Board of Governors of the Federal Reserve System

International Finance Discussion Papers

Number 1320

June 2021

The Economic Effects of Firm-Level Uncertainty: Evidence Using Subjective Expectations

Giuseppe Fiori and Filippo Scoccianti

Please cite this paper as:
Fiori, Giuseppe and Filippo Scoccianti (2021). "The Economic Effects of Firm-Level Uncertainty: Evidence Using Subjective Expectations," International Finance Discussion Papers 1320. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/IFDP.2021.1320.

The Economic Effects of Firm-Level Uncertainty: Evidence Using Subjective Expectations*

Giuseppe Fiori Filippo Scoccianti

June 7, 2021

Abstract

This paper uses over two decades of Italian survey data on business managers' expectations to measure *subjective* firm-level uncertainty and quantify its economic effects. We document that firm-level uncertainty persists for a few years and varies across firms' demographic characteristics. Uncertainty induces long-lasting economic effects over a broad array of real and financial variables. The source of uncertainty matters with firms responding only to *downside* uncertainty, that is, uncertainty about future adverse outcomes. Economy-wide uncertainty, constructed aggregating firm-level uncertainty, is countercyclical but uncorrelated with typical proxies in the literature, and accounts for a sizable amount of GDP variation during crises.

JEL Classification: D24, E22, E24
Keywords: Uncertainty, business cycles, investment, expectations, cash holdings, downside uncertainty

*First version: April 13, 2020. We are grateful to Danilo Cascaldi-Garcia, Brian Doyle, Thiago Ferreira, Steffen Henzel, Matteo Iacoviello, Cosmin Ilut, Andrea Lanteri, Francesca Lotti, Hyunseung Oh, Andrea Prestipino, Plutarchos Sakellaris, Enrico Sette, Frank Warnock, and participants to various seminars and to the "11th IFO Conference on Macro and Survey Data" for useful comments. Giuseppe Fiori: Board of Governors of the Federal Reserve System, Division of International Finance, 20th and C St. NW, Washington D.C. 20551, United States (email: giuseppe.fiori@frb.gov; webpage: http://www.giuseppefiori.net); Filippo Scoccianti: Banca d'Italia, Via Nazionale 91, Rome, Italy (email: filippo.scoccianti@bancaditalia.it).

1 Introduction

Economic theory emphasizes the role that uncertainty about future macroeconomic and microeconomic outcomes (such as GDP and growth rate of firms' sales) plays for firms' decisions. The subject of economic uncertainty has a long tradition in economics, and, on the heels of Bloom (2009), a vast literature has greatly improved the measurement and the understanding of the nature and economic consequences of macroeconomic, or aggregate, time-varying uncertainty. The literature on *firm-level* uncertainty is instead scant and mostly limited by data availability.

We advance the literature on subjective uncertainty by using Italian survey data on firm-level expectations that span over 20 years and cover multiple business cycle episodes.[1] Our analysis yields three main insights.

First, we construct a measure of ex ante uncertainty using survey data on firm-level expectations about future sales for a representative sample of Italian firms. We document that firm-level uncertainty is mostly an idiosyncratic process that persists for a few years. These results suggest that changes in consumers' tastes or shifts in technology are more relevant sources of uncertainty than aggregate factors. Also, we show that the level of firms uncertainty about their future business prospects depends upon demographic characteristics, such as age, size, and the sector in which firms operate.

Second, we characterize the propagation mechanism of fluctuations in firm-level uncertainty over a broad set of real and financial variables. While most of the existing literature typically focuses on the role of uncertainty for capital accumulation, we show that this emphasis neglects labor's critical role (in both hours and number of workers) and capacity utilization. Uncertainty also affects the financial structure of firms that increase their cash holdings when perceived uncertainty increases. We obtain our results controlling for a plethora of confounding factors, including changes in the first moment of the probability distribution of future sales. Also, our data's granularity allows disentangling the source of uncertainty fluctuations between "down-

[1] The Bank of Italy survey constitutes a unicum in the existing literature, as most surveys that track uncertainty on firm level outcomes span only a few years. In particular, for the United States, Altig et al. (2020*b*) developed a monthly panel Survey of Business Uncertainty (SBU) starting in 2014 that features about 1,750 firms in 50 states. In Germany, the IFO Institute surveyed firms' expectations from 2013 to 2016, see Bachmann et al. (2018) and Bachmann et al. (2020). A longer monthly time-series starting in 1980 and based on qualitative expectations, is used in Bachmann, Elstner and Sims (2013) and Massenot and Pettinicchi (2018). For the United Kingdom, the Decision Maker Panel (DMP) survey was launched in August 2016.

side" or "upside" uncertainty —that is, uncertainty about adverse or positive outcomes.

Third, we construct an *economy-wide* measure of uncertainty for the Italian economy, aggregating individual firm-level data, and find it to be countercyclical. While this countercyclicality reproduces the literature's typical result, we emphasize that our measure is uncorrelated to standard proxies for macroeconomic uncertainty employed in the literature. This little correlation indicates that typical proxies based on ex post outcomes, such as dispersion in sales or innovations in total factor productivity (TFP), may understate the amount of ex ante uncertainty perceived by firms.

The source of the data on expectations is the Survey of Industrial and Service Firms (or INVIND), an extensive annual business survey conducted by the Bank of Italy on a sample of Italian firms representative of the aggregate economy. As discussed in Section 2, the survey elicits managers' expectations over the average, the minimum, and the maximum one-year ahead growth rates of sales. Thus, we directly observe the first moment of the subjective probability distribution of future sales and the distribution's support, i.e. the range between the maximum and minimum expected outcome, or max–min range. Using the 2005 and 2017 waves of INVIND that elicited the *full* probability distribution of expected sales, we show that the max–min range measures the dispersion of future expected outcomes while being orthogonal to the third moment of the distribution, or skewness. The nearly deterministic relationship between the max–min range and the dispersion of future sales allows us to use the max–min range to measure firm-level uncertainty for the whole sample. Directly observing the first and the second moments of the distribution of expected outcomes enables us to overcome one of the existing literature's main challenges, disentangling the economic effect of fluctuations in uncertainty from changes to the first moment.

In Section 3, we show that, in a given year, the median firm perceives uncertainty equal to 8 percentage points around its mean expectation. Uncertainty varies with specific demographic characteristics. Small and medium-sized firms (less than 50 workers) and young firms (less than five years) tend to display higher uncertainty than large and mature firms. Interestingly, the source of uncertainty for young firms is upside uncertainty (caused by the maximum expected future sales). Instead, it is downside uncertainty for small and medium-sized firms (driven by the minimum).

To show that uncertainty is a persistent process, we exploit the 2017 wave of INVIND, which elicits the full probability distribution of expected sales one year and three years ahead. On average, these two measures of uncertainty are strongly and positively correlated (0.64). If a firm displays high uncertainty about its future sales one year ahead, the same is true, on average, three years ahead, indicating that uncertainty does not abate quickly at the firm level.

In Section 4, we further match INVIND expectations with balance sheet data to measure the impact of uncertainty on real and financial outcomes, such as hours, investment, labor, capacity utilization, and cash holdings. The availability of a broad cross-section and a long time-series dimension allows us to perform a panel regression analysis to characterize, at various horizons, how firms adjust following fluctuations in uncertainty.

While the existing microeconomic literature has mainly focused on the response of investment, we highlight that firms also use other margins to adjust to uncertainty fluctuations. Specifically, following an increase in uncertainty, firms immediately reduce the extensive and intensive margins of labor (number of workers and hours per worker), decrease capacity utilization, and hoard cash for a few periods. With a lag, firms reduce the accumulation of capital that persists for a few periods. Over time the dynamics are reversed, with investment overshooting its steady-state level before converging back to it as the shock dissipates. Results are confirmed when we instrument current uncertainty with its lagged values. Our evidence on investment aligns well with model predictions in Bloom (2009) and Bloom et al. (2018). Also, our evidence on the negative effects of uncertainty complements models emphasizing financial frictions that lead to higher cost of finance (Arellano, Bai and Kehoe, 2019; Gilchrist, Sim and Zakrajšek, 2014), and precautionary saving effects (Fernández-Villaverde et al., 2015; Basu and Bundick, 2017). In Section 5, we decompose total firm-level uncertainty into a downside and an upside component to investigate whether *all uncertainties are all alike*. Specifically, we study what are the economic effects of higher dispersion in positive and negative outcomes. While both components are significant contributors of the total variance of uncertainty, we find that only the downside component matters—that is, only uncertainty about future negative outcomes generates significant economic effects. Instead, firms are unresponsive to the upside component, indicating that the source of uncertainty determines its economic effects.

The differentiated response to downside and upside uncertainty provides practical overidentifying restrictions against which to test competing macro theories aimed at quantifying the aggregate effects of uncertainty (see Section 6). In the context of real options theories, the response to downside or upside uncertainty is informative about the frictions faced by firms to increase or decrease durable inputs, (see the discussion in Abel et al., 1996). Our evidence emphasizes costly downsizing of capital or labor, such as the one induced by input irreversibility and the ensuing "bad news principle" discussed by Bernanke (1983). Downside uncertainty may also increase the likelihood of firms becoming financially constrained in the future, leading to a decrease in the accumulation of inputs see Lin, Bloom and Alfaro (2017). Also, to the extent that the minimum of future sales is interpreted as a summary statistic of the worst-case scenario, the sensitivity to downside uncertainty may be loosely interpreted as agreeing with the predictions of theories that emphasize ambiguity aversion, as in Hansen, Sargent and Tallarini (1999) and Ilut and Schneider (2014). In those models, agents form beliefs over a range of possible scenarios and act as if the worst scenario will occur.

After studying the microeconomic dimension of uncertainty, we exploit our representative sample and construct an economy-wide measure by aggregating firm-specific uncertainty (see Section 7). We consider this bottom-up approach noteworthy because our proxy is the first ex ante measure of aggregate uncertainty covering over two decades of firm-level expectations and spanning multiple business cycle episodes. Notwithstanding the little correlation with typical proxies for aggregate uncertainty, we find that our measure increased sharply during economic crises, such as the Great Financial Crisis and the latest COVID-19 recession, as well as periods with elevated political uncertainty.

Using our firm-level estimates that isolate the "pure" effect of uncertainty from changes to the mean, we find that uncertainty is a significant contributor to aggregate fluctuations, over and beyond fluctuations induced by first-moment shocks. On average, uncertainty accounts for about 15 percent of GDP response over the 2009 and 2012 recessions. Also, the unprecedented spike in aggregate uncertainty due to the COVID-19 pandemic reduced GDP's growth rate by about 1 percentage point in 2020. Moving forward, we expect uncertainty to have more muted effects as the downside component largely recovered in 2021.

The paper is organized as follows. In Section 1.1, we review the existing literature. In Section 2, we describe the data. In Section 3, we detail the construction of our measure of ex-ante uncertainty based on subjective expectations. We characterize the economic effects of uncertainty in Sections 4 and 5. In Section 6, we discuss the implications of our results for macroeconomic modeling. In Section 7, we construct a measure of aggregate uncertainty based on firm-level uncertainty and quantify the aggregate effects of uncertainty across multiple business cycle episodes. Section 8 concludes.

1.1 Literature Review

Our work connects to many strands of the existing literature on uncertainty and aggregate fluctuations. While the existing literature provides a sizeable number of surveys eliciting consumer expectations, less is known about quantitative measures of uncertainty at the firm level.[2] Our data source INVIND is the forerunner of DMP for the United Kingdom discussed in Altig et al. (2020*a*) and SBU for the United States described in Altig et al. (2020*b*). Another important example is the IFO survey employed in Bachmann et al. (2018) and Bachmann et al. (2020).[3] 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 in recent years, albeit at a higher frequency.

In relating survey data to economic outcomes, our paper is related to the pioneering work of Guiso and Parigi (1999) and Bontempi, Golinelli and Parigi (2010).[4] Relative to these contributions that also use INVIND, the panel dimension of our sample allows us to expand the scope of the analysis characterizing the effect of uncertainty on a broad array of real and financial variables (not only investment). Besides, we show that the source of uncertainty matters for its economic effects. Our sample includes important business cycle episodes in recent history, both on the upside in the years 2005 to 2007 and in the deep financial recession that followed

[2] 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).

[3] Ben-David and Graham (2013) and Gennaioli, Ma and Shleifer (2016) study executives' stock return expectations.

[4] Another example is Morikawa (2013) that uses two-point distributions from the survey conducted at the Research Institute of Economy, Trade and Industry. He focuses on uncertainty related to the tax system and trade policy matters for firms' capital investment and overseas activities.

from 2008 to 2013 and the subsequent recovery.

A second strand of the literature has investigated the economic effects of uncertainty, typically focusing on investment and pointing to a negative uncertainty-investment relationship when dealing with micro-level uncertainty. Leahy and Whited (1996) and Bloom, Bond and Van Reenen (2007) use realized stock return volatility as a measure of firm-level uncertainty and show a negative relationship between uncertainty and business investment. Stein and Stone (2013) use the option price to create a forward-looking measure of uncertainty and arrive at a similar conclusion on the uncertainty-investment relationship. Gulen and Ion (2016) use the policy uncertainty index developed by Baker, Bloom and Davis (2016) to show that firm-level capital investment is negatively affected by the uncertainty associated with future policies. Moreover, firm-level uncertainty appears to vary in both the cross section and the time series. Bachmann, Elstner and Hristov (2017) and Senga (2015) find substantial cross-sectional heterogeneity and time variation in measures of firm-idiosyncratic uncertainty using survey data. Senga (2015) also finds that smaller and younger firms face greater uncertainty. Based on our results, we argue that uncertainty is more detrimental for small firms rather than young firms because it originates from downside uncertainty.

Besides differences in the considered measure of uncertainty, our analysis shows that the effects of uncertainty extend beyond capital accumulation and affect the labor market and financial decisions. The broad focus on firm-level economic outcomes aligns our work with Lin, Bloom and Alfaro (2017) with three critical distinctions related to our uncertainty measure. First, rather than relying on the *realized* or implied annual volatility of stock returns, we employ an ex ante measure of uncertainty that allows us to tease out changes in the dispersion of expected outcomes from fluctuations in the first moment of future expectations. Second, our empirical analysis shows that the economic effects of uncertainty last for a few years, with investment overshooting its steady-state level. Third, we distinguish the source of fluctuations in uncertainty between a downside and an upside component, showing that only the former matters for its economic effects.

Our work also connects to the literature that studies aggregate uncertainty and its cyclical properties along the business cycle. A robust finding in the literature is that cross-sectional measures of uncertainty rise in recessions. Bloom (2009) finds that a variety of cross-sectional dispersion measures, like the standard deviation of firms' profit growth, positively correlates with time-series stock market volatility. Bloom et al. (2018) show that the cross-sectional dispersion of establishment-level TFP shocks is countercyclical (see also Kehrig (2015) and Bloom (2014) for discussion on the cyclicality of uncertainty measures). Bachmann, Elstner and Sims (2013) use disagreement among professional forecasters as a proxy for aggregate uncertainty and find that forecaster disagreement is higher in downturns. Baker, Bloom and Davis (2016) develop a measure of economic policy uncertainty based on the frequency of articles mentioning the words "uncertain" or "uncertainty" and find this measure is also countercyclical.[5] Our economy-wide measure of uncertainty is also countercyclical, but uncorrelated to most of the existing proxies of aggregate uncertainty. We interpret this finding as indicating that current proxies may not fully capture the aggregate dimension of ex-ante firm-level uncertainty. We refer the reader interested in a comprehensive review of the literature to Datta et al. (2017) and Fernández-Villaverde and Guerrón-Quintana (2020).

2 Data: Subjective Firm-Level Expectations

This section describes the data sources that constitute the basis for measuring firm-level uncertainty and its economic effects. We first provide details about our data source in Section 2.1. Then, we describe the measures of firm-level expectations and their statistical properties in Section 2.2 and in Section 2.3, respectively.

2.1 Data Sources

We obtained our data set by combining different sources. We first construct our measure of uncertainty 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 (manufacturing, energy, and extractive industries) and non-financial private services, with administrative headquarters in Italy. The sample is representative of the Italian economy, based on the branch of activity (according to an

[5] In a similar vein of research Hassan et al. (2019) and Caldara et al. (2020) use textual analysis to study firm-level political uncertainty and explore the quantitative implications of trade policy uncertainty, respectively.

11-sector classification), size class, and region in which the firm's head office is located. We then use detailed information on yearly balance sheets from Cerved Group S.P.A. (Cerved Database) to obtain data on investment (equipment and structures), cash holdings, and realized sales. Total hours, number of employees, and capacity utilization are part of INVIND. Industry-specific price deflators are obtained from the Italian National Institute of Statistics. The sample period extends over 25 years, from 1993 to 2018. The matched data set includes about 25,000 firm-year observations from an average of more than 900 firms per year. We refer the reader to Appendix A for more details. We note that the number of firm-year observations in INVIND depends on the variable of interest and includes more than 30,000 observations. However, not all of the observations can be matched with balance sheet data in Cerved, reducing the sample to about 25,000 observations. Next we report statistics using all the available data and accounting for each firm's share in the population of Italian firms.

2.2 Firm-Level Expectations: Variables Description

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

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

Shaped by idiosyncratic 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 emphasize that we do not directly observe the probability mass over the support except for the 2005 and 2017 waves. We overcome this limitation in Section 3 by showing that 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. We connect the range with the dispersion in future sales exploiting the 2005 and

2017 waves of the survey that elicit the entire probability distribution, asking firms to provide a quantitative assessment of their business prospects.

We now describe the statistical properties of s^e_{avg}, s^e_{min}, and s^e_{max}.

2.3 Statistical Properties: Minimum, Maximum, and Average of Expected Future Sales Growth

Table 1 reports a set of statistics comparing actual outcomes (the growth rate of sales) and the minimum (worst-case scenario), the maximum (best-case scenario), and the average expected growth rates of sales. Statistics are reported for the whole sample taking into account each firm's weight in the entire population of firms. Growth rates are expressed in percent.

Table 1: Firm-Level Expectations: Descriptive Statistics

	No. of Obs.	Mean	St. Dev.	Skew.	P_{10}	P_{25}	P_{50}	P_{75}	P_{90}
$s^e_{avg,f,t}$	49674	3.56	11.30	1.07	-7.20	0.00	2.60	7.20	14.30
$s^e_{min,f,t}$	30958	-3.89	9.91	-0.01	-12.00	-10.00	-2.00	1.00	5.00
$s^e_{max,f,t}$	30976	7.07	9.82	1.37	0.00	2.00	5.00	12.00	15.00
$\Delta Sales_{t,t-1}$	41934	0.93	18.70	-0.51	-19.90	-7.51	1.76	10.40	21.10

Note: Statistics are computed over the whole sample period 1996 to 2018, weighting firm-specific observations based on the share of the entire population they represent. The number of observations refers to the number of firms effectively sampled in the data. Table entries are computed over growth rates (expressed in percent). s^e_{avg}, s^e_{min}, s^e_{max} denote the *average*, *minimum*, and *maximum* expected growth rates of sales one-year ahead, while $\Delta Sales$ reports the growth rate of *realized* sales. P_X reports the X^{th} percentile of the distribution.

We start from describing the properties of s^e_{avg}. The median firm expects sales to grow by 2.6 percentage points, in line with the median of actual sales. Turning to s^e_{min} and s^e_{max}, we find that the median firm expects the worst-case scenario to result in a decrease of sales of about 2 percentage points and the best-case scenario in an expansion of 5. Also, for both variables, the interquartile range ($P_{75} - P_{25}$) is about 10 percentage points. The three measures of expectations display a lower standard deviation than the *realized* growth rate of sales. As shown in Table 2, the s^e_{avg}, s^e_{min}, and s^e_{max} are as procyclical as actual sales.

Table 2: Cyclicality of Expectations

	$s^e_{avg,f,t}$	$s^e_{min,f,t}$	$s^e_{max,f,t}$	$\Delta Sales_{f,t}$
$\Delta GDP_{t,t-1}$	0.25	0.28	0.18	0.28

Note: Statistics are computed over the whole sample period 1996 to 2018, weighting firm-specific observations based on their share of the entire population. The number of observations refers to the firms directly observed in the data. Table entries report the unconditional correlation between s^e_{avg}, s^e_{min}, s^e_{max} and the growth rate of GDP. s^e_{avg}, s^e_{min}, s^e_{max} denote the *average*, *minimum*, and *maximum* expected growth rates of sales one year ahead. ΔGDP denotes the yearly growth rate of real GDP.

Notably, we find that the statistical properties of expectations display sizeable differences conditioning on firms' size, age, and sector in which they operate. Results are reported in Table *A*.1 in Appendix B. Starting from firms' size, small and medium-sized firms (defined as firms employing between 20 and 50 workers) display a lower expected growth rate in the worst- and the best-case scenarios than large firms (with more than 50 employees).[6] This property shows despite a similar expected growth rate, s^e_{avg}. We note that small and medium-sized firms do not perfectly overlap with the definition of young firms. Young firms (less than five years) tend to expect higher growth both on average and in the best-case scenario than mature and old ones (more than five years). Intuitively, this outcome lines up with firms' life-cycle dynamics that, conditional on survival, grow to reach their optimal size. Finally, firms in the manufacturing sector expect faster growth than those in the service sector. This result reflects the faster growth rate of sales experienced by the manufacturing sector that we conjecture is being driven by the higher degree of international openness relative to the service sector.

[6]Because of the design of the survey, we do not observe firms with less than 20 employees.

3 Measuring Firm-Level Uncertainty with Subjective Expectations

We now describe how we use INVIND expectations to construct a time-varying measure of individual firms' subjective uncertainty and provide a set of stylized facts on firm-level uncertainty. In Section 3.1, we show that there is a near equivalence in the range between the maximum and minimum future expect sales (or the best- and worst-case scenario, $s^e_{max,f,t} - s^e_{min,f,t}$) and the dispersion (or second moment) of future expected sales. Exploiting this link, we use the max–min range as a measure of firm-level uncertainty and establish a new set of stylized facts on the properties of uncertainty conditioning across age, size, and sector in which the firms operate in Section 3.2. In Section 3.3, we exploit the granularity of our data to trace back the source of firm-level uncertainty to its upside (driven by uncertainty about positive outcomes) or downside (negative outcomes) component. Finally, we analyze how firm-specific and aggregate variables covariate with uncertainty in Section 3.4 and conclude by showing that uncertainty is a persistent process that does not abate quickly in Section 3.5.

3.1 The Max–Min Range Measures Dispersion in Future Expected Sales

INVIND provides us with the range between the best- and the worst-case scenario about the expected growth rate of sales one-period ahead. We now show that this range, denoted by $\sigma_{max-min}$, measures the second moment of the probability distribution of expected outcomes.[7] To do so, we use data from the 2005 and 2017 waves of INVIND. Unlike other years in our sample, these waves elicited the full probability distribution of expected sales over a discretized support of intervals ranging from <-10 percent to >10 percent.[8]

We compute the mean, standard deviation, and skewness of the subjective probability distribution of expected sales for every firm. Our calculations are carried out applying standard

[7] Bachmann et al. (2018) refer to the max–min range as *span*.

[8] In 2005, the support of the probability distribution of expected sales x was discretized using 11 bins: $\leq$-10 percent, -10 percent<x$\leq$-6 percent, -6 percent<x$\leq$-4 percent, -4 percent<x$\leq$-2 percent, -2 percent<x<0 percent, 0, 0 percent<x$\leq$2 percent, 2 percent<x$\leq$4 percent, 4 percent<x$\leq$6 percent, 6 percent<x$\leq$10 percent, $\geq$10 percent. In 2017, the grid between -6 percent and +6 percent was finer, with intervals of one percentage point rather than two. By the nature of INVIND, the 2005 and 2017 waves asks agents about *one* distribution of expected outcomes. Bachmann et al. (2020) innovates on this front distinguishing between Bayesian and Knightian agents.

Table 3: $\sigma_{max-min}$ and Moments of the Subjective Probability Distribution

	$St.Dev._f$ (1)	$Skew._f$ (2)	$St.Dev._f$ (3)	$Skew._f$ (4)
$\sigma_{f,max-min}$	0.29***	-0.10		
	(0.00)	(0.21)		
$s^e_{f,min}$			-0.29***	0.11
			(0.00)	(0.17)
$s^e_{f,max}$			0.29***	-0.10
			(0.00)	(0.20)
R^2	0.88	0.00	0.88	0.00
Observations	920	920	920	920

Note: Each equation is estimated with ordinary least squares using 2005 wave of the Survey of Industrial and Service Firms data. P values in parentheses. Stars denote significance level of the coefficient they refer to: * p-value<0.10, ** p value<0.05, *** p-value<0.01. The dependant variable reported on columns is the second moment ($St.Dev._f$) and the third-moment ($Skew._f$) of the firm-specific probability distribution of expected sales for the year 2005. For every firm f, $\sigma_{f,max-min}$ denotes the difference between $s^e_{f,max}$, and $s^e_{f,min}$, the maximum and minimum expected growth rate of sale one-year ahead.

formulas and using, for each bin, the midpoint of the respective interval and its associated probability. Notably, as we observe the probability distribution of future sales, we do not need to impose any distributional assumption.

Finally, we regress each moment of the subjective distribution on $\sigma_{max-min}$, and, in a separate regression, the best- and worst-case scenarios. Table 3 reports the results for the 2005 wave of INVIND.

The main result is that the range between the best- and worst-case scenarios measures the second moment of the probability distribution of future sales. Specifically, firms with higher dispersion in expected outcomes also display a wider range of $\sigma_{max-min}$. Column 1 shows a near equivalence between $\sigma_{maxmin,f}$ and the true standard deviation of the probability distribution. The coefficient on $\sigma_{max-min}$ is statistically significant, and the R^2 is very close to one, indicating that the range accounts for almost the total variance of the dependent variable. The fit is similar when $s^e_{f,max}$ and $s^e_{f,min}$ enter the specification as separate regressors. A decrease in $s^e_{f,min}$

(a deterioration in the worst-case scenario) and an increase in $s^e_{f,max}$ (an improvement in the best-case scenario) increase uncertainty. Interestingly, $s^e_{max-min,f}$ is virtually orthogonal to the third moment, the skewness, allowing us to rule out that the range captures fluctuations in the skewness.

We run the same regression using the 2017 wave of INVIND. Results (not shown) are mainly unchanged both in terms of estimated coefficients and fit, providing additional support that the range $\sigma_{max-min}$ captures the standard deviation of the probability distribution of expected outcomes.[9]

Finally, we connect measures of the worst- and best-case future sales with the probability mass of future sales (not shown). Firms with lower s^e_{min} exhibit a higher probability mass in bins associated to intervals close to s^e_{min}. The same association holds for s^e_{max} and mass probability for intervals close to s^e_{max}. We exploit this result in Section 5 when we study the sources of uncertainty fluctuations.

3.2 Firm-Level Uncertainty Varies by Age, Size, and Sector

Our measure of firm-level uncertainty has three advantages. First, $\sigma_{max-min}$ is an ex ante measure of the uncertainty perceived by firms about future outcomes. Second, $\sigma_{max-min}$ reflects the managers' expectations—that is, the decision-makers of the firm. Third, $\sigma_{max-min}$ can be easily interpreted as it relates to economic outcomes.

Table 4 reports descriptive statistics on $\sigma_{max-min}$. The data indicate that, on average, firms' uncertainty around their average expected future sales is 9.33 percentage points. The median uncertainty is instead 8. Using the results in Table 3, we find that the coefficient of variation, the ratio between the standard deviation and the mean s^e_{avg}, is for the median firm about 1. Moreover, $\sigma_{max-min}$ is virtually acyclical, as its correlation with the growth rate of real GDP is -0.07.[10]

We find significant heterogeneity in firms' uncertainty, based on their age, size, and the sector in which they operate. Young firms (less than five years), on average, perceive the higher level

[9] Using the 2017 wave, we find that the R^2 is 0.76 for the specification in column 1 and 0.86 in column 3. As in Table 3, independently of the specification, $\sigma_{max-min,f}$ explains, at most, 4 percent of the skewness variance.

[10] The correlation between firm-level uncertainty and the first lag (the first lead) of real GDP is -0.03 (0.00).

Table 4: Firm-Level Uncertainty $\sigma_{max-min}$: Descriptive Statistics

No. of Obs.	Mean	St. Dev.	Skew.	P_{10}	P_{25}	P_{50}	P_{75}	P_{90}
Full Sample								
30735	11.00	9.81	1.35	1.00	3.00	8.00	20.00	24.00
Small and Medium Firms: $20 \leq$ Labor Force ≤ 50								
5082	13.70	10.60	0.82	1.20	4.00	11.00	24.00	24.00
Large Firms: Labor Force > 50								
25443	9.50	8.99	1.78	1.00	3.00	6.00	13.00	24.00
Young Firms: Age ≤ 5								
866	13.30	10.30	1.05	2.00	5.00	10.00	24.00	24.00
Mature and Old Firms: Age > 5								
29869	11.00	9.79	1.35	1.00	3.00	7.50	20.00	24.00
Manufacturing Sector								
21450	11.00	9.59	1.47	2.00	4.00	8.00	19.00	24.00
Service Sector								
9285	11.00	10.10	1.20	1.00	2.60	7.00	24.00	24.00

Note: Statistics are computed over the whole sample period 1996 to 2018, weighting firm-specific observations based on their share of the entire population. The number of observations refers to the firms directly observed in the data. $\sigma_{max-min}$ denotes the difference between s^e_{max} and s^e_{min}, the maximum and minimum expected growth rates of sales one year ahead.

of uncertainty, together with small and medium-sized firms (defined here as having less than 50 employees). The drivers of uncertainty are also heterogeneous across firms' characteristics, as young firms expect, on average, a higher growth rate in the best-case scenario, s^e_{max}. In comparison, small and medium-sized firms expect a lower growth rate in the worst-case scenario. Large firms perceive a lower level of uncertainty than smaller and medium companies, a result consistent with life-cycle dynamics suggesting that they have already reached their optimal size or achieved a better knowledge of their demand curve. Finally, firms in the service sector face, on average, a higher level of uncertainty than those in the manufacturing sector. Old firms (with age equal to more than five years) and manufacturing firms drive the full sample results as they account for a large fraction of it.

Interestingly, $\sigma_{max-min}$ is acyclical, except for young firms and small and medium-sized firms that display a negative correlation with real GDP equal to -0.22 and -0.11, respectively. As shown in Section 3.4, this overall lack of cyclicality is due to the limited explanatory power of aggregate factors for the variability of $\sigma_{max-min}$.

3.3 Sources of Firm-Level Uncertainty: Downside and Upside Uncertainty

We now investigate the source of firm-level uncertainty and whether an increase in uncertainty is driven by firms being more uncertain about positive outcomes, negative outcomes, or both. Answering this question is not just an intellectual curiosity. As discussed in Section 6, it carries critical theoretical implications providing useful restrictions against which to test competing theoretical frameworks employed to rationalize the economic effects of uncertainty. We assess the individual contribution of positive outcomes, s^e_{max}, and negative outcomes, s^e_{min}, to the variance of the max–min range. We first compute a standard variance decomposition using data for every firm, and then pool the results to construct the unconditional distribution across firms. For every firm f, we compute the shares of the variance attributed to s^e_{max} and s^e_{min} as $\beta_{cov,s^e_{min},f} \equiv \frac{cov(s^e_{min},\sigma_{max-min})}{var(\sigma_{max-min})}$ and $\beta_{cov,s^e_{max},f} \equiv \frac{cov(s^e_{max},\sigma_{max-min})}{var(\sigma_{max-min})}$.

This decomposition shows that both margins contribute to fluctuations in uncertainty, with 42 percent of its variance accounted for by downside uncertainty $\beta_{cov,s^e_{min},f}$, and the remaining 58 percent attributable to $\beta_{cov,s^e_{max},f}$.

3.4 Firm-Level Uncertainty Correlates with Current and Future Business Conditions

This section analyzes more formally whether measures of expectations and uncertainty correlate with a set of firm-level characteristics.

Specifically, we regress $s^e_{min,f,t}$, $s^e_{max,f,t}$, and $\sigma_{max-min,f,t}$ on measures of current and future business prospects for the firm (proxied by the actual growth rate of sales and $s^e_{avg,f,t}$, respectively), the number of employees (size), cohort effects (age of the firm), and firm-specific, industry, and year effects. Concerning the role of firm characteristics, we find a small but positive correlation between the average expected growth rate of sales ($s^e_{avg,f,t}$) and uncertainty ($\sigma_{max-min,f,t}$). This result suggests that part of fluctuations in uncertainty may be driven by changes in the mean of the probability distribution of expected outcomes. Uncertainty also responds to current business conditions: A positive growth rate of current sales is associated with lower uncertainty, although the effect is rather small. Turning to Columns 2 and 3, we find that higher current sales tend to increase s^e_{min}, while uncertainty tends to be smaller for larger firms.

Table 5: Uncertainty Covariates

	$\sigma_{max-min,f,t}$	$s^e_{min,f,t}$	$s^e_{max,f,t}$
	(1)	(2)	(3)
$s^e_{avg,f,t}$	0.10***	0.67***	0.78***
	(0.00)	(0.00)	(0.00)
$\Delta Sales_{f,t-1}$	-0.03***	0.01*	-0.01***
	(0.01)	(0.08)	(0.00)
$Size_{f,t-1}$	-0.23	-0.01	-0.20
	(0.64)	(0.25)	(0.63)
$0 \leq Age_{f,t} \leq 5$	1.28	0.0271	1.32*
	(0.30)	(0.97)	(0.10)
Observations	12038	12124	12145
R^2	0.42	0.77	0.82

Note: Each regression is estimated by ordinary least squares over the sample period 1996 to 2018, and it includes year- and industry-effects. $\sigma_{max-min}$ measures firm-level uncertainty; s^e_{max}, s^e_{avg}, and s^e_{min} denote the maximum, average, and minimum one-year-ahead expected growth rates of sales, respectively.

As expected, young firms display higher uncertainty as they learn about their business prospects. Finally, average expected sales $s^e_{f,t,avg}$ covariates positively with $s^e_{min,f,t}$ and $s^e_{max,f,t}$. We emphasize that we do not attach any causal interpretation to the results in Table 5, as the estimated coefficients capture correlations between the variables of interest.

3.5 Firm-Level Uncertainty Persists for a Few Years

We now turn to study the persistence of firm-level uncertainty. Our analysis's main takeaway is that, on average, firm-level uncertainty does not abate quickly but lasts for a few years. We exploit the 2017 wave of INVIND that elicits the full probability distribution of expected sales one year ahead and three years ahead. After computing the respective standard deviation of future expected sales, we regress the one-year-ahead dispersion on the three years ahead and estimate a coefficient of 0.64, yielding an autoregressive coefficient of 0.8. Fitting an autoregressive process of order one to $\sigma_{max-min,f,t}$ yields an estimated coefficient of 0.5. Both estimates indicate that uncertainty does not abate quickly but lasts for a few years, with the half-life of a shock to uncertainty estimated to be two years.

4 The Economic Effects of Uncertainty on Capital, Labor and Cash Holdings

We now study the economic effects of uncertainty by tracing the dynamic responses of a large set of real and financial variables, broadening the analysis's scope relative to most of the existing literature. Our analysis's critical advantage is that the richness of the data allows us to separate the effects induced by time-varying uncertainty from fluctuations in the mean expectation about future sales. In Section 4.1, we describe our empirical approach. In Section 4.2, we show that fluctuations in uncertainty are associated with sizeable effects not only on investment but also on labor variables and cash holdings. Importantly, these effects do not abate quickly but last for a few years. In Section 4.3, we show that our results are robust to instrumenting firm-level uncertainty with its lagged values and including more lags of control variables.

4.1 Empirical Methodology

We estimate the economic effects of fluctuations in uncertainty, by relying on the local projection technique, discussed in Jordà (2005). We face a critical challenge because subjective expectations and the resulting uncertainty perceived by firms are jointly determined by aggregate and idiosyncratic factors, such as current and future business prospects. To tackle this issue, we proceed in steps.

We first isolate the *unpredictable* component of firm-level uncertainty by controlling for firm-specific and aggregate conditions. Specifically, we project $\sigma_{max-min,f,t}$ on current and *future* business conditions, lags of capacity utilization, lags of growth rates of labor inputs and real investment, firms' leverage, "sales surprises" (or forecast errors) defined as the difference between lagged expected ($s^e_{f,t-1}$) and the growth rate of real sales realized at time t ($\Delta Sales_{f,t,t-1}$). The empirical specification also includes firm-specific, sector, and year dummies to account for time-invariant firm characteristics, as well as industry-specific or policy factors. The resulting estimated residual, denoted by $\sigma^X_{max-min,f,t}$, is used in the second stage (described next) to characterize the propagation mechanism of fluctuations in uncertainty. This empirical strategy allows us to isolate the component of firm-level uncertainty not driven by aggregate or firm-specific factors related to observable variables or reflected in changes in expectations.

To tease out the unpredictable component of uncertainty, we proxy current business conditions with the current growth rate of sales and future business conditions with $s^e_{avg,f,t}$ the first moment of the probability distribution of expected sales one year ahead. In so doing, we explicitly control for fluctuations in the first moment of the probability distribution of expected sales that may potentially affect uncertainty and confound its effect. We also consider lags of capacity utilization and labor, as these margins of adjustment may signal news about the future not explicitly accounted for by current or future business conditions. The set of regressors also controls for firm leverage, proxied by the ratio between debts and assets. Finally, we include time t sales surprises (or forecast errors) to control for unexpected outcomes that may influence firms' expectations, as well as their perception of realized current outcomes. For instance, how a firm assesses the realized growth rate sale may depend on what the firm expected one year ago. Armed with the unpredictable component of uncertainty, we then trace the dynamic economic effects of uncertainty fluctuations over a broad range of outcomes by projecting firm-level real and financial variables at different horizons on contemporaneous $\sigma^X_{max-min,f,t}$. The variables we look at include investment, the growth rate of total hours (distinguishing between the number of workers and hours-per-worker), the capacity utilization rate, and the growth rate of liquid assets, or cash, held by the firm.

4.2 Real and Financial Effects of Uncertainty

We now show that the economic effects of uncertainty are not limited to investment but extend to the labor market and the firm's financial structure. Table 6 reports the dynamic response of firm-level variables following a 1 percentage point increase in firm-level uncertainty. Entries are expressed in percent.

Fluctuations in uncertainty induce economic effects that are statistically and economically significant. Notably, these effects do not abate quickly and last for a few years. This result is due to both the persistence of firms' perceived changes in uncertainty (as shown in Section 3.5) and the sluggishness of firms' endogenous responses that first adjust soft margins like labor and only then change investment.

Table 6: Real and Financial Effects of Firm-Level Uncertainty

	Impulse Responses - Increase in Uncertainty 1p.p.				
Horizon=h	0	1	2	3	4
Capacity Util. Rate (t+h)	-0.138***	-0.005	0.005	0.045	-0.012
	(0.00)	(0.34)	(0.94)	(0.44)	(0.43)
Total Hours (t+h)	-0.126***	0.019	0.026	0.004	0.042
	(0.01)	(0.42)	(0.60)	(0.93)	(0.58)
Real Investment (t+h)	0.058	-0.554**	-0.785**	0.229	0.387
	(0.75)	(0.03)	(0.00)	(0.41)	(0.12)
Real Cash Holdings (t+h)	0.299*	0.783**	0.722**	0.526	-0.599
	(0.08)	(0.04)	(0.03)	(0.15)	(0.23)

Note: Each equation is estimated with ordinary least squares over the sample period 1996 to 2018, and it includes firm- and sector-specific dummies, and year effects. P-values are in parentheses. Stars denote the significance level of the coefficient they refer to: * p-value<0.10, ** p-value<0.05, and *** p-value<0.01. Standard errors clustered in two-ways by firm and year. Entries are expressed in percent, and report the estimated coefficient on $\sigma^X_{max-min,f,t}$. See the text for more details.

On impact, firms also increase their cash holdings, signaling a precautionary behavior that anticipates reducing investment. We discuss these results in turn. On the real side, after an increase in perceived uncertainty equal to 1 percentage point, the firm reduces its capacity utilization rate and the growth rate of total hours by about 0.13 percentage points, equivalent to one standard deviation of both variables. Also a reduction in employed workers' growth rate, smaller than that of hours, signals that the intensive margin of labor is adjusted more swiftly. Over the same period, on the financial side, firms also increase their cash holdings. After one year, the firm starts cutting on investment, by more than 1 percent over two years (or about one-half of the investment standard deviation).[11] As the increase in uncertainty is reabsorbed, investment overshoots its steady-state level before converging, but the coefficient is not statistically significant.

Overall, our results indicate that we are capturing the effects induced by pure uncertainty rather than first-moment shocks associated with changes to the current or future business conditions (given that both are included in the set of controls).

4.3 Evidence Based on Instrumental Variables

In this section, we provide some evidence on the causal link between uncertainty and economic outcomes. Towards this goal, we instrument current uncertainty using its second lag. As in the previous section, the set of controls includes current and expected business prospects, financial variables, and aggregate and industry-specific factors. In the specification reported in Table 7, we instrument contemporaneous uncertainty using its second lag. F-statistics lie above the usual value of 10 (not reported), indicating that the instrument is relevant and captures the strong persistence of uncertainty. As in the case with ordinary least squares, instrumental variables estimates confirm that an increase in uncertainty prompts firms to reduce total hours (with the brunt of the adjustment sustained by hours per worker), increase cash holdings, and lower investment. We note that utilization is negative but not significant, with a p-value of 0.13.

5 Effects of Uncertainty through "Downside Uncertainty"

We now study whether the economic effects of uncertainty depend on the source driving the increase in dispersion of future expected sales—that is, whether it comes from downside or upside

[11] Investment is deflated using sector-specific deflators and includes capital expenditures on equipment and structures.

Table 7: IV Evidence on the Effects of Firm-Level Uncertainty

IV - Impulse Responses - Increase in Uncertainty 1p.p.					
Horizon=h	0	1	2	3	4
Capacity Util. Rate (t+h)	-0.389	0.296	0.128	0.106	-0.370
	(0.13)	(0.37)	(0.75)	(0.80)	(0.45)
Total Hours (t+h)	-0.918**	0.836*	0.016	-0.310	-0.690
	(0.02)	(0.06)	(0.97)	(0.59)	(0.37)
Real Investment (t+h)	0.478	-0.100	-0.712*	0.363	1.224
	(0.34)	(0.18)	(0.06)	(0.39)	(0.12)
Real Cash Holdings (t+h)	0.078**	0.121***	0.069	0.015	-0.076
	(0.03)	(0.01)	(0.13)	(0.77)	(0.34)

Note: Each equation is estimated with instrumental variables over the sample period 1996 to 2018, and it includes firm- and sector-specific dummies, and year effects. We use the second lag of uncertainty as an instrument. P-values are in parentheses. Stars denote the significance level of the coefficient they refer to: * p-value<0.10, ** p-value<0.05, and *** p-value<0.01. Entries are expressed in percent. See the text for more details.

uncertainty. Typically, the existing literature does not distinguish between the source of fluctuations in uncertainty, mostly because of the limitation imposed by existing data.[12] Understanding this issue is important for at least two reasons. From an empirical standpoint, the source of the increase in uncertainty is important to predict future effects. For instance, an increase in uncertainty may signal an increase (decrease) in labor and capital if driven by dispersion in positive or upside (negative or downside) outcomes. From a theoretical standpoint, measuring the effects of downside and upside uncertainty provides overidentifying restrictions against which to test competing models aimed at quantifying the aggregate effects of uncertainty. (We return to this issue in Section 6.) Following the terminology in Bernanke (1983), we define an increase in uncertainty driven by s^e_{min} (a reduction in s^e_{min} holding s^e_{max} constant) as an increase in *downside uncertainty*—that is, an increase in dispersion in negative outcomes.[13] Similarly, we denote *up-*

[12] Segal, Shaliastovich and Yaron (2015) constitute an important exception. They study the role of downside and upside (or bad and good) uncertainty for aggregate macroeconomic series and financial markets, finding that both matter.

[13] In the empirical analysis, we control for changes in the mean of future expected sales.

side uncertainty as an increase in uncertainty driven by s^e_{max} (holding s^e_{min} constant). As discussed in Section 3.1, firms that display a lower s^e_{min} (higher s^e_{max}) also display more probability mass associated with negative growth rates (positive growth rates) of sales.

How do we distinguish downside and upside uncertainty? We exploit the definition of $\sigma_{max-min}$ as the difference between s^e_{max} and s^e_{min}. Operationally, we follow the same empirical strategy in Section 4.1. First we construct $s^X_{max,f,t}$, the unpredictable component of the upside uncertainty (or best-case scenario), and $s^X_{min,f,t}$, the unpredictable component of the downside uncertainty (or worst-case scenario). Second, we regress firm-level outcomes on $s^X_{min,f,t}$ and $s^X_{max,f,t}$. Every specification includes both variables simultaneously.

The main takeaway is that firms respond to fluctuations in uncertainty only if it originates with downside uncertainty. Results are reported in Table 8. Panel A shows that an increase in downside uncertainty induces negative economic effects. Instead, Panel B shows that the coefficients on upside uncertainty are not statistically significant (except for hours per worker that increase; see Table *A*.2). The propagation mechanism of fluctuations in downside uncertainty (or equivalently an increase in uncertainty driven by a deterioration in the worst-case scenario, or downside uncertainty) is similar to the one discussed in Section 4.2. In response to an increase in downside uncertainty, firms first reduce capacity utilization and total hours and then investment. Over time, as the initial effect of the shock wanes, the dynamics are reverted.

Disentangling the individual contribution of upside and downside uncertainty sheds light on the dynamics induced by an increase in $\sigma_{max-min}$. We emphasize two aspects. First, the estimated effects of an increase in uncertainty confound the significant sensitivity of firms' decisions to the rise in downside uncertainty and its unresponsiveness to upside uncertainty. Dynamics triggered by fluctuations in downside uncertainty are statistically and economically significant, moving each variable in Panel A of Table 8 by about one standard deviation. As upside uncertainty accounts for about one-half of the variance in uncertainty, responses following shocks to $\sigma_{max-min}$ are about half of the ones following shocks to downside uncertainty.

Second, fluctuations in downside uncertainty generate "boom-bust" dynamics, with investment overshooting its steady-state level after the initial drop. On impact, firms reduce capacity utilization and hours (with two-thirds of the response accounted for by hours per worker; see Table *A*.2) and then investment. Cash holdings also increase for the first two periods. As the

Table 8: Real and Financial Effects of Firm-Level Uncertainty

Panel A - Impulse Responses: Increase in Downside Uncertainty 1p.p.

Horizon=h	0	1	2	3	4
Capacity Utilization Rate (t+h)	-0.198**	-0.077	-0.007	0.001	0.000
	(0.02)	(0.26)	(0.88)	(0.16)	(0.94)
Total Hours (t+h)	-0.217***	0.045	0.024	-0.014	0.091
	(0.00)	(0.27)	(0.68)	(0.77)	(0.30)
Real Investment (t+h)	-0.108	-0.875***	-0.977*	-0.094	0.731*
	(0.75)	(0.01)	(0.07)	(0.82)	(0.06)
Real Cash Holdings (t+h)	0.624**	0.832*	-0.151	-0.534	0.262
	(0.01)	(0.09)	(0.71)	(0.31)	(0.64)

Panel B - Impulse Responses: Increase in Upside Uncertainty 1pp

Horizon=h	0	1	2	3	4
Capacity Utilization Rate (t+h)	-0.063	-0.006	0.017	-0.000	-0.030
	(0.14)	(0.90)	(0.84)	(1.00)	(0.61)
Total Hours (t+h)	-0.024	-0.011	0.023	0.035	-0.008
	(0.53)	(0.76)	(0.63)	(0.34)	(0.91)
Real Investment (t+h)	0.005	-0.185	-0.520	0.659	-0.102
	(0.99)	(0.60)	(0.28)	(0.29)	(0.82)
Real Cash Holdings (t+h)	0.014	0.003	0.022	-0.008	-0.032
	(0.28)	(0.92)	(0.25)	(0.86)	(0.35)

Note: Each equation is estimated with ordinary least squares over the sample period 1996 to 2018, and it includes firm- and sector-specific dummies, and year effects. P-values are in parentheses. Stars denote the significance level of the coefficient they refer to: * p-value<0.10, ** p-value<0.05, and *** p-value<0.01. Standard errors are clustered in two ways, by firm and year. Entries are expressed in percent. Panel A reports the response of each variable to a 1 percentage point *decrease* in $s^X_{min,f,t}$, or equivalently an increase in downside uncertainty. Panel B reports the response of each variable to a 1 percentage point *increase* in $s^X_{max,f,t}$, or, equivalently, an increase in upside uncertainty. See the text for more details.

shock dissipates, the initial dynamics are reversed. The total effect is mostly zero for capacity utilization, while it is negative for the other variables.

6 Implications for Macroeconomic Modeling

Our microeconomic evidence shows that the adverse economic effects of firm-level uncertainty results from fluctuations in downside uncertainty. Instead, firms' decisions are insensitive to changes in upside uncertainty.

How does our evidence discipline existing theories of uncertainty, and what are the implications for macroeconomic models? As discussed in Bloom (2014), to reproduce the negative effects of uncertainty, macroeconomic frameworks rely on models of "real options" or models that emphasize financial or behavioral considerations.[14] Theories of real options emphasize "wait and see" motives due to the presence of adjustment costs that give firms the option to delay investment (or hiring) in the presence of uncertainty and make reversing decisions costly.[15] Examples of these frictions include non-convex adjustment costs and input irreversibility that have received widespread attention in the quantitative macroeconomic literature; see, for instance, Bloom (2009) and Bachmann and Bayer (2014).

As discussed in Abel et al. (1996), in the context of real options theories the specification of the capital (or labor) adjustment cost function dictates the firms' sensitivity to downside uncertainty, upside uncertainty, or both. With capital irreversibility due to firm specificity or the absence of secondary markets, Bernanke's bad news principle applies with firms responding only to fluctuations in downside uncertainty. This choice increases firm's profits in low future productivity states in which the irreversibility constraint is binding and the firm cannot downsize. Frictions

[14] On theoretical grounds, it is well known that the economic effects of uncertainty are in general ambiguous and depend on the assumptions about the production technology, competition in product markets, the shape of adjustment costs, and management attitudes toward uncertainty. Uncertainty can potentially have positive effects. Bar-Ilan and Strange (1996) show that in the presence of "time to build" or "gestation lags," uncertainty may increase investment. We refer the reader to the discussion of the literature in Dixit and Pindyck (1994), Guiso and Parigi (1999), and, more recently, Bloom (2014).

[15] Cooper and Haltiwanger (2006) estimate high capital adjustment cost, while Ramey and Shapiro (2001) emphasize sectoral specificity of physical capital and substantial costs of redeploying the capital. Similarly, there is evidence of significant hiring adjustment costs related to recruitment, training, and severance pay; see, for instance, Nickell (1987) and Bloom (2009).

that result in costly accumulation of capital prompt firms to respond to upside uncertainty.[16] Our empirical evidence supports theories of real options delivering an asymmetric adjustment cost function, in which downsizing capital (or labor) is costly. This point is also demonstrated by the reliance of the firms in using "soft margins" like the intensive margin of hours and capacity utilization rates to cope with fluctuations in uncertainty. We numerically illustrate the role of input irreversibility by solving the problem of a single firm subject to fluctuations in uncertainty in Appendix F.

Another strand of the literature emphasizes financial and behavioral considerations. Higher downside uncertainty about future sales could increase the firm's likelihood of facing financial constraints, leading to a drop in investment and hiring. Hansen, Sargent and Tallarini (1999) and Ilut and Schneider (2014) highlight the importance of "ambiguity aversion." In their models, agents cannot form a probability distribution about future events behaving as if the worst-case scenario will occur. Assuming that the minimum of future sales is a summary statistic for the probability distribution under the worst-case scenario, our evidence is also consistent with this class of models. Agents respond to a deterioration in the worst-case scenario while being insensitive to improvements in the best-case scenario.

Overall, our empirical analysis provides a set of restrictions based on microeconomic evidence against which to validate macroeconomic theories aimed to quantify the aggregate effects of uncertainty.

7 Measurement and Consequences of Aggregate Uncertainty

We now derive an economy-wide measure of ex ante uncertainty. We describe the detail of the aggregation of firm-level uncertainty in Section 7.1. In Section 7.2, we discuss how economy-wide uncertainty has evolved over the past 25 years and use firm-level estimates to quantify the contribution of uncertainty to the GDP dynamics experienced by the Italian economy during the past three recessions.

[16] Abel et al. (1996) refer to the generalization of the bad news principle as the "Goldilocks principle".

7.1 A Bottom-Up Measure of Ex Ante Aggregate Uncertainty

We construct an economy-wide measure of uncertainty based on an aggregation of the max–min range at the firm level. Uncertainty perceived by each firm is affected by both aggregate and idiosyncratic factors. By averaging across firms, we wash out the idiosyncratic component, leaving the aggregate one. Our bottom-up approach provides a unicum in the literature, as it covers multiple business cycles. Similarly, Altig et al. (2020*a*) and Altig et al. (2020*b*) use survey data to construct an aggregate proxy of aggregate uncertainty. Still, data availability limits the length of their series extending (albeit a monthly rather than yearly frequency) to the past five years. Alternative strategies include Bloom (2009), and Bloom et al. (2018) that have proxied aggregate uncertainty using dispersion in realized outcomes, such as the cross-sectional dispersion in TFP shocks. Bachmann, Elstner and Sims (2013) construct uncertainty measures based on both ex ante disagreement and ex post forecast error about future outcomes. Jurado, Ludvigson and Ng (2015) adopted a latent-variable approach to extract a measure of the common variation in uncertainty across more than 100 macroeconomic series.

Our aggregate measure, $\sigma_{agg,max-min}$, is constructed averaging firm-level uncertainty, using as weights each firm's value added and the share of each firm over the entire population. The mean and the standard deviation of $\sigma_{agg,max-min}$ are 8.53 and 1.60 percentage points, respectively. Unsurprisingly, the volatility of the series is smaller than its firm-level counterpart. As shown in Section 3 roughly two thirds of the variation in $\sigma_{max-min}$ at the firm level is idiosyncratic. Unlike firm-level uncertainty, we find that aggregate uncertainty is negatively correlated with real GDP growth (-0.58). While this countercyclicality is typically obtained in the literature, we emphasize that the correlation of our measure of ex-ante aggregate uncertainty, $\sigma_{agg,max-min}$, is uncorrelated with typical proxies currently used in the literature. For instance, the correlation between $\sigma_{agg,max-min}$ and the cross-sectional dispersion in TFP innovation and sales is zero or slightly negative, respectively. This disconnection between ex ante and ex post measures occurs even if the measures of cross-sectional dispersion are markedly countercyclical and remained elevated since 2009. We suggest that $\sigma_{max-min}$ captures a dimension of ex-ante uncertainty that, almost by construction, is distinct from *realized* uncertainty captured by standard proxies, suggesting that these measures do not capture the full extent of aggregate uncertainty.

Figure 1 reports our measure $\sigma_{max-min}$ together with the growth rate of real GDP. (The series for aggregate $\sigma_{max-min}$ is demeaned.)

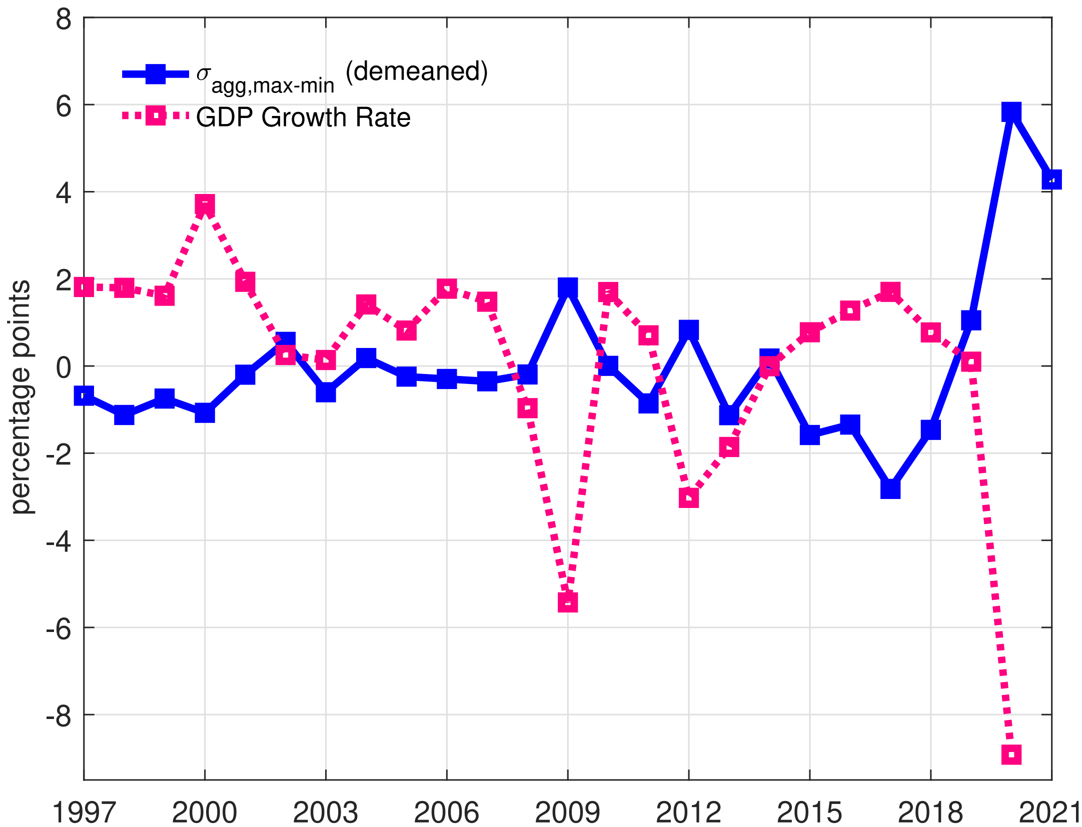

Figure 1: Uncertainty and GDP Growth

Note: The figure reports the demeaned series for aggregate $\sigma_{max-min}$, together with the growth rate of real GDP. Sample period si 1997 to 2021.

Excluding the current spike due to the COVID-19 pandemic, uncertainty peaked in the 2009 Global Financial Crisis (GFC) and rose, although to a lesser extent, in 2012 during the sovereign debt crisis (SDC). During the GFC and SDC, uncertainty increased more in the manufacturing sector relative to the service sector. In contrast, in 2020 at the peak of the COVID-19 pandemic, uncertainty nearly doubled in the service sector, and it increased by 50 percent in the manufacturing sector. For both sectors, in 2021 uncertainty is still historically high but is now driven by its upside component (the downside component recovered).

Beyond business cycle effects, our measure was also affected by political considerations in 2019, reaching levels comparable to the SDC due to elevated political uncertainty. Before turning to quantify the economic effects of aggregate uncertainty, we also note that in periods of high aggregate uncertainty, aggregate expected sales, $s^e_{agg,avg}$, have been particularly negative, see Figure A.1 in Appendix E.[17]

7.2 Economic Effects of Aggregate Uncertainty

Using survey data for the Italian economy, we find that uncertainty significantly contributed to the Italian economy's GDP losses in the past three recessions.

We use the estimates in Table 6 to measure the effects of uncertainty on GDP and assume that the same uncertainty shock hits all firms in the economy. Our calculations implicitly balanced out aggregate price responses that may reduce the GDP losses due to uncertainty and aggregate demand effects that may increase GDP losses through input—output linkages.

To pin down the size of the shock, we compute the variation in aggregate uncertainty between consecutive years. These changes are reported in the first column of Table A.5 in Appendix G. For the Italian economy, while the increase in uncertainty was of similar magnitude in 2009 and 2012, the 2020 spike is unprecedented as uncertainty doubled relative to the GFC.

According to our estimates, a deterioration in uncertainty weighs on the Italian economy's recovery, reducing capacity utilization and the growth rate of total hours and investment.[18]

We link the estimated uncertainty effects on capital and labor into a GDP equivalent employing a growth accounting approach. Through growth accounting identity, we express the growth rate of real GDP (ΔGDP) as ΔGDP= Δ TFP + α_K Δ K + (1-α_K)ΔTH, where ΔK and ΔTH denote the growth rate of capital accumulation and total hours, respectively. We set α_K to a typical value of 1/3 and assume that capacity utilization reduces TFP one-to-one. The economic effects of total hours directly map to ΔTH. Obtaining ΔK is slightly more involved. Given that the median investment rate is about 20 percent, the 4 percent reduction in investment decreases the investment rate (or the growth rate of capital) by about 1 percentage point.

Table 9 reports the final results of these calculations. We compare the actual drop in real GDP (ΔGDP) and the corresponding contribution of uncertainty for every recession. The main take-

[17] Similarly with the aggregate measure of uncertainty, $s^e_{agg,avg}$ is constructed averaging the firm-level expected sales using as weights each firm's value added and the share of each firm over the entire population.

[18] The total effect on capacity utilization and the growth rate of hours is obtained by multiplying the estimated coefficient at horizon h=0 in Table 8, -0.138 and -0.126, times the uncertainty shock. The cumulative effect of investment is computed analogously using the coefficients at horizon h=1 (-0.554) and h=2 (-0.785).

Table 9: GDP Effects of Aggregate Uncertainty

Global Financial Crisis	2009	2010	2011
ΔGDP Italy	-5.43	1.70	0.70
Contribution of Uncertainty	-0.69	-0.14	-0.20
Sovereign Debt Crisis	2012	2013	2014
ΔGDP Italy	-3.02	-1.85	-0.01
Contribution of Uncertainty	-0.45	-0.09	-0.13

Note: Entries are expressed in percentage points. ΔGDP refers to the growth rate of real GDP. The entry "Contribution of Uncertainty" reports the estimated GDP contribution of the observed increase in uncertainty during the corresponding period. See the text for details on the calculation on GDP effects.

away is that uncertainty has significant GDP effects, with an average contribution of about 15 percent to the Italian economic activity drop. Results are robust to using downside uncertainty rather than total uncertainty; see Table *A*.6 in Appendix G.

Concerning the Covid-19 pandemic, we highlight that the source of uncertainty dynamics have driven its economic effects. In 2020 spike in uncertainty accounted for about 1.2 percentage points of the 8.9 percent GDP contraction, owing to the significant decrease in downside uncertainty. As indicated by the 2021 wave of INVIND, overall uncertainty is still high. Still, the recovery in the downside component, more than the value predicted by the recovery in the mean, points to a smaller drag on GDP moving forward.

8 Final Remarks

We study the economic effects of time-varying uncertainty and offer a unique perspective that addresses some of the most pressing measurement issues regarding uncertainty at the firm-level. Access to microeconomic data allows us to construct, for a representative panel of firms, a measure of subjective ex ante uncertainty based on business managers' expectations that span over two decades and multiple business cycle episodes.

We document the properties of time-varying uncertainty across firms' size, age, and sectors. Our empirical analysis details the propagation mechanism of uncertainty fluctuations at the firm level showing that they induce long-lasting economic effects across various real and financial variables, such as capacity utilization, hours, investment, and cash holdings.

We provide evidence that not all uncertainties are all alike and the source of uncertainty matters for its overall effect. Our evidence provides a practical set of overidentifying restrictions against which to test competing macroeconomic models.

We construct an ex ante economy-wide measure of uncertainty. Our bottom-up measure captures a new dimension of aggregate uncertainty distinct from existing proxies. Although both are markedly countercyclical, our measure is uncorrelated with typical proxies of uncertainty employed in the existing literature, such as dispersion in realized TFP shocks or sales. This result indicates that existing proxies may not capture the full extent of aggregate uncertainty.

Our estimates indicate that uncertainty amplifies GDP losses during economic downturns, accounting for about 15 percent of the GDP losses during the past three recessions. Higher uncertainty has contributed to the 2020 GDP hit. Still, we expect these forces to subside given the large recovery in downside uncertainty and exert a minor drag on the recovery of the Italian economy from the COVID-19 crisis.

References

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.

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*a*. "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. 2020*b*. "Surveying Business Uncertainty." *Journal of Econometrics*, in press.

Arellano, Cristina, Yan Bai, and Patrick J. Kehoe. 2019. "Financial Frictions and Fluctuations in Volatility." *Journal of Political Economy*, 127(5): 2049–2103.

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.

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 Atanas Hristov. 2017. "Surprise, Surprise–Measuring Firm-Level Investment Innovations." *Journal of Economic Dynamics and Control*, 83: 107–148.

Bachmann, Rüdiger, Steffen Elstner, and Eric R. Sims. 2013. "Uncertainty and Economic Activity: Evidence from Business Survey Data." *American Economic Journal: Macroeconomics*, 5(2): 217–249.

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

Bar-Ilan, Avner, and William C Strange. 1996. "Investment Lags." *American Economic Review*, 86(3): 610–622.

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

Ben-David, Itzhak, and John R. Graham. 2013. "Managerial Miscalibration." *The Quarterly Journal of Economics*, 128(4): 1547–1584.

Bernanke, Ben S. 1983. "Irreversibility, Uncertainty, and Cyclical Investment." *The Quarterly Journal of Economics*, 98(1): 85–106.

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, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry. 2018. "Really Uncertain Business Cycles." *Econometrica*, 86(3): 1031–1065.

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

Bontempi, Maria Elena, Roberto Golinelli, and Giuseppe Parigi. 2010. "Why Demand Uncertainty Curbs Investment: Evidence from a Panel of Italian Manufacturing Firms." *Journal of Macroeconomics*, 32(1): 218–238.

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.

Cooper, Russell W., and John C. Haltiwanger. 2006. "On the Nature of Capital Adjustment Costs." *Review of Economic Studies*, 73(3): 611–633.

Datta, Deepa Dhume, Juan M. Londono, Bo Sun, Daniel O. Beltran, Thiago Revil T. Ferreira, Matteo Iacoviello, Mohammad Jahan-Parvar, Canlin Li, Marius del Giudice Rodriguez, and John H. Rogers. 2017. "Taxonomy of Global Risk, Uncertainty, and Volatility Measures." Board of Governors of the Federal Reserve System (U.S.) International Finance Discussion Papers 1216.

Dixit, Avinash K., and Robert S. Pindyck. 1994. *Investment under Uncertainty. Economics Books*, Princeton University Press.

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.

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. 2018. "Aggregate Dynamics and Microeconomic Heterogeneity: The Role of Vintage Technology." *Working Paper*.

Gennaioli, Nicola, Yueran Ma, and Andrei Shleifer. 2016. "Expectations and Investment." *NBER Macroeconomics Annual*, 30(1): 379–431.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajšek. 2014. "Uncertainty, Financial Frictions, and Investment Dynamics." National Bureau of Economic Research, Inc NBER Working Papers 20038.

Guiso, Luigi, and Giuseppe Parigi. 1999. "Investment and Demand Uncertainty." *The Quarterly Journal of Economics*, 114(1): 185–227.

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, Lars Peter, Thomas J. Sargent, and Thomas D. Tallarini. 1999. "Robust Permanent Income and Pricing." *Review of Economic Studies*, 66(4): 873–907.

Hassan, Tarek A., Stephan Hollander, Laurence van Lent, and Ahmed Tahoun. 2019. "Firm-Level Political Risk: Measurement and Effects." *The Quarterly Journal of Economics*, 134(4): 2135–2202.

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

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

Jordà, Óscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review*, 95(1): 161–182.

Judd, Kenneth L. 1998. *Numerical Methods in Economics.* MIT Press.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. 2015. "Measuring Uncertainty." *American Economic Review*, 105(3): 1177–1216.

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

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.

Lin, Xiaoji, Nicholas Bloom, and Ivan Alfaro. 2017. "The Finance-Uncertainty Multiplier." *Mimeo*.

Massenot, Baptiste, and Yuri Pettinicchi. 2018. "Can Firms See into the Future? Survey Evidence from Germany." *Journal of Economic Behavior & Organization*, 145: 66 – 79.

Morikawa, Masayuki. 2013. "What Type of Policy Uncertainty Matters for Business?" Research Institute of Economy, Trade and Industry (RIETI).

Nickell, Stephen J. 1987. "Dynamic Models of Labour Demand." In *Handbook of Labor Economics*. Vol. 1, Chapter 9, 473–522. Elsevier.

Ramey, Valerie A., and Matthew D. Shapiro. 2001. "Displaced Capital: A Study of Aerospace Plant Closings." *Journal of Political Economy*, 109(5): 958–992.

Segal, Gill, Ivan Shaliastovich, and Amir Yaron. 2015. "Good and Bad Uncertainty: Macroeconomic and Financial Market Implications." *Journal of Financial Economics*, 117(2): 369 – 397.

Senga, Tatsuro. 2015. "A New Look at Uncertainty Shocks: Imperfect Information and Misallocation." Working Paper.

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*.

Tauchen, George. 1986. "Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions." *Economics Letters*, 20(2): 177–181.

APPENDIX

A Data Sources

Our data on expected sales growth (the average, the minimum and the maximum) 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 non-financial 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 7 buckets), and region in which the firm's head office is located. In recent years, each wave has 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 question between the minimum and maximum expected growth rate of sales (min—max gap) covers around 900 firms on average per year, from 1993 to 2007, and 1,677 firms on average per year from 2008 to 2018. 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.

B Heterogeneity in Firm-Level Expectations

Table A.1 describes the properties of firms' expectations conditioning on size, age, and sectors.

C Estimation Details

We characterize the dynamic response of investment, labor, and capacity utilization after an increase in the unpredictable component of uncertainty, $\sigma^X_{f,t,max-min}$. Towards this goal, we esti-

Table $A.1$: Firm-Level Expectations: Descriptive Statistics

	No. of Obs.	Mean	St. Dev.	Skew.	P_{10}	P_{25}	P_{50}	P_{75}	P_{90}
Full Sample									
s^e_{avg}	49674	3.59	11.60	1.00	-7.10	0.00	2.70	7.10	14.50
s^e_{min}	30958	-3.57	10.40	-0.20	-12.00	-10.00	-2.00	1.00	5.00
s^e_{max}	30976	6.91	10.70	1.63	-1.00	1.50	5.00	12.00	15.00
Small and Medium Firms: $20 \leq$ Labor Force ≤ 50									
s^e_{avg}	3059	3.53	10.20	1.07	-4.80	0.00	2.40	5.90	14.30
s^e_{min}	5115	-5.97	10.60	-0.42	-14.00	-12.00	-5.00	0.00	4.00
s^e_{max}	5120	6.63	10.40	0.75	-2.00	1.00	5.10	12.00	12.70
Large Firms: Labor Force ≥ 50									
s^e_{avg}	46339	3.60	11.70	0.99	-7.40	0.00	2.80	7.30	14.60
s^e_{min}	25630	-2.14	10.00	-0.01	-12.00	-6.00	-1.00	2.00	7.00
s^e_{max}	25646	7.09	10.80	2.09	-1.00	2.00	5.00	12.00	16.20
Young Firms: Age ≤ 5									
s^e_{avg}	1367	6.27	14.90	1.20	-7.40	0.00	4.00	10.50	22.30
s^e_{min}	873	-3.60	11.60	0.66	-12.00	-12.00	-3.00	1.00	8.00
s^e_{max}	871	9.91	12.00	1.60	0.00	3.00	10.00	12.00	21.00
Old Firms: Age > 5									
s^e_{avg}	48307	3.54	11.50	0.98	-7.00	0.00	2.70	7.10	14.40
s^e_{min}	30085	-3.57	10.30	-0.23	-12.00	-10.00	-2.00	1.00	5.00
s^e_{max}	30105	6.85	10.60	1.62	-1.00	1.50	5.00	12.00	15.00
Manufacturing Sector									
s^e_{avg}	33873	4.28	12.20	0.83	-7.50	0.00	3.50	8.50	16.00
s^e_{min}	21592	-3.08	11.00	-0.26	-12.00	-10.00	-1.20	2.00	7.00
s^e_{max}	21607	7.48	11.20	1.41	-1.00	2.00	5.60	12.00	18.00
Service Sector									
s^e_{avg}	15801	2.55	10.40	1.30	-6.40	-0.10	1.80	5.10	11.30
s^e_{min}	9366	-4.25	9.43	-0.16	-12.00	-12.00	-2.00	0.20	4.00
s^e_{max}	9369	6.14	9.82	2.00	-1.00	1.00	5.00	12.00	12.00

Note: Statistics are computed pooling all the firm-specific observations over the whole sample period 1996 to 2018. Table entries are computed over growth rates expressed in percent. s^e_{avg}, s^e_{min}, and s^e_{max} denote the *average*, *minimum*, and *maximum* expected growth rates of sales one-year ahead, while $\Delta Sales$ reports the growth rate of *realized* sales. P_X reports the X^{th} percentile of the distribution.

mate the following specification at different horizons:

$$Y_{f,t+h} = \alpha + \beta_h \sigma^X_{max-min,f,t} + \epsilon_{f,t}, \forall h = 0...4 \tag{A.1}$$

for every $h \geq 0$. The firm-level dependent variables $Y_{f,t}$ are, the log of investment, the growth rate of total hours at the firm level, the capacity utilization rate, and the growth rate of cash holdings. We remind the reader that including firm- and industry-specific effects, and year dummies in Equation A.1 is irrelevant given that those effects have already been extracted from $\sigma^X_{max-min,f,t}$. The set of control variables depends on the dependent variable. Importantly, we include the stock of capital (in logs) when the dependent variable is investment.

D Firm-Level Uncertainty and Labor Market Dynamics

Table A.2 reports the decomposition of the impulse responses of the growth rate of total hours into the intensive margin, the growth rate of hours-per-worker, and the extensive margin, the number of employees. Panel A reports the impulse responses following an increase in overall uncertainty. Panel B reports the labor market dynamics following an increase in downside uncertainty. Panel C reports the responses following an increase in upside uncertainty. The key message is that most of the adjustment to total hours occurs through the intensive margin.

Table $A.2$: Firm-Level Uncertainty: Labor Market Dynamics

Panel A - Impulse Responses - Increase in Uncertainty 1p.p.

Horizon=h	0	1	2	3	4
Growth Rate of Hours-per-Worker (t+h)	-0.072**	0.041	0.022	-0.025	0.059
	(0.02)	(0.22)	(0.48)	(0.29)	(0.25)
Growth Rate of No. of Employees (t+h)	-0.058**	-0.017	-0.006	0.035	-0.016
	(0.02)	(0.53)	(0.79)	(0.49)	(0.69)

Panel B - Impulse Responses - Increase in Downside Uncertainty 1pp

Horizon=h	0	1	2	3	4
Growth Rate of Hours-per-Worker (t+h)	-0.176***	0.072*	0.045	-0.020	0.103*
	(0.01)	(0.10)	(0.31)	(0.40)	(0.05)
Growth Rate of No. of Employees (t+h)	-0.055***	-0.018	-0.015	0.016	0.003
	(0.01)	(0.59)	(0.44)	(0.77)	(0.93)

Panel C - Impulse Responses - Increase in Upside Uncertainty 1pp

Horizon=h	0	1	2	3	4
Growth Rate of Hours-per-Worker (t+h)	0.043*	0.003	-0.009	-0.015	0.010
	(0.09)	(0.93)	(0.82)	(0.68)	(0.92)
Growth Rate of No. of Employees (t+h)	0.059	-0.013	0.005	0.054	-0.037
	(0.14)	(0.65)	(0.89)	(0.37)	(0.52)

Note: Each equation is estimated with ordinary least squares over the sample period 1996 to 2018, and it includes firm- and sector-specific dummies, and year effects. P-values are in parentheses. Stars denote the significance level of the coefficient they refer to: * p-value<0.10, ** p-value<0.05, *** p-value<0.01. Standard errors two-way clustered by firm and year. Entries are expressed in percent and report each variable's response to a 1 percentage point in uncertainty. See the text for more details.

E Aggregate Expected Sales and GDP Growth

Figure A.1 reports the evolution of $s^e_{agg,avg}$, an aggregate measure of the expected growth rate of sales one period ahead. We aggregate firm-level expected growth rates using as weights each firm's share in the population and value added. The series $s^e_{agg,avg}$ in the figure has been demeaned.

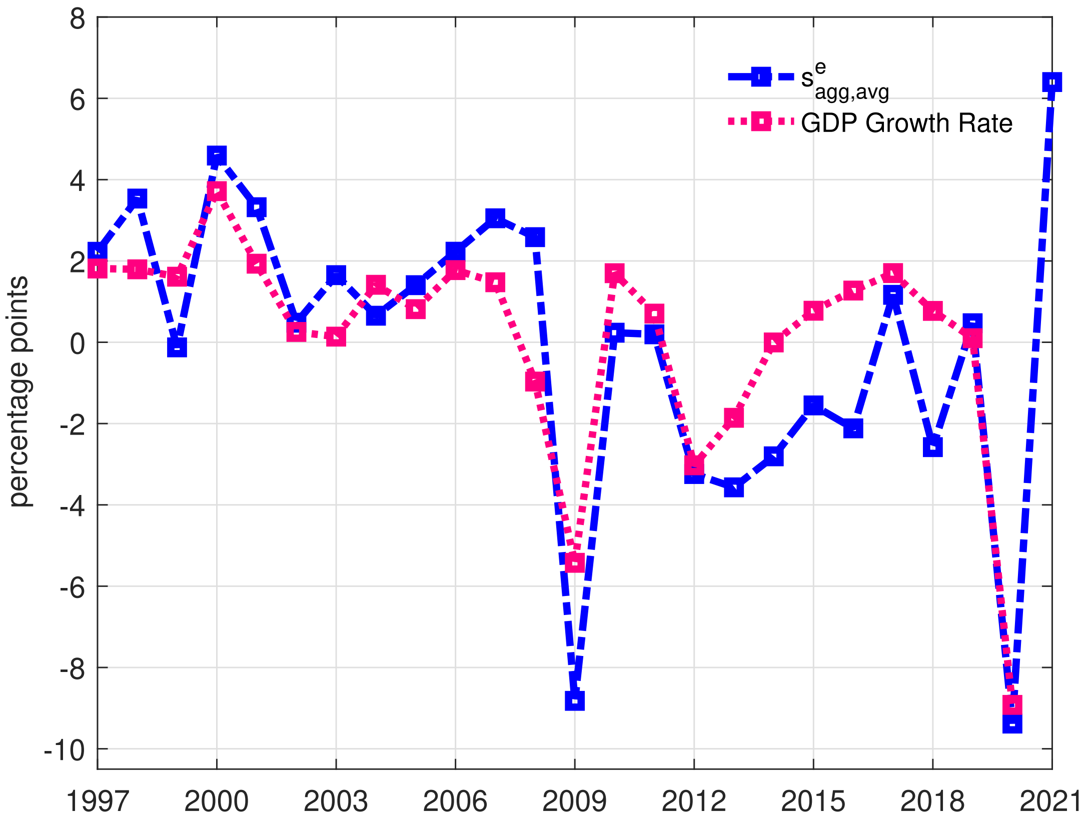

Figure A.1: Expected Aggregate Sales and GDP Growth

Note: The figure reports the (demeaned) series for aggregate expected growth rate of sales one-year ahead, denoted by$s^e_{agg,avg}$, together with the growth rate of GDP.

F Theory: Input Irreversibility

This section describes the theoretical framework that we employ to study the link in our evidence on the economic effects of uncertainty playing through downside uncertainty and economic theory. The main goal is to reconcile the sensitivity of investment to fluctuations in downside uncertainty (and the muted response to upside uncertainty) with the optimizing behavior of a profit-maximizing firm.

The model features input irreversibility as in Bernanke (1983), where firms cannot disinvest. We describe the environment in Sections F.1 and F.2 and the firm's problem featuring input irreversibility in Section F.3. We detail the model's parameterization and the result of our numerical simulation in Sections F.4 and F.5.

F.1 Production

Each firm has access to an increasing and concave production function that combines predetermined capital stock k with its available technology ε to produce output y:

$$y = \varepsilon k^{\theta}, \tag{A.2}$$

where $\theta > 0$ and $0 < \theta < 1$. ε denotes the idiosyncratic productivity. The latter follows a first-order Markov with autocorrelation ρ_ε with time-varying conditional standard deviation, σ_ε. In turn, σ_ε follows an autoregressive process with persistence $\rho_{\sigma_\varepsilon}$ and volatility $\sigma_{\sigma_\varepsilon}$. Fluctuations in σ_ε capture the time-varying uncertainty faced by the firm.[19]

F.2 Firm's Input Accumulation Decision

We consider two alternative scenarios: input irreversibility and non-convex adjustment cost. Under input irreversibility, the firm can adjust the accumulation of input without incurring any cost, while decreasing input above its depreciation rate is not feasible, in the spirit of Bernanke (1983). (Assuming that the firm can sell its input at a discount, as in Bloom (2009), does not alter our conclusions.)

F.3 Value of a Firm and Profit Maximization

Let $V^1(\varepsilon_l, \sigma_\varepsilon, k)$ denote the expected discounted value of a firm entering the period with $(\varepsilon_l, \sigma_\varepsilon, k)$. The dynamic optimization problem for the typical firm is described using a functional equation

[19] To be precise, $\sigma'_\varepsilon = \bar{\sigma}_\varepsilon(1 - \rho_{\sigma_\varepsilon}) + \rho_{\sigma_\varepsilon}\sigma_\varepsilon + \epsilon_{\sigma_\varepsilon}$.

defined by ($A.3$) and ($A.4$). The firm's profit maximization problem is then described by

$$\begin{aligned} V^1(\varepsilon, \sigma_\varepsilon, k, \xi) &= \max_{k^*} \left\{ \begin{array}{c} [F(\varepsilon, k) + (1-\delta)k] + \\ +R(\varepsilon, \sigma_\varepsilon^{'}, k^*) \end{array} \right\} \\ s.t.\ k^* \geq k(1-\delta) \end{aligned} \tag{A.3}$$

where $R(\varepsilon, \sigma_\varepsilon^{'}, k^{'})$ represents the continuation value associated with a given combination of the idiosyncratic shock, first and second moments, and the stock of capital:

$$R(\varepsilon, \sigma_\varepsilon^{'}, k^{'}) \equiv -\gamma k^{'} + \beta \sum_{m=1}^{N_\varepsilon} \pi_{lm}^{\varepsilon} V^0(\varepsilon_m, \sigma_\varepsilon^{'}, k^{'}) \tag{A.4}$$

F.4 Model Parameterization

We solve the problem of the individual firm defined in Section F.3 by value function iteration. We refer the reader to Appendix F.6 for details on the computation.

As is customary in the quantitative business cycle literature, we parameterize the model to reproduce key characteristics of Italian firms. Table $A.3$ summarizes parameter values and data sources. We are to assign values to six parameters related to the production process (δ, θ) , discount factor (β), and the persistence and the volatility of the idiosyncratic productivity process and its time-varying volatility (ρ_ε, $\bar{\sigma}_\varepsilon$, $\rho_{\sigma_\varepsilon}$, and $\sigma_{\sigma_\varepsilon}$). One period in the model represents one year, which corresponds to the frequency of the data employed in Section 4.2. The depreciation rate is estimated by the Italian National Institute of Statistics and is equal to 9 percent. The discount factor β is set to 0.975 to reproduce the data's real annual interest rate. The elasticity of output to capital is estimated from the data using the procedure in Bachmann and Bayer (2014). This strategy results in θ equal to 0.19.

To select the remaining parameters, we calibrate the persistence using the estimates in Fiori and Scocciantі (2018) and use the estimated dispersion in expected future sales from our survey data. This choice yields ρ_ε and $\bar{\sigma}_\varepsilon$ equal to 0.87 and 0.031, respectively. $\rho_{\sigma_\varepsilon}$ and $\sigma_{\sigma_\varepsilon}$ are instead equal to 0.64 and 0.03.

Table $A.3$: Benchmark Calibration

Parameter		Value	Target
Depreciation rate	δ	0.091	Data
Discount factor	β	0.975	Annual real interest rate = 2.3%
Elasticity of output w.r.t. capital	θ	0.19	Data
Persistence idiosyncratic productivity	ρ_ε	0.87	Data
Mean st.dev idiosyncratic productivity	$\bar{\sigma}_\varepsilon$	0.081	Data
Persistence st.dev idiosyncratic productivity	$\rho_{\sigma_\varepsilon}$	0.84	Data

F.5 Data and Model Comparison

The goal of this section is to take the model to the data. Can the framework in Section 6 reproduce qualitatively the asymmetry of the estimated investment responses following an increase in downside and upside uncertainty?

To answer this question, we compute how the firm's optimal capital k^* varies across different uncertainty regimes σ_ε. We assume that the firm's productivity (ε) is unchanged. We assume that volatility can take three regimes: (i) a baseline value, (ii) uncertainty increases driven by higher downside uncertainty, and (iii) uncertainty increases driven by upside uncertainty. Scenarios (ii) and (iii) are mean-preserving, in that they do not imply a change in the mean.

As is well known in the literature, without input irreversibility, an increase in uncertainty *increases* investment. This result occurs because the marginal value product of capital is a convex function of the firm's uncertainty. Thus, more significant uncertainty increases investment via the usual Jensen inequality effect: Greater uncertainty raises the marginal valuation of one additional unit of capital. Increasing the fixed cost or introducing input irreversibility reverses the neoclassical result: Greater uncertainty *reduces* capital accumulation.

Table $A.4$ shows how the optimal k varies with downside and upside uncertainty. Panel A shows that the model with input irreversibility reproduces the asymmetric response between downside and upside uncertainty. After an increase in downside uncertainty, the firm reduces k by 0.28 percent, while the response to upside uncertainty is muted. The firm reduces its capital today to avoid being stuck with too much capital if adverse states materialize. In contrast, the response to upside uncertainty is muted because the firm can always readjust its capital upward.

Table $A.4$: Downside and Upside Uncertainty: Optimal Capital

Input Irreversibility

	Baseline	Downside Uncertainty	Upside Uncertainty
Δk^*	n.a.	-0.28%	0.04%

Note: Δk^* indicates how optimal capital changes across different volatility regimes in percent relative to the baseline. n.a. Not available

F.6 Computational Details: Value Function Iteration

The value function to solve the firm's problem defined in equations ($A.3$) and ($A.4$) is the basis of our numerical solution of the economy. The solution algorithm involves repeated application of the contraction mapping to solve for firms' value function. More specifically, the firm's problem amounts to find the next-period value of capital $k^{'}$. To do so, we resort on a golden section search to allow for continuous control. We discretize the state space using a fine grid between 0.1 and 8.5 for capital k. We approximate the process for the idiosyncratic processes ε and σ_{ε} using the procedure in Tauchen (1986) over 91 and 22 possible values. We compute the value function exactly at the grid points above and interpolate for in-between values. This procedure is implemented using a multidimensional cubic splines procedure, with a so-called "'not a knot"' condition to address the large number of degrees of freedom problem, when using splines; see Judd (1998).

G GDP Effects of Aggregate Uncertainty: Downside Uncertainty

Table $A.5$ reports how the variation in uncertainty ($\sigma_{agg,max-min}$), the best-case scenario ($s^{e}_{agg,max}$), the worst-case scenario ($s^{e}_{agg,min}$) and the average expectation ($s^{e}_{agg,avg}$) about future sales fluctuates during the Global Financial Crisis, the sovereign debt crisis, and the COVID-19 pandemic.

Table $A.6$ reports the estimated effects of uncertainty on GDP using downside uncertainty.

Table $A.5$: Crises and Aggregate Uncertainty

Global Financial Crisis

	$\sigma_{agg,max-min}$	$s^e_{agg,max}$	$s^e_{agg,min}$	$s^e_{agg,avg}$
2008	8.52	7.22	-1.26	6.11
2009	10.52	-1.33	-11.82	-5.30
$\Delta 2009 - 2008$	2.00	-8.55	-10.56	-11.41

Sovereign Debt Crisis

	$\sigma_{agg,max-min}$	$s^e_{agg,max}$	$s^e_{agg,min}$	$s^e_{agg,avg}$
2011	7.86	6.54	-1.37	3.72
2012	9.55	3.32	-5.15	0.28
$\Delta 2012 - 2011$	1.69	-3.22	-3.78	-3.44

Covid-19 Pandemic

	$\sigma_{agg,max-min}$	$s^e_{agg,max}$	$s^e_{agg,min}$	$s^e_{agg,avg}$
2019	9.77	7.17	-2.12	3.99
2020	14.55	2.02	-11.56	-5.86
2021	13.00	12.34	-0.11	9.92
$\Delta 2020 - 2019$	4.78	-5.14	-9.44	-9.85
$\Delta 2021 - 2020$	-1.55	10.32	11.45	15.78

Note: Entries are expressed in percentage points. $\sigma_{agg,max-min}$ denotes our measure of aggregate uncertainty. $s^e_{agg,avg}$, $s^e_{agg,min}$, and $s^e_{agg,max}$ denote the aggregate measure of average, minimum, and maximum expected growth rates of sales one year ahead. Δ refers to the change between two consecutive years.

Table $A.6$: GDP Effects of Aggregate Downside Uncertainty

Global Financial Crisis	2009	2010	2011
ΔGDP Italy	-5.43	1.70	0.70
Contribution of Downside Uncertainty	-1.00	-0.21	-0.23

Sovereign Debt Crisis	2012	2013	2014
ΔGDP Italy	-3.02	-1.85	-0.01
Contribution of Downside Uncertainty	-0.51	-0.10	-0.12

Note: Entries are expressed in percentage points. ΔGDP refers to the growth rate of real GDP. The entry "Contribution of Downside Uncertainty" reports the estimated GDP contribution of the observed increase in downside uncertainty during the corresponding period purged by fluctuations in $s^{e}_{agg,avg,t}$. See the text for details on the calculation on GDP effects.