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

Giuseppe Fiori Filippo Scoccianti

May 4, 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 ex-ante firm-level uncertainty is a persistent process that does not abate quickly and varies across firms' size, age and sectors. Controlling for several confounding factors, including the first moment of the probability distribution of expected outcomes, we characterize the propagation mechanism of uncertainty fluctuations over a broad array of real and financial variables. Following an increase in firm-level uncertainty, firms reduce investment, labor hours and the capacity utilization rate. Financial considerations are also important, with firms increasing their cash holdings. These effects persist for a few years with investment overshooting its steady state level. Our analysis shows that the source of firm-level uncertainty is crucial to determine its economic effects. Firms respond only to an increase in uncertainty about future adverse outcomes, or *downside* uncertainty, in line with the "bad news principle" described in Bernanke (1983). The firms' sensitivity to downside uncertainty points to irreversibility as a key factor behind the propagation mechanism of time-varying uncertainty. We exploit our representative sample to construct an aggregate measure of uncertainty for the Italian economy. Uncertainty is countercyclical but uncorrelated with typical proxies such as dispersion in sales or TFP innovations. According to our estimates, uncertainty accounts for about 15 percent of the Italian economy's GDP losses during the Great Financial Crisis, the Sovereign Debt Crisis, and the ongoing COVID-19 pandemic.

JEL Codes: D42; D92; E32; G31; G32.
Keywords: Uncertainty, expectations, investment, labor, cash holdings, downside uncertainty

*First version: April 13, 2020. We are grateful to Danilo Cascaldi-Garcia, Brian Doyle, Matteo Iacoviello, Francesca Lotti, Andrea Prestipino, Enrico Sette, and participants to the "11^{th} IFO conference" 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). The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System (or of any other person associated with the Federal Reserve System) or the Bank of Italy.

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' decision. 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 firm-level uncertainty by using over two decades of Italian survey data on firm-level expectations that span over 20 years and covers multiple business cycle episodes.[1] Our analysis yields three main insights.

First, we construct a measure of *ex-ante*, firm-level 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 does not abate quickly and persists for a few years. These results suggest that changes in consumers' tastes or shift in technology are more relevant sources of firm-level 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 uncertainty over a broad set of real and financial variables at the firm level. 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 (both in 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. Our results are obtained con-

[1]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 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). 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 Data Manager Panel surveys was launched in August 2016.

trolling 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 "downside" or "upside" uncertainty, i.e. uncertainty about adverse or positive outcomes.

Third, we construct an *economy-wide* measure of uncertainty for the Italian economy aggregating individual firm-level uncertainty and find it to be countercyclical. While this counterclicality reproduces the literature's typical result, we emphasize that our measure is uncorrelated to standard proxies for macroeconomic uncertainty employed in the literature. One possibility is that this little correlation indicates that firm-level uncertainty identifies a distinct dimension of ex-ante uncertainty not typically captured by dispersion in realized ex-post outcomes, such as dispersion in sales or innovations in total factor productivity (TFP).

The source of the data on expectations is the Survey on 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 subjective expectations over the average, the minimum, and the maximum one-year ahead growth rate of sales from managers. Thus, we directly observe the first moment of the probability distribution of expected 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 wave 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 expected 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-moment of the distribution of expected outcomes enables us to overcome one of the existing literature's main challenges. Specifically, we can disentangle the economic impact 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 (with less than 50 workers) and young firms (with less than five years of age) tend to display higher uncertainty than mature and larger 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 firms (driven by the minimum).

To show that uncertainty is a persistent process, we exploit the 2017 wave of INVIND, that elicits the full probability distribution of expected sales one- and three-year 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. As we do not rely on proxies, our study offers a unique perspective on measuring firm-level uncertainty and assessing its economic effects.

While the literature has mainly focused on the response of investment to an increase in uncertainty, we highlight that investment is only one of the margins that firms use to adjust to a more uncertain environment. Specifically, following an increase in uncertainty, firms immediately reduce the extensive and intensive margin of labor (number of workers and hours per worker), 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 its steady-state level as the shock dissipates. Results are confirmed when we use an instrumental variables (IV) estimator, using lagged values of firm-level uncertainty as an instrument.

In Section 5, we investigate whether all uncertainties are all alike. Specifically, we study whether uncertainty about positive and negative outcomes have similar economic effects. We find that the economic uncertainty come from "downside" uncertainty, an increase in uncertainty driven by the firm perceiving higher dispersion about future negative outcomes (controlling for the change to the mean). Instead, firms are unresponsive to upside uncertainty. This evidence carries important theoretical implications and aligns with the "bad news principle" discussed in the context of capital accumulation by Bernanke (1983). Specifically, it is consistent with models that emphasize full or partial irreversibility of production inputs but not with models that rely exclusively on *symmetric* non-convex adjustment costs at the firm level. While both types of adjustment costs imply that an increase in uncertainty reduces investment, only models featuring irreversibility deliver the "bad news principle", i.e. firms reacting only to uncertainty about future negative outcomes. Intuitively, under irreversibility, an increase in downside uncertainty exposes firms to the possibility of being unable to reduce their labor force or disinvest (or being able to do so only at a price significantly lower than the purchase price of capital) if hit by future negative shocks. Hence, to the extent that the dispersion of future negative shocks increases, firms reduce input accumulation. In Section 6, we provide numerical simulations that corroborate this point.

In Section 7 we exploit our representative sample and construct an economy-wide measure of uncertainty by aggregating firm-specific uncertainty. We consider this bottom-up approach noteworthy because our proxy is the first measure of aggregate uncertainty constructed from over two decades of firm-level expectations spanning multiple business cycle episodes. Notwithstanding the little correlation with typical proxies for aggregate uncertainty, we find that uncertainty increased sharply during the Great Financial Crisis and the latest COVID-19 recession, and to a lesser extent during 2012 Sovereign Debt Crisis.

Using our estimates on the effects of uncertainty at the firm level, that isolates the "pure" 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. 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 will constitute a considerable drag on the Italian economy's recovery from the recession-induced by the pandemic. According to our estimates, the increase in uncertainty reduced GDP's growth rate by about one percentage point in 2020, and a cumulative 0.6 percentage points in 2021 and 2022.

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 Section 4 and 5. In Section 6 we link our estimates with economic theory showing that the sensitivity to downside uncertainty is consistent with the behavior of an optimizing firm that faces input irreversibility. 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. Starting from the measurement of firm-level uncertainty using surveys to elicit firms' expectation, INVIND is the forerunner of the Survey of Business Uncertainty (SBU) for the U.S. described in Altig et al. (2020*b*) and the Data Manager Panel (DMP) for the United Kingdom in Altig et al. (2020*a*). The critical advantage of INVIND is that it has surveyed firms' expectations for over two decades, allowing us to compare how uncertainty has evolved over multiple business cycles. In contrast, SBU and DMP started only in recent years, albeit at a monthly 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).[2] 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 real and financial variables (and not only investment). Besides, we show that the source of uncertainty is important for its economic effects. Our sample includes important business

[2] Another example is Morikawa (2013) that uses 2-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.

cycles episodes in recent history, both on the upside in the years 2005-2007 and in the deep financial recession that followed 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 returns 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. Using the policy uncertainty index developed by Baker, Bloom and Davis (2016), Gulen and Ion (2016) show that firm-level capital investment is negatively affected by the uncertainty associated with future policies. Moreover, firm-level uncertainty appears to vary both in the cross-section and in 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. 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 downside and upside uncertainty showing that only the former matters for its economic effects.

Our work also connects to the literature that studies 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 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 amongst 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, which counts the frequency of articles mentioning the words "uncertain or uncertainty" and find this measure is also countercyclical. Our economy-wide measure of uncertainty is also countercyclical, but it is uncorrelated to most of the existing proxies of aggregate uncertainty. One possible interpretation of this result is that standard proxies do not capture the aggregate dimension of ex-ante firm-level uncertainty.

Finally, our work related to Hassan et al. (2019) and Caldara et al. (2020) that using textual analysis study firm-level political uncertainty and explore the quantitative implications of trade policy uncertainty, respectively.[3]

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 proceed in steps. First, we 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, combining different sources. We first construct our measure of uncertainty using data on firm-level expectations from the Italian Survey on Industrial and Service Firms (INVIND). INVIND is an annual business survey conducted (between February and April every year) by the Bank of Italy on a representative sample of firms operating in industrial sectors (manufacturing, energy, and extractive industries)

[3]We refer the reader interested in a comprehensive review of the literature to Datta et al. (2017).

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 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 the INVIND survey. Industry-specific price deflators are obtained from the Italian National Statistical Institute (ISTAT). 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 over 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. Below 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, expected growth rate of sales one-year ahead, denoted by $s^e_{max,f,t}$.
3. The *minimum*, or worst-case scenario, expected 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. 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 expected future sales exploiting the 2005 and 2017 wave of the survey that elicits 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: Min, Max, and Avg 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 rate 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. 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

Notes: Statistics are computed over the whole sample period 1996-2018, 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*, *maximum* expected growth rate 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}, the median firm expects the worst-case scenario to result in a decrease of sales of about two 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 ten 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

Notes: Statistics are computed over the whole sample period 1996-2018, 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*, *maximum* expected growth rate 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 and age, and sectors. Results are reported in Table *A*.1 in Appendix B. Starting from firms' size, small and medium-size firms (defined as firms employing between 20 and 50 workers) display a lower expected growth rate in the worst-case and the best-case scenario, than large firms (with over 50 employees).[4] 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 (aged five or younger) tend to expect higher growth both on average and in the best-case scenario than mature and old ones (above five years of age). 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 in the services sector. This result reflects the faster growth rate of sales experienced by the manufacturing sector that we conjecture being driven by the higher degree of international openness relative to

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

the service sector.

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 between the range between the maximum and minimum future expect sales (or best- and the 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

The INVIND survey 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. To do so, we use data from the 2005 and 2017 waves of the INVIND survey. 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% to >10%.[5]

[5] In 2005, the support of the probability distribution of expected sales x was discretized using 11 bins: $\leq$-10%, -10%<x$\leq$-6%, -6%<x$\leq$-4%, -4%<x$\leq$-2%, -2%<x<0%, 0, 0%<x$\leq$2%, 2%<x$\leq$4%, 4%<x$\leq$6%, 6%<x$\leq$10%, $\geq$10%. In 2017, the grid between -6% and +6% was finer, with intervals of one percentage point rather than

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

Notes: Each equation is estimated with ordinary least squares (OLS) using 2005 INVIND 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.

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 formulas, and using, for each the 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 the worst-case scenario. Table 3 reports the results for the 2005 wave of INVIND.

The main result is that the range between the best- and the worst-case scenario 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 $\sigma_{max-min}$. Col-

two.

umn 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, $s^e_{maxmin,f}$ 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 of $\sigma_{max-min}$ captures the standard deviation of the probability distribution of expected outcomes.[6]

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} exhibits 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, i.e. 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 indicates 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, 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

[6] Using the 2017 wave, 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.

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

Notes: Statistics are computed over the whole sample period 1996-2018, 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 rate of sale one-year ahead.

of real GDP is -0.07.[7]

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

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

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 services sector face, on average, a higher level of uncertainty than those in the manufacturing sector. Old firms (with age equal or above 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 and small and medium 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 owes 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 or negative outcomes, or both. This is not just an intellectual curiosity. As discussed in Section 5, it carries critical theoretical implications providing useful restrictions against which to test competing theoretical frameworks against which to rationalize the economic effects of uncertainty. We assess the individual contribution of positive, 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 analyses 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), 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 condition: a positive growth rate of current sales is associated with lower uncertainty, although the effect is rather small. Turning to Column 2 and 3, we find that higher current sales tend to increase s^e_{min}, while for larger firms uncertainty tends to be smaller.

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 not only one-year ahead but also three-year ahead. After computing the respective standard deviation of future expected sales, we regress the one-year ahead dispersion on the three-year 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

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

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

abate quickly, but lasts for a few years with the half-life of a shock to uncertainty shock estimated to be two years.

4 Uncertainty: Sizeable and Persistent Effects Not Only on Capital but also on Labor and Cash Holdings

We now study the economic effects of uncertainty 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 (LP), discussed in Jordà (2005). A critical challenge that we face is that 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, capacity utilization, 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 below) 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 as the contemporaneous response of capacity utilization and labor, as these margins of adjustment may signal news about the future not specifically accounted 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 "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 dynamics 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), 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 one 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 owes both to 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.

On impact, firms also increase their cash holdings, signaling a precautionary behaviour that anticipates reducing investment. We discuss these results in turn. On the real side, after an increase in perceived uncertainty equal to one 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. There is also a reduction

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

	Impulse Responses - Increase in Uncertainty 1pp				
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)

Notes: Each equation is estimated with ordinary least squares (OLS) over the sample period 1996-2018 and it includes firm- and sector-specific dummies, and year effects. 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. Standard errors two-way clustered 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.

in employed workers' growth rate, smaller than that of hours, signaling 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 one percent over two years (or about one half of the investment standard deviation).[8] 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).

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

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 baseline specifications reported in Table 7, controls enter only contemporaneously, but the results are robust to the inclusion of the first lag. We instrument contemporaneous uncertainty using its second lag. As indicated by F-statistics above the usual value of 10 (not reported), the instrument is relevant and captures the strong persistence of uncertainty. As the case with OLS, 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.

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

IV - Impulse Responses - Increase in Uncertainty 1pp					
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)

Notes: Each equation is estimated with instrumental variables (IV) over the sample period 1996-2018 and it includes firm- and sector-specific dummies, and year effects. We use the second lag of uncertainty as an instrument. 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. Entries are expressed in percent. See the text for more details.

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, i.e. whether it comes from downside or upside uncertainty. Typically, the existing literature does not distinguish between the source of fluctuations in uncertainty, mostly because of the limitation imposed by existing data.[9] 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 testing competing theories of real options. The (in)ability to adjust inputs of production may result in an extreme sensitivity to bad news under input irreversibility, the so-called "bad news principle" in Bernanke (1983), or to news that are "not too hot, nor too cold" in "Goldilocks principle" discussed by Abel et al. (1996), that generalizes Bernake's principle. What uncertainty is relevant depends on the firm's adjustment cost structure and its ability to adjust its input in anticipation of the future expected states. (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*. Similarly, we denote *upside uncertainty* 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). Then, we regress firm-level

[9] Segal, Shaliastovich and Yaron (2015) constitutes 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.

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, 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 large 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, after the initial drop, overshooting its steady-state level. 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 shock dissipates, the initial dynamics are reversed. The total effect is mostly zero for capacity utilization, while it is negative for the other variables.

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

Panel A - Impulse Responses: Increase in Downside Uncertainty 1pp

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)

Notes: Each equation is estimated with ordinary least squares (OLS) over the sample period 1996-2018 and it includes firm- and sector-specific dummies, and year effects. 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. Standard errors two-way clustered 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.

6 Squaring Empirical Evidence with Economic Theory

Our empirical analysis indicates that economic effects of uncertainty are quantitatively sizeable and driven by fluctuations in downside uncertainty. Instead, firms are insensitive to changes in upside uncertainty.

We now relate our empirical evidence with the large theoretical literature that has studied the relationship between uncertainty and input accumulation. On theoretical grounds, it is well known that the economic effects of uncertainty depend on the assumptions about the production technology, competition in product markets, the shape of adjustment costs, and management attitudes toward uncertainty. We refer the reader to the discussion of the literature in Dixit and Pindyck (1994), Guiso and Parigi (1999), and, more recently, Bloom (2014). Typically, to reproduce the negative economic effects of uncertainty, economic models need to feature frictions such as non-convex adjustment costs or input irreversibility that generate real options. These two frictions have received widespread attention in quantitative macroeconomics, see, for instance, Bloom (2009), and Bachmann and Bayer (2014).

To connect our empirical analysis with economic theory, we study the optimization problem of a firm that faces non-convex costs of input adjustment and input irreversibility. The firm uses a durable input to produce output with decreasing marginal returns and is also subject to a stochastic productivity process with time-varying idiosyncratic uncertainty, both upside and downside. In their plain-vanilla implementation, both features deliver a negative relationship between uncertainty and durable input accumulation.

In a numerical illustration described in Appendix F, we show that only the model with irreversibility is consistent with the empirical result that the negative effects of total uncertainty come from downside uncertainty. Instead, in the model with non-convex costs, uncertainty's adverse effects come from both upside and downside uncertainty.

The logic behind these results is straightforward. Under irreversibility, the firm's increase in downside uncertainty is met with a reduction in durable input accumulation. This choice reduces firms losses in low future productivity states in which the irreversibility constraint is binding, and the firm cannot downsize. This mechanism is the "bad news principle" discussed in Bernanke (1983).[10] Instead, as the firm can always increase inputs at no cost, upside uncertainty has muted effects on input accumulation. This asymmetric response contrasts with the case under non-convex adjustment cost. The firm responds rather symmetrically to downside and upside uncertainty; upon paying the adjustment cost, the firm can reset its capital in response to both upside and downside uncertainty.

Our analysis supports the presence of input irreversibility as a key propagation mechanism of fluctuations in time-varying 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 4.2, we use estimates on the economic impact of firm-level uncertainty to quantify the contribution of uncertainty to the GDP losses experiences by the Italian economy during the last three recessions.

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 uncertainty observed at the firm level. Uncertainty perceived by each firm is affected both by aggregate and idiosyncratic factors. By averaging across firms, the idiosyncratic component washes out, 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, but data availability limits the length of their series that extends (albeit a monthly, rather than yearly frequency) to the last 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 total factor productivity shocks. Bachmann, Elstner and Sims (2013) construct uncertainty measures

[10] For a generalization into the "Goldilocks principle" see Abel et al. (1996).

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 over 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. Not surprisingly, 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. One possible interpretation of this result is that $\sigma_{max-min}$ captures a dimension of *ex-ante* uncertainty that, almost by construction, is distinct from textitrealized uncertainty captured by standard proxies.

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.)

Excluding the current spike due to the COVID-19 pandemic, uncertainty peaked in the 2009 Global Financial Crisis (GFC) and raised, 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, during the Covid-19 pandemic, uncertainty nearly doubled in the service sector, and it increased by 50 percent in the manufacturing sector.

Before turning to quantify the economic effects of aggregate uncertainty, we note that also aggregate expected sales, $s^e_{agg,avg}$ sharply dropped in correspondence of recession, see Figure *A*.1 in Appendix E.[11]

[11] Similarly with the aggregate measure of uncertainty, $s^e_{agg,avg}$ is constructed averaging the firm-level ex-

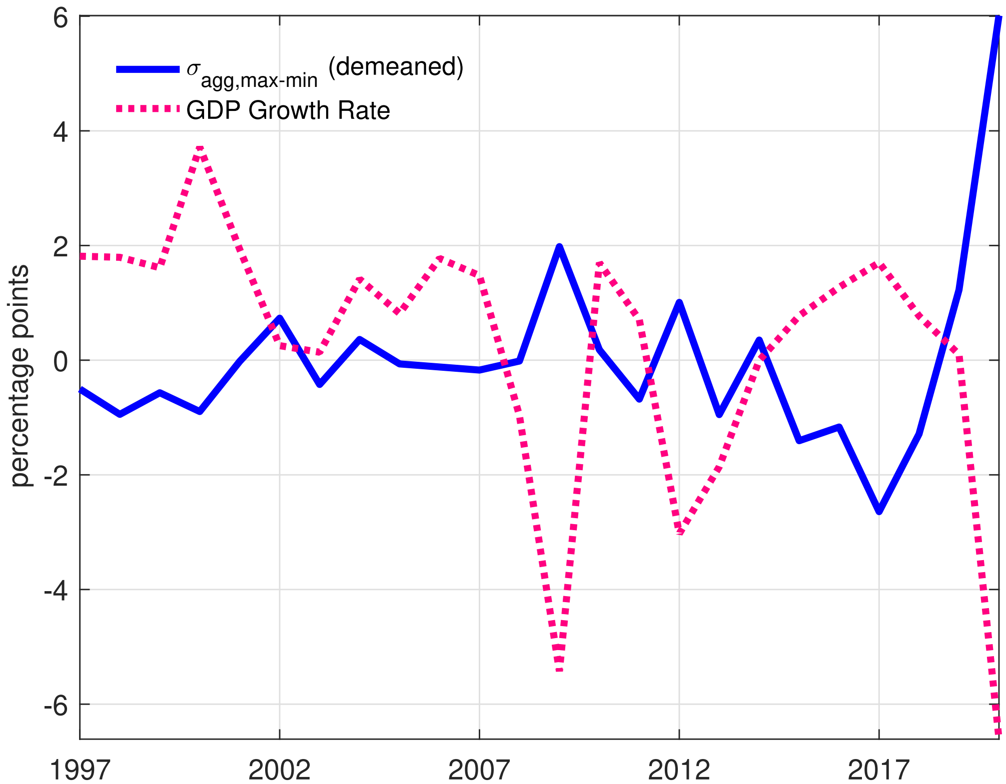

Figure 1: Uncertainty and GDP Growth

Notes: The figure reports the demeaned series for aggregate $\sigma_{max-min}$, together with the growth rate of real GDP. Sample period 1997-2020.

7.2 Aggregate Effects of Uncertainty

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

We use the estimates in Table 6 to measure the effects of uncertainty on GDP and assume that all firms in the economy are hit by the same increase in uncertainty during the last three recessions. Our calculations implicitly balanced out aggregate prices responses that may reduce the GDP losses due to uncertainty, and aggregate demand effects that may instead 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

pected sales using as weights each firm's value added and the share of each firm over the entire population.

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.[12]

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
Covid-19 Pandemic	2020	2021	2022
ΔGDP Italy	-8.92	N.a.	N.a.
Contribution of Uncertainty	-1.27	-0.26	-0.36

Notes: 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.

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= $\Delta\ TFP + \alpha_K\ \Delta\ K$ + (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 total factor productivity (TFP) one-to-one. The economic effects of total hours directly

[12]The total effect on capacity utilization and the growth rate of hours is obtaining 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).

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 one 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 takeaway 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.

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 support the "principle of bad news" discussed in Bernanke (1983). Uncertainty fluctuations produce economic consequences only when originating from downside uncertainty. This result helps distinguish competing theoretical mechanisms and supports inputs irreversibility, such as capital and labor, as a critical component of the propagation mechanism of uncertainty fluctuations.

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.

Our estimates indicate that uncertainty amplifies GDP losses during economic downturns, accounting for about 15 percent of the GDP losses during the last three recessions. We expect the spike in uncertainty observed during the Covid-19 pandemic to exert a considerable drag on the Italian economy's recovery.

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*.

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, Ricardo J. Caballero, and Eduardo M. R. A. Engel. 2013. "Aggregate Implications of Lumpy Investment: New Evidence and a DSGE Model." *American Economic Journal: Macroeconomics*, 5(4): 29–67.

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.

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.

Caballero, Ricardo J., and Eduardo M. R. A. Engel. 1999. "Explaining Investment Dynamics in U.S. Manufacturing: A Generalized (S,s) Approach." *Econometrica*, 67(4): 783–826.

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. SI:APR2019 CRN CONFERENCE.

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.

Fiori, Giuseppe. 2012. "Lumpiness, Capital Adjustment Costs and Investment Dynamics." *Journal of Monetary Economics*, 59(4): 381–392.

Fiori, Giuseppe, and Filippo Scoccianti. 2018. "Aggregate Dynamics and Microeconomic Heterogeneity: The Role of Vintage Technology." *Working Paper*.

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

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

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.

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*.

Khan, Aubhik, and Julia K. Thomas. 2008. "Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics." *Econometrica*, 76(2): 395–436.

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).

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." *Hiring, and R&D: Causal Evidence from Equity Options (October 4, 2013)*.

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

Thomas, Julia K. 2002. "Is Lumpy Investment Relevant for the Business Cycle?" *Journal of Political Economy*, 110(3): 508–534.

APPENDIX

A Data Sources

Our data on expected sales growth (the average, the minimum and the maximum) comes from the Survey on 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 1677 firms on average per year from 2008 up to 2018. The dataset 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.

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

Notes: Statistics are computed pooling all the firm-specific observations over the whole sample period 1996-2018. Table entries are computed over growth rates expressed in percent. s^e_{avg}, s^e_{min}, s^e_{max} denote the *average*, *minimum*, *maximum* expected growth rate 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.

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 estimate the following specification at different horizons:

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

for every $h \geq 0$. The firm-level dependent variable $Y_{f,t}$ are, the log of investment, the growth rate of total hours at the firm level, the capacity utilization rate, 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 being 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, and Panel C 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 1pp					
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)

Notes: Each equation is estimated with ordinary least squares (OLS) over the sample period 1996-2018, and it includes firm- and sector-specific dummies, and year effects. 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. Standard errors two-way clustered by firm and year. Entries are expressed in percent, and report each variable's response to a one 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 the share of firms population accounted for by each firm and value added. The series $s^e_{agg,avg}$ in the figure has been demeaned.

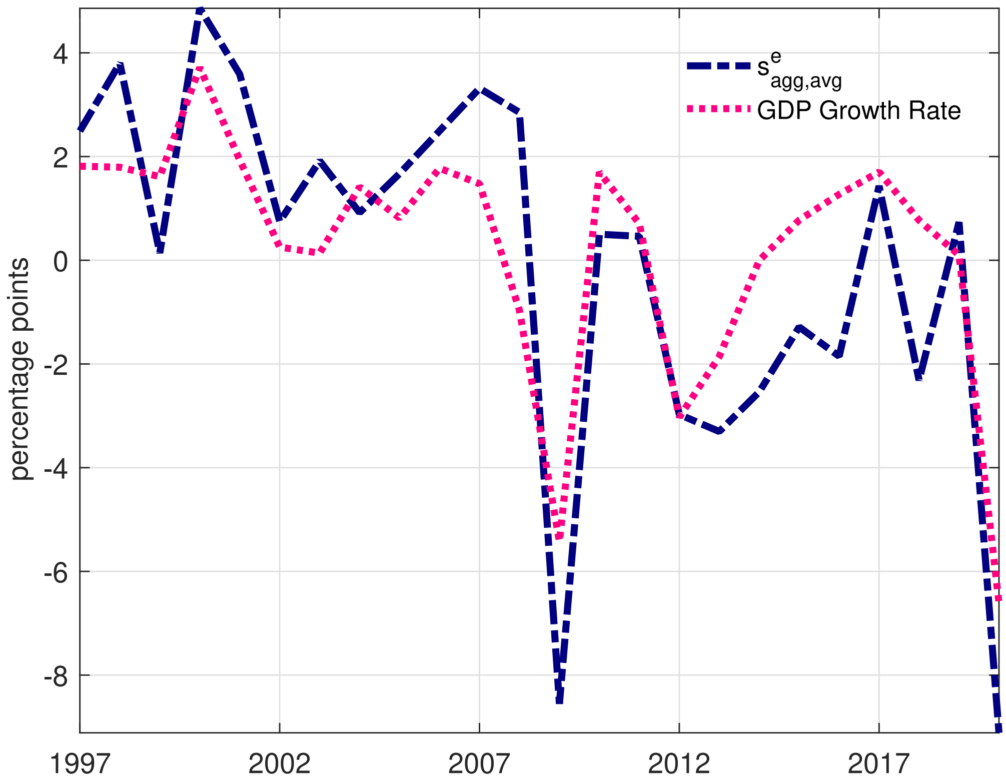

Figure A.1: Expected Aggregate Sales and GDP Growth

Notes: 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 and Non-Convex Adjustment Cost

This section describes the theoretical framework that we employ to study the link 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, and non-convex adjustment cost as in Bachmann and Bayer (2014) and Bloom (2009).[13] We describe the environment in Section F.1, F.2, the firm's problem featuring input irreversibility in Section F.3, and the one with non-convex adjustment cost in Section F.4. We detail the model's parameterization and the result of our numerical simulation in Section F.5 and F.6.

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.[14]

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.) Under non-convex adjustment cost,

[13] The framework of Bachmann and Bayer (2014), in turn, can be interpreted as a version of Khan and Thomas (2008) and Bachmann, Caballero and Engel (2013) with time-varying idiosyncratic uncertainty.

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

the firm can adjust its capital stock upon the payment of a fixed cost $\xi \in [0, \bar{\xi}]$, which is denominated in units of output. This modelling choice follows Caballero and Engel (1999) and Thomas (2002). As in Thomas (2002), we assume that ξ is independently and identically distributed across firms and across time.[15] Every period, each firm draws its current cost of vintage adoption $\xi \geq 0$ (denominated in units of output) from the time-invariant distribution G.

F.3 Value of a Firm and Profit Maximization: Input Irreversibility

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 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-moment, 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 Value of a Firm and Profit Maximization: Non-Convex Adjustment Cost

Let $v^1(\varepsilon_l, \sigma_\varepsilon, k, \xi)$ denote the expected discounted value of a firm entering the period with $(\varepsilon_l, \sigma_\varepsilon, k,)$ and drawing an adjustment cost ξ. The dynamic optimization problem for the typical firm is described using a functional equation defined by ($A.5$)–($A.7$). First, we

[15] Fiori (2012) shows that a two-sector model with non-convex adjustment costs reproduces the autocorrelation of U.S. aggregate investment.

define the beginning-of-period expected value of a firm before the realization of its fixed cost draw, but after the determination of $(\varepsilon_l, \sigma_\varepsilon, k)$:

$$V^0(\varepsilon_l, \sigma_\varepsilon, k) = \int_0^{\bar{\xi}} V^1(\varepsilon_l, \sigma_\varepsilon, k, \xi) dG(\xi). \tag{A.5}$$

The firm's profit maximization problem is then described by

$$\begin{aligned} V^1(\varepsilon, \sigma_\varepsilon, k, \xi) \quad &= \quad \max_{k^*,\, k^C} \left\{ \begin{array}{c} [F(\varepsilon, k) + (1-\delta)k] + \\ \max \left[\begin{array}{c} -\xi w + R(\varepsilon, \sigma_\varepsilon^{'}, k^*), \\ R(\varepsilon, \sigma_\varepsilon^{'}, (1-\delta)k/\gamma) \end{array} \right] \end{array} \right\} \\ s.t.\ k^* \in \mathbf{R}_+ \end{aligned} \tag{A.6}$$

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

$$R(\varepsilon, \sigma_\varepsilon^{'}, k^{'}) \equiv -\gamma k^{'} + \beta \sum_{m=1}^{N_\varepsilon} \pi_{lm}^{\varepsilon} V^0(\varepsilon_m, \sigma_\varepsilon^{'}, k^{'}) \tag{A.7}$$

F.5 Model Parameterization

We solve the problem of the individual firm defined in Section F.3 and F.4 by value function iteration. We refer the to Appendix F.7 for details on the computation.

As 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 7 parameters related to the production process (δ, θ) , discount factor (β), and the persistence and the volatility of idiosyncratic productivity process and its time-varying volatility (ρ_ε, $\bar{\sigma}_\varepsilon$, $\rho_{\sigma_\varepsilon}$, and $\sigma_{\sigma_\varepsilon}$). In the non-convex cost model, we also need to calibrate the adjustment cost function ($\bar{\xi}$). 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 taken from the Italian National Statistical Institute 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.

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
Upper support adj. cost distribution	$\bar{\xi}$	0.014	Fixed cost 1 percent of firm's output

To select the remaining parameters, we calibrate the persistence using the estimates in Fiori and Scoccianti (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.

In the absence of empirical guidance, we set the upper support of the adjustment cost function ($\bar{\xi}$) so that in the median productivity state the adjustment is equal to one percent of the firm output.

F.6 Data and Model Comparison

The goal of this section is to take the model to the data. Can the framework in Section 6 reproduce the 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 (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 it is well-known in the literature, without input irreversibility or non-convex cost ($\xi = 0$), 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%, while the response to upside uncertainty is muted. As discussed in the main text, the firm reduces its capital today to avoid being stuck with too much capital if adverse states were to materialize. In contrast, the response to upside uncertainty is muted because the firm can always readjust its capital upward. This result contrasts with the response under non-convex adjustment cost, where the firm responds both to downside and upside uncertainty. The logic is straightforward. Once the firm pays the adjustment cost, the firm can reset the target capital without constraint. In this sense, the firm can readjust *symmetrically* its target capital.

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

Panel A: Input Irreversibility

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

Panel B: Non-Convex Adjustment Cost

	Baseline	Downside Uncertainty	Upside Uncertainty
Δk^*	n.a.	-0.07%	0.18%

Notes: Δk^* indicates how optimal capital changes across different volatility regimes in percent relative to baseline.

F.7 Computational Details: Value Function Iteration

The value function to solve the firm's problem defined in equation ($A.3$) and ($A.4$) (for the model with input irreversibility), and in equation ($A.5$)-($A.7$) (for the model with non-convex adjustment cost) 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
$\Delta 2020 - 2019$	4.78	-5.14	-9.44	-9.85

Notes: 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, maximum expected growth rate 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

Covid-19 Pandemic	2020	2021	2022
ΔGDP Italy	-8.92	N.a.	N.a.
Contribution of Downside Uncertainty	-0.98	-0.20	-0.22

Notes: 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.