Demand Uncertainty, Cost Uncertainty, and the State Dependence of Monetary Policy*

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Abstract

The source of uncertainty determines its effect on prices: demand uncertainty is disinflationary, supply uncertainty is inflationary, a distinction existing measures conflate. Using firm-level survey data from Italy (INVIND) and the United States (SBU), we measure demand uncertainty as the dispersion of expected sales growth and supply uncertainty as the dispersion of expected price growth, and instrument both using a shift-share design based on industry exposure to economic policy uncertainty and oil price volatility. A one-standard-deviation increase in demand uncertainty reduces firm price growth by 0.3 percentage points and contracts real sales; the same increase in supply uncertainty raises price growth by 0.6 percentage points while also contracting real sales. Monetary policy transmission inherits this state-dependence: under supply uncertainty, price pass-through to an accommodative shock rises by 25 percent and its effect on real output falls by 40 percent; under demand uncertainty, the pattern reverses. Both results replicate in the United States. JEL Codes: C83; D22; D84; E31; E32; E52.

Keywords: Uncertainty, demand and supply shocks, firm pricing, subjective expectations, monetary policy transmission.

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1 Introduction

Uncertainty rises sharply in recessions and around episodes of geopolitical conflict, yet its consequences for inflation and real activity differ across episodes (Baker, Bloom and Davis, 2016; Jurado, Ludvigson and Ng, 2015; Altig et al., 2022). The post-2008 period combined elevated uncertainty with subdued inflation (Leduc and Liu, 2016); the 2021–2022 episode combined elevated uncertainty with an inflation surge driven by cost shocks (Blanchard and Bernanke, 2023). Whether uncertainty is inflationary or disinflationary, and whether it amplifies or attenuates the real effects of monetary policy, remains an open empirical question.

We show that the source of uncertainty resolves this question: uncertainty about future demand conditions—which we measure as dispersion in expected sales growth—compresses firm price growth and amplifies the real effects of monetary accommodation, while uncertainty about future supply conditions—which we measure as dispersion in expected price growth— raises prices and attenuates them. Standard uncertainty measures conflate these two channels, recovering a net effect whose sign depends on sample composition and generating contradictory findings across studies without any individual study being wrong. We construct firm-level measures of each and use them to separately identify the causal effect of both channels on pricing behavior and monetary transmission.

Uncertainty about demand conditions induces firms to compress prices and contract output, consistent with a negative demand shock (Mills, 1959; Bloom, 2009; Leduc and Liu, 2016; Ilut, Valchev and Vincent, 2020). Uncertainty about supply conditions induces firms to raise prices to protect margins, consistent with a negative supply shock (Kimball, 1995; Fernández-Villaverde et al., 2015). Coibion, Gorodnichenko and Kumar (2023) and Bachmann et al. (2020) document that higher uncertainty compresses prices at the firm level, recovering the demand channel; the supply channel is absent from both analyses. Klepacz (2024) documents that oil price volatility shocks expand the cross-sectional dispersion of price changes in producer price data, consistent with the supply channel; Vavra (2014) documents the same pattern for idiosyncratic volatility in consumer price data. Aastveit, Natvik and Sola (2017), Castelnuovo and Pellegrino (2018), Pellegrino (2021), and Castelnuovo, Pellegrino and Særkjær (2025) provide panel and VAR evidence that uncertainty dampens the real effects of monetary policy and amplifies inflationary pressure in high-inflation regimes, but their estimates pool both channels. Separately identifying the supply channel requires firm-level measures of demand and supply uncertainty that are distinct and orthogonal to first-moment expectations. We construct such measures and use them to test both predictions.

We construct these measures using two business surveys that elicit subjective probability distributions from senior managers: INVIND, conducted by the Bank of Italy, and the Survey of Business Uncertainty (SBU, Altig et al., 2022), conducted by the Federal Reserve Bank of Atlanta. INVIND asks managers to report the minimum, average, and maximum of expected real sales growth for the full sample from 1997 to 2021, and of expected price growth for a subsample covering 2016–2021; the SBU elicits full probability distributions over sales revenue growth from 2016 and over price growth from 2024. In both surveys the average constitutes the point forecast—the first moment—and the spread around it is our measure of uncertainty—the second moment (Fiori and Scoccianti, 2023). Controlling for point expectations in all specifications isolates the contribution of uncertainty from the confounding influence of optimism or pessimism. The joint elicitation of expectations and uncertainty over both sales and prices in the same survey wave allows us to hold demand uncertainty fixed when estimating the supply channel, and vice versa. The measures reflect the information set of the agent making the pricing decision, are observed at the firm level, and are based on quantitative responses about the firm's own operations.

We address endogeneity using the shift-share strategy of Alfaro, Bloom and Lin (2024). The demand uncertainty instrument interacts industry-level sensitivity of sales to EPU—estimated on the Cerved universe of two million Italian firms—with changes in aggregate EPU volatility. The supply uncertainty instrument interacts industry-level sensitivity of output prices to oil—estimated on the INVIND sample—with changes in aggregate oil price volatility. In all specifications we control for the levels of EPU and oil prices, so that identification comes from differential firm exposure to volatility rather than from aggregate level changes.

The central finding is that the source of uncertainty determines the direction of the price response. A one-standard-deviation increase in demand uncertainty reduces firm price growth by 0.3 percentage points; the same increase in supply uncertainty raises it by 0.6 percentage points. Both IV estimates are an order of magnitude larger than OLS, indicating substantial attenuation bias in the raw measures. The joint response of prices and quantities confirms the interpretation: demand uncertainty moves prices and output in the same direction, consistent with a negative demand shock; supply uncertainty moves them in opposite directions, consistent with a negative supply shock. These patterns extend to the cross-sectional distribution of prices within sectors: demand uncertainty compresses the upper tail while supply uncertainty expands it, providing the firm-level causal mechanism for the aggregate price dispersion documented by Klepacz (2024) and Vavra (2014). Monetary policy transmission inherits this state-dependence: under elevated supply uncertainty the price pass-through of an accommodative shock rises by 25 percent and its effectiveness at stimulating real output falls by 40 percent; under elevated demand uncertainty the real output response is amplified by 50 percent and price pass-through falls by 10 percent. Both sets of results replicate in the SBU for the United States.

These results contribute to three literatures. First, the source of uncertainty determines the direction of the price response: supply uncertainty is inflationary and demand uncertainty is disinflationary, with causal magnitudes an order of magnitude larger than OLS estimates. Coibion, Gorodnichenko and Kumar (2023) and Bachmann et al. (2020) find that higher uncertainty compresses prices, while Klepacz (2024) and Vavra (2014) find that cost volatility expands price dispersion upward; both sets of findings are correct for the channel they identify, and the sign of the net effect depends on which channel dominates in a given episode. Second, monetary policy transmission is state-dependent in a way that mirrors the demand-supply decomposition: supply uncertainty amplifies inflationary pass-through by 25 percent and attenuates real output gains by 40 percent; demand uncertainty does the opposite, amplifying the real output response substantially. This qualifies Aastveit, Natvik and Sola (2017), Castelnuovo and Pellegrino (2018), and Castelnuovo, Pellegrino and Særkjær (2025): their finding that uncertainty amplifies inflationary pressure and dampens real monetary policy effects holds when supply uncertainty dominates—as in high-inflation episodes—but reverses when demand uncertainty dominates. Third, both results are enabled by direct measurement of firm-level uncertainty from subjective distributions elicited in INVIND and the SBU, which separately identify first and second moments at the firm level. The findings replicate for the United States, confirming they reflect a structural feature of firm pricing behavior rather than an artifact of the Italian context.

The paper is organized as follows: Section 1.1 reviews the related literature, Section 2 describes the data and constructs the uncertainty measures, Section 3 presents the identification strategy, Section 4 reports the main results, Section 5 examines monetary policy transmission using corroborating SBU evidence, Section 6 draws out the implications for monetary policy, and Section 7 concludes.

1.1 Related Literature

A large literature measures uncertainty using asset price volatility, forecast dispersion, and text-based indices (Baker, Bloom and Davis, 2016; Jurado, Ludvigson and Ng, 2015; Hassan et al., 2019; Caldara and Iacoviello, 2022; Caldara et al., 2020, 2025). Survey-based measures offer a complementary approach by eliciting subjective distributions directly from decision-makers, with the advantage of separating first from second moments and capturing firm-specific uncertainty rather than aggregate conditions (Dominitz and Manski, 1994; Bachmann, Elstner and Sims, 2013; Manski, 2017; Altig et al., 2022; Andrade et al., 2022, 2025; Holzmeister et al., 2020). Our paper extends this approach in two directions. First, we exploit the three-point elicitation design of INVIND—which has surveyed Italian firms for over two decades, predating newer surveys such as the Decision Maker Panel (Altig et al., 2020) and SBU (Altig et al., 2022)—to construct separate firm-level measures of demand uncertainty, as the max-min range of expected sales growth, and supply uncertainty, as the max-min range of expected price growth. Second, we complement Bachmann et al. (2019) and Bachmann et al. (forthcoming), who use the IFO survey to study pricing under uncertainty, and Alfaro, Bloom and Lin (2024), who exploit firm exposure to financial volatility, with instruments based on EPU and oil price volatility that separately target each channel.

A growing literature documents how uncertainty shapes firm pricing and real outcomes. Bachmann et al. (2019) use the IFO Business Climate Survey to show that idiosyncratic volatility raises the probability of price adjustment; Bachmann et al. (forthcoming) document that higher uncertainty is associated with lower planned prices, recovering the demand channel. A vast empirical literature establishes that uncertainty reduces investment and hiring (Leahy and Whited, 1996; Bloom, Bond and Van Reenen, 2007; Gulen and Ion, 2016; Fiori and Scoccianti, 2023; Alfaro, Bloom and Lin, 2024), but causal evidence on pricing is scarce. We share with Bachmann et al. (forthcoming) a focus on price levels and extend their analysis by separately identifying demand and supply uncertainty through instrumental variables, establishing causal effects.

Our monetary policy transmission results connect to a literature documenting state-dependent effects of nominal shocks.[1] Panel and VAR evidence in Aastveit, Natvik and Sola (2017), Castelnuovo and Pellegrino (2018), Pellegrino (2021), and Castelnuovo, Pellegrino and Særkjær (2025) shows that uncertainty dampens the real effects of monetary policy and amplifies inflationary pressure in high-inflation regimes. Andreasen et al. (2024) show that risk matters more in recessions.[2] We extend this evidence by showing that the direction of state-dependence reverses depending on the source of uncertainty: supply uncertainty steepens the effective Phillips curve while demand uncertainty flattens it.

Our findings connect to a theoretical literature studying the aggregate implications of uncertainty for pricing and inflation. On the demand side, Basu and Bundick (2017) show that in models with nominal rigidities uncertainty shocks act as negative demand shocks, contracting output and raising markups; Ilut, Valchev and Vincent (2020) formalize this mechanism as Knightian uncertainty about the demand function, generating price rigidity and monetary non-neutrality. On the supply side, models with uncertain production costs generate inflationary pressure through the inverse Oi-Hartman-Abel effect (Born and Pfeifer, 2014; Caldara et al., 2020). Fernández-Villaverde et al. (2015) show that both mechanisms can coexist: cost uncertainty raises markups in partial equilibrium through the inverse Oi-Hartman-Abel effect, with the net price effect depending on the monetary policy response. Bianchi, Kung and Tirskikh (2023) jointly model demand- and supply-side uncertainty in general equilibrium, with implications for risk premia and aggregate dynamics. We provide the first firm-level causal evidence that maps directly onto this theoretical split: demand un-

[1] The policy implications of uncertainty have received growing attention in policy circles, including in the context of the Federal Reserve's 2025 review of its monetary policy framework. Bauer et al. (2025) provide a taxonomy of policy-relevant uncertainty — covering uncertainty about the state and structure of the economy and the formation of expectations — and survey the tools available to assess, quantify, and communicate risks to monetary policymakers. Garga et al. (2025) examine how uncertainty affects the optimal design and communication of monetary policy, with implications for the conduct of policy under imperfect information.

[2] A related literature studies firm-level uncertainty and monetary transmission through the investment margin: Lakdawala and Moreland (2026) show that firms facing higher stock-return volatility exhibit a muted investment response to monetary policy shocks, and de la Horra, Perote and De La Fuente (2021) document that policy-rate transmission to investment weakens in high-uncertainty environments, with stronger attenuation for firms with high investment irreversibility, low cash flow, and low innovation intensity.

certainty reduces price growth by 0.3 percentage points and supply uncertainty raises it by 0.6 percentage points,

A related literature studies how the frequency of price adjustment in menu-cost models shapes the real effects of monetary policy, and how this frequency responds to volatility. Vavra (2014) shows that higher realized dispersion raises adjustment frequency, making monetary policy less effective. Klepacz (2024) shows that aggregate cost volatility raises price dispersion without raising frequency, leaving monetary policy effectiveness unchanged. Aruoba et al. (2025) show that an anticipated increase in future dispersion has the opposite effect on frequency—lowering it today—and therefore the opposite implication for monetary policy effectiveness relative to the realization channel in Vavra (2014). Baley and Blanco (2019) show that uncertainty about the persistence of idiosyncratic shocks generates heterogeneity in price-setting that amplifies monetary non-neutrality through a separate channel. Whether uncertainty raises or lowers the real effects of monetary policy thus depends on its source and on whether it is realized or anticipated. Our firm-level evidence identifies one such source—demand versus supply—and quantify their effects.

2 Data, Expectations, and Uncertainty

This section describes the data sources that constitute the basis for measuring price inflation and subjective firm-level uncertainty. Details about our data source are in Section 2.1. In Section 2.2, we describe the INVIND measures of prices and sales and establish their validity in accounting for aggregate series by comparing them with CPI and GDP. Then, we detail the subjective expectations and uncertainty measures in Section 2.3 and report their statistical properties in 2.4.

2.1 Data Sources

The central data source is INVIND, an annual survey conducted by the Bank of Italy between February and May on a sample of Italian firms in industry, construction, and private services. The sample is stratified by branch of activity, size class, and region, and is representative of the Italian economy along all three dimensions.

INVIND elicits two types of information. First, managers report the expected growth rate of real sales and of firm prices over the following year—the first moment of their subjective distribution. Second, managers report the minimum and maximum of expected real sales growth around this point forecast; for a subsample, they report the same range for expected price growth. The max-min range is our measure of uncertainty—the second moment—constructed separately for sales and for prices, as described in Section 2.3.

INVIND also records realized outcomes: the firm's average price change over the calendar year, employment, and capacity utilization. Firms report price changes for year t when surveyed in year $t+1$, so the realized price variable reflects the cumulative twelve-month change over the preceding year. The sample runs from 1997 to 2021. We use SIGE, a quarterly survey with a different firm sample, to verify that the quarterly dynamics of price changes are consistent with the annual patterns in INVIND.

We match INVIND to firm-level balance sheet data from Cerved, which covers up to 80 percent of Italian value added between 1995 and 2021 and provides the sales, wage bill, and material purchase data used to construct markups and price margins. Following Alfaro, Bloom and Lin (2024), we use WTI oil prices and exchange rates from Haver, and the economic and political uncertainty indexes of Baker, Bloom and Davis (2016), to construct the instruments described in Section 3. Further detail on all sources is in Appendix A.

2.2 INVIND: Representative of GDP and Inflation Dynamics

Aggregating INVIND firm-level data reproduces the dynamics of GDP and inflation in the Italian economy. INVIND reports each firm's average price change relative to the previous year, which we denote $\Delta P_{f,t}$ for firm f in year t. Matching INVIND to Cerved gives firm-level sales, which we deflate using headline CPI.

Figure 1 compares headline CPI inflation and GDP growth with the sales-weighted mean of firm-level inflation and sales growth in INVIND. INVIND tracks CPI inflation closely throughout the sample, particularly at turning points, and the same holds for GDP growth. Inflation was below the ECB target from 2012 on, as in the rest of the euro area; in 2021 INVIND overshoots the rise in CPI inflation, anticipating the 2022 burst.

Figure *A.2* shows that INVIND and SIGE—a quarterly survey covering a different set

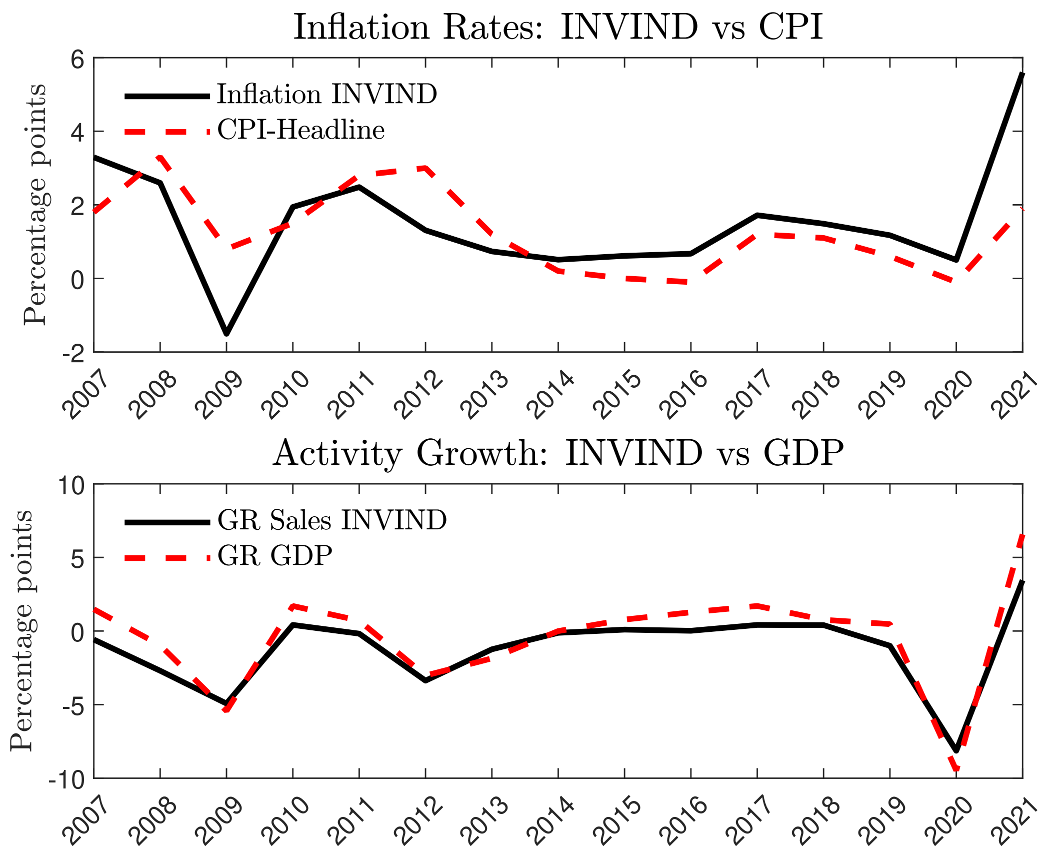

Figure 1: Aggregation of INVIND firm data and aggregate series.

of firms—track the same aggregate price dynamics: stable price changes over 2015–2019, a mild compression in 2020, and a sharp surge in 2021. We next turn to firms' expectations of sales and prices, which underlie our measures of firm-level uncertainty.

2.3 Firm-Level Expectations and Uncertainty: Variables Description

INVIND elicits from senior managers their expectations about real sales growth and price changes one year ahead. For the full sample, the survey reports the average, maximum, and minimum expected growth rate of real sales: $s^e_{avg,f,t}$, $s^e_{max,f,t}$, and $s^e_{min,f,t}$. For a subsample, it reports the same three statistics for expected price growth: $p^e_{avg,f,t}$, $p^e_{max,f,t}$, and $p^e_{min,f,t}$. The survey imposes no bounds on the maximum or minimum, so respondents report their own scenarios rather than probabilities over pre-specified thresholds. This design draws attention to the tails of the subjective distribution and is cognitively natural for managers planning around best- and worst-case outcomes (Dominitz and Manski, 1994; Altig et al., 2022). The detailed survey questions are in Appendix A.

We construct two measures of uncertainty as the max-min range of each distribution. Fiori and Scoccianti (2023) show, using the 2006 and 2017 cross-sections in which the full distribution is elicited, that the sales range is near-deterministically related to the standard deviation of expected sales and uncorrelated with higher moments—so the range captures dispersion rather than skewness or tail risk, and this interpretation extends to the full 1997–2021 sample where only the range is observed. The first measure, $\sigma^s_{f,t} \equiv s^e_{max,f,t} - s^e_{min,f,t}$, is the range of expected sales growth; we refer to it interchangeably as sales uncertainty or demand uncertainty. The second, $\sigma^C_{f,t} \equiv p^e_{max,f,t} - p^e_{min,f,t}$, is the range of expected price growth; we refer to it interchangeably as price/cost uncertainty or supply uncertainty.

In the standard pricing relationship $p_{it} = (1 + \mu_{it}) \cdot MC_{it}$, uncertainty about future prices reflects uncertainty about the markup μ_{it} and about marginal cost MC_{it}. Two arguments support interpreting $\sigma^C_{f,t}$ as primarily reflecting cost uncertainty. First, regressing realized price changes on firms' reported cost changes using quarterly SIGE data yields $R^2 = 0.547$, rising to 0.70 with firm and date fixed effects, and remains between 0.60 and 0.80 across specifications and sample periods (Table 1)—costs are the dominant driver of price changes. Second, because INVIND elicits sales and price uncertainty jointly, we control for $\sigma^s_{f,t}$ in all specifications, isolating the cost-side component of $\sigma^C_{f,t}$.

Table 1: Share of Price Variation Explained by Cost Dynamics

	(1)	(2)	(3)	(4)
R^2	0.547	0.703	0.400	0.618
Firm's Costs	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Date FE	No	Yes	No	Yes
Controls	No	No	Yes	Yes
Sample	2016–2021	2016–2021	2016–2019	2016–2019
Observations	33,880	33,287	13,997	13,518

Notes: The dependent variable is the realized price change Δp_{it}. Column (1) includes only firm cost changes as a regressor. Column (2) additionally absorbs firm and date fixed effects. Columns (3)–(4) replicate columns (1)–(2) over the pre-pandemic subsample. Standard errors are clustered at the firm level.

2.4 Firm-Level Expectations and Uncertainty: Validation and Properties

We compare the realized growth rate, the minimum, the maximum, the max-min range, and the average expected growth rate of firms' sales and prices, pooling the sample with INVIND survey weights. Growth rates are in percent.

Managers' point forecasts are unbiased: the median firm expects sales growth of 2.6 percentage points, close to realized sales, with a two-way clustered t-test failing to reject equality (p-value 0.21); the median firm expects price growth of 1 percentage point, equal to the realized median, with the same result (p-value 0.54).

Realized sales and prices fall within the max-min range in about 75 percent of observations, so the range corresponds, on average, to the 10th-90th percentile of the realized distribution. For sales, the median range is about 8 percentage points, from -2 in the worst case to 5 in the best; the interquartile range across firms is about 10 points for both the worst and best case. For prices, the median range is about 4 percentage points, from 0 in the worst case to 4 in the best; the interquartile range across firms is about 3 points for both the worst and best case. Managers' reported ranges are not arbitrary: they correspond closely to the actual dispersion of outcomes firms go on to experience, supporting their use as a measure of perceived uncertainty.

The max-min range is largely orthogonal to the point forecast: the correlation between expected sales growth and $\sigma^s_{f,t}$ is 0.07, and between expected price growth and $\sigma^C_{f,t}$ is 0.10. $\sigma^s_{f,t}$ and $\sigma^C_{f,t}$ are moderately correlated with each other at 0.3, while expected sales and price growth are weakly negatively correlated at -0.1. Uncertainty is therefore close to orthogonal to firms' point forecasts, which lets us control for the first moment without removing the variation we use to identify the effect of uncertainty.

Figure 2 shows the cross-sectional distribution of expected sales growth. Between 2016 and 2019 the median firm expected sales growth of 1 to 1.7 percentage points and the distribution was stable. In 2020 the entire distribution compressed—the median fell to -1.4, the 25th percentile to -9.5, and the 90th percentile to 6.4, below its pre-pandemic range of 8 to 10—before rebounding sharply in 2021, with the median at 3 and the 90th percentile at 21.5, the highest value in the sample.

Figure 3 shows the cross-sectional distribution of $\sigma^s_{f,t}$. The interquartile range widens

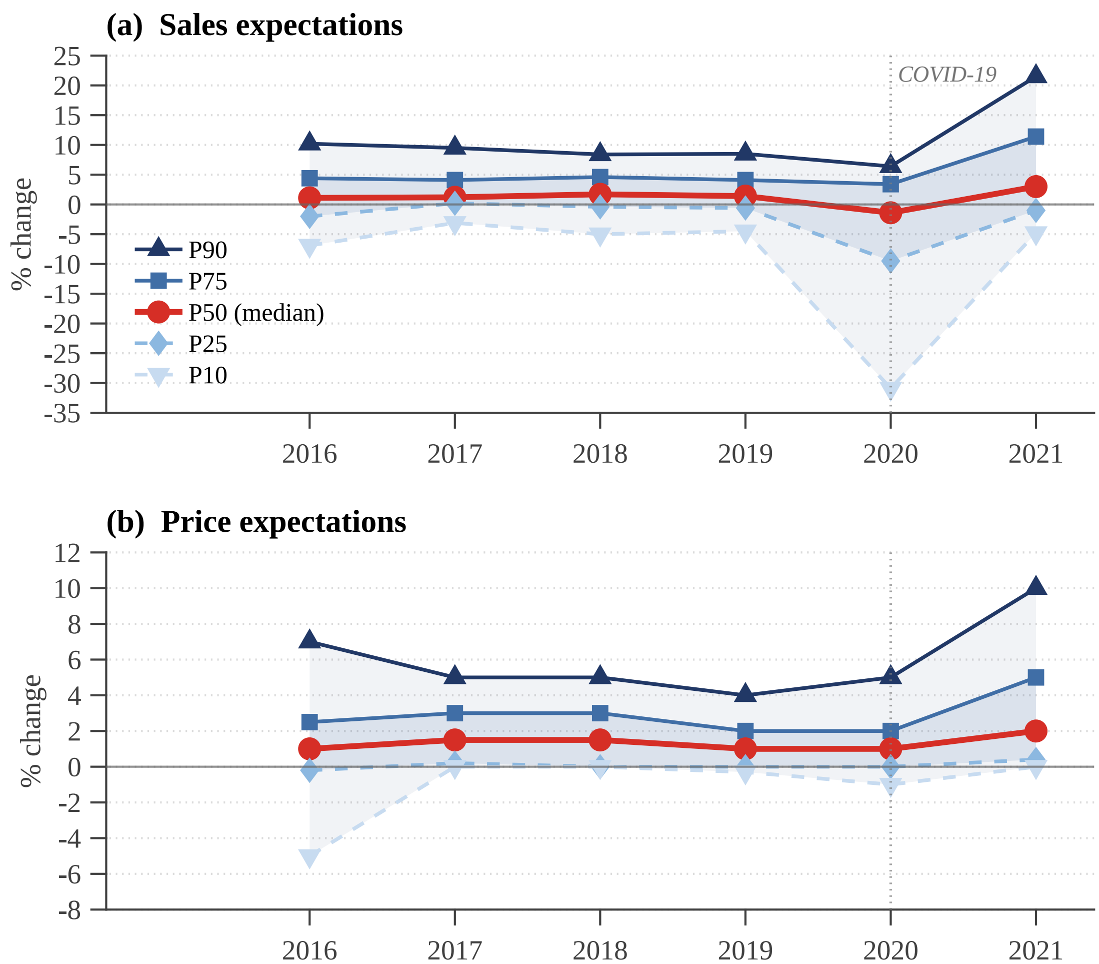

Figure 2: Cross-sectional distribution of firms' expectations for the growth rates of sales and prices.

from 2-9 percentage points in 2016 to 4-18 by 2021. Uncertainty is stable between 2016 and 2019, with the median between 4 and 5 and the 90th percentile between 11 and 15, then rises sharply in 2020 and again in 2021, reaching a median of 10 and a 90th percentile of 25—both the highest values in the sample. The increase in 2021 raises uncertainty at every quartile, indicating that the rise was broad-based rather than concentrated in the tails.

3 Identification Strategy

We adopt the instrumentation strategy of Alfaro, Bloom and Lin (2024), which constructs firm-level instruments by exploiting heterogeneous exposure to aggregate volatility shocks.

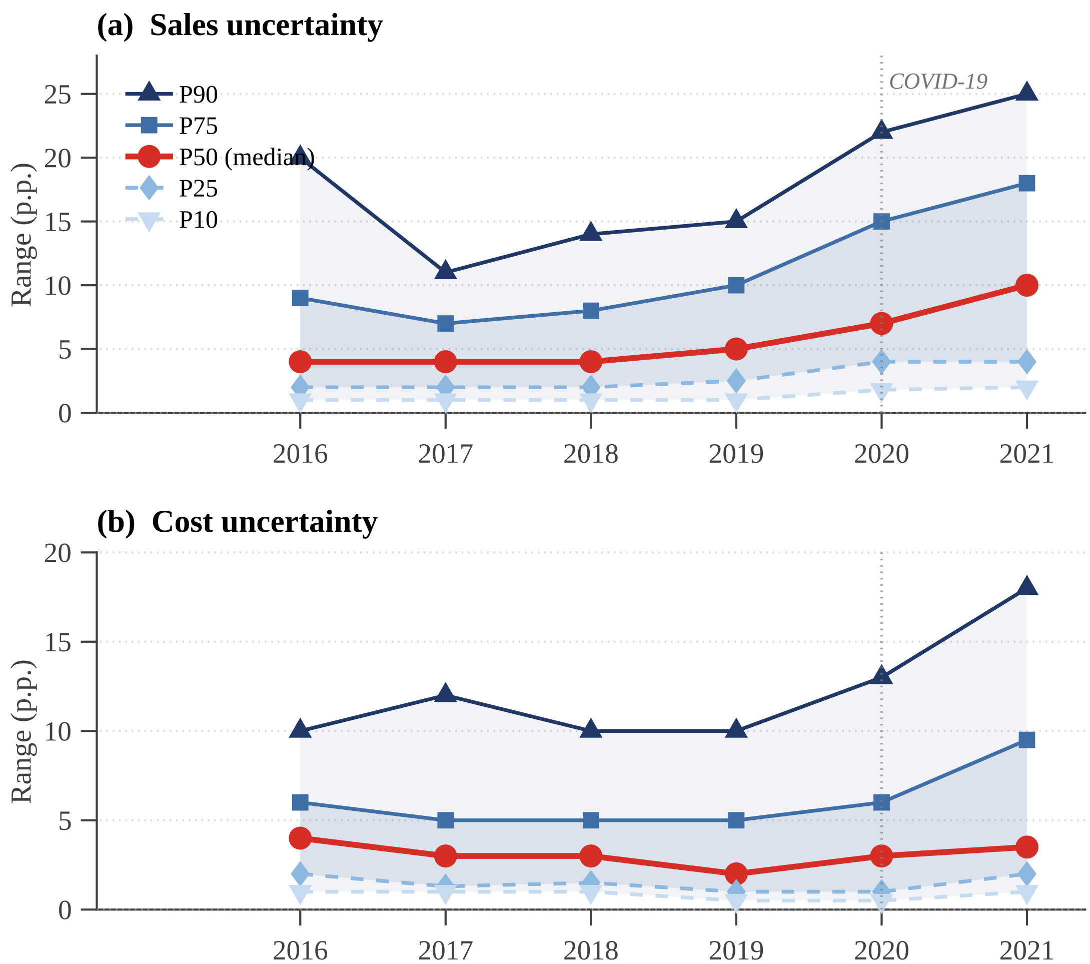

Figure 3: Cross-sectional distribution of firms' uncertainty for the growth rates of sales and prices.

Section 3.1 describes the identification logic, including the distinction between level and volatility exposure and the form of the exclusion restrictions. Sections 3.2 and 3.3 construct the instruments for sales and cost uncertainty. Section 3.4 presents the first- and second-stage specifications. Section 3.5 discusses robustness checks.

3.1 Overview

We adopt the instrumentation strategy of Alfaro, Bloom and Lin (2024), which constructs firm-level instruments by interacting aggregate shocks—oil prices, economic policy uncertainty (EPU), and exchange rates—with sector-specific, pre-determined exposure weights, in the spirit of the shift-share design of Goldsmith-Pinkham, Sorkin and Swift (2020).

The identification rests on a distinction between a firm's exposure to the *level* of an aggregate variable and its exposure to the *volatility* of that variable. Level exposure can be positive or negative: an oil price increase raises some firms' costs and lowers others'. Volatility exposure cannot: greater aggregate volatility raises the dispersion of outcomes for any firm with non-zero level exposure, regardless of its sign. A firm with a large negative level exposure therefore faces more uncertainty from higher volatility just as a firm with a large positive exposure does, even though the two firms' outcomes move in opposite directions on average. Taking the *absolute value* of each firm's estimated sensitivity before interacting it with changes in realized aggregate volatility captures this: the resulting instrument tracks the magnitude of exposure, and therefore predicted uncertainty, rather than its direction. We control separately for first-moment exposure—the level interaction—to absorb the direct effect of aggregate level changes on the outcome. The exclusion restriction is that, conditional on first-moment controls and firm fixed effects, differential exposure to aggregate volatility affects pricing only through firm-level uncertainty.

We instrument sales and cost uncertainty separately, using exposures estimated from distinct data sources, distinct outcome variables, and distinct aggregate shocks, as described in the following subsections.

3.2 Instrument for Sales Uncertainty

The instrument for sales uncertainty is built from the sensitivity of firm sales to Italy's EPU, estimated on the full Cerved universe of approximately two million firms. Cerved's coverage allows us to estimate 3-digit ATECO industry sensitivities precisely, with exposure weights that are less sensitive to outlier firms than estimates from the smaller INVIND sample would be.

The logic of the instrument is that EPU operates through demand: when policy uncertainty rises, firms face greater dispersion in expected revenues, and this dispersion is larger for firms whose sales have historically responded more to policy conditions. We estimate this sensitivity on the Cerved universe,

$$\Delta\text{Sales}_{f,t} = \alpha_f + \beta_j^{\text{EPU},s} \cdot \text{EPU}_t + \sum_{e \in \{\text{EURGBP,EURUSD}\}} \gamma_j^{e,s} \cdot r_t^e + \gamma_j^{\text{oil},s} \cdot \text{oil}_t + \varepsilon_{f,t}^s, \tag{1}$$

controlling for oil prices and exchange rates so that $\beta_j^{\text{EPU},s}$ is purged of the co-movement between EPU and other aggregate variables. The γ coefficients serve only this purpose and are not used in instrument construction. The instrument for firm f in industry j is

$$z_{f,t-1}^{S} = \left|\beta_{j,\tau-1}^{\text{EPU},s}\right| \cdot \Delta\sigma_{t-1}^{\text{EPU}}, \tag{2}$$

where $\beta_{j,\tau-1}^{\text{EPU},s}$ is the lagged, pre-determined sensitivity of industry j's sales to EPU and $\Delta\sigma_{t-1}^{\text{EPU}}$ is the lagged change in realized EPU volatility.

EPU may affect pricing directly—through demand compression or credit tightening—independently of firm-level uncertainty. We address this by controlling for the contemporaneous level of EPU in all specifications, so identification comes from differential exposure to EPU *volatility* rather than to its level. The exclusion restriction is that, conditional on EPU-level exposure and firm fixed effects, a firm's historical sales sensitivity to EPU, interacted with aggregate EPU volatility, shifts sales uncertainty without independently shifting prices. Because $\beta_{j,\tau-1}^{\text{EPU},s}$ is estimated conditional on oil prices and exchange rates, it captures the demand-side response of sales to EPU rather than a composite that conflates demand and cost channels.

3.3 Instrument for Cost Uncertainty

The instrument for cost uncertainty is built from the sensitivity of firm prices to oil prices, estimated on INVIND. Cerved records balance sheets but not output prices; INVIND elicits price realizations directly from managers, which lets us estimate the cost pass-through sensitivity $\beta_j^{\text{oil},p}$ from actual price responses rather than from indirect proxies.

The logic of the instrument is that oil price volatility operates through costs: when aggregate oil volatility rises, firms face greater dispersion in expected input costs, and this dispersion is larger for firms whose prices have historically responded more to oil, reflecting greater energy intensity. We estimate this sensitivity on the INVIND sample,

$$\Delta\text{Prices}_{f,t} = \alpha_f + \beta_j^{\text{oil},p} \cdot \text{oil}_t + \gamma_j^{\text{EPU},p} \cdot \text{EPU}_t + \sum_{e\in\{\text{EURGBP},\text{EURUSD}\}} \gamma_j^{e,p} \cdot r_t^e + \varepsilon_{f,t}^{p}, \tag{3}$$

controlling for EPU and exchange rates so that $\beta_j^{\text{oil},p}$ is purged of omitted variable bias. The γ coefficients serve only this purpose and are not used in instrument construction. The instrument for firm f in industry j is

$$z^C_{f,t-1} = \left|\beta^{\text{oil},p}_{j,\tau-1}\right| \cdot \Delta\sigma^{\text{oil}}_{t-1}, \tag{4}$$

where $\beta^{\text{oil},p}_{j,\tau-1}$ is the lagged, pre-determined sensitivity of industry j's prices to oil and $\Delta\sigma^{\text{oil}}_{t-1}$ is the lagged change in realized oil price volatility.

The exclusion restriction here is harder than for sales uncertainty: oil price volatility may affect pricing through input costs independently of uncertainty. We address this in two ways. First, we control for the level of oil prices in all specifications, absorbing the contemporaneous cost channel. Second, $\beta^{\text{oil},p}_{j,\tau-1}$ is estimated conditional on EPU and exchange rates, so it captures the cost-side pass-through of oil into prices, purged of demand-side co-movement between oil and these other aggregates. The instrument thus captures uncertainty about future cost trajectories for firms with high historical pass-through, not the contemporaneous cost channel absorbed by the level control. The exclusion restriction is that, conditional on oil price levels and firm fixed effects, historical price sensitivity to oil—net of demand-side confounders—does not predict pricing through channels other than cost uncertainty.

3.4 Empirical Specification

We estimate sensitivities using annual data, while Alfaro, Bloom and Lin (2024) use daily asset returns. This is necessitated by our data—sales and price growth are observed annually in both Cerved and INVIND—but it also matches the horizon at which firms make pricing decisions. The instruments remain annual in both approaches, so this difference affects the precision of the exposure weights but not the identification strategy. Following Alfaro, Bloom and Lin (2024), sensitivities are estimated in nine-year rolling windows. The exposure weight $\beta^{c,y}_{j,\tau}$ used at time t is estimated from a window ending in $t-1$, ensuring predetermination.

The two instruments are estimated on different samples. The sales uncertainty instrument $z^S_{f,t-1}$, built from sales sensitivity to EPU using the Cerved universe, is available over the long INVIND sample, 2007–2021, allowing us to assess the robustness of our results to the inclusion of the COVID period. The cost uncertainty instrument $z^C_{f,t-1}$, built from price sensitivity to oil using INVIND, is available only for 2016–2021, the period over which INVIND elicits price realizations.

This sample structure shapes the estimation. For sales uncertainty, we estimate over the long sample, with $z^S_{f,t-1}$ as the sole instrument, identifying the effect across the business cycle. For cost uncertainty, we estimate over 2016–2021 with $z^C_{f,t-1}$ as the instrument, including observed sales uncertainty $\sigma^S_{f,t}$ as a control. This isolates the effect of cost uncertainty by absorbing the sales channel without a separate first stage in the shorter sample. The two specifications are complementary: the long sample traces sales uncertainty over the business cycle, while 2016–2021 identifies cost uncertainty conditional on sales uncertainty during a period of substantial cost volatility.

We set to zero sensitivities with p-values exceeding 10 percent to reduce collinearity across instruments; retaining all sensitivities affects instrument strength but not the sign or significance of the point estimates. The first stage regresses realized uncertainty on the relevant instrument, first-moment controls, and firm and time fixed effects, γ_f. In the long sample,

$$\sigma^S_{f,t} = \gamma_f + \lambda^S \cdot z^S_{f,t-1} + \sum_c \delta_c \cdot \beta^{c,y}_{j,\tau-1} \cdot r^c_{t-1} + \Xi_t + \nu_{f,t}; \tag{5}$$

in 2016–2021,

$$\sigma^C_{f,t} = \gamma_f + \lambda^C \cdot z^C_{f,t-1} + \sum_c \delta_c \cdot \beta^{c,y}_{j,\tau-1} \cdot r^c_{t-1} + \Xi_t + \nu_{f,t}. \tag{6}$$

Ξ_t denotes year fixed effects, and $\beta^{c,y}_{j,\tau-1} \cdot r^c_{t-1}$ are the first-moment controls that absorb the direct effects of EPU, oil prices, and exchange rates, isolating each instrument's residual variation to the volatility channel. We report first-stage F-statistics for both specifications.

The second stage estimates the effect of predicted uncertainty on firm outcomes. In the long sample,

$$y_{f,t} = \gamma_f + \beta^S \cdot \hat{\sigma}^S_{f,t} + \sum_c \delta_c \cdot \beta^{c,y}_{j,\tau-1} \cdot r^c_{t-1} + \text{Controls}_t + \epsilon_{f,t}; \tag{7}$$

in 2016–2021, only cost uncertainty is instrumented and sales uncertainty enters as an observed control,

$$y_{f,t} = \gamma_f + \beta^C \cdot \hat{\sigma}^C_{f,t} + \beta^S \cdot \sigma^S_{f,t} + \sum_c \delta_c \cdot \beta^{c,y}_{j,\tau-1} \cdot r^c_{t-1} + \text{Controls}_t + \epsilon_{f,t}. \tag{8}$$

$\hat{\sigma}^C_{f,t}$ is the first-stage prediction from (6); $\sigma^S_{f,t}$ is observed and controls for the sales channel without a separate instrument. γ_f denotes firm fixed effects, included in both stages. $y_{f,t}$ denotes in turn price growth $\Delta P_{f,t}$, real sales growth $\Delta RS_{f,t}$, and capacity utilization. Controls_t includes sector and year dummies and the first moment of managers' expectations, separating the second-moment effects of interest from the first-moment expectations that shape pricing and output contemporaneously.

3.5 Robustness

We assess the robustness of our identification strategy along two dimensions, discussed in Sections 3.2 and 3.3.

An alternative instrument for sales uncertainty. The United Kingdom is Italy's largest export market outside the EU together with the United States, so EUR/GBP volatility generates revenue uncertainty whose incidence varies across industries with their historical reliance on UK exports. EUR/GBP volatility is driven by forces distinct from EPU—Brexit-related trade policy, Bank of England policy—providing an independent check on the baseline instrument:

$$z^{S,\text{EURGBP}}_{f,t-1} = \left|\beta^{\text{EURGBP},s}_{j,\tau-1}\right| \cdot \Delta\sigma^{\text{EURGBP}}_{t-1}, \tag{9}$$

where $\beta^{\text{EURGBP},s}_{j,\tau-1}$ is industry j's sensitivity of sales to EUR/GBP, recovered from equation (1) with no additional estimation, and $\Delta\sigma^{\text{EURGBP}}_{t-1}$ is the lagged change in EUR/GBP volatility. The exclusion restriction is that, conditional on the level of EUR/GBP and firm fixed effects, industry exposure to EUR/GBP volatility shifts sales uncertainty without independently affecting margins—most credible for firms whose exposure reflects trade relationships rather than financial hedging.

Two-year lagged exposure weights. The baseline lags $\beta^{c,y}_{j,\tau}$ by one year; we replace this with a two-year lag, $\beta_{j,\tau-2}$, recoverable from the same rolling-window estimates. A longer lag widens the buffer against reverse causality—if pricing responses to macro shocks alter customer or supplier relationships, a one-year lag may not break this channel—and separates the exposure estimation period from the outcome period. Point estimates and significance are stable across both lags, consistent with the instrument capturing predetermined structural exposure rather than a contemporaneous response.

4 Pricing Effects of Firm-Level Subjective Uncertainty

The source of uncertainty determines the sign of its effect on prices. Sales uncertainty acts as a negative demand shock: price growth and real activity fall together. Cost uncertainty acts as a negative supply shock: prices rise while activity contracts. A single aggregate measure of uncertainty cannot distinguish these two cases, yet the sign of its effect on inflation depends entirely on which one dominates.

Section 4.1 estimates the price effect of each source. Section 4.2 shows that the joint response of prices and quantities identifies the demand and supply channels separately. Section 4.3 shows the cross-sectional counterpart: sales uncertainty compresses the upper tail of the sectoral price growth distribution, while cost uncertainty expands it.

4.1 Firm's Price Growth with Cost and Demand Uncertainty

Table 2 reports the effect of uncertainty on price growth, separating sales and cost uncertainty.

Column (1) reports the OLS estimate for sales uncertainty over 2007–2019: a one-unit increase reduces price growth by 0.025 percentage points.[3] Column (2), covering 2016–2021, gives a larger coefficient on sales uncertainty (-0.069) and a positive coefficient on cost uncertainty (0.155). Sales uncertainty lowers price growth; cost uncertainty raises it.

Columns (3) and (4) instrument each measure, as described in Section 3. In column (3), the IV coefficient on sales uncertainty is -0.533, about twenty times the OLS estimate. The gap is consistent with attenuation bias from measurement error, as in Alfaro, Bloom and Lin (2024). In column (4), cost uncertainty is instrumented and sales uncertainty is included as

[3] We lose the first ten years of the INVIND sample, which begins in 1997, to build the exposure measures and lag the instruments.

Table 2: The Source of Uncertainty Determines The Price Response

	(1)	(2)	(3)	(4)
	OLS		IV	
	$\Delta Prices$	$\Delta Prices$	$\Delta Prices$	$\Delta Prices$
Sales Uncertainty	-0.025^{***}	-0.069^{**}	-0.533^{*}	-0.233^{**}
	(0.007)	(0.032)	(0.306)	(0.089)
Cost Uncertainty		0.155^{***}		1.409^{**}
		(0.045)		(0.630)
Observations	11,035	2,381	10,124	2,393
First-stage F-test			40.76	10.59
Sample period	2007-2019	2016-2021	2007-2019	2016-2021
IV first-moment exposure			✓	✓
Firm-specific effects	✓	✓	✓	✓
Sector effects	✓	✓	✓	✓
Time effects	✓	✓	✓	✓

Columns (1) and (3): long sample 2007–2019, sales uncertainty only, with EPU level exposure controls. Columns (2) and (4): restricted sample 2016–2021, both uncertainty measures included, with oil price level exposure controls; in column (4) sales uncertainty enters as a control and cost uncertainty is instrumented. All columns include the lagged dependent variable, first-moment expectations of Δ prices and Δ real sales, and firm, sector, and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

a control: the coefficient on cost uncertainty is 1.409, and sales uncertainty remains negative at -0.233. Both first-stage F-statistics exceed the conventional threshold of 10 for weak instruments: 40.76 in column (3) and 10.59 in column (4), the latter close to this cutoff.

The sign of the price response depends on the source of uncertainty. Higher sales uncertainty lowers price growth, consistent with precautionary pricing under demand uncertainty (Mills, 1959). Higher cost uncertainty raises price growth, as firms protect margins against uncertain input costs (Fernández-Villaverde et al., 2015). A one-standard-deviation increase in EPU volatility lowers price growth by about 0.3 percentage points; the same increase in oil price volatility raises it by about 0.6 percentage points, scaling the IV estimates by average industry exposure. The cost-side effect is roughly twice the size of the demand-side effect.

These results relate to Coibion, Gorodnichenko and Kumar (2023) and Bachmann et al. (2020), who find that higher uncertainty leads firms to plan lower prices and attribute this to a demand channel. Column (3) supports this finding for sales uncertainty. But neither paper identifies a separate cost channel, and both attribute the negative uncertainty-price relationship entirely to demand. Column (4) shows this is incomplete: cost uncertainty raises price growth. Aggregate uncertainty measures combine both channels: supply-side disruptions, such as the 2021–2022 energy price shock, generate a positive relationship between uncertainty and prices, while demand-driven episodes, such as the period following the financial crisis, generate the negative relationship found in earlier work.

These results are robust to a battery of alternative specifications, discussed in Appendix B, including alternative measures of uncertainty, alternative instrument sets, and alternative sample restrictions.

4.2 Sales and Cost Uncertainty as Demand and Supply Shocks

Table 3 reports IV estimates for price growth and real sales growth, allowing us to characterize the effects of sales and cost uncertainty on both prices and quantities.

Columns (1) and (2) show that the price compression documented in Section 4.1 is accompanied by a contraction in real sales growth. An increase in sales uncertainty reduces both price growth and real sales, with both coefficients significant at the 10 percent level. This pattern is consistent with a negative demand shock.

Columns (3) and (4) show the opposite pattern. An increase in cost uncertainty raises price growth while reducing real sales growth, with both coefficients significant at the 5 percent level. Sales uncertainty moves prices and quantities in the same direction; cost uncertainty moves them in opposite directions. The latter pattern is consistent with a negative supply shock: firms facing greater uncertainty about future input costs raise output prices while reducing real activity. The first-stage F-statistic for column (4) is 5.08, below the conventional threshold of 10. The corresponding coefficient on real sales growth, -2.107, should therefore be interpreted as suggestive rather than precisely identified; the price growth result in column (3), with an F-statistic of 10.59, is better identified.

These results are consistent with a standard demand-supply decomposition: sales uncertainty can be interpreted as demand uncertainty, and cost uncertainty can be interpreted as supply uncertainty. This decomposition qualifies Leduc and Liu (2016), who interpret uncertainty shocks as demand shocks because uncertainty reduces both output and inflation.

Table 3: Prices and Real Sales Growth Responses to Uncertainty

	Sales Uncertainty		Cost Uncertainty	
	ΔPrices	ΔSales	ΔPrices	ΔSales
Coefficient	-0.569^{*}	-2.500^{*}	1.409^{**}	-2.107^{**}
	(0.31)	(1.40)	(0.63)	(0.94)
Observations	10,124	9,191	2,393	1,609
First-stage F-stat	40.76	18.38	10.59	5.08
Sample period	2007-2019	2007-2019	2016-2021	2016-2021
IV first-moment exposure	✓	✓	✓	✓
Firm-specific effects	✓	✓	✓	✓
Sector effects	✓	✓	✓	✓
Time effects	✓	✓	✓	✓

IV estimates. Columns (1) and (2): long sample 2007–2019, sales uncertainty only, with EPU level exposure controls. Columns (3) and (4): restricted sample 2016–2021, both uncertainty measures included, with oil price level exposure controls; in columns (3) and (4) sales uncertainty enters as a control and cost uncertainty is instrumented. Columns (1) and (2) also include the lagged dependent variable. All columns include first-moment expectations of Δ prices and Δ real sales, and firm, sector, and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Our results show that this holds for sales uncertainty but not for cost uncertainty, which raises prices while reducing output. The sign of the aggregate price response to uncertainty therefore depends on which channel dominates in a given episode.

This decomposition also qualifies Coibion, Gorodnichenko and Kumar (2023) and Bachmann et al. (2020), who find that uncertainty compresses both prices and activity. Our results confirm this for sales uncertainty. Cost uncertainty produces a comparable contraction in real activity but raises prices rather than lowering them, a pattern not identified in earlier work. The 2021–2022 period illustrates this channel. A rise in cost uncertainty over this period, driven by energy price volatility and supply chain disruptions, raised output prices while reducing real activity relative to trend. This combination contributed to the stagflationary dynamics of that period.

4.3 Cross-Sectional Implications for Prices of Sales and Cost Uncertainty

The firm-level estimates in Sections 4.1 and 4.2 establish that sales and cost uncertainty generate opposing effects on price growth at the firm level. This section examines whether the same patterns emerge in the cross-sectional distribution of prices across firms within sectors, providing evidence that the precautionary pricing behavior identified at the firm level has measurable aggregate counterparts in the shape of the price distribution.

To construct the sector-level outcomes, we collapse firm-level price growth to sectoral percentiles by year at the 2-digit ATECO level, yielding nine dependent variables corresponding to P_{10} through P_{90} of the within-sector price growth distribution. We then estimate OLS regressions of each sectoral percentile on sector-level averages of sales and cost uncertainty, controlling for the sector median growth rates of sales and prices as first-moment controls, the lagged dependent variable, and sector and year fixed effects. The specification mirrors the firm-level analysis in Section 4.1, with the sector replacing the firm as the unit of observation.

Table 4 reports the results. Panel A, estimated over the 2007–2019 sample, documents the response of the price growth distribution to sales uncertainty. The coefficients on sales uncertainty are negative across all percentiles, but the effects are concentrated in the upper tail: the coefficients at P_{60} through P_{90} are statistically significant, ranging from -0.051 at P_{60} to -0.093 at P_{90}, while those at P_{10} through P_{50} are small and insignificant. To gauge the economic magnitude, a move from the median to the third quartile of sectoral sales uncertainty (an increase of 2.74 percentage points) compresses the upper tail of the price growth distribution by between 0.12 percentage points at P_{70} and P_{80} and 0.26 percentage points at P_{90}. This pattern indicates that sales uncertainty compresses the upper tail of the price growth distribution while leaving the lower tail unchanged, consistent with the firm-level evidence that uncertainty induces firms to moderate price increases rather than cut prices. The distribution narrows from above: firms that would otherwise raise prices pull back under greater sales uncertainty, while firms at the lower end of the distribution are unaffected. Our results are quantitatively robust to the inclusion of the COVID period.

Panel B, estimated over 2016–2021, reports the response of the price growth distribution to cost uncertainty. The pattern is the reverse of Panel A: cost uncertainty coefficients are positive across all percentiles and statistically significant in the upper tail, ranging from 0.276 at P_{70} to 0.359 at P_{90}. A move from the median to the third quartile of sectoral cost uncertainty, an increase of 1.08 percentage points, raises the upper tail of the price growth distribution by 0.30 percentage points at P_{70} and 0.39 percentage points at P_{90}. Cost uncer-

Table 4: Uncertainty and the Distribution of Price Growth

	Percentiles of the Sectoral Price Growth Distribution								
	P_{10}	P_{20}	P_{30}	P_{40}	P_{50}	P_{60}	P_{70}	P_{80}	P_{90}
Panel A: Sample 2007-2019									
Sales Uncertainty	-0.004	-0.007	-0.014	-0.003	-0.015	-0.051^{***}	-0.045^{**}	-0.045^{*}	-0.093^{***}
	(0.037)	(0.024)	(0.022)	(0.018)	(0.018)	(0.019)	(0.019)	(0.023)	(0.029)
R-squared	0.469	0.375	0.326	0.336	0.371	0.384	0.441	0.451	0.506
Observations	728	728	728	728	728	728	728	728	728
Panel B: Sample 2016-2021									
Cost Uncertainty	0.149	0.138	0.140	0.151	0.152	0.155	0.276^{*}	0.309^{*}	0.359^{*}
	(0.131)	(0.128)	(0.127)	(0.130)	(0.126)	(0.123)	(0.156)	(0.167)	(0.193)
R-squared	0.385	0.336	0.337	0.347	0.376	0.393	0.359	0.421	0.490
Observations	242	242	242	242	242	242	242	242	242
Sector effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: OLS estimates. The dependent variables are sector-level percentiles of the firm-level price growth distribution. Panel A includes sales uncertainty only, estimated over the 2007–2019 sample. Panel B includes both sales and cost uncertainty, estimated over the 2016–2021 sample. All specifications include the lagged dependent variable, sector average sales growth and price growth as first-moment controls, and sector and year fixed effects. Standard errors clustered by sector in parentheses. P_k denotes the k-th percentile of the cross-sectional distribution of firm-level price growth, where sectors are defined at the 2-digit ATECO level. * denotes a p-value $p < 0.10$, ** denotes a p-value $p < 0.05$, *** denotes a p-value $p < 0.01$.

tainty raises the upper tail of the price growth distribution as firms with greater exposure to input cost uncertainty pass that uncertainty through into higher output prices. The lower percentiles are unaffected, the same asymmetry found for sales uncertainty in Panel A. Together, the two panels show that the opposing firm-level price responses documented in Section 4.1 appear in the cross-section as compression and expansion of the upper tail of the price distribution.

These findings relate to the literature on uncertainty and price dispersion. Vavra (2014), Klepacz (2024), and Bachmann et al. (2019) find that higher volatility raises price dispersion, though through different margins.[4] Our results show that the source of uncertainty, cost or demand, determines the direction of this effect on price dispersion.

[4] Bachmann et al. (2019) use German data to show that idiosyncratic volatility raises both the probability of a price change and the size of price adjustments. Aruoba et al. (2025) find that for Chile, distress lowers the frequency of price adjustment but raises the size of adjustment conditional on a change.

5 Monetary Policy Implications of Subjective Uncertainty

We now examine the implications of subjective uncertainty for monetary policy transmission. The cross-sectional evidence in Section 4.3 establishes that sales and cost uncertainty shift the price growth distribution in opposing directions: sales uncertainty compresses the upper tail, reducing inflation pressure, while cost uncertainty expands it, raising prices at the same time that real activity contracts. These distributional shifts have direct implications for how monetary policy propagates through prices and real activity. When sales uncertainty dominates, monetary stimulus operates mainly through quantities, since the compressed upper tail leaves prices more room to adjust. By contrast, when cost uncertainty dominates, the expanding upper tail steepens the effective Phillips curve, and the nominal impulse is absorbed by prices rather than real activity.

We show that monetary policy transmission to both prices and real sales is state-dependent, depending on whether uncertainty originates in demand or in costs. Section 5.1 sets out the empirical strategy and the interaction specification. Section 5.2 describes the high-frequency monetary policy shocks and discusses identification. Section 5.3 reports the main estimates and robustness checks. Section 5.4 provides corroborating evidence from the U.S. Survey of Business Uncertainty.

5.1 Empirical Strategy

This section examines whether monetary policy transmission to prices and real sales is state-dependent, varying with the source of uncertainty firms face, and whether any such heterogeneity is consistent with the demand-supply decomposition established above.

Empirical Specification. To examine the effects of monetary policy on firm-level price growth and real sales growth under each source of uncertainty, we add interaction terms between the monetary policy shock $\varepsilon_{\text{mon},t}$ and each firm-level uncertainty measure to the baseline specification. The estimating equation, estimated separately for $y_{f,t} = \Delta P_{f,t}$ and $y_{f,t} = \Delta \text{Real Sales}_{f,t}$, is:

$$
\begin{aligned}
y_{f,t} \;=\; & \sum_{f=1}^{F} \alpha_f + \beta_\sigma^S \cdot \sigma_{f,t}^S + \beta_\sigma^C \cdot \sigma_{f,t}^C \\
& + \beta_\varepsilon^S \cdot \varepsilon_{\text{mon},t} \cdot (\sigma_{f,t}^S - \bar{\sigma}_f^S) + \beta_\varepsilon^C \cdot \varepsilon_{\text{mon},t} \cdot (\sigma_{f,t}^C - \bar{\sigma}_f^C) \\
& + \sum_{c=1}^{C} \eta_c \cdot \text{Controls}_{c,f,t} \;+\; \epsilon_{f,t},
\end{aligned}
\tag{10}
$$

where $\sigma_{f,t}^S$ and $\sigma_{f,t}^C$ denote sales and cost uncertainty as defined in Section 2.3, and $\varepsilon_{\text{mon},t}$ is the monetary policy shock. β_σ^S and β_σ^C capture the direct effects of each uncertainty source on each outcome and correspond to the estimates in Tables 2 and 3. The coefficients of interest are β_ε^S and β_ε^C, which measure whether a monetary policy shock amplifies or attenuates the response of price growth and real sales growth depending on the source of uncertainty.

Sections 4.1 and 4.2 show that demand uncertainty compresses prices while cost uncertainty raises them. If monetary policy transmission follows this same decomposition, β_ε^S and β_ε^C carry opposite signs across the two outcomes. Under demand uncertainty, firms moderate price increases, so monetary stimulus operates mainly through the quantity channel: a negative interaction term on real activity indicates amplified transmission to output, and a positive interaction term on prices indicates weaker pass-through to inflation than under average uncertainty. Under cost uncertainty the pattern reverses: firms raise prices in response to cost pressures, so monetary stimulus is less effective at stimulating real activity, and prices respond more strongly than under average uncertainty—a positive interaction term on output and a negative interaction term on inflation.

Interaction Term. The interaction terms follow Ottonello and Winberry (2020). Identifying the heterogeneous response of price growth and real sales growth to monetary policy requires demeaning each firm-level uncertainty measure using its own time-series mean before interacting it with $\varepsilon_{\text{mon},t}$. The cross-sectional mean of uncertainty may be correlated with average monetary policy transmission for reasons unrelated to the mechanism of interest: firms with persistently higher uncertainty differ from low-uncertainty firms in size, sector, and financial structure, and these differences independently shape their pricing and output responses to monetary shocks. Demeaning $\sigma_{f,t}^S$ and $\sigma_{f,t}^C$ at the firm level ensures that identification comes from within-firm variation in uncertainty around each firm's own historical average. This removes the influence of permanent firm heterogeneity and isolates the differential response of price growth and real sales growth to a common monetary shock driven by transitory fluctuations in firm-level uncertainty.

Control Variables. $\text{Controls}_{c,f,t}$ includes the same controls used in the baseline specifications of Sections 4.1 and 4.2: the expected growth rate of sales and prices one year ahead. These controls separate uncertainty effects from information embedded in firms' first-moment expectations, addressing the concern that measured uncertainty is correlated with anticipated changes in business conditions that independently affect both pricing and real activity. All specifications include firm fixed effects α_f, which absorb time-invariant heterogeneity across firms, and year fixed effects α_t, which absorb the main effect of any aggregate time-varying forces, including the monetary policy shock itself. Because the monetary policy shock enters the specification only through its interaction with firm-level uncertainty, the year fixed effects do not absorb the identifying variation of interest. Identification instead comes from cross-sectional variation in uncertainty exposure across firms within the same period: conditional on common aggregate shocks being absorbed by the time fixed effects, the differential response of firms facing high versus low uncertainty to a given monetary policy shock traces out the heterogeneous transmission mechanism that is the focus of this paper.

5.2 Measuring Monetary Policy Shocks and Identification

We identify monetary policy shocks using the high-frequency event-study measures of Altavilla et al. (2019). Their approach computes intraday asset price changes in narrow windows around ECB policy announcements, isolating the component of market movements attributable to the policy decision itself. A well-known concern with this class of measures is that raw high-frequency surprises may conflate genuine monetary policy impulses with the information the central bank conveys about its assessment of economic conditions, the central bank information effect (Jarociński and Karadi, 2020). The existence and magnitude of this effect remain debated (Miranda-Agrippino and Ricco, 2021; Bauer and Swanson, 2023*a*), and we take no stance on it here; our aim is simply to show that our results are robust regardless of which interpretation is correct. Since firms' uncertainty measures may themselves be correlated with the ECB's economic outlook, an apparently positive interaction between monetary shocks and uncertainty could reflect the ECB tightening in response to conditions that independently raise firm-level uncertainty, rather than genuine heterogeneous transmission.

We assess robustness by re-estimating the main specifications with the pure monetary policy shock of Jarociński and Karadi (2020), who decompose raw surprises into a policy component and an information component using sign restrictions on the joint co-movement of a composite interest rate factor and the Euro Stoxx 50, retaining only the component orthogonal to the information channel. Our baseline measure is the surprise in the three-month OIS rate (ΔOIS_{3M}), aggregated to annual frequency by summing announcement surprises from the last week of April to the end of year t. This window minimizes overlap with the INVIND survey, which elicits firm uncertainty between February and mid-May of year t; results are unchanged when we restrict to shocks realized after the survey closes. We also consider the one-year OIS surprise (ΔOIS_{1Y}), which loads more heavily on forward guidance and is therefore informative given that the ECB operated at or near the effective lower bound throughout 2016–2021, and a weighted annual shock that assigns greater weight to surprises occurring earlier in the year.[5] Appendix C discusses the ECB's policy stance and the implications of the effective lower bound for identification.

Identification Concerns. A related concern is the potential endogeneity of the state variable. Gonçalves et al. (2024) show that state-dependent local projections recover the true population response to structural shocks only when the conditioning state is exogenous. If the state variable responds to the same shocks used for identification, as would be the case if firms' uncertainty were itself driven by monetary policy surprises, the estimator recovers only the response to an infinitesimal shock, and threshold crossings induced by the shock of interest can contaminate the estimated interaction effects. In our setting, this concern would arise if monetary policy shocks realized between the last week of April and December of year t systematically shifted firms' uncertainty in the subsequent survey wave, moving firms across uncertainty regimes in response to the same shocks used to identify heterogeneous transmission. We address this directly in Section 5.3.1, where lagged monetary policy

[5] Formally, $\varepsilon_t^w = \sum_{q=2}^{4} w_q \, \varepsilon_{q,t}$, where $w_2 = 0.75$, $w_3 = 0.50$, and $w_4 = 0.25$. Weights are not normalized to sum to unity so that the scale of the weighted shock remains comparable to the unweighted annual sum.

shocks have no discernible effect on firm-level uncertainty, supporting the predetermined treatment of the uncertainty state in the interaction regressions.

5.3 Measuring the Effectiveness of Monetary Policy under Uncertainty

Main Results Table 5 reports estimates of equation (10) for firm-level price growth ΔP and real sales growth ΔRS. Column (1) contains the central result of this section. An accommodative monetary policy shock ($\varepsilon_{\text{mon}} < 0$) reduces price growth and stimulates real sales in the average-uncertainty environment, the standard transmission channel confirmed by the level estimates in column (4). The interaction terms ask whether this transmission is amplified or attenuated when a firm faces uncertainty above its own historical average. The estimates follow the demand-supply decomposition established in Section 4: under cost uncertainty, the transmission of monetary stimulus to real activity is attenuated and the nominal impulse falls more heavily on prices; under sales uncertainty, the price response is compressed and the real activity response is amplified.

Monetary Policy and Cost Uncertainty The interaction between the monetary policy shock and demeaned cost uncertainty, $\varepsilon_{\text{mon}} \times (\sigma^C - \bar{\sigma}^C)$, enters with a coefficient of -0.061 on price growth and 0.120 on real sales growth, both significant at the 1 percent level. A negative coefficient on ΔP together with a positive coefficient on ΔRS means that, relative to baseline, an accommodative shock generates more price growth and less real sales growth as cost uncertainty rises. The stimulus is absorbed into prices rather than quantities: monetary accommodation becomes less effective at raising real activity and more inflationary than in the average-uncertainty baseline.

Monetary Policy and Sales Uncertainty The interaction between the monetary policy shock and demeaned sales uncertainty, $\varepsilon_{\text{mon}} \times (\sigma^S - \bar{\sigma}^S)$, shows the opposite pattern: 0.010 on price growth (significant at 10 percent) and -0.095 on real sales growth (significant at 1 percent). A positive coefficient on ΔP together with a negative coefficient on ΔRS means that under elevated sales uncertainty, an accommodative shock generates less price growth and more real sales growth relative to baseline. The stimulus operates through quantities rather than prices: monetary accommodation becomes more effective at raising real activity and less inflationary than in the average-uncertainty baseline. Sales uncertainty acts as a demand shock that suppresses price adjustment and amplifies real transmission, while cost uncertainty acts as a supply shock that steepens the effective Phillips curve and shifts the impulse from output to prices.

The Effects of Monetary Policy Under Uncertainty To quantify these estimates, consider a firm that moves from the median to the 75th percentile of demeaned uncertainty, corresponding to increments of $\Delta\sigma^C = 0.7$ for cost uncertainty and $\Delta\sigma^S = 1.3$ for sales uncertainty. These increments are calibrated to the pre-Covid period (2016–2019). The percentage change in monetary policy effectiveness relative to the average-uncertainty baseline is the ratio of the interaction-induced increment, $\hat{\beta}_\varepsilon \times \Delta\sigma$, to the main effect of the monetary shock in column (4), $\hat{\beta}_{\text{mon}}$. The size of the shock cancels in this ratio.[6]

Under elevated cost uncertainty, the pass-through of monetary stimulus into output prices is amplified by approximately 27 percent, while its effectiveness at stimulating real sales falls by approximately 38 percent relative to the average-uncertainty baseline. Firms already adjusting prices in response to cost pressures absorb the nominal impulse into output prices, crowding out the real activity response. Under elevated sales uncertainty, the pattern reverses. Monetary stimulus becomes approximately 55 percent more effective at raising real sales growth, while its pass-through to price growth is attenuated by approximately 8 percent relative to baseline. Firms uncertain about future revenues let the stimulus translate into real activity rather than prices. This pattern matches the cross-sectional evidence in Section 4.3: under sales uncertainty, the compressed upper tail of the price distribution leaves room for the nominal impulse to operate through quantities; under cost uncertainty, the expanding upper tail absorbs the stimulus into prices and crowds out the real activity response. The firm-level interaction effects are the micro-level counterpart of these distributional shifts.

[6]Formally, the percentage change in effectiveness is $(\hat{\beta}_\varepsilon \times \Delta\sigma \,/\, \hat{\beta}_{\text{mon}}) \times 100$, where $\hat{\beta}_{\text{mon}}$ is taken from column (4) — -0.156 for ΔP and -0.223 for ΔRS — and $\hat{\beta}_\varepsilon$ is the relevant interaction coefficient from column (1). For cost uncertainty ($\Delta\sigma^C = 0.7$): price response change $= (-0.061 \times 0.7) \,/\, (-0.156) \approx 0.274$; real sales response change $= (0.120 \times 0.7) \,/\, (-0.223) \approx -0.377$. For sales uncertainty ($\Delta\sigma^S = 1.3$): price response change $= (0.010 \times 1.3) \,/\, (-0.156) \approx -0.083$; real sales response change $= (-0.095 \times 1.3) \,/\, (-0.223) \approx 0.554$.

Robustness I: Inclusion of Interactions with First-Moment Expectations Columns (2) and (3) of Table 5 add interactions of the monetary shock with the first-moment expectations of sales growth and price growth, to check that the interaction effects in column (1) reflect genuine uncertainty transmission rather than the co-movement of uncertainty with expected business conditions. In column (2), the interaction $\varepsilon_{\text{mon}} \times \Delta\text{Sales}^e$ enters with coefficients of 0.006 on ΔP and -0.027 on ΔRS, neither significant. In column (3), the interaction $\varepsilon_{\text{mon}} \times \Delta P^e$ enters with -0.076 on ΔP and 0.053 on ΔRS, also insignificant. Across both columns, the coefficients on the uncertainty interaction terms are unchanged from column (1) in magnitude and significance. This stability indicates that the interaction effects are not driven by firms with higher uncertainty also having different first-moment expectations: the second moment of the firm's subjective forecast distribution carries information about monetary policy transmission that the first moment does not capture.

Robustness II: Consistency Across Alternative Shock Measures. Table *A*.5 in Appendix D reports estimates under three alternative monetary policy shock measures: ΔOIS_{3M} in column (1), ΔOIS_{1Y} in column (2), and the information-purged shock of Jarociński and Karadi (2020) in column (3). The sign pattern and interpretation of all interaction terms are unchanged across the three columns. Under ΔOIS_{1Y}, the magnitudes are larger: -0.073 and 0.264 for the cost uncertainty interaction on ΔP and ΔRS, and 0.010 and -0.202 for sales uncertainty. This is consistent with the one-year OIS capturing more persistent policy signals that firms incorporate more fully into pricing and real activity decisions. The pure monetary policy shock of Jarociński and Karadi (2020) yields interactions of -0.034 and 0.093 for cost uncertainty and 0.011 and -0.082 for sales uncertainty, smaller than the raw OIS measures but with the same sign pattern and statistical significance. The smaller magnitude is expected: purging the central bank information component removes variation that may be correlated with firms' cost conditions, leaving a cleaner but smaller source of identifying variation. The stability of the sign pattern across measures spanning different maturities, different treatments of the effective lower bound period, and different approaches to the information channel indicates that the heterogeneous transmission of monetary policy under demand and cost uncertainty is a structural feature of the data rather than an artifact of a particular identification choice.

Table 5: Monetary Policy Transmission under Sales and Cost Uncertainty

	(1)		(2)		(3)		(4)	
	ΔP	ΔRS	ΔP	ΔRS	ΔP	ΔRS	ΔP	ΔRS
$\varepsilon_{\text{mon}} \times (\sigma^C - \bar{\sigma}^C)$	-0.061^{***}	0.120^{***}	-0.058^{***}	0.111^{**}	-0.045^{**}	0.108^{**}		
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.05)		
$\varepsilon_{\text{mon}} \times (\sigma^S - \bar{\sigma}^S)$	0.010^{*}	-0.095^{***}	0.008	-0.083^{***}	0.013^{**}	-0.099^{***}		
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)		
$\varepsilon_{\text{mon}} \times \Delta\text{Sales}^e$			0.006	−0.027				
			(0.01)	(0.02)				
$\varepsilon_{\text{mon}} \times \Delta P^e$					−0.076	0.053		
					(0.06)	(0.06)		
ε_{mon}							-0.156^{***}	-0.223^{*}
							(0.06)	(0.13)
Cost Uncertainty (σ^C)	0.183^{***}	-0.327^{***}	0.172^{***}	-0.329^{***}	0.142^{**}	-0.319^{**}	0.090	−0.181
	(0.06)	(0.12)	(0.06)	(0.13)	(0.06)	(0.13)	(0.06)	(0.13)
Sales Uncertainty (σ^S)	-0.089^{***}	0.102	-0.077^{**}	0.115	-0.083^{***}	0.132	-0.049^{**}	0.034
	(0.03)	(0.09)	(0.03)	(0.09)	(0.03)	(0.09)	(0.02)	(0.08)
Monetary Shock	ΔOIS_{3M}		ΔOIS_{3M}		ΔOIS_{3M}		ΔOIS_{3M}	
First-moment controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm-specific effects	✓	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓		
Macro effects							✓	✓
R-squared	0.561	0.618	0.582	0.554	0.585	0.553	0.541	0.612
Observations	2,488	2,488	2,443	2,443	2,443	2,443	2,488	2,488
Sample period	2016–2021	2016–2021	2016–2021	2016–2021	2016–2021	2016–2021	2016–2021	2016–2021

Notes: The dependent variables are firm price growth ΔP and real sales growth ΔRS. σ^C and σ^S denote cost and sales uncertainty respectively, demeaned at the firm level ($\sigma^C - \bar{\sigma}^C$ and $\sigma^S - \bar{\sigma}^S$) prior to interaction following Ottonello and Winberry (2020). ε_{mon} is the annual sum of three-month OIS surprises (ΔOIS_{3M}) from Altavilla et al. (2019), aggregated from the last week of April to the end of year t. Column (2) adds the interaction of the monetary shock with expected sales growth. Column (3) adds the interaction with expected price growth. Column (4) drops time effects to estimate the main effect and, given the absence of time effects, includes lagged core CPI and GDP growth as macro controls. Columns (1) through (3) include first-moment expectations of Δ prices and Δ real sales, and firm and year fixed effects. Standard errors in parentheses, clustered by firm. * denotes p-value $p < 0.10$, ** denotes p-value $p < 0.05$, *** denotes p-value $p < 0.01$.

Robustness III: Results with SIGE Table *A.7* in Appendix D reports evidence from an alternative dataset that merges quarterly price observations from SIGE with the annual uncertainty measures from INVIND. This exercise checks that the main results are not an artifact of the annual aggregation of monetary policy shocks or of the frequency at which firm outcomes are observed, and traces the dynamic response of price growth across quarterly horizons. Since INVIND elicits expectations once per year, the uncertainty measures are held constant within the year; identification exploits within-year variation in quarterly monetary policy shocks, conditioning on a predetermined uncertainty state.

The results match the annual estimates. The level effects of sales and cost uncertainty on price growth retain their signs across significant horizons, negative for sales uncertainty and positive for cost uncertainty, confirming that the source of uncertainty determines the direction of the price response. The interaction terms reinforce the main result in Table 5: under elevated sales uncertainty, monetary stimulus generates less price growth than at baseline, with the effect significant on impact and at a three-quarter horizon; under elevated cost uncertainty, the same accommodative shock generates more price growth, with significant effects at $h = 0$ and $h = 3$. The differential transmission dissipates by $h = 4$, consistent with the annual estimates capturing the net effect over a full twelve-month window.

5.3.1 Response of Uncertainty to Monetary Policy Shocks

A necessary condition for the interaction estimates in Table 5 to identify heterogeneous monetary policy transmission is that the uncertainty measures are not themselves systematically driven by the monetary policy shocks used for identification. The timing of the INVIND survey provides a natural safeguard: uncertainty is elicited between February and the first two weeks of May of year t, while the monetary policy shocks are aggregated from the last week of April to December of the same year, so the overlap between the two windows is minimal. Results using shocks realized after INVIND closes are unchanged. The more substantive concern, raised by Gonçalves et al. (2024), is whether monetary conditions in the preceding year shift firms across uncertainty regimes, which could bias the interaction estimates.

Table 6 addresses this directly by regressing firm-level cost and sales uncertainty on monetary policy shocks lagged one year. Across all three shock measures, unweighted ΔOIS_{3M}, weighted ΔOIS_{3M}, and the pure monetary policy shock of Jarociński and Karadi (2020), the estimated coefficients are small and statistically indistinguishable from zero. Monetary conditions in year $t-1$ do not predict firm-level uncertainty in year t, for either uncertainty source. This evidence does not establish strict exogeneity of the state variable, but it indicates that any misclassification of uncertainty regimes induced by prior monetary policy shocks is quantitatively minor, and that the interaction estimates in Table 5 are unlikely to be meaningfully affected by endogenous state transitions of the kind discussed in Gonçalves et al. (2024). Firm-level uncertainty appears to reflect primarily idiosyncratic factors, such as firm-specific demand and cost conditions. The variation in these factors is large relative

Table 6: Lagged Monetary Policy Shocks and Uncertainty

	(1)		(2)		(3)	
	Cost Unc. σ^C	Sales Unc. σ^S	Cost Unc. σ^C	Sales Unc. σ^S	Cost Unc. σ^C	Sales Unc. σ^S
$\Delta \text{OIS}_{3M,t-1}$	0.024	-0.037				
	(0.07)	(0.11)				
$\Delta \text{OIS}_{3M,t-1}$ (weighted)			-0.217	-0.249		
			(0.25)	(0.37)		
JK $\texttt{mp\_pm}_{t-1}$					0.022	-0.011
					(0.03)	(0.05)
Firm-specific effects	✓	✓	✓	✓	✓	✓
R-squared	0.599	0.596	0.599	0.596	0.599	0.596
Observations	2,777	2,777	2,777	2,777	2,777	2,777

Notes: The dependent variables are cost uncertainty σ^C and sales uncertainty σ^S, measured at the beginning of year t when INVIND is administered. The regressors are monetary policy shocks lagged one year ($t-1$), ensuring that the shocks are predetermined with respect to the uncertainty measures. This timing is the correct test of exogeneity: since the shocks used in the transmission analysis occur after uncertainty is elicited, the relevant concern is whether monetary conditions in the *preceding* year systematically predict current firm-level uncertainty. Column (1) uses the unweighted annual sum of three-month OIS surprises (ΔOIS_{3M}) from Altavilla et al. (2019). Column (2) uses the weighted sum of ΔOIS_{3M}, assigning greater importance to shocks occurring earlier in the year. Column (3) uses the pure monetary policy shock (mp_pm) from Jarociński and Karadi (2020), which separates monetary policy surprises from ECB information effects via a penalty function approach. The absence of statistically significant coefficients across all columns indicates that monetary conditions in the preceding year do not systematically predict firm-level uncertainty, supporting the exogeneity of the shock measures used in Table 5. All specifications include firm fixed effects. Standard errors in parentheses, clustered by firm. * denotes p-value $p < 0.10$, ** denotes p-value $p < 0.05$, *** denotes p-value $p < 0.01$.

to aggregate monetary conditions, which leave no detectable imprint on the cross-sectional distribution of uncertainty.

5.4 U.S. Evidence: Survey of Business Uncertainty

We complement the Italian evidence with data from the Survey of Business Uncertainty (SBU), a monthly panel survey of US firms conducted by the Federal Reserve Bank of Atlanta (Altig et al., 2022). The SBU shares the key design feature of INVIND: it elicits subjective probability distributions from senior managers over own-firm outcomes at a one-year look-ahead horizon, giving firm-level measures of both the mean and the standard deviation of expected future outcomes. Sales growth expectations and uncertainty are available at bimonthly frequency from 2016; from 2024 the survey moved to quarterly frequency and extended coverage to price growth expectations and uncertainty, with prices and sales collected in consecutive non-overlapping months. These data limitations constrain the analysis to a subset of the results established for Italy, which we treat as cross-country corroboration rather than a full replication.

Table 7 shows that the qualitative patterns documented for Italian firms carry over to the US setting. Controlling for first-moment expectations, price uncertainty σ^P enters positively on realized price growth on impact: a one-standard-deviation increase (0.024) raises price growth by approximately 0.38 percentage points. Sales uncertainty σ^S enters negatively on real sales growth: a one-standard-deviation increase (0.046) lowers real sales growth by approximately 1.66 percentage points. Both signs match the demand-supply decomposition of Section 4: price uncertainty raises prices while sales uncertainty contracts real activity. Two features of the data are worth noting. First, the sample differs across specifications: price uncertainty is available only from 2024, so joint specifications draw on a shorter sample than the single-outcome columns. Second, since price and sales expectations are elicited in consecutive non-overlapping months, so sales uncertainty enters the joint regressions with a one-period lag.

The monetary policy exercise on SBU data, using the high-frequency shocks of Bauer and Swanson (2023*b*) for the long sample and the shocks of Acosta et al. (2025) where the Bauer-Swanson series is unavailable, and reported in full in Appendix E, tells a story broadly consistent with the Italian evidence. Under elevated sales uncertainty, monetary stimulus generates less price growth and more real sales growth than at baseline. Under elevated price uncertainty, the stimulus falls more heavily on prices and less on real activity, the same pattern documented for Italian firms. A firm moving from the median to the 75th percentile of sales uncertainty experiences a price pass-through attenuated by approximately 38 percent and a real sales response amplified by approximately 28 percent; under price uncertainty, the same interquartile shift amplifies price pass-through by approximately 23 percent and attenuates the real sales response by approximately 31 percent.

Two caveats apply. First, the joint price and sales specifications are available only from June 2024, limiting the precision of the price uncertainty estimates, which we treat as suggestive rather than conclusive. Second, the SBU elicits expectations over nominal sales revenue growth, while INVIND asks about real sales growth; to the extent that nominal and real sales uncertainty differ, particularly in high-inflation episodes, direct comparisons of magnitudes should be interpreted with this difference in mind. The appendix reports the long-sample

Table 7: U.S. Data: Prices and Real Sales Growth Responses to Uncertainty

	Panel A: Price Growth					
	Prices only			Prices and Sales		
	$h = 0$	$h = 3$	$h = 6$	$h = 0$	$h = 3$	$h = 6$
Price Uncertainty (σ^P)	0.163***	0.113*	0.013	0.182**	−0.053	−0.102
	(0.05)	(0.07)	(0.09)	(0.08)	(0.09)	(0.10)
Sales Uncertainty (σ^S) (-1)				0.072	−0.104*	−0.090
				(0.05)	(0.06)	(0.07)
R-squared	0.606	0.657	0.719	0.595	0.643	0.771
Observations	3,605	2,045	1,380	1,666	1,159	808
	Panel B: Real Sales Growth					
	Sales only			Prices and Sales		
	$h = 0$	$h = 2$	$h = 4$	$h = 2$	$h = 5$	$h = 8$
Sales Uncertainty (σ^S) (-1)	−0.362***	−0.093	−0.141*	−0.439**	−0.058	−0.563
	(0.07)	(0.07)	(0.08)	(0.19)	(0.27)	(0.42)
Price Uncertainty (σ^P)				−0.046	−0.636*	−0.125
				(0.29)	(0.36)	(0.56)
R-squared	0.332	0.313	0.332	0.568	0.645	0.739
Observations	8,765	8,819	7,347	1,103	770	404
Firm-specific effects	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓

Notes: Sample period ranges between $2024 : M6$ to $2025 : M9$ for Panel A and Panel B "Prices and Sales". For Panel B "Sales only" the sample period $2016 : M9$ to $2023 : M6$ The dependent variables are firm price growth (Panel A) and real sales growth (Panel B) at horizon h quarters ahead, from the Survey of Business Uncertainty (Altig et al., 2022). ΔPrice^e and ΔSales^e denote the mean of managers' price and real sales growth expectations (`price_gr_dhsforecast` and `sr_gr_dhsforecast`) respectively. σ^P and σ^S denote price and sales uncertainty, measured by the standard deviation of the corresponding expectations (`price_gr_dhssd` and `sr_gr_dhssd`). In the joint specifications (right three columns of each panel), the expectations and uncertainty of the other outcome variable enter with a one-period lag. All specifications include firm and time fixed effects. Standard errors in parentheses, clustered by firm. * denotes $p < 0.10$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

sales uncertainty evidence and robustness to first-moment controls.

Taken together, the SBU evidence shows that the differential transmission of monetary policy under demand and price uncertainty is not specific to the Italian institutional context or to the INVIND survey design. The pattern extends to the U.S. setting and appears to be a general feature of firm-level monetary policy transmission.

6 Uncertainty, Monetary Policy, and the Covid Experience

Cost and demand uncertainty have opposite effects on monetary policy transmission, and the direction depends entirely on the source. A median-to-75th-percentile increase in cost uncertainty raises inflationary pass-through by 27 percent and reduces the real output response by 38 percent; the same increase in demand uncertainty amplifies the real output response by 55 percent and reduces inflationary pass-through by only 8 percent. The source of uncertainty determines which margin monetary policy hits.

The Covid period illustrates this mechanism directly. Both cost and demand uncertainty surged between 2019 and 2021, but they hit different parts of the economy—the correlation between the two firm-level series is 0.25, similar to the pre-Covid period [INSERT PRE-COVID CORRELATION], suggesting the sectoral sorting predates the pandemic. Cost uncertainty rose more sharply among manufacturers and importers, where supply chain disruptions and input price volatility drove cost uncertainty higher; demand uncertainty rose more sharply among service providers, where pandemic-driven swings in spending patterns drove demand uncertainty higher. The p1–p99 trimmed mean of demeaned cost uncertainty rose from $(\sigma^C - \bar{\sigma}^C) = 0.097$ in 2019 to 0.551 in 2020 and 0.673 in 2021; the same statistic for demand uncertainty shifted from $(\sigma^S - \bar{\sigma}^S) = -0.439$ in 2019 to 1.753 in 2020 and 1.890 in 2021. Both channels operated simultaneously. Cost uncertainty pushed the monetary impulse into prices, amplifying inflationary pass-through by approximately 22 percent in 2020 and 26 percent in 2021; demand uncertainty pushed it into quantities, amplifying the real sales response by approximately 75 percent in 2020 and 80 percent in 2021. The aggregate result was monetary accommodation that was simultaneously more inflationary and more stimulative than the pre-pandemic baseline—a combination that a single uncertainty index cannot recover.

These findings connect to the literature on volatility and monetary non-neutrality. Vavra (2014) shows that higher volatility raises the frequency of price adjustment and reduces the real effects of nominal stimulus by approximately 55 percent. Klepacz (2024) shows that aggregate cost volatility raises price dispersion without raising adjustment frequency, shutting down this channel. Both papers study a single source of volatility. Our results suggest that whether this channel is operative depends on whether the underlying volatility originates in demand or costs.

Our findings also reframe the aggregate evidence that uncertainty dampens the real effects of monetary policy (Aastveit, Natvik and Sola, 2017; Castelnuovo and Pellegrino, 2018; Caggiano, Castelnuovo and Pellegrino, 2023; Pellegrino, 2021). That result holds when supply uncertainty dominates, as in samples that include episodes of oil price volatility, but reverses when demand uncertainty dominates. The aggregate literature pools two regimes with opposite implications, and the sign of the net effect in any given sample depends on their relative intensity. This is consistent with Castelnuovo, Pellegrino and Særkjær (2025), who show that monetary effectiveness depends on trend inflation through the price-flexibility channel: when trend inflation is high, prices adjust more frequently and accommodation shifts from output to prices, consistent with what we find under elevated cost uncertainty.

A policymaker who observes a rise in aggregate uncertainty cannot infer, from that measure alone, whether accommodation will transmit to prices or to output. Demand uncertainty and cost uncertainty are largely orthogonal and push transmission in opposite directions. Identifying which source is driving the rise in uncertainty is necessary to determine the direction and magnitude of monetary policy transmission.

7 Conclusion

The source of uncertainty determines its effect on prices. Using firm-level survey data from Italy and the United States, we show that demand uncertainty—measured as the dispersion of expected sales growth—reduces price growth and contracts real activity, consistent with a negative demand shock. Supply uncertainty—measured as the dispersion of expected price growth—raises price growth while also contracting real activity, consistent with a negative supply shock. Standard uncertainty measures conflate these two channels, recovering a net effect whose sign depends on which source dominates in a given sample.

This distinction has direct implications for monetary policy transmission: under elevated supply uncertainty, the price pass-through of an accommodative shock rises by 25 percent and its effect on real output falls by 40 percent; under elevated demand uncertainty, the pattern reverses, with the real output response amplified by 50 percent. The same aggregate level of uncertainty can therefore correspond to opposite policy implications, depending on a composition that aggregate measures do not observe. Our results reconcile evidence that uncertainty amplifies inflationary pressure and dampens real activity in some samples (Aastveit, Natvik and Sola, 2017; Castelnuovo and Pellegrino, 2018; Castelnuovo, Pellegrino and Særkjær, 2025) with evidence that it compresses prices and output in others (Coibion, Gorodnichenko and Kumar, 2023; Bachmann et al., 2020): both are correct, for the regime they study.

Our approach—measuring demand and supply uncertainty separately using subjective probability distributions elicited directly from firms—is made possible by survey designs that ask managers for both a point forecast and a range around it. The replication of our results in the United States, despite differences in survey design, sample period, and institutional context, suggests that the distinction between demand and supply uncertainty is a structural feature of firm pricing behavior rather than a feature of the Italian setting.

Our evidence is at the level of prices and quantities; whether the channels we identify operate through the frequency or the size of price adjustments, in the spirit of Vavra (2014), Klepacz (2024), and Aruoba et al. (2025), and how the two channels interact over the business cycle, are questions for future work. A single notion of uncertainty is not sufficient to answer them.

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Online Appendix

A Data Sources

A.1 INVIND Data

Our data on expectations come from the Survey of Industrial and Service Firms (INVIND), a large annual business survey conducted by the Bank of Italy on a representative sample of Italian firms. Since 2002, the target population has comprised firms with at least 20 employees operating in industry (manufacturing, energy, and extractive sectors) and non-financial private services, as well as firms with at least 10 employees in the construction sector, all with administrative headquarters in Italy. The survey adopts a one-stage stratified sample design, where strata are defined by branch of activity (according to an 14-sector classification, see Table $A.1$), size class (measured by number of employees, classified into seven buckets), and region of the firm's head office. In recent years, each wave has comprised around 5,000 firms, of which approximately 3,000 operate in industrial sectors, 1,000 in services, and 600 in construction. The sampling fractions are higher for firms with 50 or more workers and firms in the South and Islands.

Table $A.1$: Sector aggregation used in the survey

Main sector	NACE section	NACE divisions	Economic activity
Industry excl. construction	C	10–12	Food products
	C	13–15	Textiles, clothing
	C	19–22	Chemical products
	C	23	Non-metallic minerals
	C	24–30, 33	Basic metals and engineering
	C	16–18, 31–32	Other manufactures
	B	05–09	Mining and quarrying
	D–E	35–39	Electricity and water supply
Construction	F	41–43	Construction
Private non-financial services	G	45–47	Wholesale and retail trade
	I	55–56	Lodging and catering
	H	49–53	Transport and storage
	J	58–63	Information and communication
	L, M, N	68–75, 77–82	Other services

Notes: L = real-estate activities; M = professional, scientific and technical activities; N = renting, travel agencies, and support services to enterprises.

The data are collected by the Bank of Italy's local branches between February and May of each year. A key advantage of INVIND relative to Cerved is that it provides both realized price changes and managers' expectations about future sales and prices. On average, nearly 60% of survey respondents hold managerial positions within their firms. The question on the maximum and minimum expected growth rates of sales, which forms the basis of our max–min measure of uncertainty, is answered by roughly half of the respondents. The dataset has a panel dimension: firms observed in the previous wave are contacted again if they remain part of the target population, while those no longer willing to participate are replaced by firms in the same branch of activity and size class. To limit the influence of outliers, we winsorize the 1% tails of all variables. Below we report the survey question used to elicit respondents' maximum and minimum expected sales growth rates.

Figure *A*.1 reproduces the original survey questions from INVIND. Firms are asked to report total sales for the past year (`v209`), the current year (`v210`), and the year ahead (`v437`). Although a breakdown by domestic and foreign sales is also elicited, the available information is insufficient to separately identify the two components in a meaningful way, and we therefore work with total sales throughout. A parallel set of questions elicits the average price change of the goods sold by the firm, both for the current year (`v220A`) and the year ahead (`v440`); firms are additionally asked to provide a minimum (`MINV440`) and a maximum (`MAXV440`) around their price growth forecast, which we use to construct our measure of price uncertainty. Finally, firms are asked about the expected growth rate of real sales — net of price changes — for the year ahead (`V540`), together with a minimum (`V541`) and a maximum (`V542`) around that forecast, which form the basis of our sales uncertainty measure.

Figure *A*.1: INVIND Survey Questions: Sales and Price Expectations

Fatturato, prezzi e risultato di esercizio

Fatturato *(in migliaia di euro)*	**2018**	**2019**	**Prev. 2020**	**Prev. 2020/2019**
Fatturato per vendita di beni e servizi nell'anno	V209	V210	V437	V539 % (a)
- di cui: per esportazione	V211	V212	V438	(a) *Calcolato come: (fatturato 2020/2019 - 1) * 100*

Fatturato per vendita di beni e servizi nell'anno. Includere i ricavi derivanti da: vendita di beni e/o servizi dell'impresa, lavorazioni eseguite per conto terzi, vendita di prodotti rivenduti senza trasformazione da parte dell'impresa, prestazioni di servizi industriali.

Variazione percentuale media annua dei prezzi dei beni e dei servizi da Voi **fatturati**	**2019/2018**		**Previsione 2020/2019**
- mercato interno ed estero	% V220A	(b)	% V440
- solo mercato interno	% V220AI		% V220AIP
- solo mercato estero *(in euro)*	% V220AE		% V220AEP

Sapreste fornire un intervallo per la **variazione** dei prezzi dei beni fatturati dall'impresa **prevista** per il 2020/2019?	*Minimo (segno e var. %)*	% MINV440	*Massimo (segno e var. %)*	% MAXV440

In termini di **variazioni percentuali 2020/2019** Voi avete già fornito una previsione di fatturato, al netto delle variazioni percentuali dei prezzi, approssimativamente pari al *(segno e variazione percentuale)* .... *(calcolare come* ***(a)-(b)****)* % V540 (c)

Sapreste fornire un intervallo intorno a questo valore, cioè fornire una **previsione** di **variazione** minima e massima del fatturato (anch'essa al netto della variazione dei prezzi)? .... *Minimo (segno e var. %)* % V541 *Massimo (segno e var. %)* % V542

A.2 SIGE Data

The Survey on Inflation and Growth Expectations (SIGE) is a quarterly rotating panel survey conducted by the Bank of Italy since 1999Q4. It collects information from approximately 1,000 Italian industrial, service, and construction firms with at least 50 employees, stratified by number of employees, geographical area, and sector. The survey elicits point estimates of consumer inflation expectations over horizons of six months, one year, and two years ahead, as well as reported changes in firms' own selling and purchasing prices and expectations of sales and employment conditions. The data collection takes place over approximately three weeks during the last month of each reference quarter.

As shown in Figure *A*.2, the two surveys display broad agreement in the distribution of firm-level price changes despite differences in sample composition, timing, and survey design. To ensure a like-for-like comparison, we collapse the quarterly SIGE price changes to an annual frequency before comparing them with the INVIND measures. This agreement lends credibility to the distributional patterns documented in Section 4.3 and supports the use of INVIND price uncertainty as a proxy for cost uncertainty in the SIGE-based specifications. Annual firm-level price change measures of this kind have been widely used in the pricing literature to document the key stylized facts of price-setting behavior and to discipline structural menu-cost models (Vavra, 2014; Klepacz, 2024).

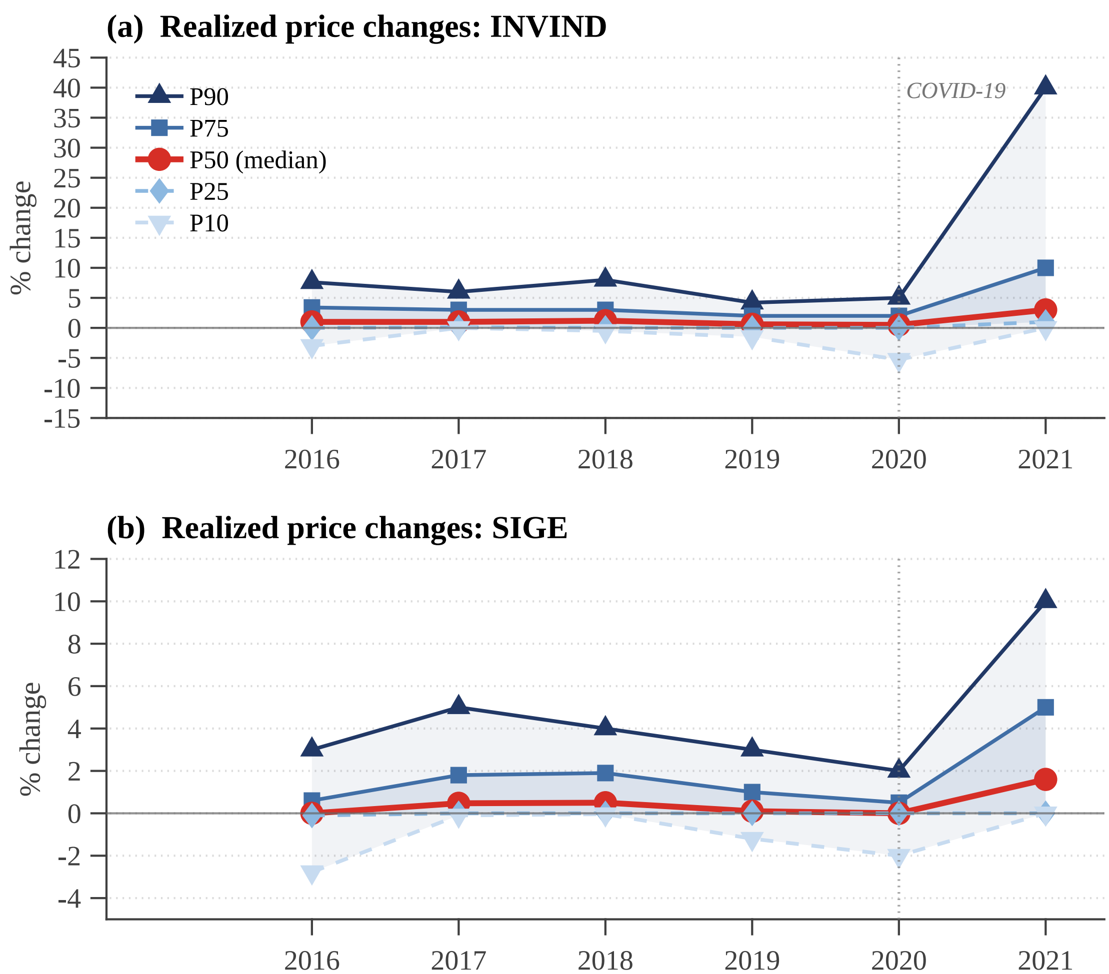
Figure *A*.2 shows that they track the same aggregate dynamics remarkably closely: both sources record subdued and stable price changes over 2015–2019, a mild compression in 2020, and a sharp broad-based surge in 2021, consistent with the post-pandemic inflationary episode. The broad agreement across sources—despite differences in sample composition, timing, and survey design—lends credibility to the distributional patterns we document and supports the use of price uncertainty from INVIND as a proxy for cost uncertainty in the SIGE-based specifications. This type of annual price-change measure has been widely employed in the firm-level pricing literature to document the key stylized facts of price-setting behavior and to discipline structural menu-cost models.

A.3 Cerved Data

Detailed information on yearly balance sheets comes from Cerved Group S.P.A. (Cerved database), while data on employment and wages are obtained from the Italian National Institute of Social Security (INPS). Industry-specific price deflators and depreciation rates are obtained from the Italian National Statistical Institute (ISTAT). Sectors are constructed by aggregating available data from two-digit industries, according to the 2007 NACE classification. The agricultural sector includes industries 1, 2, 3, and 8. The manufacturing sector comprises industries 10, 11, and 13-33.

Electricity and gas supply includes industry 35. The water supply sector includes industries 36-39. The construction sector includes industries 41-43. The wholesale and retail trade sector includes industries 45-47. The transportation and storage activities sector includes industries 49-53. The accommodation and food service sector includes industries 55 and 56. The information and communication sector includes industries 58-63. The financial and insurance activities sector includes industry 66. The real estate activities sector includes industry 68. The professional, scientific, and technical activities sector includes industries 69-75. The administrative and support service activities sector includes industries 77-82. The public administration and defense sector includes industry 85. The education sector includes industries 86-88. The human health and social work sector includes industries 90-93. The other activities sector includes industries 95 and 96. The composition of the data set by sector is reported in Table *A*.2.

Figure A.2: Cross-sectional distribution of firm-level prices in INVIND and SIGE, 2015–2021



Note: The figure reports the P10, P25, P50 (median), P75, and P90 percentiles of the cross-sectional distribution of firm-level 12-month price inflation across survey waves from 2015 to 2021. The shaded areas indicate the interquartile range (dark) and the P10–P90 range (light). The vertical dotted line marks the onset of the COVID-19 pandemic in 2020.

Table $A.2$: Sectoral Data

Sector	No. of Obs.
Agriculture, forestry, and fishing	96,087
Manufacturing	1,487,826
Electricity and gas supply	12,324
Water supply	40,249
Construction	614,258
Wholesale and retail trade	1,324,078
Transportation and storage activities	189,789
Accommodation and food service	267,581
Information and communication	223,826
Financial and insurance activities	25,160
Real estate activities	60,759
Professional, scientific, and technical activities	224,766
Administrative and support service activities	172,656
Public administration and defense	31,138
Education	121,044
Human health and social work	66,950
Other activities	46,403

B IV Robustness: Alternative Instruments and Timing of Instruments

B.1 Alternative Instruments and Covid Exclusion

Alternative sales uncertainty instrument. To assess whether the baseline EPU-based results reflect genuine sales uncertainty effects rather than EPU-specific channels, we construct an alternative instrument based on firm-level sensitivity to the EUR/GBP exchange rate. The United Kingdom is Italy's largest non-EU export market, so EUR/GBP fluctuations generate revenue uncertainty whose incidence varies across industries according to their historical reliance on UK markets. Because EUR/GBP volatility is driven by forces largely distinct from those underlying EPU—including post-Brexit trade policy and Bank of England monetary policy—it constitutes an informative out-of-sample check. The instrument is:

$$z_{f,t-1}^{S,\text{EURGBP}} = \left|\beta_{j,\tau-1}^{\text{EURGBP},s}\right| \cdot \Delta\sigma_{t-1}^{\text{EURGBP}} \tag{A.1}$$

where $\beta_{j,\tau-1}^{\text{EURGBP},s}$ is the lagged sensitivity of industry j's sales growth to EUR/GBP, estimated from equation (1) on Cerved data, and $\Delta\sigma_{t-1}^{\text{EURGBP}}$ is the lagged change in realized EUR/GBP volatility. Since $\beta_{j,\tau-1}^{\text{EURGBP},s}$ is recovered from the same equation, the switch from $z_{f,t-1}^{S}$ to $z_{f,t-1}^{S,\text{EURGBP}}$ requires no additional estimation and preserves predetermination of the exposure weight. The exclusion restriction requires that, conditional on the EUR/GBP level and firm fixed effects, differential industry exposure to EUR/GBP volatility shifts sales uncertainty without independently affecting pricing margins—a restriction most credible for firms whose exposure reflects historical trade relationships rather than active financial hedging.

Sales uncertainty reduces both price growth and real sales growth under the UK instrument, as it does under the Italy EPU instrument, in both the 2007–2019 and 2007–2021 samples. The coefficients are larger in magnitude under the UK instrument, but the first-stage F-statistics are weaker: three of the four UK specifications fall below the conventional threshold of 10, most notably for real sales growth in the 2007–2021 sample ($F = 4.76$).

Table *A*.3: Sales Uncertainty: Italy vs. EURGBP Instruments

	Italy EPU Instrument		EURGBP Instrument	
	ΔPrices	ΔSales	ΔPrices	ΔSales
Panel A: Sample 2007–2019				
Sales Uncertainty	-0.533^{*}	-1.859^{***}	-0.776^{**}	-2.272^{*}
	(0.30)	(0.58)	(0.32)	(1.34)
Observations	10,126	7,752	10,124	7,635
First-stage F-test	40.76	45.61	11.60	8.42
Panel B: Sample 2007–2021				
Sales Uncertainty	-0.881^{**}	-1.819^{***}	-0.743^{**}	-3.803^{*}
	(0.41)	(0.61)	(0.32)	(2.06)
Observations	12,331	9,292	12,331	9,174
First-stage F-test	24.89	37.29	8.42	4.76

IV estimates. Dependent variables are price growth (ΔPrices) and real sales growth (ΔSales). Sales uncertainty is instrumented using the Italy EPU instrument (columns 1–2) and the UK instrument (columns 3–4). Panel A covers the 2007–2019 sample; Panel B extends the sample to 2007–2021. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Timing

Table *A*.4 To assess the robustness of the timing of the exposure to factors, we now use a two-year lag of the measured exposure to EPU and OIL ($\beta^{c}_{j,t-2}$) in the construction of the instrument z, rather than a one-year lag as in the baseline.

C ECB Monetary Policy Stance, 2016–2021: Identification and the Information Channel

The Effective Lower Bound and the Shift in Policy Instruments. During the period spanning 2016 to 2021, the ECB's monetary policy stance was characterized by a sustained com-

Table $A.4$: Alternative Exposure: Prices and Real Sales Growth Responses to Uncertainty

	Sales Uncertainty		Cost Uncertainty	
	ΔPrices	ΔSales	ΔPrices	ΔSales
Coefficient	-1.266^{***}	-1.892^{***}	1.181^{*}	-1.072^{*}
	(0.37)	(0.58)	(0.69)	(0.62)
Observations	10,130	7,752	2,330	2,190
First-stage F-stat	9.45	15.26	11.78	10.80
Sample period	2007–2019	2007–2019	2016–2021	2016–2021
IV first-moment exposure	✓	✓	✓	✓
Firm-specific effects	✓	✓	✓	✓
Sector effects	✓	✓	✓	✓
Time effects	✓	✓	✓	✓

IV estimates. Columns (1) and (2): long sample 2007–2019, sales uncertainty only, instrumented with EPU volatility interacted with two-year pre-determined industry-level exposures to EPU. Columns (3) and (4): restricted sample 2016–2021, cost uncertainty measured as the within-firm max-minus-min range of price expectations (`p_maxmin`), instrumented with oil price volatility interacted with two-year pre-determined industry-level price sensitivities; sales uncertainty enters as a control. All columns include first-moment expectations of Δ prices and Δ real sales, and firm, sector, and year fixed effects. Columns (1) and (2) also include the lagged dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

mitment to highly accommodative conditions operating at — and in several dimensions beyond — the effective lower bound (ELB). While the main refinancing operations (MRO) rate had historically served as the primary instrument signaling the stance of monetary policy since the inception of the euro area in 1999, the deposit facility rate (DFR) effectively assumed that role from 2016 onwards, as the corridor system collapsed into a floor regime driven by the structural excess liquidity generated through the Asset Purchase Programme (APP) and successive rounds of Targeted Longer-Term Refinancing Operations (TLTROs). With the MRO anchored at zero percent and the DFR held at -0.40 percent throughout most of the sample — and temporarily deepened to -0.50 percent in September 2019 — the ECB achieved persistently negative short-term money market rates by maintaining abundant excess reserves in the banking system, rendering the MRO rate an effectively uninformative indicator of the marginal policy impulse. In this environment, short-term interest rates and standard monetary conditions indices are no longer accurate measures of the overall monetary policy stance, with state-contingent forward guidance, asset purchases, and balance sheet expansion instead serving as the primary channels through which the Governing Council continued to ease financial conditions (Altavilla et al., 2019).

Implications for High-Frequency Shock Identification. This institutional configuration has direct implications for the high-frequency identification of monetary policy shocks. Surprises in the 3-month OIS rate (ΔOIS_{3M}) around Governing Council announcement windows, while capturing near-term policy rate expectations, are subject to a compressed signal-to-noise ratio during the ELB period: the near-invariance of the MRO renders changes in short-horizon instruments potentially ambiguous with respect to the direction and magnitude of the underlying policy impulse. Extending the identification to the 1-year OIS (ΔOIS_{1Y}) provides a richer characterization of the stance by capturing surprises along the forward guidance and rate path dimension, which constituted the ECB's primary active communication channel throughout this period (Altavilla et al., 2019).

The Information Channel and its Identification. A further and more fundamental identification challenge concerns the information content of central bank announcements themselves. Jarociński and Karadi (2020) demonstrate that ECB Governing Council announcements simultaneously convey information about the intended path of monetary policy *and* the central bank's private assessment of macroeconomic conditions, giving rise to a "central bank information" (CBI) shock that is empirically distinct from a pure monetary policy (MP) shock. Crucially, these two components induce opposite co-movements in interest rates and equity prices around announcement windows: a contractionary pure monetary policy shock raises OIS rates while depressing stock prices, whereas a positive CBI shock raises both simultaneously, as markets revise upward their assessments of the economic outlook in response to the central bank's signal. Failing to disentangle these components — as raw OIS surprises do by construction — conflates the transmission of genuine monetary impulses with the endogenous information channel, biasing inference on the real effects of policy.[7] The identification strategy of Jarociński and Karadi (2020) addresses this challenge by imposing sign restrictions on the joint high-frequency co-movement of OIS rates and the Euro Stoxx 50 around ECB announcement windows, thereby decomposing raw surprises into a pure MP shock and a CBI shock. Specifically, the composite rate factor entering the sign restriction is the first principal component of event-window OIS surprises across four

[7] The question of whether high-frequency monetary policy surprises are contaminated by an information channel has been examined primarily in the U.S. context, where two influential but contrasting positions have emerged. Miranda-Agrippino and Ricco (2021) document that standard high-frequency instruments around FOMC announcements are predictable by the Fed's internal *Greenbook* forecast revisions, which they interpret as evidence that the central bank possesses and reveals private information about macroeconomic fundamentals to agents subject to informational rigidities; projecting out this component yields an instrument under which monetary tightenings produce unambiguously contractionary effects on output, inflation, and financial conditions, resolving the price puzzle that afflicts raw surprise measures. Bauer and Swanson (2023*a*), by contrast, challenge the private-information interpretation directly. They show that the same predictability documented by Miranda-Agrippino and Ricco (2021) obtains equally well when using publicly observable *Blue Chip* forecasts in place of the confidential Greenbook, implying that the correlation between monetary surprises and forecast revisions reflects not the disclosure of Fed private information but rather a "Fed response to news" channel: both the central bank and professional forecasters respond simultaneously to incoming publicly available macroeconomic data, generating a spurious co-movement that is econometric in nature rather than informational. Under this interpretation, correcting for the endogeneity of surprises with respect to publicly observable pre-announcement data is sufficient to recover well-behaved estimates of monetary policy transmission, and there is no need to invoke private central bank information. Although the debate between these two interpretations remains open in the U.S. literature, for the ECB — the relevant institutional context of the present paper — Jarociński and Karadi (2020) provide direct evidence of a central bank information component using the joint high-frequency co-movement of OIS rates and the Euro Stoxx 50, an identification strategy that does not rely on internal forecast data and is therefore not subject to the Bauer and Swanson (2023*b*) critique in its original form. Regardless of the underlying mechanism, both camps agree that raw high-frequency surprises are endogenous with respect to pre-announcement information, and that correcting for this endogeneity is necessary for credible identification.

maturities — 1-month, 3-month, 6-month, and 1-year — scaled to have the same standard deviation as the OIS1Y surprise, and therefore spans the short-to-medium segment of the yield curve rather than loading exclusively on any single horizon. This decomposition forms the basis for the information-purged monetary policy shock series employed as a robustness check in the main analysis.

Robustness Across Shock Measures. The consistency of our empirical findings across all three measures — raw ΔOIS_{3M} surprises, ΔOIS_{1Y} surprises, and the information-purged pure monetary policy shocks of Jarociński and Karadi (2020) — lends substantial credibility to the main results. The fact that qualitatively and quantitatively similar estimates obtain regardless of which instrument is employed suggests that our conclusions are not an artifact of a particular identification choice, but rather reflect a robust feature of the data that survives alternative treatments of both the ELB constraint and the information channel.

D Robustness: Monetary Policy Under Uncertainty

This section assesses the robustness of the main results along threedimensions. First, we show that the differential transmission of monetary policy under cost and sales uncertainty is stable across alternative shock measures, spanning different maturities of the OIS curve and an information-purged shock that removes the central bank information component. Second, we verify that the results are insensitive to the precise delineation of the shock aggregation window, addressing the potential overlap between the INVIND survey period and the early part of the shock series. Third, we confirm that the findings carry over to a higher-frequency setting by merging quarterly price observations from SIGE with the annual INVIND uncertainty measures, showing that the differential transmission under cost and sales uncertainty is not an artifact of annual aggregation.

D.1 Alternative Shocks Measures

Table *A*.5 shows that the differential effects of cost and sales uncertainty on monetary policy transmission are stable across alternative shock measures.

Table A.5: Robustness I: Monetary Policy Transmission under Sales and Cost Uncertainty: Robustness to Alternative Shock Measures

	(1)		(2)		(3)	
	ΔP	ΔRS	ΔP	ΔRS	ΔP	ΔRS
Cost Uncertainty (σ^C)	0.180^{***}	-0.330^{***}	0.099^{**}	-0.196^{**}	0.140^{***}	-0.276^{**}
	(0.05)	(0.11)	(0.04)	(0.08)	(0.05)	(0.11)
$\varepsilon_{\text{mon}} \times (\sigma^C - \bar{\sigma}^C)$	-0.104^{***}	0.217^{***}	-0.073^{**}	0.264^{***}	-0.034^{*}	0.093^{**}
	(0.04)	(0.07)	(0.03)	(0.07)	(0.02)	(0.04)
Sales Uncertainty (σ^S)	-0.087^{***}	0.090	-0.078^{***}	-0.027	-0.089^{***}	0.073
	(0.03)	(0.08)	(0.02)	(0.08)	(0.03)	(0.08)
$\varepsilon_{\text{mon}} \times (\sigma^S - \bar{\sigma}^S)$	0.016^{*}	-0.162^{***}	0.010	-0.202^{***}	0.011^{*}	-0.082^{***}
	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.02)
Shock	ΔOIS_{3M}		ΔOIS_{1Y}		JK `mp_pm`	
First-moment controls	✓	✓	✓	✓	✓	✓
Firm-specific effects	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓		
Macro effects					✓	✓
R-squared	0.561	0.618	0.559	0.622	0.559	0.616
Observations	2,488	2,488	2,488	2,488	2,488	2,488
Sample period	2016-2021	2016-2021	2016-2021	2016-2021	2016-2021	2016-2021

Notes: The dependent variables are firm price growth ΔP and real sales growth ΔRS. σ^C and σ^S denote cost and sales uncertainty respectively, demeaned at the firm level ($\sigma^C - \bar{\sigma}^C$ and $\sigma^S - \bar{\sigma}^S$) prior to interaction following Ottonello and Winberry (2020). Column (1) uses the annual sum of three-month OIS surprises (ΔOIS_{3M}) from Altavilla et al. (2019). Column (2) replaces the baseline shock with the one-year OIS surprise (ΔOIS_{1Y}), which captures more persistent shifts in rate expectations. Column (3) uses the pure monetary policy shock (`mp_pm`) from Jarociński and Karadi (2020), which separates monetary policy surprises from ECB information effects via a penalty function approach. All shocks are aggregated from the last week of April of year t to the end of year t and weighted to assign greater importance to shocks occurring earlier in the year. All specifications include first-moment expectations of Δ prices and Δ real sales, and firm and sector-by-year fixed effects. Standard errors in parentheses, clustered by firm. * denotes p-value $p < 0.10$, ** denotes p-value $p < 0.05$, *** denotes p-value $p < 0.01$.

D.2 Alternative Shock Measures and Aggregation Window

Table A.6 shows that the differential effects of cost and sales uncertainty on monetary policy transmission are stable across alternative shock measures and to a stricter treatment of the shock aggregation window. Specifically, to avoid any overlap between the INVIND survey period — which runs through mid-May — and the shock series, we exclude monetary policy surprises occurring between the last week of April and May 15 from the annual aggregation. The interaction estimates are unchanged, confirming that the results are not sensitive to the precise delineation of the shock window.

Table $A.6$: Robustness II: Monetary Policy Transmission under Sales and Cost Uncertainty: Robustness to Alternative Shock Measures and Timing

	(1)		(2)		(3)	
	ΔP	ΔRS	ΔP	ΔRS	ΔP	ΔRS
$\varepsilon_{\text{mon}} \times (\sigma^C - \bar{\sigma}^C)$	-0.062^{***}	0.147^{***}	-0.052^{**}	0.130^{**}	-0.041^{**}	0.125^{***}
	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.04)
$\varepsilon_{\text{mon}} \times (\sigma^S - \bar{\sigma}^S)$	0.010^{*}	-0.115^{***}	0.010^{*}	-0.102^{***}	0.009^{*}	-0.101^{***}
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)
Cost Uncertainty (σ^C)	0.162^{***}	-0.321^{***}	0.112^{**}	-0.196^{*}	0.139^{***}	-0.300^{***}
	(0.05)	(0.11)	(0.05)	(0.10)	(0.05)	(0.10)
Sales Uncertainty (σ^S)	-0.087^{***}	0.090	-0.077^{***}	-0.004	-0.085^{***}	0.073
	(0.02)	(0.09)	(0.02)	(0.08)	(0.02)	(0.08)
Shock	ΔOIS_{3M}		ΔOIS_{1Y}		JK `mp_pm`	
First-moment controls	✓	✓	✓	✓	✓	✓
Firm-specific effects	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓
R-squared	0.560	0.620	0.559	0.617	0.559	0.619
Observations	2,488	2,488	2,488	2,488	2,488	2,488
Sample period	2016–2021	2016–2021	2016–2021	2016–2021	2016–2021	2016–2021

Notes: The dependent variables are firm price growth ΔP and real sales growth ΔRS. σ^C and σ^S denote cost and sales uncertainty respectively, demeaned at the firm level ($\sigma^C - \bar{\sigma}^C$ and $\sigma^S - \bar{\sigma}^S$) prior to interaction following Ottonello and Winberry (2020). Column (1) uses the annual sum of three-month OIS surprises (ΔOIS_{3M}) from Altavilla et al. (2019). Column (2) replaces the baseline shock with the one-year OIS surprise (ΔOIS_{1Y}), which captures more persistent shifts in rate expectations. Column (3) uses the pure monetary policy shock (`mp_pm`) from Jarociński and Karadi (2020), which separates monetary policy surprises from ECB information effects via a sign-restriction approach. All shocks are aggregated from the last week of April of year t to the end of year t and weighted to assign greater importance to shocks occurring earlier in the year. All specifications include first-moment expectations of Δ prices and Δ real sales, and firm and year fixed effects. Standard errors in parentheses, clustered by firm. * denotes $p < 0.10$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

D.3 Robustness to higher-Frequency Observation of Price Outcomes

Table *A.7* reports estimates of the price growth response to monetary policy shocks at quarterly horizons $h = 0, \ldots, 4$, obtained by merging quarterly price observations from SIGE with the annual uncertainty measures from INVIND, and confirms that the differential transmission under sales and cost uncertainty documented in the main analysis is robust to higher-frequency observation of firm price outcomes.

Table *A.7*: Price Growth Response to Monetary Policy at Quarterly Horizons

Quarters after shock	$h = 0$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
Sales Uncertainty (σ^S)	-0.084^{***}	-0.112^{***}	-0.105^{***}	-0.128^{**}	-0.020
	(0.028)	(0.026)	(0.026)	(0.049)	(0.020)
Cost Uncertainty (σ^C)	0.058^{*}	0.077^{*}	0.073^{**}	0.082	-0.026
	(0.032)	(0.044)	(0.033)	(0.058)	(0.032)
$\varepsilon_t^{\text{mon}} \times (\sigma^S - \bar{\sigma}^S)$	0.045^{**}	0.027^{*}	0.016	0.067^{**}	-0.039^{*}
	(0.017)	(0.015)	(0.016)	(0.032)	(0.020)
$\varepsilon_t^{\text{mon}} \times (\sigma^C - \bar{\sigma}^C)$	-0.055^{***}	-0.041	-0.056	-0.076^{**}	0.048
	(0.019)	(0.028)	(0.037)	(0.030)	(0.039)
R-squared	0.468	0.455	0.488	0.500	0.547
Observations	718	640	629	634	647

Notes: The dependent variable is 12-month firm price growth from SIGE, observed at quarterly frequency over 2016–2021. σ^S and σ^C denote sales and cost uncertainty respectively, constructed from annual INVIND expectations and held constant within the year. This approach exploits the within-year variation in quarterly monetary policy shocks $\varepsilon_t^{\text{mon}}$ while acknowledging that the uncertainty measures do not vary at quarterly frequency, since INVIND elicits expectations once per year between February and the first two weeks of May. The horizon h denotes the number of quarters after the monetary policy shock. σ^S and σ^C are demeaned at the firm level ($\sigma^S - \bar{\sigma}^S$ and $\sigma^C - \bar{\sigma}^C$) prior to interaction following Ottonello and Winberry (2020). All specifications include first-moment expectations of Δ prices and Δ real sales, and firm, sector, and year fixed effects. Standard errors in parentheses, clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E U.S. Evidence: SBU Details about Data and Specification

E.1 Survey of Business Uncertainty: Description

The Survey of Business Uncertainty (SBU) is a monthly panel survey conducted by the Federal Reserve Bank of Atlanta in partnership with Nicholas Bloom (Stanford University) and Steven Davis (Hoover Institution). The survey is documented in Altig et al. (2022). The principal investigators are David Altig (Federal Reserve Bank of Atlanta), José María Barrero (Instituto Tecnológico Autónomo de México), Nicholas Bloom (Stanford University), Steven J. Davis (Hoover Institution and University of Chicago Booth School of Business), Kevin Foster (Federal Reserve Bank of Atlanta), Brent H. Meyer (Federal Reserve Bank of Atlanta), and Emil Mihaylov (Federal Reserve Bank of Atlanta).

Coverage and sample. The SBU covers firms across all US regions and all major non-farm industry sectors, with a broad range of firm sizes. The sampling frame reflects the firm-size and sectoral composition of US employer businesses according to the Census Bureau's Statistics of US Businesses report. As of August 2025, the panel consists of approximately 3,000 firms, whose senior finance and managerial staff are contacted monthly by email and respond via a web-based instrument. The average monthly response rate is approximately 42 percent.

Elicitation design. The core innovation of the SBU is the elicitation of 5-point subjective probability distributions over own-firm outcomes at a one-year look-ahead horizon. Respondents freely assign probabilities to five scenario-specific outcomes for future sales growth and employment. From each distribution, the survey computes the mean — the firm's point expectation — and the standard deviation — the firm's subjective uncertainty — following the formulas described in Altig et al. (2022). All expectation and uncertainty variables are winsorized at the first and 99th percentiles prior to use; non-winsorized variants are available in the microdata with the suffix `_nw`.

Timing and frequency. The SBU was first administered to a national panel in July 2014. Panel members are split into two equal groups that rotate between the sales revenue and employment questionnaires in alternating months, so that each firm responds to each questionnaire every other month. The current panel design and standardized data collection began in September 2016. In June 2024 a third panel was introduced, eliciting realizations and expectations of own-firm prices and costs, with the price and sales questionnaires administered in consecutive non-overlapping months and the survey moving to quarterly frequency for these outcomes.

Variables used in this paper. We drop mining and utilities from the sample, as these sectors are not primarily driven by market dynamics, and use the following variables:

- `sr_gr_dhsforecast`: subjective expected sales revenue growth over the next 12 months, computed using the Davis–Haltiwanger–Schuh (DHS) symmetric growth rate formula and winsorized, our measure of ΔSales^e. Available from September 2016.

- `sr_gr_dhssd`: subjective uncertainty about sales revenue growth over the next 12 months, measured as the standard deviation of the firm's 5-point subjective probability distribution and winsorized, our measure of sales uncertainty σ^S. Available from September 2016.

- `sr_yoy`: realized growth in sales revenue over the last 12 months, computed using the DHS growth rate formula, used as the dependent variable in the real sales growth regressions of Tables 7 and *A.9*. Available from September 2016.

- `price_gr_dhsforecast`: subjective expected price growth over the next 12 months, computed using the DHS growth rate formula and winsorized, our measure of ΔPrice^e. Available from June 2024.

- `price_gr_dhssd`: subjective uncertainty about price growth over the next 12 months, measured as the standard deviation of the firm's 5-point subjective probability distribution and winsorized, our measure of price uncertainty σ^P. Available from June 2024.

- `price_dhs`: realized growth in prices over the last 12 months, computed using the DHS growth rate formula and winsorized, used as the dependent variable in the price growth regressions of Table 7. Available from June 2024.

E.2 Monetary Policy and Uncertainty

E.2.1 Empirical Strategy and Shock Measures

To examine the transmission of monetary policy under demand and cost uncertainty in the US setting, we estimate local projections of realized price growth and real sales growth on the interaction of monetary policy shocks with firm-level uncertainty measures, mirroring the specification in equation (10). The horizon structure differs across outcomes to reflect the elicitation timing of the SBU. Price growth (`price_dhs`) is observed at quarterly frequency from June 2024, and we estimate responses at horizons $h = 0, 3, 6$ quarters. Sales expectations and uncertainty are elicited in the month preceding the price questionnaire, so all sales-side variables — `sr_gr_dhsforecast` and `sr_gr_dhssd` — enter with a one-period lag ($L.$) in all specifications. Real sales growth is estimated at horizons $h = 2$ and $h = 5$ quarters, chosen to span a comparable sample window to the price growth specifications. For the longer sample running from 2016 to 2023, where price data are unavailable, we use nominal sales growth (`sr_yoy`) directly and estimate sales uncertainty effects at bimonthly frequency. For the shorter sample from June 2024 onward, where both price and sales data are available, we construct real sales growth as $L.\texttt{sr\_yoy}_{t-1} - \texttt{price\_dhs}_t$, deflating lagged nominal sales growth by realized price growth to obtain a quantity-based measure comparable to the Italian evidence.

The monetary policy shock series differ across the two sample periods. For the 2016–2023 sample, we use the orthogonalized monetary policy surprise of Bauer and Swanson (2023*b*) (`MPS_ORTH100`), scaled by 100 and aggregated to bimonthly frequency by averaging within each survey wave. For the 2024 onward sample, the Bauer and Swanson (2023*b*) series is unavailable at the required frequency, and we instead rely on the monetary policy surprises constructed by Acosta et al. (2025), aggregated to quarterly frequency to match the price and cost questionnaire cycle. As in the Italian analysis, all uncertainty and expectation measures are demeaned at the firm level prior to interaction following Ottonello and Winberry (2020), so that identification exploits within-firm variation in uncertainty around each firm's own historical mean.

We assess the predetermined treatment of the uncertainty state following the same approach as for the Italian data. Table *A*.10 shows that the Bauer and Swanson (2023*b*) shock has no discernible effect on firm-level sales uncertainty at any horizon from $h = 0$ to $h = 6$, and a similar conclusion obtains when the Acosta et al. (2025) shocks are used in their place. The monetary policy shock can therefore be treated as predetermined with respect to the uncertainty state in all specifications that follow.

E.2.2 U.S. Monetary Policy Under Uncertainty: SBU

Main Results Table A.8 reports the monetary policy interaction results for the joint sample where both price and sales uncertainty are available. The results are consistent with the Italian evidence and reinforce the demand-supply decomposition established in Section 4. A firm moving from the median to the 75th percentile of sales uncertainty experiences a price pass-through that is attenuated by approximately 38 percent and a real sales response to monetary accommodation that is amplified by approximately 28 percent relative to a firm at its historical average uncertainty level; under price uncertainty, the same interquartile shift amplifies price pass-through by approximately 23 percent and the real sales response by approximately 31 percent. These magnitudes, discussed in detail below, are consistent with the demand-supply decomposition established for Italy: sales uncertainty suppresses the inflationary consequences of monetary stimulus while amplifying its real effects, and price uncertainty does the opposite. We report only the interaction terms in the table; the main effects of the monetary shock and the level effects of uncertainty are included in all specifications but not reported separately.

Discussion of the Empirical Estimates Turning to the coefficient estimates in Panel A, the interaction $\varepsilon_{\text{mon}} \times (L.\sigma^S - \overline{L.\sigma^S})$ on price growth enters with a positive coefficient of 0.100 at $h = 3$ (significant at 5 percent) and 0.145 at $h = 6$ (significant at 10 percent), indicating that under elevated sales uncertainty monetary accommodation generates less price growth than at baseline. Scaling the $h = 6$ coefficient by the interquartile movement in demeaned sales uncertainty ($\Delta\sigma^S = 0.008$) and the baseline main effect ($\hat{\beta}_{\text{mon}} = -0.003$) yields the 38 percent attenuation reported above.[8] For the real activity response, we draw on the long-sample estimates of Table A.9, where the interaction enters with -0.125 on impact (significant at 1 percent). Scaling by $\Delta\sigma^S = 0.008$ and the baseline main effect on real sales ($\hat{\beta}_{\text{mon}} = -0.0035$) yields the 28 percent amplification reported above.[9]

The interaction $\varepsilon_{\text{mon}} \times (\sigma^P - \bar{\sigma}^P)$ on price growth enters with -0.241 at $h = 3$ (significant at 5 percent), indicating that price uncertainty amplifies the price response to monetary policy one quarter ahead, consistent with the cost-shock interpretation in which firms facing greater uncertainty about future prices adjust output prices more aggressively in response to a given nominal impulse. Scaling by the interquartile movement in price uncertainty ($\Delta\sigma^P = 0.003$) and the baseline main effect yields the 23 percent amplification reported above.[10] The effect reverts quickly, with the coefficient turning positive to 0.248 at $h = 6$ (significant at 10 percent), suggesting that the amplification of price pass-through under price uncertainty is short-lived, possibly reflecting the low persistence of price uncertainty in the relatively short sample available from June 2024. On real sales growth, the interaction with price uncertainty enters with 0.540 at $h = 2$ (significant at 10 percent), corresponding to the 31 percent amplification reported above,[11] though the effect dissipates and turns negative at $h = 5$, consistent with the same low-persistence pattern observed for price growth.

Panel B confirms that these patterns are not driven by the co-movement of uncertainty

[8] Details of the calculation: $(0.145 \times 0.007890)/0.003 \approx 38$ percent, where $\Delta\sigma^S = 0.006355 - (-0.001535) = 0.007890$ is the interquartile movement in demeaned sales uncertainty over the whole sample and $\hat{\beta}_{\text{mon}} = -0.003$ is the baseline main effect on price growth from Table A.8.

[9] Details of the calculation: $(0.125 \times 0.007890)/0.0035345 \approx 28$ percent.

[10] Details of the calculation: $(0.241 \times 0.002858)/0.003 \approx 23$ percent, using $\hat{\beta}_{\text{mon}} = -0.003$ from Table A.8.

[11] Details of the calculation: $(0.540 \times 0.002858)/0.005 \approx 31$ percent, using $\hat{\beta}_{\text{mon}} = -0.005$ from Table A.8.

with first-moment expectations. The interactions of the monetary shock with demeaned first-moment sales and price expectations are small and statistically indistinguishable from zero for price growth, while the interaction with demeaned price expectations enters negatively and significantly on real sales growth at both horizons — -0.540 at $h = 2$ and -0.908 at $h = 5$, both significant at 1 percent — suggesting that firms with higher price growth expectations face a more contractionary real activity response to monetary tightening, consistent with forward-looking price adjustment behavior. The uncertainty interaction terms are unchanged relative to Panel A in both sign and magnitude, confirming that the second moment of the subjective distribution carries independent information about monetary policy transmission beyond what is captured by the first moment.

The long-sample evidence in Table *A.9*, estimated over 2016–2023 using the Bauer and Swanson (2023*b*) shock and nominal sales growth, confirms that elevated sales uncertainty amplifies the real sales response to monetary stimulus over a sample period that predates the availability of price uncertainty data. Panel B shows this result is robust to controlling for the interaction of the shock with demeaned first-moment sales expectations, which enters insignificantly across all horizons. Taken together, the US evidence from both samples is consistent with the Italian findings: monetary policy is more effective at stimulating real activity when demand uncertainty is elevated and more inflationary when cost-side uncertainty is elevated, with the source of uncertainty determining both the direction and the magnitude of the differential transmission effect.

Table $A.8$: Dynamic Response of Prices and Real Sales to Uncertainty and Monetary Policy: SBU Evidence

	Price Growth			Real Sales Growth	
	$h=0$	$h=3$	$h=6$	$h=2$	$h=5$
Panel A: Baseline					
$\varepsilon_{\text{mon}} \times (L.\sigma^S - \overline{L.\sigma^S})$	0.022	0.100**	0.145*	−0.189	−1.211***
	(0.02)	(0.05)	(0.07)	(0.16)	(0.31)
$\varepsilon_{\text{mon}} \times (\sigma^P - \bar{\sigma}^P)$	0.025	−0.241**	0.248*	0.540*	−0.704
	(0.05)	(0.09)	(0.14)	(0.31)	(0.51)
R-squared	0.603	0.646	0.743	0.585	0.636
Observations	2,500	1,592	1,034	1,488	964
Panel B: Controlling for Interaction with First-Moment Expectations					
$\varepsilon_{\text{mon}} \times (\sigma^S - \overline{\sigma^S})(-1)$	0.023	0.084*	0.153*	−0.140	−1.185***
	(0.02)	(0.05)	(0.08)	(0.16)	(0.32)
$\varepsilon_{\text{mon}} \times (\sigma^P - \bar{\sigma}^P)$	0.022	−0.251***	0.246*	0.662**	−0.626
	(0.05)	(0.10)	(0.14)	(0.31)	(0.51)
$\varepsilon_{\text{mon}} \times (\Delta\text{Sales}^e - \overline{\Delta\text{Sales}^e})(-1)$	0.002	−0.031	0.009	0.107	0.053
	(0.01)	(0.02)	(0.03)	(0.07)	(0.12)
$\varepsilon_{\text{mon}} \times (\Delta\text{Price}^e - \overline{\Delta\text{Price}^e})$	−0.035	0.032	0.039	−0.540***	−0.908***
	(0.03)	(0.05)	(0.08)	(0.17)	(0.30)
R-squared	0.603	0.647	0.743	0.590	0.642
Observations	2,500	1,592	1,034	1,488	964
First-moment controls	✓	✓	✓	✓	✓
Firm-specific effects	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓

Notes: Sample period $2024:M6$ to $2025:M9$. The dependent variables are realized price growth (`price_dhs`, columns 1–3) and realized real sales growth (`sr_yoy` minus the `price_dhs`, columns 4–5) at horizon h quarters ahead, from the Survey of Business Uncertainty (Altig et al., 2022). ΔSales^e and σ^S denote the mean and standard deviation of managers' sales growth expectations (`sr_gr_dhsforecast` and `sr_gr_dhssd`), entering with a one-period lag ($L.$) in all specifications to reflect the non-overlapping monthly elicitation design. ΔPrice^e and σ^P denote the mean and standard deviation of managers' price growth expectations (`price_gr_dhsforecast` and `price_gr_dhssd`). ε_{mon} is the press conference surprise in Acosta et al. (2025) (`pc`), scaled by 100. All uncertainty and expectation measures are demeaned at the firm level prior to interaction following Ottonello and Winberry (2020) using the whole sample. Panel B additionally controls for the interactions of the monetary shock with demeaned first-moment expectations ($L.\Delta\text{Sales}^e - \overline{L.\Delta\text{Sales}^e}$) and ($\Delta\text{Price}^e - \overline{\Delta\text{Price}^e}$), separating the uncertainty response from the response to expected conditions. All specifications include firm, sector, and time fixed effects. Standard errors in parentheses, clustered by firm. * denotes $p < 0.10$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table $A.9$: Dynamic Response of Real Sales Growth to Uncertainty and Monetary Policy: SBU Evidence

	$h = 0$	$h = 2$	$h = 4$	$h = 6$
Panel A: Baseline				
$\varepsilon_{\text{mon}} \times (\sigma^S - \bar{\sigma}^S)$	-0.125^{***}	-0.041^{*}	-0.014	0.028
	(0.02)	(0.02)	(0.02)	(0.02)
R-squared	0.335	0.313	0.332	0.314
Observations	8,765	8,819	7,347	6,760
Panel B: Controlling for Interaction with First-Moment Expectations				
$\varepsilon_{\text{mon}} \times (\sigma^S - \bar{\sigma}^S)$	-0.126^{***}	-0.047^{**}	-0.025	0.028
	(0.02)	(0.02)	(0.02)	(0.02)
$\varepsilon_{\text{mon}} \times (\Delta\text{Sales}^e - \overline{\Delta\text{Sales}^e})$	-0.178	-1.281	-2.262^{***}	-0.096
	(0.80)	(0.81)	(0.87)	(0.89)
R-squared	0.335	0.313	0.333	0.314
Observations	8,765	8,819	7,347	6,760
First-moment controls	✓	✓	✓	✓
Firm-specific effects	✓	✓	✓	✓
Time effects	✓	✓	✓	✓

Notes: Sample period 2016 : $M9$ to 2023 : $M6$. The dependent variable is real sales growth at horizon h quarters ahead, from the Survey of Business Uncertainty (Altig et al., 2022). ΔSales^e denotes the mean of managers' real sales growth expectations (`sr_gr_dhsforecast`). σ^S denotes sales uncertainty, measured by the standard deviation of managers' real sales growth expectations (`sr_gr_dhssd`), demeaned at the firm level ($\sigma^S - \bar{\sigma}^S$) prior to interaction following Ottonello and Winberry (2020) using the sample period in estimation. ε_{mon} is the orthogonalized monetary policy surprise of Bauer and Swanson (2023*b*) (`MPS_ORTH100`), scaled by 100. Panel A includes the interaction of the monetary shock with demeaned sales uncertainty. Panel B additionally controls for the interaction of the monetary shock with demeaned first-moment sales expectations ($\Delta\text{Sales}^e - \overline{\Delta\text{Sales}^e}$), separating the uncertainty response from the response to expected sales conditions. All specifications include firm, sector, and year fixed effects. Standard errors in parentheses, clustered by firm. * denotes $p < 0.10$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table $A.10$: SBU: Response of Sales Uncertainty to Monetary Policy Shocks

	$h = 0$	$h = 2$	$h = 4$	$h = 6$
ΔS^e	-0.067^{***}	-0.023^{***}	-0.003	0.001
	(0.00)	(0.00)	(0.00)	(0.00)
$\varepsilon_t^{\text{mon}}$	-0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.628	0.636	0.656	0.679
Observations	8,820	8,595	7,224	6,641

Notes: The dependent variable is demeaned sales uncertainty ($\sigma^S - \bar{\sigma}^S$) at horizon h quarters ahead. ΔS^e (mean) denotes the mean of managers' real sales growth expectations (`sr_gr_dhsforecast`). $\varepsilon_t^{\text{mon}}$ is the orthogonalized monetary policy shock (`MPS_ORTH`), scaled by 100. The absence of statistically significant coefficients on $\varepsilon_t^{\text{mon}}$ across all horizons indicates that monetary policy shocks do not systematically predict firm-level sales uncertainty, supporting the exogeneity of the shock in the transmission analysis of Table $A.9$. All specifications include firm, sector, and year fixed effects. Standard errors in parentheses, clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.