase is not statistically significant (see Figure A.25). This contrasts with the response of one-year-ahead inflation expectations estimated on the short sample, which is in line with the IRF estimated for the long sample. Thus, expectations remain more firmly anchored over a longer horizon, and the IU shock primarily moves expectations about near-term inflation.

4 Conclusion

Buoyant consumer demand combined with supply-side constraints and geopolitical tensions have paved the way for an inflationary recovery of the U.S. economy from the COVID-19 recession, with prices soaring for a broad range of goods and services. The post-pandemic surge in prices has been accompanied by a rise in inflation uncertainty. Stochastic volatility estimates show that the uncertainty of core inflation during the pandemic has increased to the same order of magnitude as during the oil crises of the 1970s and the Volcker disinflation of the early 1980s.

In this paper, we study the relationship between the U.S. economy and inflation uncertainty. First, we document empirically that, after controlling for movements in macroeconomic and financial uncertainty, an unexpected rise in the uncertainty of core inflation leads to a significant increase in prices, consumption, and production, as well as to a rise in the short-term interest rate. These effects resemble a positive aggregate demand shock, which contrasts with the well-documented negative demand effects of macroeconomic and financial uncertainty shocks. Second, we highlight a potential transmission mechanism through which positive demand effects arise via an endogenous increase in household inflation expectations. Finally, we show that a shock to the uncertainty of headline inflation has hardly any effects on the economy when controlling for fluctuations in aggregate economic and financial uncertainty. Above all, households do not persistently change their inflation expectations after a shock to headline inflation uncertainty, and the expectations channel does not come into play.

Our results have implications for policy and future research. For policymakers they offer the insight that a sudden increase in the uncertainty of the core inflation rate can breed demand-pull inflation. One possible reason why this occurs is that households significantly and quite persistently raise their near-term inflation expectations when faced with more volatile core consumer prices. Firmly anchored inflation expectations may thus help to break the link between inflation uncertainty and soaring prices. A positive effect of shocks to core inflation uncertainty on household inflation expectations emerges as a robust empirical result. Modelling the relation between the second moment of inflation and expectations about its first moment in a structural framework is left for future research. Moreover, while we highlight one potential transmission channel through household inflation expectations, studying the role of other channels seems like a promising avenue of enquiry.

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