The Effects of Uncertainty on Firms' Pricing Behavior and Activity*

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October 7, 2025

Abstract

This paper examines the causal effects of demand uncertainty on firms' pricing behavior and economic activity using managers' subjective expectations. Employing an instrumental variables approach that exploits differential industry exposure to exogenous uncertainty sources, we find that increased uncertainty leads firms to reduce prices through lower markups and decrease activity by lowering capacity utilization. We develop a macroeconomic model where firms face capacity constraints and must commit to prices and capacity before demand uncertainty resolves. The model's putty-clay production technology generates a mechanism where capacity constraints truncate upside gains while firms bear the full extent of downside losses, leading firms to lower prices preemptively to minimize expected losses from excess capacity. Our calibrated model shows that a one standard deviation demand uncertainty shock causes output declines of approximately 0.5 percent, with producer price and consumer price inflation dropping by about one-half and one-tenth of a percentage point, respectively. These findings demonstrate that idiosyncratic demand uncertainty generates disinflationary pressures through a distinct transmission mechanism—one that complements the inflationary effects of aggregate cost uncertainty emphasized in prior work—highlighting demand uncertainty as an economically significant source of business cycle fluctuations.

JEL Codes: D24; E22; E24.
Keywords: Uncertainty, business cycles, inflation, expectations, activity.

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1 Introduction

Economic theory emphasizes that uncertainty about future outcomes shapes firms' decisions. At the macroeconomic level, the existing literature has improved the measurement and understanding of time-varying uncertainty stemming from demand factors, productivity, and economic policies.[1] These papers explore various mechanisms linking uncertainty with aggregate fluctuations, drawing from extensive theoretical microeconomic literature on prices and activity.[2] On the empirical front, evidence on these mechanisms is typically limited to investment outcomes, with a notable exception such as Alfaro, Bloom and Lin (2024), who examines causal effects of uncertainty on real and financial outcomes. Little is known about how firms' prices and activity respond to time-varying uncertainty, with existing evidence primarily focused on aggregate variables and derived from Vector Autoregressive Models (VARs) or estimated DSGE models.[3]

This paper uses managers' subjective expectations to examine the causal effects of time-varying demand uncertainty on firms' price-setting behavior and activity. Our empirical findings show that increased perceived uncertainty leads firms to reduce prices through lower markups and decrease activity by lowering capacity utilization. We rationalize these findings through a macroeconomic model in which firms must commit to capacity and prices before demand uncertainty is resolved. In this setting, firms face capacity constraints that limit their ability to exploit high demand realizations while bearing full losses from low demand realizations. When uncertainty increases, spreading probability mass toward both tails of the demand distribution, expected profits fall because capacity constraints truncate upside gains while firms bear the full extent of downside losses. We model capacity con-

[1]The literature on uncertainty in aggregate models is vast. Examples include Bloom (2009), Basu and Bundick (2017), Born and Pfeifer (2014), Fernández-Villaverde et al. (2015), and Caldara et al. (2020), just to name a few.

[2]Bloom (2014) and Fernández-Villaverde and Guerrón-Quintana (2020) provide concise reviews of the literature on uncertainty and business cycles. Abel et al. (1996) offers a comprehensive review of the microeconomic foundations.

[3]See, for instance, the discussion in Born and Pfeifer (2014).

straints through putty-clay production technology where capital and labor are substitutes ex ante but complements ex post. Unable to adjust capacity once demand is realized, firms optimally respond to higher uncertainty by lowering prices preemptively, thereby increasing the probability of operating near capacity and minimizing expected losses from excess capacity.

The data source for our uncertainty measure is the Survey of Industrial and Service Firms (INVIND), an extensive annual business survey conducted by the Bank of Italy on a representative sample of Italian firms. As detailed in Section 2, the survey elicits managers' expectations about average, minimum, and maximum one-year-ahead sales growth rates. We directly observe both the first moment of the subjective probability distribution of future sales and the max–min range around the mean prediction. As shown in Fiori and Scoccianti (2023), these expectations are informative about mean outcomes and uncertainty in firm-level results.[4] Matching INVIND with the Cerved Database, which contains detailed balance sheet information, allows us to observe key firm-level variables for empirical analysis: inflation rates, actual sales growth, capacity utilization indices, and the first and second moments of expected sales growth.

We explicitly address endogeneity concerns when estimating uncertainty effects by adopting the novel instrumentation strategy for firm-level uncertainty proposed by Alfaro, Bloom and Lin (2024).[5] This approach exploits differential industry-level exposure to exchange rates, factor prices, and policy uncertainty, controlling for exposure to changes in factors' means while separately identifying exogenous variation in firm volatility from increased exposure to factors' volatility. We implement this approach at the industry level, exploiting approximately 2 million observations in Cerved.

[4] Fiori and Scoccianti (2023) find no systematic bias in firms' expectations, with realized sales falling within the ex ante max–min range in approximately 75 percent of observations. Using the 2005 and 2017 INVIND waves that elicited full probability distributions of expected sales, they show that the max–min range effectively measures the dispersion of future expected outcomes while remaining orthogonal to the distribution's skewness.

[5] For models of reverse causality, see Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2011), Pástor and Veronesi (2012), and Veldkamp and Orlik (2016).

The instrumentation strategy performs well in practice, delivering first-stage F-statistics above the threshold value of 10 and satisfying exclusion restrictions in Sargan-Hansen overidentification tests. Our results indicate that uncertainty causally reduces firms' inflation rates and sales growth, effects partly driven by lower markups and capacity utilization. These results suggest that, at the firm level, demand uncertainty acts as a negative demand shock, with firms reducing prices and output while lowering capacity utilization.

Our macroeconomic model rationalizes these empirical patterns through a pricing mechanism related to avoiding excess capacity. Building on the approaches of Fagnart, Licandro and Portier (1999) and Alvarez-Lois (2006), which echo insights from Mills (1959), the model features firms that face capacity constraints and must commit to prices and capacity before demand uncertainty resolves. As demand uncertainty rises, expected profits fall because capacity constraints limit upside gains from high demand while firms bear the full impact of low demand realizations. Unable to adjust capacity once demand is realized, firms optimally respond to higher uncertainty by lowering prices preemptively, minimizing expected losses from excess capacity.

This pricing mechanism generates aggregate disinflationary dynamics consistent with our microeconomic evidence in response to an increase in demand uncertainty. With lower expected profits due to increased uncertainty, firms reduce input demand, leading to lower equilibrium wages and consumption that in turn weaken demand even further. Quantitatively, a one standard deviation demand uncertainty shock generates an impact decline in annual GDP of approximately 0.5 percentage points and reduces annual producer price and consumer price inflation by about one-half and one-tenth of a percentage point, respectively. These magnitudes highlight demand uncertainty as an economically significant source of business cycle fluctuations.

Our findings complement existing literature emphasizing cost-side uncertainty channels. In models with nominal rigidities and full obligation at posted prices, cost uncertainty generates higher markups through an "inverse Oi–Hartman–Abel effect": firms facing convex marginal profit functions charge higher prices when uncertainty rises because selling too much at low prices generates larger losses than selling too little at high prices. This mechanism, emphasized by Fernández-Villaverde et al. (2015), Born and Pfeifer (2014), and Basu and Bundick (2017), operates distinctly from our demand uncertainty channel. By incorporating meaningful capacity constraints, we isolate demand uncertainty effects and demonstrate that the source of uncertainty—whether originating from demand or cost shocks—critically determines its inflationary consequences. Demand uncertainty, constrained by capacity limitations, emerges as inherently disinflationary.

The paper proceeds as follows. Section 2 describes our data sources and establishes that INVIND accurately represents aggregate dynamics. Section 3 details our identification strategy and instrument construction. Section 4 presents causal estimates of uncertainty's effects on prices, markups, and activity. Section 5 connects our findings to existing theory. Section 6 develops our macroeconomic model with capacity constraints and quantifies aggregate effects. Section 7 concludes.

Related Literature Our paper builds on three broad literatures. First, our work connects with papers using quantitative measures of surveys for firms and consumers. Our data source INVIND is the forerunner of the Decision Maker Panel (DMP) for the United Kingdom discussed in Altig et al. (2020), and Survey of Business Uncertainty (SBU) for the United States described in Altig et al. (2022).[6] Another important example is the IFO survey employed in Bachmann, Elstner and Sims (2013), Bachmann et al. (2019), Bachmann et al. (2018) and Bachmann et al. (2020) that use survey data to measure firms' uncertainty. Further examples of this approach are Scotti (2016), Awano et al. (2018), Manski (2017), and

[6]Examples of consumer surveys include the U.S. Health and Retirement Study (Hurd and McGarry, 2002), the Bank of Italy's Survey on Household Income and Wealth (Guiso, Jappelli and Terlizzese, 1992; Guiso, Jappelli and Pistaferri, 2002), the Survey of Economic Expectations (Dominitz and Manski, 1994), the University of Michigan Surveys of Consumers (Dominitz and Manski, 2004) and the New York Fed's very recent Survey of Consumer Expectations (Armantier et al., 2015).

Holzmeister et al. (2020). The critical advantage of INVIND is that it has surveyed firms' expectations for over two decades, allowing us to study how uncertainty has evolved over multiple business cycles. In contrast, DMP and SBU started only recently, albeit at a higher frequency.

Second, a vast empirical literature studies the economic effects of uncertainty, typically focusing on investment and pointing to a negative uncertainty-investment relationship when dealing with micro-level uncertainty.[7] The work on pricing behavior of individual firms has been more limited, with Bachmann et al. (2019) as the notable exception. Using micro data from the German Ifo Business Climate Survey, they find that heightened firm-level uncertainty increases the probability of a price change. Our approach complements and extends the results of the firm's pricing behavior response by measuring the reaction of prices, markups, and activity while explicitly dealing with the endogeneity of uncertainty.

Third, our work connects with the large macro literature that has studied the role of aggregate uncertainty shocks for inflation and activity. Vavra (2014) explores the implications of aggregate uncertainty in a menu cost model, where firms' pricing behavior depends on conflicting "wait-and-see" effects and the probability of larger shocks induced by higher uncertainty. Basu and Bundick (2017) show that a model with nominal rigidities and effective demand features reproduces the comovement between aggregate series in response to uncertainty shocks. Models incorporating cost-side uncertainty, such as Born and Pfeifer (2014), Fernández-Villaverde and Guerrón-Quintana (2020), and Caldara et al. (2020), typically generate inflationary effects through an "inverse Oi–Hartman–Abel effect" where firms raise markups when uncertainty increases.[8] Our paper contributes to this lit-

[7]Studies differ on the measure of firm level uncertainty with Leahy and Whited (1996), and Bloom, Bond and Van Reenen (2007) using realized stock return volatility; Stein and Stone (2013) using the option price, and Gulen and Ion (2016) using the policy uncertainty index developed by Baker, Bloom and Davis (2016*a*); Fiori and Scoccianti (2023) look at the effects of managers' expectations on a broad array of real and financial variables as Alfaro, Bloom and Lin (2024).

[8]Empirical evidence on the relationship between various measures of uncertainty and inflation is typically obtained from estimated DSGE models or VAR analysis. Examples include Basu and Bundick (2017), Fernández-Villaverde et al. (2015), Ilut and Saijo (2021), Caldara and Iacoviello (2022), and Caldara et al. (2020). Other approaches include Ilut and Schneider (2014), who model uncertainty as ambiguity aversion;

erature by isolating demand uncertainty effects through a model with meaningful capacity constraints, following Fagnart, Licandro and Portier (1999), Alvarez-Lois (2006), and Mills (1959). This approach demonstrates that idiosyncratic demand uncertainty generates disinflationary pressures through a distinct transmission mechanism—one that complements the inflationary effects of aggregate cost uncertainty emphasized in prior work—and provides micro-level evidence on firms' prices and markups that can serve as useful overidentifying restrictions to discipline different mechanisms in macro models.

2 Data, Instruments, and Addressing Endogeneity

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

We obtained our data set by combining different sources. The key object of the analysis is the measure of subjective uncertainty constructed using data on firm-level expectations from INVIND. INVIND is an annual business survey conducted between February and April of every year by the Bank of Italy on a representative sample of firms operating in industrial sectors, construction, and nonfinancial private services, with administrative headquarters in Italy. The sample is representative of the Italian economy, based on the branch of activity (according to an 11-sector classification), size class, and region in which the firm's head of-

Berger, Dew-Becker and Giglio (2020), who distinguish between news and uncertainty; and Gourio (2012), who focuses on disaster risks.

fice is located. INVIND elicits managers' expectations about expected sales and prices one year ahead and the growth rate prices each firm charges (or firm's inflation rates). Useful in constructing our measure of firm-level uncertainty, for every firm INVIND elicits the range between an expected maximum and a minimum of sales around the mean expectations, or max-min range. As detailed in Section 2.3, the max-min range measures managers' subjective uncertainty used in the empirical analysis. INVIND also contains data on firms' demographics, such as the number of employees, and an index that measures the firm's capacity utilization. The sample period extends from 1997 to 2021. We complement INVIND data with detailed information on yearly balance sheets from Cerved Group S.P.A. (Cerved Database) to obtain sales, the wage bill, and material purchases, which are useful to construct the firm's markups and price margins. Cerved spans about 30 years, from 1995 to 2016, and matches the size and the distribution of Italian firms accounting for up to 80 percent of the value added produced in the Italian economy. Consistent with their share of the economy, the manufacturing and trade sectors constitute more than one-half of the observations in the data. To construct the instrumental variables for firms' uncertainty, as in Alfaro, Bloom and Lin (2024), we rely on exchange rate data from the Haver database and the indexes of economic and political uncertainty constructed by Baker, Bloom and Davis (2016*b*). We refer the reader to Appendix A for detailed information on data sources.

2.2 INVIND Representative of the GDP and Inflation dynamics

In this section, we show that the series obtained by aggregating INVIND firm-level data accurately represents the dynamics of GDP and inflation in the Italian economy. Starting from firm-level prices, INVIND reports the *average* growth rate of prices (relative to the previous year) each firm charges for sold goods. To establish notation, we denote the firm's own inflation rate by $\pi_{f,t}$, where f indexes the firm and t the year the variable refers to. By matching INVIND with the Cerved database, we obtain firms' sales and deflate them using

CPI headline.

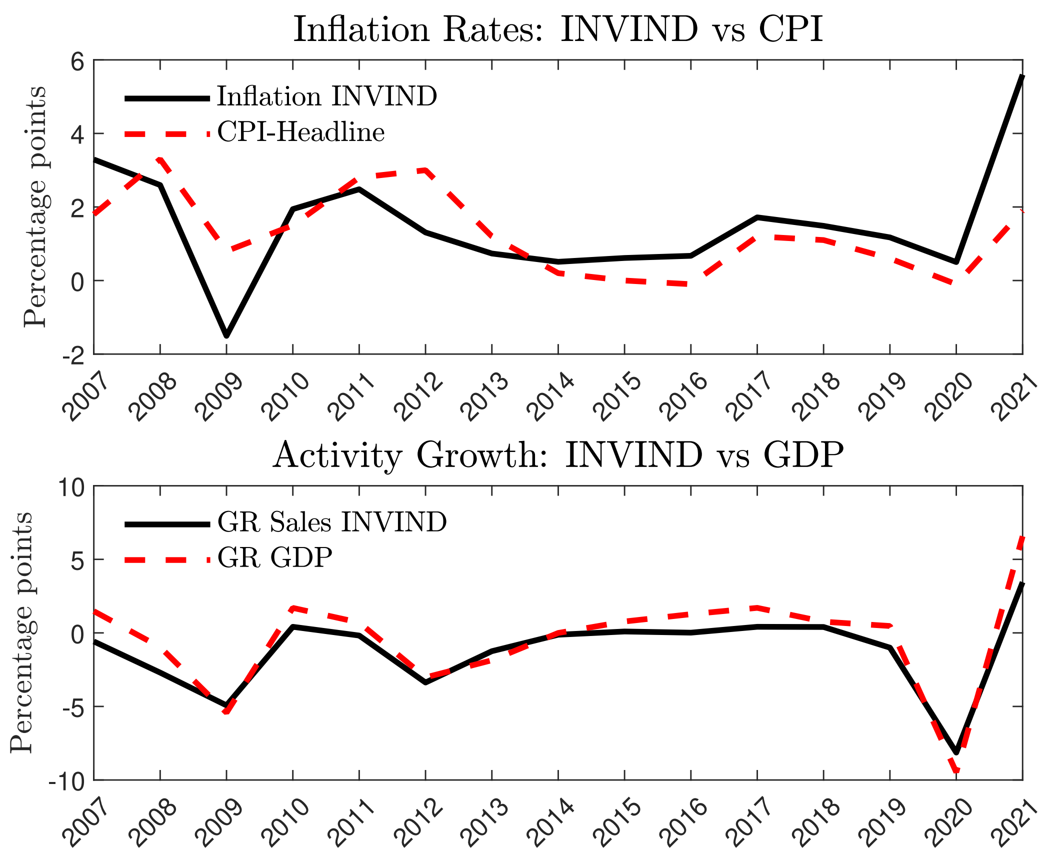

Figure 1: Aggregation of INVIND firm data and aggregate series.

Figure 1 compares the aggregate series for headline CPI inflation and the growth rate of GDP with the weighted mean of the cross-sectional distribution of firms' inflation and sales growth in INVIND, using as weights the product between the sample weight for each firm in the survey and its level of sales. As shown in the top panel, INVIND tracks closely economywide headline CPI inflation rates throughout the sample, especially at turning points. A similar conclusion is warranted for the dynamics of GDP growth. In Italy, as for the euro area as a whole, inflation was below the ECB target from 2012 on. Interestingly, the survey overshoots the increase in CPI inflation in 2021, anticipating the inflationary burst in 2022.

We now turn to discussing firm's expectations of sales and price changes that constitute the basis of our measure of firm-level uncertainty.

2.3 Firm-Level Expectations and Uncertainty: Variables Description

INVIND elicits expectations about future real sales and price changes from surveyed firms. Specifically, the survey reports three critical variables for our purposes:

1. The expected, or *average*, growth rate of real sales one year ahead, denoted by $s^e_{avg,f,t}$.
2. The *maximum* expected growth rate of real sales one year ahead, denoted by $s^e_{max,f,t}$.
3. The *minimum* expected growth rate of real sales one year ahead, denoted by $s^e_{min,f,t}$.

Shaped by firm-specific, sectoral, and aggregate factors, these variables allow us to directly observe the *first moment* of the probability distribution of the expected growth rate of sales and the *range* of subjective uncertainty around this point. We do not directly observe the probability mass over the support except for sales with the 2006 and 2017 waves, which we use to motivate the use of the max-min range as a measure of firm-level uncertainty or dispersion in expected sales.

We connect the max-min range to the second moments of the distribution of expected sales one year ahead, exploiting two results shown in Fiori and Scoccianti (2023). First, there is a near-deterministic relationship between the range and the standard deviation, or *second moment*, of the probability distribution of expected sales at the firm level. The result is obtained using the 2006 and 2017 cross-sections that elicit the entire probability distribution (waves from 1997 to 2021 instead elicit the max-min range). The relationship between the max-min range and the second moment of the distribution of expected sales allows us to extend the range interpretation as a measure of dispersion in expected sales for the whole sample. Second, the max-min range captures the dispersion in expected outcomes rather than higher moments. Using the 2006 and 2017 waves, we show that the dispersion computed using the full distribution is uncorrelated with moments higher than the second, supporting the interpretation of the max-min range as an uncertainty measure. Motivated by this evidence, we use the max-min range of the expected sales growth rate one year ahead, denoted by $\sigma_{f,t}$, as a measure of firm-level uncertainty.

2.4 Firm-Level Expectations and Uncertainty: Statistical Properties

We now discuss a set of statistics comparing the realized growth rate, the minimum, the maximum, the max-min range, and the average expected growth rates of firms' sales and prices. Statistics are reported pooling data for the whole sample and considering the INVIND sample weight represented by each firm in the entire population of firms and firms' sales. Growth rates are expressed in percent.

Starting with sales, the median firm expects sales ($s^e_{avg,f,t}$) to grow by 2.6 percentage points, not far from the median of actual sales. To assess whether managers' expectations are biased relative to realized sales, we performed a two-sided t-test using two-way clustered standard errors by firm and year to account for common shocks across firms. The test shows that the gap between expected and realized sales is not statistically different from zero (p-value 0.21), indicating no systematic bias in the firm's forecast.

The median firm expects the worst-case scenario ($s^e_{min,f,t}$) to result in a decrease in sales of about 2 percentage points, and the best-case scenario ($s^e_{max,f,t}$) in an expansion of 5. Also, for both variables, the interquartile range ($P_{75} - P_{25}$) is about 10 percentage points. The interval between the best- and worst-case scenario is informative about the uncertainty each firm faces as sales realized one year ahead fall within the max–min range in about 75 percent of the observations. Through the lens of this metric, the max–min range can be interpreted, on average, as firms reporting the 10-90 percentile of expected outcomes. In our sample, uncertainty around managers' average expected future sales is about 8 percentage points. The max-min range displays a low correlation with the mean expected sales of about 0.07.

Concerning prices, the median firm expects price changes ($\pi^e_{avg,f,t}$) to increase by 1 percentage point, the same as the median growth of actual prices. To assess whether managers'

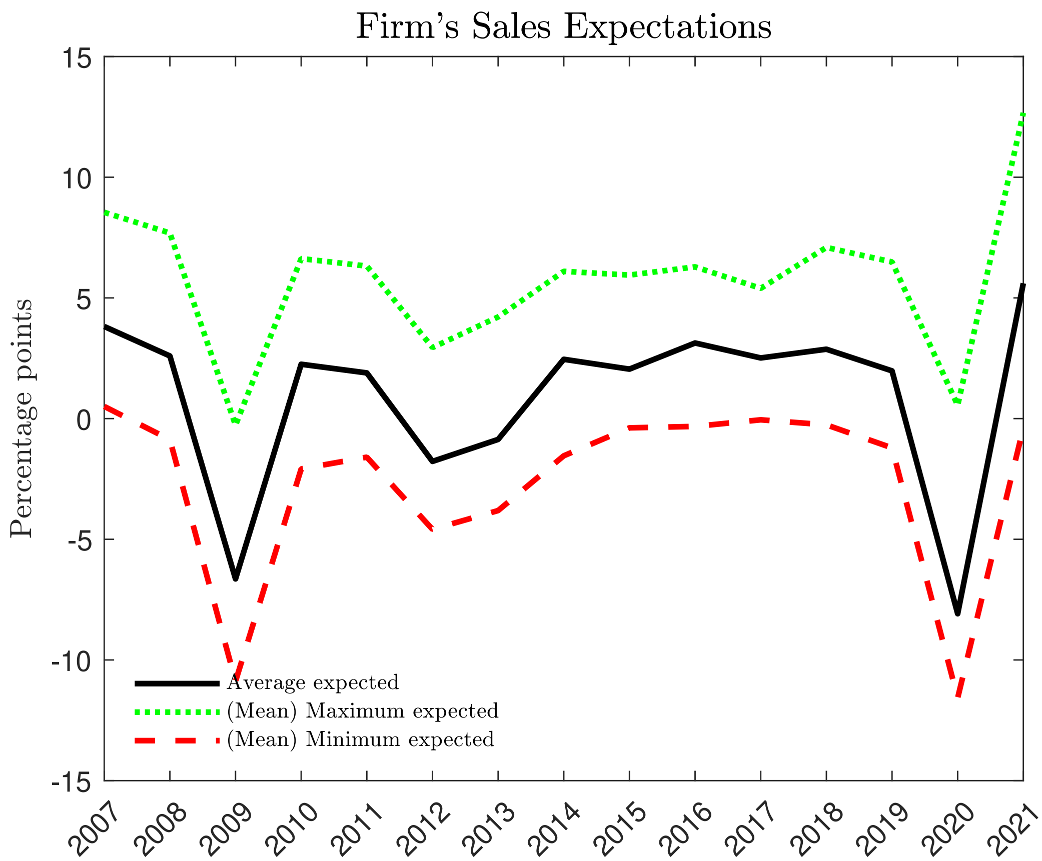

Figure 2: Mean of the cross-sectional distributions of the average, minimum, maximum expected growth rates of sales one year ahead.

expectations display a bias relative to realized prices, we performed a two-sided t-test using two-way clustered standard errors by both firm and year to account for common shocks across firms. The test shows that the gap between expected and realized sales is not statistically different from zero (p-value 0.54), indicating no systematic bias in the firm's price forecast.

Figure 2 shows the evolution of the *means* of the cross-sectional distributions for the expected minimum, average, and maximum of sales one year ahead. The three series tend to comove, reaching troughs in 2009 during the Global Financial Crisis and 2020 at the onset of the pandemic.

Figure 3 reports moments of the cross-sectional distribution of firm-level uncertainty. We take two main takeaways. First, there is substantial heterogeneity in the managers' per-

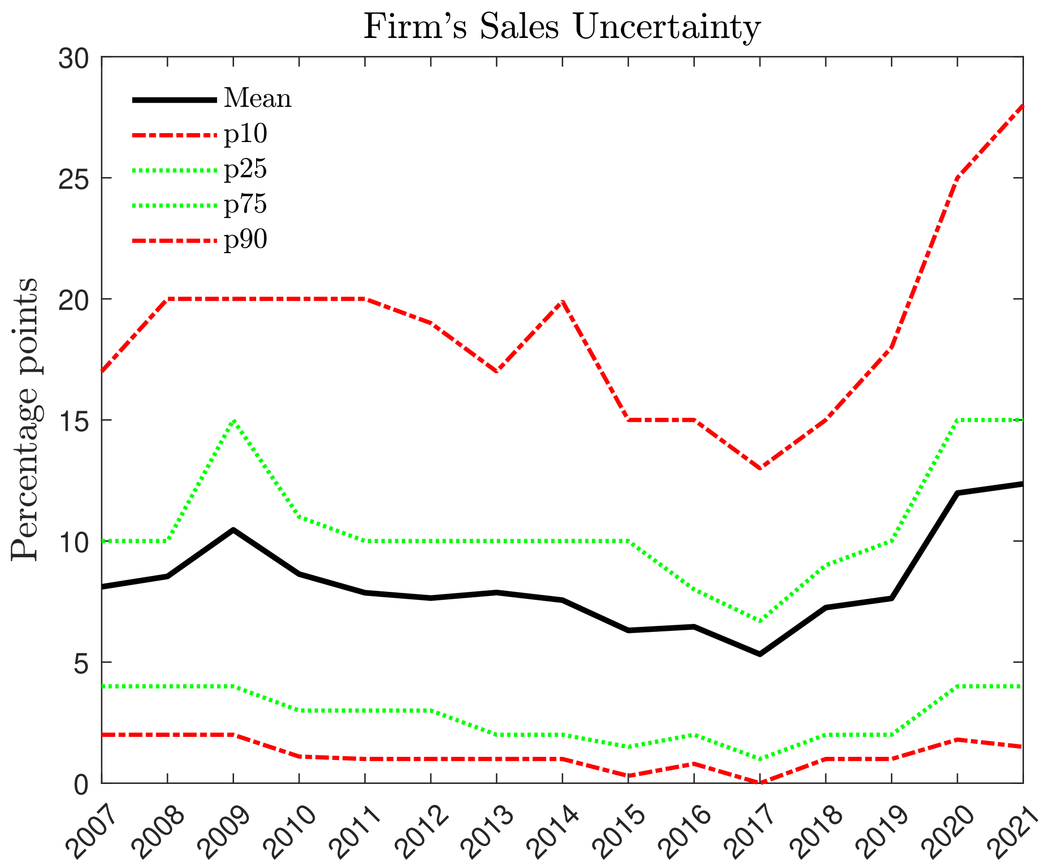

Figure 3: Cross-sectional distribution of firms' uncertainty for the growth rates of sales one year ahead.

ceived uncertainty around their sales forecast. Second, firm-level uncertainty varies over time, with the tail of high-uncertainty firms (the 75th and the 90th percentile) increasing around periods of economic stress in 2009 but also reaching historically high levels in 2018, a period of high domestic political uncertainty. In 2021, firm-level uncertainty increased from 8 to 12 percentage points for the median firm. We note that, in absolute terms, the uncertainty perceived at each quartile also increased substantially, showing an overall increase in uncertainty for a large share of firms.

3 Empirical Strategy, Identification, and Instruments

This section discusses the empirical approach we employ to measure the effects of a firm's uncertainty on its pricing behavior and activity, explicitly dealing with the endogeneity of uncertainty. In Section 3.1, we describe the identification strategy. In Sections 3.2 and 3.3, we describe how to implement our empirical approach detailing how we estimate the exposure to volatility factors useful to construct the instruments for firm-level uncertainty.

3.1 Identification Strategy

We examine the causal relationship between uncertainty and firms' pricing behavior adopting the novel instrumentation strategy in Alfaro, Bloom and Lin (2024). They exploit the differential exposure to exchange rates, oil prices, and policy uncertainty to identify exogenous variations in firm-level volatility. As discussed in Alfaro, Bloom and Lin (2024), to identify exogenous variation in firm volatility using, for example, measures of economic policy uncertainty (EPU), the strategy calls for distinguishing between the effect of the *level* of EPU and the change in the *volatility* of EPU in measuring the firm's directional exposure. While firms may be positively or negatively sensitive (or neutral) relative to shifts in the *level* of EPU, their exposure to uncertainty increases (or is constant) to shifts in the *volatility* of EPU. This distinction is key to the strategy's success, which permits controlling for level exposure while separately identifying exogenous variation in firm volatility from EPU uncertainty. This approach allows us to deal with the endogeneity of firm-level uncertainty while controlling for first-moment changes in the instruments (described in the next section). Unlike Alfaro, Bloom and Lin (2024), we observe the first and the second moment of expected outcomes directly from INVIND. Operationally, we consider four sources of uncertainty: the EPU index for Italy constructed by Baker, Bloom and Davis (2016*b*), the pair of exchange rates Euro-US Dollar, Euro-British Pound, and oil prices, a subset of the volatility factors considered in Alfaro, Bloom and Lin (2024). Adopting their larger set of volatility factors does not affect the result of the paper but makes the instruments' power somewhat weaker. This result occurs because of the high correlation at the yearly frequency for some of the series as we estimate sensitivities using yearly rather than daily data as in Alfaro, Bloom and Lin (2024).[9] We turn to this issue in the next section.

3.2 Estimation of Exposure to Volatility Factors

We estimate the exposure to energy, currency, and policy at the sectoral level by regressing at yearly frequency the growth rate of firms' actual sales at time t on the yearly mean change in oil prices, exchange rates, and EPU. Specifically, we recover the sensitivity for firm f in industry j by estimating the following specification:

$$\Delta Sales_{f,t} = \alpha_f + \Sigma_c \beta_j^c \times r_t^c + \varepsilon_{f,t} \tag{1}$$

The sensitivities to the volatility factors, β_j^c, are estimated using yearly data at the 3-digit ATECO industry level to reduce the role of the idiosyncratic noise.[10] As in Alfaro, Bloom and Lin (2024), we allow these coefficients to be time-varying by estimating equation 1 in 9-year rolling windows aligning the last year in the sample with the sensitivity $\beta_{j,\tau}^c$.[11] We estimate the sensitivities using the full universe of firms in Cerved that contains about 2 million observations rather than the smaller sample in INVIND to reduce the sample uncertainty around the estimated β_j^c coefficients.

3.3 Instruments and Empirical Specifications

To construct the instruments, denoted by $z_{c,t-1}$, we multiply the absolute value of the estimated $\beta_{j,\tau}^c$ by the shocks to the realized volatility of the aggregate variable $\Delta\sigma_t^c$ so that:

$$z_{i,t-1}^c = \mid \beta_{j,\tau}^c \mid \times \Delta\sigma_{t-1}^c \tag{2}$$

[9] Alfaro, Bloom and Lin (2024) apply their strategy to the US economy, considering EPU, oil prices, and the exchange rate between the US dollar and the seven major currencies.

[10] ATECO codes are the Italian equivalent of 2007 NACE classification.

[11] For instance, if the sample runs from 1997 to 2005, the estimated coefficient $\beta_{j,\tau}^c$ is the sensitivity for the year 2005.

To ensure that the sensitivities are predetermined in the key specifications (discussed below), we lagged the sensitivity $\beta^c_{j,\tau}$ by one year. To be clear, we instrument the uncertainty elicited by INVIND at the beginning of year t, with the instrument $z^c_{i,t-1}$. Given the annual frequency of our data, to reduce collinearity, our baseline estimates are adjusting the exposure by their statistical significance as measured by the weighted average of t-statistics . Specifically, we set to zero $\beta^c_{j,\tau}$ with an associated p-value larger than 10 percent. Maintaining all the estimated $\beta^c_{j,\tau}$ typically affects the strength of the instruments but not the point estimates and their significance.

Our baseline specification estimates the effects of uncertainty for a firm's pricing behavior and activity by ordinary least squares (OLS) and instrumental variables (IV):

$$y_{f,t} = \sum_{f=1}^{F} \alpha_f + \beta_{max-min} \times \sigma_{max-min,f,t} + \\ Controls_t + \epsilon_{f,t}; \tag{3}$$

where $y_{f,t}$ denotes the dependent variable that is, in turn, the firm's inflation rate $\pi_{f,t}$ and a measure of market power; the growth rate of sales and the capacity utilization index. The panel structure of our data allows us to control in every specification for time-invariant factors specific to each firm, α_f, ruling out that our results are driven by the correlation between the means of the uncertainty measures and those of the dependent variables. the set of *Controls* also features sector and year dummies to account for unobserved industry-specific characteristics and time-varying aggregate factors potentially related to policy changes or business cycle fluctuations. To tease out the second-moment effects from the first moment, we include the first moment of the managers' expectations about sales and prices that we directly observe. Also, we include exposure to mean factors of energy, currency, and EPU for Italy. The latter is computed as $\beta^c_{j,\tau} \times r^c_{t-1}$, denoted in the tables reporting results as "IV first-moment controls." We also include a set of "Firm-level controls": the growth rate of material and labor costs; and, to account for potential autocorrelation in the dependent variable, we also include the one-year lags of the dependent variables. In the next section, we discuss the empirical findings to assess the plausible causal effect of uncertainty on a firm's pricing behavior and activity.

4 The Effects of Subjective Firm-Level Uncertainty on Firms

We now study the effects of uncertainty on firms' pricing behavior and activity by tracing the responses of a firm's inflation rate, measures of markups, sales growth, and capacity utilization. In Section 4.1, we show that an increase in uncertainty reduces the growth rate of a firm's prices. In Section 4.2, we show that lower prices result from lower markups, shedding light on the underlying forces that result in lower prices. In Section 4.3, we provide evidence that sales uncertainty can be interpreted as demand uncertainty by showing that higher uncertainty results in a lower growth rate of sales and lower capacity utilization. In Section B, we examine the robustness of our results to alternative assumptions about the timing of exposure to the volatility of the factors in constructing the set of instruments.

4.1 Firm's Inflation and Uncertainty

Table 1 presents the effect of uncertainty shocks on the firm's growth rate of prices (the firm's inflation rate). Column 1 presents the OLS regression estimates of the firm's inflation rate ($\pi_{f,t}$) on managers' subjective uncertainty. The specification includes managers' sales and price expectations, firm-specific, sector, and time fixed-effects. Standard errors were clustered at the 3-digit level, the same levels of disaggregation used to measure the exposure to volatility factors. The sample includes INVIND firms matched with Cerved using data from 2007 to 2019.[12] The point estimate indicates that an increase of one percentage point in

[12] Relative to the full INVIND sample that starts in 1997, we lose the first 10 years of data as we need to initialize the estimation of the sectoral exposure to the volatility factors and lag the instruments.

the subjective uncertainty perceived by managers reduces the growth rate of a firm's prices by 0.018 percent. In Column 2, we also add a set of firm-level controls. The estimated relationship is statistically significant but quantitatively negligible in both cases, showing that uncertainty predicts lower prices. Despite our efforts to control for mean expected variables, OLS inference may suffer from endogeneity bias due to omitted variables and simultaneity bias. To explicitly treat endogeneity, Columns 3 and 4 report results instrumenting the firm's volatility with the instruments described in Section 3.2 using the set of controls in Columns 1 and 2, respectively. Uncertainty leads to a significant drop in a firm's inflation rates, one order of magnitude larger than those of the OLS regressions, a result similar to what Alfaro, Bloom and Lin (2024) find for investment.

Table 1: Firm's Inflation and Uncertainty

	$\pi_{f,t}$ (1)	$\pi_{f,t}$ (2)	$\pi_{f,t}$ (3)	$\pi_{f,t}$ (4)
$\sigma_{max-min,f,t}$	-0.018^{**}	-0.020^{***}	-0.600^{**}	-0.720^{**}
	(0.01)	(0.01)	(0.29)	(0.34)
Observations	11035	10126	10124	9930
First-stage F-test			12.58	10.28
Sargan-Hansen J-test p-value			0.163	0.534
Estimator	OLS	OLS	IV	IV
Firm-level controls$_{i,t-1}$		✓		✓
IV$_{i,t-1}$ first-moment controls				✓
Firm-specific effects	✓	✓	✓	✓
Sector effects	✓	✓	✓	✓
Time effects	✓	✓	✓	✓

Note: The dependent variable $\pi_{f,t}$ denote the firm's inflation rate in percent. $\sigma_{max-min,f,t}$ denotes firm-level uncertainty as measured by managers' subjective expectations about sales one year ahead. Standard errors are reported in parentheses. The sample period ranges from 2007 to 2019. $**$ denotes a p-value < 0.05; $***$ denotes a p-value < 0.01.

Our identification strategy works well in practice, with sizeable first-stage $F - tests$; we report the heteroskedasticity-robust Kleibergen and Paap (2006) *rk* Wald F-statistic, above 10 in all the specifications. The Sargan-Hansen overidentification $J - test$ does not reject the validity of our instruments, with p-values of 0.163 and 0.534.

4.2 Uncertainty and Markups

As the response of prices is the byproduct of fluctuations in markups and marginal costs, to shed light on the propagation mechanism behind lower prices, we estimate the response of markups to uncertainty. To construct measures, we follow alternative strategies. First, we start by computing a measure of market power close in spirit to the Lerner index. Specifically, for every firm we define $\Lambda_{f,t} = \frac{value\ added - wage\ bill}{value\ added}$. We then construct markups as $\mu_{f,t} = \frac{1}{1-1/\Lambda_{f,t}}$. Second, we use the growth rate of the price margin as a measure of market power, computed as the difference between the growth rate of the firm's prices, $\pi_{f,t}$, and the marginal cost, proxied by the wage growth rate; see, for instance, Nekarda and Ramey (2020). Third, we consider additional proxies of markups: the inverse of the labor share, and the inverse cost share multiplies by the estimated elasticity of inputs with respect to output.[13]

Table 2: Markups, Price Margins, and Uncertainty

	$\mu_{f,t}$	$\mu_{f,t}$	P. M.	P. M.	Inv. labor share	$\frac{\alpha_{mat}}{costshare}$ $material$	$\frac{\alpha_{lab}}{costshare}$ $labor$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sigma_{max-min,f,t}$	-0.012^{**}	-0.255^{**}	-0.016^{**}	-0.732^{**}	-1.346^{*}	-0.149^{**}	-0.787^{*}
	(0.01)	(0.11)	(0.01)	(0.34)	(0.75)	(0.07)	(0.46)
Observations	10182	10126	10349	9930	11571	11360	11402
First-stage F-test		12.58		10.27	17.82	18.25	18.76
Sargan-Hansen J-test p-value		0.499		0.161	0.224	0.291	0.149
Estimator	OLS	IV	OLS	IV	IV	IV	IV
Firm-level controls$_{i,t-1}$	✓	✓	✓	✓	✓	✓	✓
IV$_{i,t-1}$ first-moment controls		✓		✓	✓	✓	✓
Firm-specific effects	✓	✓	✓	✓	✓	✓	✓
Sector effects	✓	✓	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓	✓	✓

Note: The dependent variables $\mu_{f,t}$, *P.M.* and $\pi_{f,t}$ denotes the firm's log of the markup, the growth rate of the price margin, and additional proxies of the markup, respectively. Variables are expressed in percent, except for the price margin that is expressed in percentage points. $\sigma_{max-min,f,t}$ denotes firm-level uncertainty as measured by managers' subjective expectations about sales one year ahead. Standard errors in parentheses. The sample period ranges from 2007 to 2019. $*$ denotes a p-value < 0.10; $**$ denotes a p-value < 0.05; $***$ denotes a p-value < 0.01.

[13]The elasticities are obtained by estimating production functions using sales or value added, employing the approach in Wooldridge (2009) with a second-degree polynomial. This method efficiently accounts for the simultaneity between TFP realization and input choice.

Table 2 examines the effects of uncertainty on measures of markups and the robustness of our results to altering the timing of the exposure to volatility factors in constructing the instruments. Column 1 shows a negative correlation between uncertainty and markups. An increase of one percentage point is associated with a reduction in the firm's markup equal to -0.1 percent. As was the case with the firm's inflation, instrumenting uncertainty shows that uncertainty has larger effects on markups, now equal to about -0.25 percent. The estimates are statistically significant, with $F - tests$ above 10 and $J - tests$ that do not reject the validity of our instruments. Columns 3 and 4 use the price margin as a dependent variable, confirming that uncertainty leads firms to charge lower prices by reducing markups.

4.3 Firm's Activity and Uncertainty: Demand Uncertainty

Table 3 reports results for the effects of uncertainty on the realized growth rates of sales and the firm's capacity utilization index. Estimating these specifications allows us to clarify whether sales uncertainty captures a dimension of uncertainty more related to demand or to cost. This distinction, featured in theoretical literature since Mills (1959), is important because demand and cost uncertainty operate through fundamentally different mechanisms with opposite implications for pricing behavior. Understanding which channel dominates allows us to discriminate among competing theoretical predictions about how uncertainty affects markups and economic activity.[14]

We proceed in steps. First, we include the growth rate of sales as the dependent variable in the baseline specification; we verify how uncertainty moves not only prices but also quantities. Second, we focus on the capacity utilization index reported by firms. Third, we report suggestive evidence trying to disentangle the role of demand and cost uncertainty explicitly. Towards this goal, we include in the baseline regression the *price* max-min range perceived by managers about the firm's growth rate of prices one year ahead. Unfortunately, the price

[14]On the role of cost and demand uncertainty, see also Oi (1961), Hartman (1972), and Abel (1983).

max-min range, denoted $\sigma_{\pi,f,t}$, is available only for 5 years (2 of which during Covid).[15] As

Table 3: Sales Uncertainty as Demand Uncertainty

	$\Delta Sales_{f,t}$ (1)	$\Delta Sales_{f,t}$ (2)	Log Util. (3)	Log Util. (4)	$\pi_{f,t}$ (5)
$\sigma_{max-min,f,t}$	-0.186^{***}	-1.591^{***}	-0.151^{***}	-1.082^{**}	-0.883^{**}
	(0.05)	(0.56)	(0.04)	(0.48)	(0.39)
$\sigma_{\pi,max-min,f,t}$					0.405^{*}
					(0.21)
Observations	9013	10526	6792	6540	3848
First-stage F-test		17.27		6.90	2.16
Sargan-Hansen J-test p-value		0.950		0.742	0.182
Estimator	OLS	IV	OLS	IV	IV
Firm-specific controls$_{i,t-1}$	✓	✓	✓	✓	✓
IV$_{i,t-1}$ First-moment controls		✓		✓	✓
Firm-specific effects	✓	✓	✓	✓	✓
Sector effects	✓	✓	✓	✓	✓
Time effects	✓	✓	✓	✓	✓

Note: The dependent variables $\Delta Sales_{f,t}$, "Log Util" and $\pi_{f,t}$ denotes the realized growth rate of sales, the log of the capacity utilization index reported by firms, and the firm's inflation rate, respectively. Variables are expressed in percent. $\sigma_{max-min,f,t}$ and $\sigma_{\pi,max-min,f,t}$ denote firm-level uncertainty as measured by managers' subjective expectations about sales and prices one year ahead. Standard errors in parentheses. The sample period in Columns 1 through 4 ranges from 2007 to 2019, and from 2016 to 2019 in Column 5. $*$ denotes a p-value < 0.10; $**$ denotes a p-value < 0.05; $***$ denotes a p-value < 0.01.

the variance of the expected price one year ahead correlates with cost variables, we interpret price uncertainty as a measure of *cost* uncertainty. Including the latter in the baseline specification allows us to study whether the max-min range of expected sales proxies more closely *demand* or cost uncertainty.

Column 1 through 4 indicates that the max-min range of expected sales ($\sigma_{max-min,f,t}$) reduces the growth rate of sales and the capacity utilization index, as well as the firm's inflation rate. These two results support the interpretation that uncertainty about sales proxies demand uncertainty, acting as a negative demand shock.

[15]INVIND elicits for the whole sample uncertainty about the growth rate of real sales one year ahead and the price max-min range for the sample from 2016 to 2021. Real sales and price uncertainty are positively correlated (0.29).

We now disentangle demand and cost uncertainty through direct proxies. Column 5 shows that cost uncertainty ($\sigma_{\pi,max-min,f,t}$) acts as a cost-push shock that foreshadows higher prices; sales uncertainty *increases* the firm's price. The effects on sales are muted (not shown). The limited sample and the low F-stats indicate that the results in Column 5 are suggestive evidence. To assess the robustness of the timing of the exposure to factors, we follow Alfaro, Bloom and Lin (2024), and use a three-year lag of the measured exposure to volatility factors ($\beta^{c}_{j,t-3}$) in the construction of the instrument z, rather than a one-year lag. Even with this alternative timing assumption, our estimates (reported in Appendix B) indicate that an increase in uncertainty reduces firm's inflation and markups/price margin.

5 Taking Stock: Micro Evidence and Macro Theory

Our main result is that firms reduce price growth and markups decline in response to an increase in demand uncertainty. Rather than providing a comprehensive literature review, this section discusses how our findings connect with the existing macroeconomic literature. The extensive theoretical literature has identified several microeconomic mechanisms through which uncertainty affects economic activity: Oi–Hartman–Abel effects, real option effects, and precautionary savings. Broad reviews of these effects on investment and output can be found in Bloom (2009) and Born and Pfeifer (2014).

Cost Uncertainty and the Inverse Oi–Hartman–Abel Effect In the New Keynesian literature, Fernández-Villaverde et al. (2015), Born and Pfeifer (2014), and Pintér (2023) emphasize the role of cost uncertainty, which results in higher markups. When prices cannot be fully adjusted and firms face full obligation at posted prices, the marginal profit curve becomes convex in relative prices—the so-called "inverse Oi–Hartman–Abel effect." Setting prices too low forces firms to sell more goods at lower markups or higher losses, while setting prices too high reduces sales volume but increases profit per unit. Consequently, firms choose higher prices and markups over marginal costs when uncertainty increases. In these frameworks, demand uncertainty affects prices only to the extent that it generates cost uncertainty. When demand takes the form of a constant elasticity of substitution (CES) consumption bundle with no link between demand and cost uncertainty, demand uncertainty does not affect prices under risk neutrality (see the discussion in Appendix G of Fernández-Villaverde et al. (2015)).

Demand Uncertainty and Capacity Constraints Our results complement this literature by highlighting a new mechanism that emerges specifically from demand uncertainty and emphasizes the role of capacity constraints. In a partial equilibrium setting, Mills (1959) demonstrates that demand uncertainty leads to lower prices when firms choose output capacity together with prices before uncertainty is resolved. Lower prices occur because firms reduce the expected loss from discarding unsold production.[16] An additional mechanism consistent with our evidence operates through the kinked demand structure in Kimball (1995). Kimball preferences nest CES Dixit-Stiglitz preferences as a limiting case and imply a quasi-kinked demand curve where firms lose more customers by raising prices above the market price than they gain by lowering them below. This asymmetric loss structure implies that firms uncertain about their demand charge lower prices than they would under certainty. As we show in the next section, lower prices combined with capacity constraints result in contractionary effects of higher uncertainty.

6 Model: Capacity Constraints and Demand Uncertainty

We now quantify the aggregate implications of demand uncertainty in a model that reproduces the empirical findings documented in Section 4: firms reduce price growth and markups in response to increases in demand uncertainty. Standard models analyzing ag-

[16] Under additive demand uncertainty, Karlin and Carr (1960) generalize Mills' result for both static and multiperiod cases with inventory carryover, showing that additive uncertainty tends to reduce prices for risk-neutral firms.

gregate uncertainty shocks to tax policy or households' discount rates typically require markup increases to generate negative aggregate effects of uncertainty; see, for instance, Basu and Bundick (2017) and Fernández-Villaverde et al. (2015). In contrast, we show that when uncertainty originates from idiosyncratic demand shocks, introducing meaningful capacity constraints at the firm level generates lower prices, markups, and capacity utilization—consistent with our empirical evidence. Despite this markup reduction, demand uncertainty triggers a recession at the aggregate level, with declines in output, consumption, labor, and GDP.

The economy consists of households, a central bank conducting monetary policy, and two productive sectors: a competitive final goods sector and a monopolistic intermediate goods sector. The intermediate sector provides input goods that serve as the sole inputs for final good production, which is allocated to consumption or investment. Our framework extends a standard two-sector dynamic New Keynesian model by introducing capacity utilization (distinct from capital utilization) following Fagnart, Licandro and Portier (1999) and Alvarez-Lois (2006) who develop the structure in Mills (1959). The central innovation relative to standard frameworks concerns the production technology of intermediate firms, which incorporates two key features that generate a tractable concept of productive capacity.

First, intermediate firms employ putty-clay production technology where capital and labor are substitutes *ex ante* (before investment decisions) but complements *ex post* (once equipment is installed). This structure requires firms to make capacity choices during investment by selecting both the amount of capital and the maximum level of work stations (employment capacity) that can be utilized with the chosen capital level. Crucially, firms make these irreversible investment decisions under demand uncertainty, as they must choose productive capacity before observing future demand realizations.

Second, monopolistic firms face uncertainty about the position of their demand curve, with demand shifters realized only after pricing and investment decisions. We characterize this dispersion through an uncertainty variable σ_t that follows a stochastic process. High uncertainty periods feature large σ_t values and substantial cross-firm outcome dispersion, while low uncertainty periods exhibit the reverse. This specification aligns with extensive evidence documenting countercyclical cross-sectional dispersion in economic variables.[17]

The capacity utilization mechanism is crucial for generating pricing responses to uncertainty consistent with our empirical evidence. When uncertainty rises, declining expected profits prompt firms to reduce markups. Expected profits decline because low demand states generate reduced sales, while high demand states cannot be fully exploited due to supply constraints. When demand is low, firms operate on their demand curves and can support sales by lowering prices. Capacity constraints, however, prevent firms from capitalizing on high demand realizations.

We proceed by analyzing the final goods sector, followed by intermediate goods firms, and conclude with the household problem and the central bank policy rule.

6.1 Final Sector Firms

A representative firm produces a single final good $\mathbf{Y}_t$ sold on a competitive market for consumption or investment. The production technology follows a constant returns-to-scale CES function over a continuum of intermediate inputs $y_t(j)$, $j \in [0,1]$,

$$\mathbf{Y}_t = \left[\int_0^1 (y_{j,t})^{(\varepsilon-1)/\varepsilon} (v_{j,t})^{1/\varepsilon} dj \right]^{\varepsilon/(\varepsilon-1)}, \tag{4}$$

where $\varepsilon > 1$ is the elasticity of substitution between inputs, $y_{j,t}$ is the quantity of in-

[17] For example, Bloom (2009) documents that various cross-sectional dispersion measures for firms in panel datasets are countercyclical. Kehrig (2015) uses plant-level data to show that the dispersion of total factor productivity in US durable manufacturing is greater in recessions than in booms. Vavra (2014) presents evidence that the cross-sectional variance of price changes at the product level is countercyclical. Bachmann and Bayer (2014) documents countercyclical dispersion of investment. Fiori and Scoccianti (2023) provide evidence of countercyclical TFP dispersion for the Italian economy.

put j used in production, and $v_{j,t} \geq 0$ represents idiosyncratic productivity shocks drawn independently across time and firms from a log-normal distribution $F(v, \sigma)$ where μ and σ_t^2 denote the mean and the time-varying variance of the underlying normal distribution, respectively. In the model, we refer to σ_t^2, the time period t cross-sectional standard deviation of ν as *demand* uncertainty. Demand uncertainty, σ_t^2, evolves stochastically following an autoregressive process of order one.

The final goods firm purchases intermediate goods at prices $P_{j,t}$ subject to supply constraints $q_{j,t}$ and sells output at price $\mathbf{P}_t$. The firm's optimization problem is:

$$\max_{\{\mathbf{Y}_t, y_{j,t}\}} \mathbf{P}_t \mathbf{Y}_t - \int_0^1 P_{j,t} Y_{j,t} dj \tag{5}$$

$$\text{subject to } y_{j,t} \leq q_{j,t}. \tag{6}$$

Since the final goods firm observes all prices and productivity realizations when maximizing profits, the optimal input allocation follows a deterministic rationing scheme:

$$Y_{j,t} = \begin{cases} (P_{j,t}/\mathbf{P}_t)^{-\varepsilon} \mathbf{Y}_t v_{j,t} & \text{if } v_{j,t} \leq \bar{v}_{j,t} \\ q_{j,t} & \text{if } v_{j,t} > \bar{v}_{j,t} \end{cases} \tag{7}$$

where $\bar{v}_{j,t} = \bar{Y}_{j,t}/[(P_{j,t}/\mathbf{P}_t)^{-\varepsilon}\mathbf{Y}_t]$ is the critical productivity level at which unconstrained demand equals supply capacity.

The term $(P_{j,t}/\mathbf{P}_t)^{-\varepsilon}$ captures the market power of firms with spare capacity and represents a spillover effect from capacity-constrained to unconstrained firms. This term, smaller than unity and decreasing in the fraction of capacity-constrained firms, amplifies the market share of firms with idle resources and plays a crucial role in the model's dynamics.

Assuming *ex ante* symmetry across intermediate firms yields identical prices ($P_{j,t} = P_t$) and capacities ($q_{j,t} = q_t$). Under this symmetry and applying the law of large numbers, final output becomes:

$$\mathbf{Y}_t = q_t \left[\int_0^1 v^{1/\varepsilon} dF(v, \sigma_t) \right]^{\varepsilon/(\varepsilon-1)}. \tag{8}$$

Combining the optimal allocation with the symmetry assumption yields the aggregate final output, where the second term recognizes that firms with demand above the cutoff vale $\bar{\nu}$ face capacity constraints:

$$\mathbf{Y}_t = \left[\int_0^{\bar{v}_t} v dF(v, \sigma_t) + \bar{v}_t^{(\varepsilon-1)/\varepsilon} \int_{\bar{v}_t}^1 v^{1/\varepsilon} dF(v, \sigma_t) \right]^{\varepsilon/(\varepsilon-1)}. \tag{9}$$

Moreover, $F(\bar{v}_t, \sigma_t)$ represents the proportion of firms with spare capacity, while $1 - F(\bar{v}_t, \sigma_t)$ denotes the proportion operating at full capacity.

6.2 Intermediate Sector Firms

A continuum of monopolistically competitive firms produce intermediate goods using capital and labor combined through putty-clay technology. Each firm begins period t with predetermined productive capacity that cannot be adjusted within the period. Investment in period $t-1$ becomes productive at time t, consisting of simultaneous choices of capital K_t and work stations N_t according to a Cobb–Douglas technology:

$$y_t = Z_t K_t^{\alpha} N_t^{1-\alpha}, \tag{10}$$

where $\alpha \in (0, 1)$, and, as discussed in the previous subsection, the subscript j is dropped because of symmetry. Z_t has mean one and represents the stochastic aggregate productivity that follows an autoregressive process of order one:

$$\log(Z_t) = \rho_A \log Z_{t-1} + \varepsilon_{A,t}. \tag{11}$$

With N_{t-1} representing maximum work stations and capital-labor ratio $X_{t-1} = K_{t-1}/N_{t-1}$, capacity becomes:

$$q_t = Z_t X_{t-1}^{\alpha} N_{t-1}. \tag{12}$$

This specification yields constant returns to scale in labor, so firm j using labor $L_{j,t} \leq N_{t-1}$ produces $Z_t X_{t-1}^{\alpha} L_{j,t}$ units of output. Once aggregate and idiosyncratic shocks are revealed, firms instantaneously adjust labor demand to meet production needs:

$$L_{j,t} = \frac{Y_{j,t}}{Z_t X_{t-1}^{\alpha}} = \frac{1}{Z_t X_{t-1}^{\alpha}} \min\{\mathbf{Y}_t v_{j,t} (P_t/\mathbf{P}_t)^{-\varepsilon}, q_t\}. \tag{13}$$

Each firm maximizes the discounted stream of expected profits by choosing prices and investment:

$$\max \sum_{s=t}^{\infty} \mathrm{E}_t[\beta^s \Lambda_s \Pi_s], \tag{14}$$

where $\beta^s \Lambda_s$ is the stochastic discount factor. Nominal profits are:

$$\Pi_t = P_t \mathrm{E}_v\{y_t\} - W_t \mathrm{E}_v\{L_t\} - P_t(I_t + \mathcal{A}_{k,t}), \tag{15}$$

where $I_t = K_t - (1-\delta)K_{t-1}$ is net investment, $\mathcal{A}_{k,t} = \frac{\phi_k}{2}\left(\frac{I_t}{K_{t-1}}\right)^2 K_{t-1}$ represents quadratic capital adjustment costs.

Expected sales depend on the realization of idiosyncratic shocks:

$$\mathrm{E}_v\{y_t\} = (P_t/\mathbf{P}_t)^{-\varepsilon} \mathbf{Y}_t \int_0^{\bar{v}_t} v \, dF(v, \sigma_t) + q_t \int_{\bar{v}_t}^{1} dF(v, \sigma_t). \tag{16}$$

Since firms announce prices before observing idiosyncratic shocks, despite the assumption of CES demand the optimal pricing decision under *ex ante* result in a markup rule that depends upon capacity constraints:

$$P_t = \left(1 - \frac{1}{\varepsilon G(\bar{v}_t), \sigma_t}\right)^{-1} \frac{W_t}{Z_t X_{t-1}^{\alpha}} \tag{17}$$

where $G(\bar{v}_t, \sigma_t)$ represents a weighted average of the probability of excess capacity and is defined as follows:

$$G(\bar{v}_t, \sigma_t) = \frac{\int_0^{\bar{v}_t} v\, dF(v, \sigma_t)}{\int_0^{\bar{v}_t} v\, dF(v, \sigma_t) + \bar{v}_t \int_{\bar{v}_t}^{1} dF(v, \sigma_t)}. \tag{18}$$

$G(\bar{v}_t, \sigma_t)$ depends upon the cutoff, in turn linked to aggregate output and the firm's relative, as well as the time-varying probability distribution functions linked to the demand uncertainty shock. An increase in $G(\bar{v}_t, \sigma_t)$ indicates that a larger share of the effective capacity comes from states operating below their capacity threshold $\bar{v}_t$, reflecting greater aggregate excess capacity. We notice that, keeping the cutoff $\bar{v}_t$ and therefore aggregate demand and firms' prices constant, an increase in σ_t mechanically leads to a decrease in G (with one exception at very low thresholds). As discussed in Section 6.6, in equilibrium, the increase in demand uncertainty leads to lower expected sales, to which firms optimally respond by lowering price growth, and despite a reduction in the cutoff $\bar{v}_t$, an increase in the function G indicating higher probability of having excess capacity. In turn, as firms expect a higher probability of having excess capacity–represented by larger $G(\bar{v}_t, \sigma_t)$–this reduces firms' market power and therefore markups.

The optimal choice of investment in capital K_t is given by the following equation:

$$\begin{aligned} &\mathrm{E}_t \left\{ (\Psi_t + \mathcal{W}_t) - \beta_{t,t+1} \frac{\mathbf{P}_{t+1}}{\mathbf{P}_t} \left(\Psi_{t+1}(1-\delta) + \frac{K_{t+1}}{K_t} \mathcal{W}_{t+1} \right) \right\} \\ &= \mathrm{E}_t \left\{ \beta_{t,t+1} \frac{\mathbf{P}_{t+1}}{\mathbf{P}_t} \left(P_{t+1} - \frac{W_{t+1}}{A_{t+1} X_t^{\alpha}} \right) \frac{\bar{Y}_{t+1}}{K_t} (1 - F(\bar{v}_{t+1}, \sigma_{t+1})) \right\} \end{aligned} \tag{19}$$

where $\beta_{t,t+1}$ is the stochastic discount factor and is equal to $\beta\Lambda_t + 1/\Lambda_t$. The maximum employment capacity X_t is given by:

$$\mathrm{E}_t \left\{ \beta_{t,t+1} \left(P_{t+1} - \frac{W_{t+1}}{A_{t+1} X_t^{\alpha}} \right) \frac{\alpha(\varepsilon - 1)\bar{Y}_{t+1}}{\bar{v}_{t+1}} \frac{1}{X_t} \int_0^{\bar{v}_{t+1}} v \, dF(v, \sigma_{t+1}) \right\}$$
$$= \mathrm{E}_t \left\{ \beta_{t,t+1} \left(P_{t+1} - \frac{W_{t+1}}{A_{t+1} X_t^{\alpha}} \right) \frac{\bar{Y}_{t+1}}{X_t} \int_{\bar{v}_{t+1}}^{\infty} dF(v, \sigma_{t+1}) \right\}, \tag{20}$$

where

$$\Psi_{t+h} = 1 + \frac{\phi_k}{2} \left(\frac{I_{t+h}}{K_{t-1+h}} - \delta \right)^2 \quad \text{for } h = 0, 1 \tag{21}$$

and

$$\mathcal{W}_{t+h} = \left(\frac{K_{t+h}}{K_{t+h}} - 1 \right) \frac{I_{t+h}}{K_{t-1+h}} \phi_k \quad \text{for } h = 0, 1. \tag{22}$$

Equation (19) characterizes the optimal choice of capital by an intermediate goods firm. This condition equates the expected user cost of one extra unit capital, including their corresponding adjustment costs, with the expected revenue of using such an additional unit of capital. The expected revenue is given by the discounted increase in profits generated by the extra unit of capital, corrected by the probability of operating it. Equation (20) characterizes the optimal choice of firms' productive capacity. This condition reveals the existence of the following trade-off: on the one hand, an increase in the capital–labor ratio raises firms' labor productivity, which is given by $Z_t A_{t+1} X_t^{\alpha}$. This fact has a favorable effect on firms' competitive position and on their potential profits; on the other hand, increasing the capital–labor ratio reduces the maximum level of employment available to the firm, and likewise the maximum volume of sales as well as their potential profits. The optimal capital–labor ratio will be such that these two opposite effects on profits are equal on the margin.

6.3 Households

Identical and infinitely living households have time-separable preferences over consumption and labor:

$$U_t = \sum_{s=t}^{\infty} \mathrm{E}_t \left\{ \beta^{s-t} \left[\log(c_s) - \xi L_s) \right] \right\}$$

where c_s and L_s are consumption and labor during $s \geq t$, β is the subjective discount rate. We rely on indivisible labor specification as in Hansen (1985) and Rogerson (1988).

Each household enters period t with predetermined financial assets a_t, receives wage income $w_t l_t$, firm profits Π_t, and asset returns $(1 + r_t)a_t$. The budget constraint is:

$$a_{t+1} + c_t \leq (1 + r_t)a_t + w_t l_t + \Pi_t. \tag{23}$$

The optimality conditions for the household's problem are such that the household supplies labor until the marginal rate of substitution is equated to the real wage, w_t:

$$w_t = \xi c_t. \tag{24}$$

Moreover, the household's saving policy result in a standard Euler equation:

$$\frac{1}{c_t} = \beta \mathrm{E}_t \left[\frac{1 + r_{t+1}}{c_{t+1}} \right]. \tag{25}$$

Monetary Authority We close the model by assuming that the Central Bank sets the nominal interest rate according to a standard Taylor rule that responds to consumer price inflation.

6.4 Equilibrium

Given initial conditions for K_0 and X_0 and the stochastic process for Z_t and σ_t, the general equilibrium for any period $t \geq 0$ consists of price vector $P_t, \mathbf{P}_t, W_t, r_t$, quantity vector $\mathbf{Y}_t, C_t, L_t, K_{t+1}, X_{t+1}$, and proportion $F(\nu)$ of intermediate firms such that: (i) P_t, K_{t+1}, X_{t+1} maximize expected profits where; (ii) the final good market clears: $\mathbf{Y}_t = C_t + I_t + \mathcal{A}_{k,t}$, where final output $\mathbf{Y}_t$ is given by equation 8; (iii) the asset market clears: $a_{t+1} = K_{t+1}$; (iv) labor supply equals aggregate labor demand. As the equilibrium exhibits symmetry: all intermediate firms choose identical capacity and pricing. Under symmetric pricing, aggregate employment equals:

$$L_t = \frac{(P_t/\mathbf{P}_t)^{-\varepsilon}\mathbf{Y}_t}{A_t X_{t-1}^{\alpha}} \int_0^{\bar{v}_t} v \, dF(v, \sigma_t) + \frac{K_{t-1}}{X_{t-1}} \int_{\bar{v}_t}^1 dF(v, \sigma_t). \tag{26}$$

A key equilibrium property is that the relative intermediate goods price $P_t/\mathbf{P}_t < 1$. This relative price can be expressed as:

$$\frac{P_t}{\mathbf{P}_t} = \left[\int_0^{\bar{v}_t} v \, dF(v, \sigma_t) + \bar{v}_t^{(\varepsilon-1)/\varepsilon} \int_{\bar{v}_t}^1 v^{1/\varepsilon} \, dF(v, \sigma_t) \right]^{1/(\varepsilon-1)}. \tag{27}$$

This expression increases in $\bar{v}_t$ and is bounded above by unity. As discussed in Alvarez-Lois (2006), the term $(P_t/\mathbf{P}_t)^{-\varepsilon} > 1$ captures the spillover effect from capacity-constrained to unconstrained firms, amplifying the market power of firms with excess capacity.

Supply constraints create scarcity that raises the marginal cost of final production beyond input costs. With the final good price adjusting to this higher marginal cost in equilibrium, intermediate inputs become relatively less expensive, yielding a relative price below one.

6.5 Calibration

To illustrate the aggregate effects of an increase in demand uncertainty, the model is calibrated to reproduce selected targets of the aggregate Italian economy, with one period representing one year to match the data frequency in the empirical section. All parameters are reported in Table 4. The share of labor in production $(1-\alpha)$ is calibrated to match the aggregate labor share observed in the data. The discount factor $\beta = 1.03^{-0.25}$ is set so that the steady-state real interest rate equals 3%. The depreciation rate $\delta = 0.09$ reflects the average sectoral depreciation rate computed by ISTAT. Following Hansen (1985), we assume linear disutility of labor, with ξ set to reproduce the observed employment rate in the economy. The elasticity of substitution in the CES aggregator, ε, is set to 25. This value represents a compromise between the range typically found in the macro literature (between 6 and 11) and the higher values used in macromodels of uncertainty, such as Fernández-Villaverde et al. (2015). However, this calibration produces an implausibly high markup of approximately 60%. To reduce the magnitude of the aggregate markup, we follow a strategy similar to Rotemberg and Woodford (1992) by incorporating fixed costs of production, z, (expressed in units of intermediate goods). In the steady state, the markup expression becomes:

$$markup = \frac{(1-z)^{-1}\varepsilon G(\bar{v}, \sigma_t)}{(1-z)^{-1}\varepsilon G(\bar{v}, \sigma_t) - 1}. \tag{28}$$

We calibrate the parameters of the lognormal distribution such that the underlying normal distribution reproduces both the average capacity utilization observed in the data and the dispersion of log sales. The parameters of the stochastic process for σ_t (namely, ρ_σ and σ_σ) are inferred from the persistence and standard deviation of the cross-sectional dispersion of log sales in the data. This procedure yields a persistence of 0.84 and a standard deviation of 0.04. Our results remain robust when using an alternative approach that infers the process for σ_t from the properties of firm-level uncertainty. Under this alternative specification, ρ_σ and σ_σ equal 0.56 and 0.06, respectively (see the discussion in Fiori and Scoccianti (2023)). For simplicity, the baseline version of the economy assumes no price or capital adjustment costs. Note that even in the absence of price adjustment costs, the model displays a form of price rigidity since prices are set before observing demand. Finally, following standard practice for the Euro Area (Smets and Wouters, 2003; Gerali et al., 2010), we set the inflation coefficient in the Taylor rule to 2.0, within the commonly used range of 1.5 to 2.0.[18]

Table 4: Calibration: Parameter Values

	Symbol	Value
Capital share in production	α	0.40
Intertemporal discount rate	β	$1.03^{-0.25}$
Depreciation rate	δ	0.09
Elasticity intermediate goods	ε	25
Labor disutility	ξ	1.44
Mean normal distribution	μ	-6.84
St. dev. normal distribution	σ	1.30
Labor disutility	ξ	1.44
Capital adjustment costs	ϕ_k	0
Persistence demand uncertainty	ρ_σ	0.84
Standard deviation demand uncertainty	σ_σ	0.09
Steady state gross inflation	π	1
Taylor rule: inflation response	ϕ_π	1.5

6.6 Aggregate Effects of Demand Uncertainty

We now quantify the aggregate effects of a mean-preserving increase in demand uncertainty, σ_t. The model dynamics are computed using an approximation accurate to the first order. Even if we focus on idiosyncratic uncertainty, mean-preserving changes in σ_t have first-order effects on model variables given the presence of capacity constraints. Figure 4 reports the impulse response functions. An increase in demand uncertainty has negative effects on aggregate activity and prices. At the firm level, higher demand uncertainty spreads probability mass toward both tails of the ν distribution. While firms suffer losses from low demand realizations, they cannot fully capitalize on high demand realizations due to capacity constraints. Consequently, the increase in uncertainty reduces expected profits. In response, firms lower prices to mitigate the sales decline. The cutoff $\bar{\nu}$, the ratio between the capacity

[18]For example, Smets and Wouters (2003) estimate 1.7 for the Euro Area, while Smets and Wouters (2007) find values around 2.0 for the US. Christiano, Motto and Rostagno (2014) use values in the 1.5-2.0 range for their Euro Area analysis.

installed and the firm's demand net of ν, decreases because lower prices reduce the demand shock ν needed to reach capacity. Despite a lower cutoff, the increase in demand uncertainty leads firms to cut markups as they expect greater excess capacity, i.e., $G(\bar{\nu}, \sigma_t)$ increases. Expecting lower sales and profitability, firms reduce demand for investment inputs and labor, leading to lower wages. Households, facing reduced income, cut consumption contributing the slowdown in aggregate activity. Overall, macroeconomic variables move together on impact: economic activity contracts, producer prices (PPI) and consumer prices (CPI) decline, and nominal interest rates fall.

After the first period, firms have lower capacity and demand uncertainty starts reverting to its steady state value. The economy remains depressed as the shock is persistent and reverts back to its steady state level gradually. We note that the response of markups displays virtually no persistence, as markups return to their steady state level one period after the shock. This behavior is related to the probability of excess capacity $G(\bar{\nu}, \sigma_t)$, which is influenced by two factors: the rebound in prices in the intermediate sector that pushes the cutoff up, and lower installed capacity that pushes it down. Together with the change in demand uncertainty, these two effects largely cancel each other out, resulting in markups being virtually at their steady state level one period after the shock. Lower profitability continues to keep labor demand, investment, and output below steady state. Over time, the economy recovers from its trough as uncertainty reverts back to steady state.

We note that a one standard deviation shock produces sizable aggregate effects, highlighting the importance of demand uncertainty shocks as a source of meaningful aggregate dynamics. Annual GDP drops on impact by approximately 0.5 percent and investment by about 1 percent. On the nominal side, lower markups and marginal costs reduce PPI inflation by roughly 0.5 percentage points. Lower producer prices are reflected in lower CPI inflation, although the effect is smaller than for PPI. On the one hand, lower input prices make the final consumption bundle cheaper. On the other hand, higher uncertainty increases the dispersion of demand realizations across firms, with high-productivity varieties hitting their capacity constraints more frequently and being unable to fully satisfy demand, while low-productivity varieties receive more demand than in the absence of uncertainty. This compositional shift toward lower-quality goods would, all else equal, raise the effective price of the consumption bundle. However, the direct price reduction effect dominates, resulting in a CPI decline of approximately 0.1 percentage points.

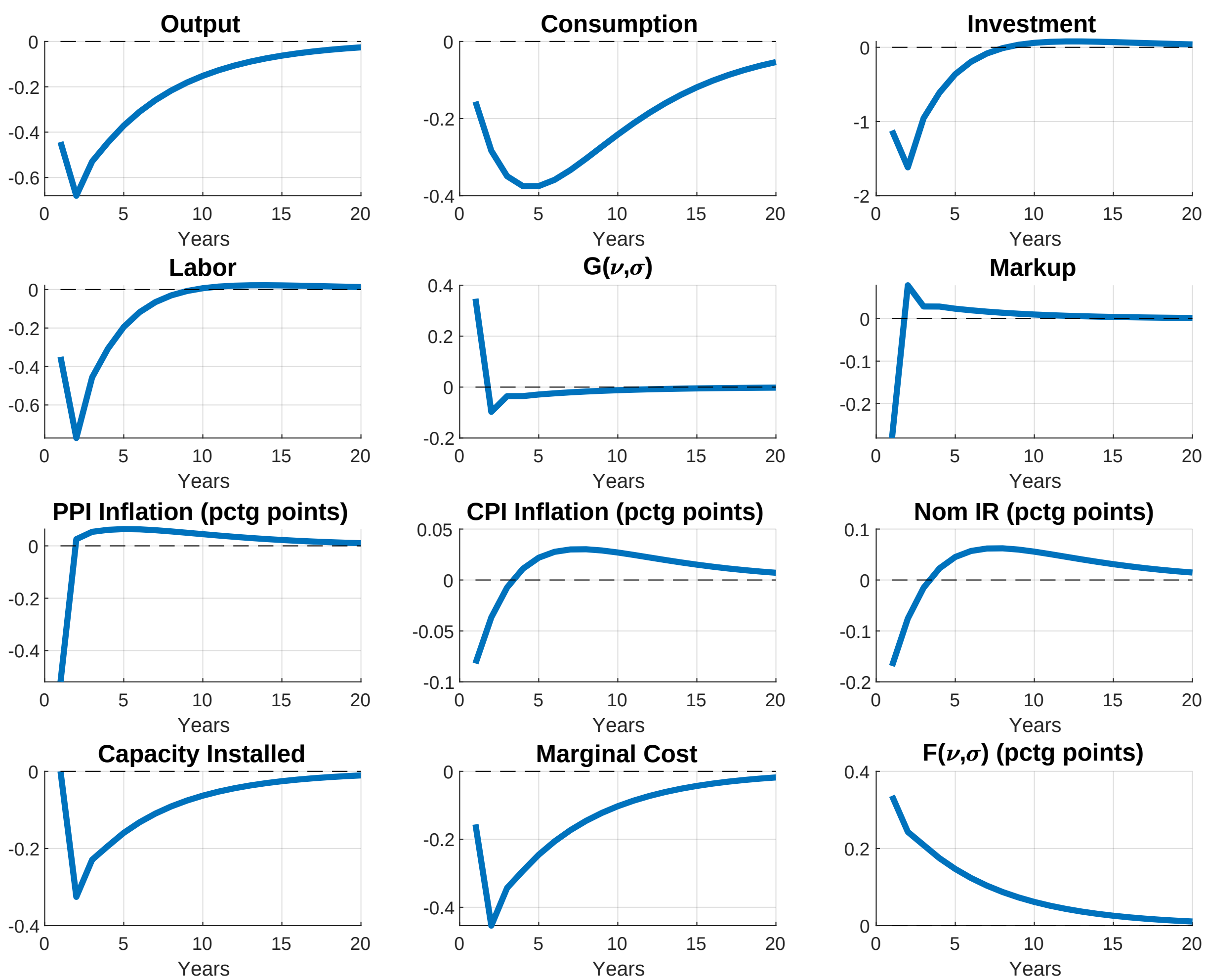

Figure 4: Impulse response function following a persistent demand uncertainty shock. Variables in percent deviation from their deterministic steady state except for nominal variables and the probability of excess capacity that are in percentage points.

The model generates comovement across macroeconomic series through idiosyncratic demand uncertainty, rather than through aggregate demand or cost uncertainty as in Basu and Bundick (2017) and Fernández-Villaverde et al. (2015). We conclude by noting that, abstracting from capacity constraints, it is possible to obtain lower markups in response to increased uncertainty. For instance, assuming preferences follow Kimball (1989) would produce lower markups in response to higher aggregate uncertainty. However, in the standard model without capacity constraints, lower markups would generate an expansion rather than a recession.

6.7 Prices, Capacity Constraints and Demand Uncertainty

To deepen our understanding of the relationship between profits and uncertainty, we examine the deterministic steady state, reminding the reader that idiosyncratic demand uncertainty is present even in this equilibrium. To isolate the role of demand uncertainty for profits, we employ the following procedure: we first compute the steady state, then, holding all parameters and endogenous variables fixed, we vary the relative price charged by the firm. We repeat this procedure for different levels of demand uncertainty. As shown in the left panel of Figure 5, a key feature of the firm's profit function is its asymmetry: losses from setting prices too low are smaller in magnitude than losses from setting prices too high. This asymmetry arises because capacity constraints truncate demand at the firm's capacity level, preventing firms from fully exploiting high demand realizations while allowing low demand realizations to translate directly into forgone sales. The right panel of Figure 5 demonstrates that the marginal profit function is concave. Combined with the asymmetry in the left panel, this concavity implies that an increase in demand uncertainty—which spreads probability mass toward both tails of the demand distribution—reduces expected profits. Firms respond to this reduction in expected profitability through a downward pricing bias: they lower prices to increase the probability of operating near capacity and to mitigate losses associated with excess capacity. This pricing behavior constitutes a central mech-

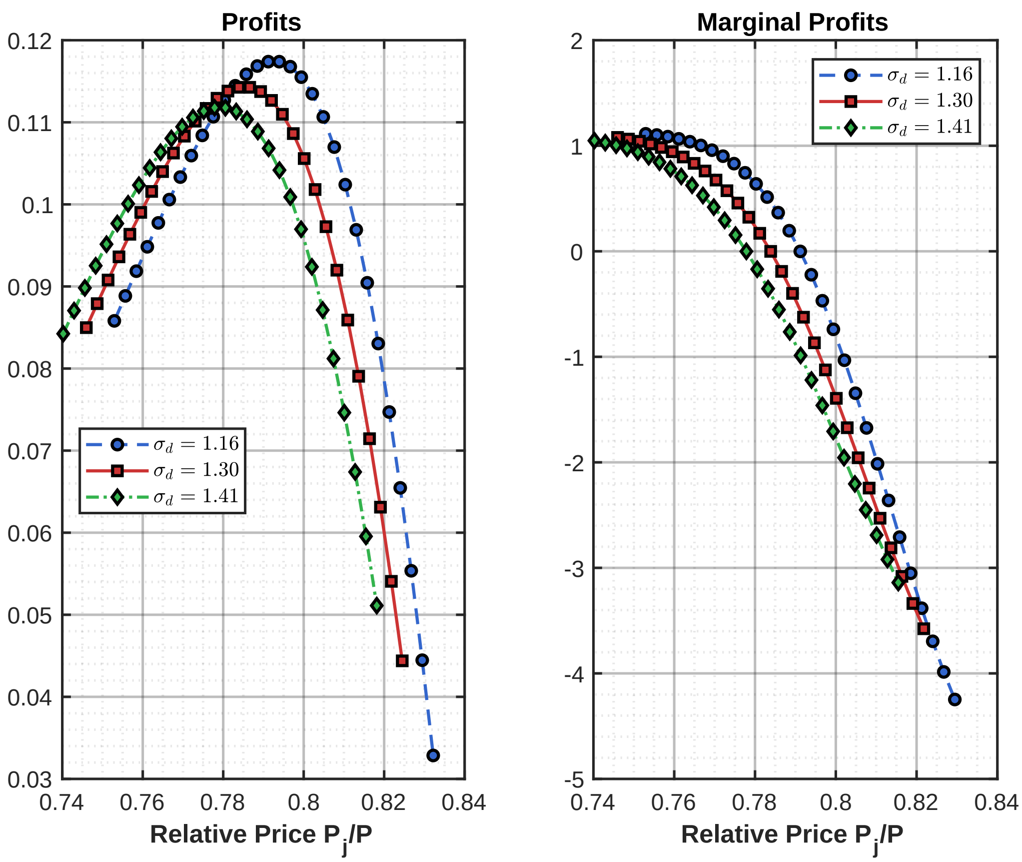

Figure 5: Profits and marginal profits computed around the optimal price.

anism through which idiosyncratic uncertainty affects aggregate outcomes in our model.

7 Final Remarks

We use firm-level data to examine how subjective uncertainty affects firms' pricing behavior and activity. Our causal evidence shows that increased uncertainty acts as a negative demand shock: firms reduce price growth and markups to mitigate the decline in sales. This price reduction reflects a fundamental asymmetry. Firms with capacity constraints cannot fully exploit high demand realizations but bear full losses from low demand realizations. This asymmetry creates a systematic incentive to lower prices and markups when uncertainty rises, establishing demand uncertainty as an important disinflationary force. Our results indicate that heightened demand uncertainty contributes to subdued inflation through firms' endogenous pricing responses.

We formalize a general equilibrium model incorporating demand uncertainty and capacity constraints to ensure consistency with our microeconomic evidence and to quantify aggregate effects. The model shows how firm-level responses propagate through general equilibrium channels. When firms simultaneously reduce prices, markups, investment, and labor demand under elevated uncertainty, several reinforcing mechanisms emerge. Lower labor demand decreases wages, reduced income constrains consumption, and weakened consumption further dampens output. This amplification mechanism depresses economic activity while exerting disinflationary pressure.

Our quantitative analysis shows that standard increases in demand uncertainty produce substantial declines in GDP and investment, accompanied by reduced inflation and interest rates. Notably, this transmission channel operates distinctly from cost-side and aggregate uncertainty mechanisms in the prior literature.

References

Abel, Andrew B. 1983. "Optimal Investment under Uncertainty." *American Economic Review*, 73(1): 228–233.

Abel, Andrew B., Avinash K. Dixit, Janice C. Eberly, and Robert S. Pindyck. 1996. "Options, the Value of Capital, and Investment." *The Quarterly Journal of Economics*, 111(3): 753–777.

Alfaro, Ivan, Nicholas Bloom, and Xiaoji Lin. 2024. "The Finance-Uncertainty Multiplier." *Journal of Political Economy*, 132(2): 577–615.

Altig, Dave, Scott Baker, Jose Maria Barrero, Nicholas Bloom, Philip Bunn, Scarlet Chen, Steven J. Davis, Julia Leather, Brent Meyer, Emil Mihaylov, Paul Mizen, and Nicholas and Parker. 2020. "Economic uncertainty before and during the COVID-19 pandemic." *Journal of Public Economics*, 191(C).

Altig, David, Jose Maria Barrero, Nicholas Bloom, Steven J. Davis, Brent Meyer, and Nicholas Parker. 2022. "Surveying business uncertainty." *Journal of Econometrics*, 231(1): 282–303. Annals Issue: Subjective Expectations & Probabilities in Economics.

Alvarez-Lois, Pedro P. 2006. "Endogenous capacity utilization and macroeconomic persistence." *Journal of Monetary Economics*, 53(8): 2213–2237.

Armantier, Olivier, Wändi Bruine de Bruin, Giorgio Topa, Wilbert Klaauw, and Basit Zafar. 2015. "Inflation Expectations and Behavior: Do Survey Respondents Act on Their Beliefs?" *International Economic Review*, 56: 505–536.

Awano, Gaganan, Nicholas Bloom, Ted Dolby, Paul Mizen, Rebecca Riley, Tatsuro Senga, John van Reenen, Jenny Vyas, and Philip Wales. 2018. "A firm-level perspective on micro- and macro-level uncertainty; An analysis of business expectations and uncertainty from the UK Management and Expectations Survey." Economic Statistics Centre of Excellence (ESCoE) Economic Statistics Centre of Excellence (ESCoE) Discussion Papers ESCoE DP-2018-10.

Bachmann, Rüdiger, and Christian Bayer. 2014. "Investment Dispersion and the Business Cycle." *American Economic Review*, 104(4): 1392–1416.

Bachmann, Rüdiger, Kai Carstensen, Stefan Lautenbacher, and Martin Schneider. 2018. "Uncertainty and Change: Survey Evidence of Firms' Subjective Beliefs." *Working Paper*.

Bachmann, Rüdiger, Kai Carstensen, Stefan Lautenbacher, and Martin Schneider. 2020. "Uncertainty Is More Than Risk – Survey Evidence on Knightian and Bayesian Firms." *Working Paper*.

Bachmann, Rüdiger, Steffen Elstner, and Eric R Sims. 2013. "Uncertainty and Economic Activity: Evidence from Business Survey Data." *American Economic Journal: Macroeconomics*, 5(2): 217–49.

Bachmann, Ruediger, and Giuseppe Moscarini. 2011. "Business Cycles and Endogenous Uncertainty." Society for Economic Dynamics 2011 Meeting Papers 36.

Bachmann, Rüdiger, Benjamin Born, Steffen Elstner, and Christian Grimme. 2019. "Time-varying business volatility and the price setting of firms." *Journal of Monetary Economics*, 101: 82–99.

Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016*a*. "Measuring Economic Policy Uncertainty." *The Quarterly Journal of Economics*, 131(4): 1593–1636.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis. 2016*b*. "Measuring Economic Policy Uncertainty." *The Quarterly Journal of Economics*, 131(4): 1593–1636.

Basu, Susanto, and Brent Bundick. 2017. "Uncertainty Shocks in a Model of Effective Demand." *Econometrica*, 85: 937–958.

Berger, David, Ian Dew-Becker, and Stefano Giglio. 2020. "Uncertainty Shocks as Second-Moment News Shocks." *Review of Economic Studies*, 87(1): 40–76.

Bloom, Nicholas. 2009. "The Impact of Uncertainty Shocks." *Econometrica*, 77(3): 623–685.

Bloom, Nicholas. 2014. "Fluctuations in Uncertainty." *Journal of Economic Perspectives*, 28(2): 153–76.

Bloom, Nicholas, Stephen Bond, and John Van Reenen. 2007. "Uncertainty and Investment Dynamics." *The Review of Economic Studies*, 74(2): 391–415.

Born, Benjamin, and Johannes Pfeifer. 2014. "Policy risk and the business cycle." *Journal of Monetary Economics*, 68: 68–85.

Caldara, Dario, and Matteo Iacoviello. 2022. "Measuring Geopolitical Risk." *American Economic Review*, 112(4): 1194–1225.

Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo. 2020. "The Economic Effects of Trade Policy Uncertainty." *Journal of Monetary Economics*, 109: 38 – 59. Special Issue: April 2019 Carnegie-Rochester-NYU Conference.

Christiano, Lawrence J., Roberto Motto, and Massimo Rostagno. 2014. "Risk Shocks." *American Economic Review*, 104(1): 27–65.

Dominitz, Jeff, and Charles F. Manski. 1994. "Using Expectations Data to Study Subjective Income Expectations." National Bureau of Economic Research, Inc NBER Working Papers 4937.

Dominitz, Jeff, and Charles F. Manski. 2004. "How Should We Measure Consumer Confidence?" *Journal of Economic Perspectives*, 18(2): 51–66.

Fagnart, Jean-François, Omar Licandro, and Franck Portier. 1999. "Firm Heterogeneity, Capacity Utilization and the Business Cycle." *Review of Economic Dynamics*, 2(2): 433–455.

Fernández-Villaverde, Jesús, and Pablo A. Guerrón-Quintana. 2020. "Uncertainty Shocks and Business Cycle Research." *Review of Economic Dynamics*, 37: S118–S146. The Twenty-Fifth Anniversary of "Frontiers of Business Cycle Research".

Fernández-Villaverde, Jesús, Pablo Guerrón-Quintana, Keith Kuester, and Juan Rubio-Ramírez. 2015. "Fiscal Volatility Shocks and Economic Activity." *American Economic Review*, 105(11): 3352–3384.

Fiori, Giuseppe, and Filippo Scoccianti. 2023. "The Economic Effects of Firm-Level Uncertainty: Evidence Using Subjective Expectations." *Journal of Monetary Economics*, 140: 92–105.

Gerali, Andrea, Stefano Neri, Luca Sessa, and Federico M. Signoretti. 2010. "Credit and Banking in a DSGE Model of the Euro Area." *Journal of Money, Credit and Banking*, 42(s1): 107–141.

Gourio, Francois. 2012. "Disaster Risk and Business Cycles." *American Economic Review*, 102(6): 2734–2766.

Guiso, Luigi, Tullio Jappelli, and Daniele Terlizzese. 1992. "Earnings Uncertainty and Precautionary Saving." *Journal of Monetary Economics*, 30(2): 307–337.

Guiso, Luigi, Tullio Jappelli, and Luigi Pistaferri. 2002. "An Empirical Analysis of Earnings and Employment Risk." *Journal of Business & Economic Statistics*, 20(2): 241–253.

Gulen, Huseyin, and Mihai Ion. 2016. "Policy Uncertainty and Corporate Investment." *The Review of Financial Studies*, 29(3): 523–564.

Hansen, Gary D. 1985. "Indivisible Labor and the Business Cycle." *Journal of Monetary Economics*, 16(3): 309–327.

Hartman, Richard. 1972. "The Effects of Price and Cost Uncertainty on Investment." *Journal of Economic Theory*, 5(2): 258–266.

Holzmeister, Felix, Jürgen Huber, Michael Kirchler, Florian Lindner, Utz Weitzel, and Stefan Zeisberger. 2020. "What Drives Risk Perception? A Global Survey with Financial Professionals and Laypeople." *Management Science*, 66(9): 3977–4002.

Hurd, Michael D., and Kathleen McGarry. 2002. "The Predictive Validity of Subjective Probabilities of Survival." *Economic Journal*, 112(482): 966–985.

Ilut, Cosmin, and Hikaru Saijo. 2021. "Learning, confidence, and business cycles." *Journal of Monetary Economics*, 117: 354–376.

Ilut, Cosmin L., and Martin Schneider. 2014. "Ambiguous Business Cycles." *American Economic Review*, 104(8): 2368–99.

Karlin, Samuel, and Charles Carr. 1960. "Prices and Optimal Inventory Policy,." *Mathematical Methods in Social Sciences 1959*, , ed. S. Karlin and P. Carr, Chapter 11. Stanford University Press.

Kehrig, Matthias. 2015. "The Cyclical Nature of The Productivity Distribution." *US Census Bureau Center for Economic Studies Paper No. CES-WP-11-15*.

Kimball, Miles S. 1989. "The effect of demand uncertainty on a precommitted monopoly price." *Economics Letters*, 30(1): 1–5.

Kimball, Miles S. 1995. "The Quantitative Analytics of the Basic Neomonetarist Model." *Journal of Money, Credit and Banking*, 27(4): 1241–1277.

Kleibergen, Frank, and Richard Paap. 2006. "Generalized reduced rank tests using the singular value decomposition." *Journal of Econometrics*, 133(1): 97–126.

Leahy, John V., and Toni M. Whited. 1996. "The Effect of Uncertainty on Investment: Some Stylized Facts." *Journal of Money, Credit and Banking*, 28(1): 64–83.

Manski, Charles F. 2017. "Survey Measurement of Probabilistic Macroeconomic Expectations: Progress and Promise." National Bureau of Economic Research, Inc NBER Working Papers 23418.

Mills, Edwin S. 1959. "Uncertainty and Price Theory." *The Quarterly Journal of Economics*, 73(1): 116–130.

Nekarda, Christopher J., and Valerie A. Ramey. 2020. "The Cyclical Behavior of the Price-Cost Markup." *Journal of Money, Credit and Banking*, 52(S2): 319–353.

Oi, Walter Y. 1961. "The Desirability of Price Instability Under Perfect Competition." *Econometrica*, 29(1): 58–64.

Pintér, Gábor. 2023. "Inflation and uncertainty in New Keynesian models: A note." *Economics Letters*, 222(C).

Pástor, Lubos, and Pietro Veronesi. 2012. "Uncertainty about Government Policy and Stock Prices." *Journal of Finance*, 67(4): 1219–1264.

Rogerson, Richard. 1988. "Indivisible Labor, Lotteries and Equilibrium." *Journal of Monetary Economics*, 21(1): 3–16.

Rotemberg, Julio J., and Michael Woodford. 1992. "Oligopolistic Pricing and the Effects of Aggregate Demand on Economic Activity." *Journal of Political Economy*, 100(6): 1153–1207.

Scotti, Chiara. 2016. "Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises." *Journal of Monetary Economics*, 82: 1–19.

Smets, Frank, and Rafael Wouters. 2003. "An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area." *Journal of the European Economic Association*, 1(5): 1123–1175.

Smets, Frank, and Rafael Wouters. 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review*, 97(3): 586–606.

Stein, Luke C.D., and Elizabeth Stone. 2013. "The Effect of Uncertainty on Investment, Hiring, and R&D: Causal Evidence from Equity Options." *Working Paper*.

Van Nieuwerburgh, Stijn, and Laura Veldkamp. 2006. "Learning asymmetries in real business cycles." *Journal of Monetary Economics*, 53(4): 753–772.

Vavra, Joseph. 2014. "Inflation Dynamics and Time-Varying Volatility: New Evidence and an Ss Interpretation." *The Quarterly Journal of Economics*, 129(1): 215–258.

Veldkamp, Laura, and Anna Orlik. 2016. "Understanding Uncertainty Shocks and the Role of the Black Swan." New York University, Leonard N. Stern School of Business, Department of Economics Working Papers 16-04.

Wooldridge, Jeffrey M. 2009. "On estimating firm-level production functions using proxy variables to control for unobservables." *Economics Letters*, 104(3): 112–114.

Online Appendix

A Data Sources

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.

Table A.1: 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

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 $A.1$. Our data on expected sales growth comes 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 firms. Since 2002, the reference universe in INVIND consists of firms with at least 20 employees operating in industrial sectors (manufacturing, energy, and extractive industries) and nonfinancial private services, with administrative headquarters in Italy. The survey adopts a one-stage stratified sample design. The strata are combinations of the branch of activity (according to an 11-sector classification), size class (in terms of number of employees classified in seven buckets), and region in which the firm's head office is located. In recent years, each wave has had around 4,000 firms (3,000 industrial firms and 1,000 service firms). The data are collected by the Bank of Italy's local branches between February and April every year. The advantage of INVIND, relative to Cerved, is that it provides managers' expectations about future sales. The data set has a panel dimension. The firms observed in the previous edition of the survey are always contacted again if they are still part of the target population. In contrast, those no longer wishing to participate are replaced with others in the same branch of activity and size class. To limit the impact of outliers, we winsorize the 1% tails of the average expected sales.

B Robustness: Alternative Timing of Instruments

To assess the robustness of the timing of the exposure to factors, we follow Alfaro, Bloom and Lin (2024), and use a three-year lag of the measured exposure to volatility factors ($\beta^c_{j,t-3}$) in the construction of the instrument z, rather than a one-year lag.

Table $A.2$: Alternative Timing of Instruments

	$\pi_{f,t}$ (1)	$\mu_{f,t}$ (2)	P. M. (3)	$\Delta Sales_{f,t}$ (4)	Inv. wage bill (5)	$\frac{\alpha_{mat}}{costsharemat}$ (6)	$\frac{\alpha_{lab}}{costsharelab}$ (7)
$\sigma_{max-min,f,t}$	-0.442^{*}	-0.197^{**}	-0.406^{**}	-2.064^{***}	-1.316^{**}	-0.194^{*}	-0.785^{**}
	(0.23)	(0.09)	(0.20)	(0.68)	(0.54)	(0.11)	(0.34)
Observations	10316	11375	9930	8835	11534	11324	11366
First-stage F-test	10.79	10.70	7.93	6.35	17.23	18.24	19.48
Sargan J-test p-value	0.604	0.730	0.120	0.921	0.459	0.147	0.658
Estimator	IV	IV	IV	IV	IV	IV	IV
Firm controls$_{i,t-1}$	✓	✓	✓	✓	✓	✓	✓
IV$_{i,t-3}$ controls	✓	✓	✓	✓	✓	✓	✓
Firm fixed eff.	✓	✓	✓	✓	✓	✓	✓
Sector eff.	✓	✓	✓	✓	✓	✓	✓
Time eff.	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01

Note: The dependent variables $\pi_{f,t}$,$\mu_{f,t}$, $P.M.$, and $\Delta Sales_{f,t}$ denotes the firm's inflation rate, log of the markup, the growth rate of the price margin, and the growth rate of sales, respectively. Variables are expressed in percent, except for the price margin that is expressed in percentage points. $\sigma_{max-min,f,t}$ denotes firm-level uncertainty as measured by managers' subjective expectations about sales one year ahead. Standard errors in parentheses. The sample period ranges from 2007 to 2019. $*$ denotes a p-value < 0.10; $**$ denotes a p-value < 0.05; $***$ denotes a p-value < 0.01.

Columns 1 through 4 in Table $A.2$ estimate the IV specification for firms' inflation rates, markups, price margin, and sales growth rate, employing an alternative timing for instruments. Across all specifications, our estimates indicate that an increase in uncertainty reduces firm's inflation and markups/price margin. In addition, the $F - tests$ and the $J - tests$ support the identification strategy, although the instrument's strength weakens somewhat, especially for sales and the price margin.