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

Giuseppe Fiori* Filippo Scoccianti

May 6, 2023

Abstract

Using over two decades of Italian survey data on business managers' expectations we measure *subjective* firm-level uncertainty and quantify its economic effects. Firm-level uncertainty persists for a few years and varies across firms' demographic characteristics. Uncertainty induces sizable and long-lasting economic effects over a broad array of real and financial variables only when driven by its *downside* component—that is, uncertainty about future adverse outcomes. Economy-wide uncertainty, constructed aggregating firm-level uncertainty, is countercyclical but uncorrelated with typical proxies in the literature.

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

*Corresponding author: Giuseppe Fiori, Board of Governors of the Federal Reserve System, Division of International Finance, 20th and C Sts. NW, Washington DC 20551, United States (email: giuseppe.fiori@frb.gov; webpage: http://www.giuseppefiori.net). Filippo Scoccianti: Banca d'Italia, Via Nazionale 91, Rome, Italy. First version: April 13, 2020. We are grateful to the Associate Editor Cosmin Ilut, an anonymous referee, our formal discussants Steve Davis and Steffen Henzel, Danilo Cascaldi-Garcia, Brian Doyle, Thiago Ferreira, Matteo Iacoviello, Cosmin Ilut, Nir Jaimovich, Andrea Lanteri, Francesca Lotti, Shannon Luk, Hyunseung Oh, Andrea Prestipino, Plutarchos Sakellaris, Enrico Sette, Frank Warnock, and participants to various seminars and conferences for useful comments. 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 that uncertainty about future macroeconomic and microeconomic outcomes shapes firms' decisions. Economic uncertainty has a long tradition in economics, and, on the heels of Bloom (2009), a vast literature has improved the measurement and understanding the nature of and economic consequences of macroeconomic, or aggregate, time-varying uncertainty. The literature on *firm-level* uncertainty is scant and limited mainly by data availability.

We advance the literature on subjective uncertainty by using Italian survey data on firm-level expectations that span over 20 years and cover multiple business cycle episodes to study the properties and economic effects of firm-level uncertainty.[1] The granularity of our data allows us to tease out the effects of uncertainty from a plethora of confounding factors, including past business conditions, changes in the first moment of the probability distribution of future sales, and firm-specific characteristics. Our analysis yields three main insights on the persistence of firm-level uncertainty, its economic effects, and the properties of aggregate uncertainty across business cycles.

First, we construct a measure of ex ante firm-level uncertainty using survey data on managers' expectations about future sales for a representative sample of Italian firms. Firm-level uncertainty is a persistent process that lasts for a few years. 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, the detrimental effects of higher firm-level uncertainty over a broad set of real

[1] The Bank of Italy survey constitutes a unicum in the existing literature, as most surveys that track uncertainty on firm-level outcomes span only a few years. In particular, for the United States, Altig et al. (2022) developed a monthly panel Survey of Business Uncertainty (SBU) starting in 2014 that features about 1,750 firms in 50 states. In Germany, the IFO Institute surveyed firms' expectations from 2013 to 2016, see Bachmann et al. (2018) and Bachmann et al. (2020). A longer monthly time-series starting in 1980 and based on qualitative expectations is used in Bachmann et al. (2013) and Massenot and Pettinicchi (2018). The Decision Maker Panel (DMP) survey was launched for the United Kingdom in August 2016.

and financial outcomes occur when the increase in total uncertainty is driven by its downside component—the part of the uncertainty accounted for by below mean outcomes. The firm is instead insensitive to changes in upside uncertainty. In this sense, *not all uncertainties are alike*. An increase in (downside) uncertainty predicts a contemporaneous reduction in total hours (both in the number of workers and hours per worker), a decrease in capacity utilization, and cash hoarding for a few periods. With a lag, firms reduce capital accumulation for a few years.

Third, we construct an *economy-wide* measure of uncertainty for the Italian economy, aggregating individual firm-level data, and find it to be countercyclical. While this countercyclicality reproduces the literature's typical result, we emphasize that our bottom-up aggregate uncertainty is uncorrelated to measures of cross-sectional dispersion, which are standard proxies for macroeconomic uncertainty employed in the literature. This lack of correlation suggests that much of the variation in cross-sectional measures is not driven by ex ante uncertainty.

The source of the data on expectations is the Survey of Industrial and Service Firms (or INVIND), an extensive annual business survey conducted by the Bank of Italy on a sample of Italian firms representative of the aggregate economy. As discussed in Section 2, the survey elicits managers' expectations over the average, the minimum, and the maximum one-year-ahead sales growth rates. Thus, we directly observe the first moment of the subjective probability distribution of future sales and the range between the maximum and minimum or max–min range, around the mean prediction. Expectations are informative about the mean and the uncertainty in firm-level outcomes as there is no systematic bias in firms' expectations, and realized ex post sales fall in the ex ante max–min range in about 75 percent of observations. Using the 2005 and 2017 waves of INVIND that elicited the *full* probability distribution of expected sales, we show that the max–min range measures the dispersion of future expected outcomes while being orthogonal to the third moment of the distribution, or skewness. An equivalent strategy shows that the gap between the average and the minimum, and the maximum and the average of expected sales are the main determinants of the downside and upside component of uncertainty, respectively. The nearly deterministic relationship between the max–min range and the dispersion of future sales and between the proxies of the downside and upside uncertainty allows us to use the max–min range and its components to measure firm-level uncertainty for the whole sample. Directly observing the first and the second moments of the distribution of expected outcomes enable us to overcome one of the existing literature's main challenges, disentangling the economic effect of fluctuations in uncertainty from changes to the first moment. Also, the panel structure of our data allows us to control for firm-specific and sectoral effects as well as time effects.

Our first insight is to show that uncertainty and its components are persistent processes by fitting an autoregressive process of order one and exploiting the 2017 wave of INVIND. The 2017 wave elicits the full probability distribution of expected sales one year ahead and three years ahead, allowing us to study how uncertainty about 2020 sales evolved from 2017 to 2019. We view both approaches as complimentary as they offer different strengths related to the sample length and bias in the estimated yearly persistence with panel data. We balance these considerations and take 0.56, an average of the estimates obtained with each approach, as our best estimate for the persistence of overall firm-level uncertainty. Similar results apply to downside and upside uncertainty, implying a half-life of a shock to uncertainty equal to about one year and a half.

Our second insight indicates that firm-level uncertainty has sizable and persistent economic effects across a broad array of real and financial variables. Matching INVIND with balanced sheets data allows us to perform panel regression analysis at various horizons and broaden the scope of the analysis to real and financial outcomes. Our findings indicate that a one standard deviation increase in uncertainty predicts a drop in utilization and total hours of about 1 percent and, with a lag, a drop in investment of about 3 percent in each of the following two years. Cash holdings increase on impact and then return to initial levels after two years. Our closest antecedent is Alfaro et al. (2017), who studies the effect of firm-level uncertainty on real and financial outcomes to one year out horizon. Relative to Alfaro et al. (2017), our estimate results on the effects of uncertainty on investment to be twice as large one year out and even more detrimental on real variables considering the full horizon of our estimates. Concerning cash holdings, we find smaller effects of uncertainty.

The differentiated response and the persistence of the estimated effects of the downside uncertainty provide practical overidentifying restrictions against which to test competing models to quantify uncertainty's effects. Two points are worth highlighting. First, the immediate fall in hours following an increase in uncertainty indicates that labor is not determined purely by static variables; rather, it behaves like a durable input similar to capital. Second, our evidence on the sensitivity of firms to downside uncertainty emphasizes costly downsizing of capital or labor, such as the one induced by input irreversibility and the ensuing "bad news principle" discussed by Bernanke (1983). Other mechanisms are consistent with our results. Downside uncertainty may also increase the likelihood of firms becoming financially constrained in the future, leading to a decrease in the accumulation of inputs; see, for instance, Alfaro et al. (2017) and Christiano et al. (2014). Also, to the extent that the minimum of future sales is interpreted as a summary statistic of the worst-case scenario, the sensitivity to downside uncertainty may be loosely interpreted as agreeing with the predictions of theories that emphasize ambiguity aversion, as in Hansen et al. (1999) and Ilut and Schneider (2014). In those models, agents form beliefs over a range of possible scenarios and act as if the worst scenario will occur.

Our third insight indicates that much of the variation in the cross-sectional dispersion is not linked to uncertainty. Our bottom-up measure of aggregate uncertainty about future sales is countercyclical, increasing sharply during economic crises, such as the Great Financial Crisis and the latest COVID-19 recession, as well as periods with elevated political uncertainty. The little correlation between our proxy and measures of cross-sectional dispersion points to a disconnection between ex ante uncertainty and realized risk at the *aggregate* level. At the firm level, we find a positive but quantitatively small relationship between current uncertainty and the size of future absolute forecast errors, a proxy of realized risk. The small quantitative link rationalizes the little correlation between ex ante uncertainty and cross-sectional dispersion. Our evidence agrees which uncertainty ex ante does not necessarily result in realized ex post risk such as Ilut and Schneider (2014) and Ilut and Saijo (2021) based on ambiguity aversion, or the work of Angeletos et al. (2018).

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 and its components in Sections 4 and 5, respectively. In Section 6, we discuss the implications of our results for macroeconomic modeling. In Section 7, we construct a measure of aggregate uncertainty based on firm-level uncertainty. Section 8 concludes.

1.1 Literature Review

Our work connects to many strands of the existing literature on uncertainty and aggregate fluctuations. While the current literature provides a sizable number of surveys eliciting consumer expectations, less is known about quantitative measures of uncertainty at the firm level.[2] Our data source INVIND is the forerunner of the DMP for the United Kingdom

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

discussed in Altig et al. (2020) and SBU for the United States described in Altig et al. (2022). Another important example is the IFO survey employed in Bachmann et al. (2018) and Bachmann et al. (2020). Holzmeister et al. (2020) uses survey data to study how risk is perceived by financial professionals emphasizing that skewness of expected returns determines their perception of risk.[3] The critical advantage of INVIND is that it has surveyed firms' expectations for over two decades, allowing us to study how uncertainty has evolved over multiple business cycles. In contrast, DMP and SBU started only recently, albeit at a higher frequency.

In using survey data to study the economic outcomes of subjective uncertainty, our paper builds on the pioneering work of Guiso and Parigi (1999) and Bontempi et al. (2010).[4] Relative to these contributions that also use INVIND, the panel dimension of our sample allows us to expand the scope of the analysis characterizing the effect of uncertainty on a broad array of real and financial variables beyond investment. Besides, we show that the source of uncertainty matters for its economic effects, with only the downside component of uncertainty having sizable economic effects.

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. Studies differ on the measure of firm-level uncertainty with Leahy and Whited (1996) and Bloom et al. (2007) using realized stock return volatility; Stein and Stone (2013) using the option price; and Gulen and Ion (2016) using the policy uncertainty index developed by Baker et al. (2016).

Moreover, firm-level uncertainty appears to vary in both the cross section and the time series. Bachmann et al. (2017) and Senga (2015) find substantial cross-sectional heterogeneity and time variation in measures of firm-idiosyncratic uncertainty using survey data. Senga

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

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

(2015) also finds that smaller and younger firms face greater uncertainty.

Besides differences in the considered measure of uncertainty, our analysis shows that the effects of uncertainty extend beyond capital accumulation and affect the labor market and financial decisions. The broad focus on firm-level economic outcomes aligns our work with Alfaro et al. (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 when the shock is reabsorbed. Third, we distinguish the source of fluctuations in uncertainty between a downside and an upside component, showing that only the former matters for its economic effects.

Our work also connects to the literature on aggregate uncertainty and its cyclical properties along the business cycle. A robust finding since, at least, Bloom (2009) is that cross-sectional measures of uncertainty rise in recessions. Bloom et al. (2018) find countercyclical establishment-level total factor productivity shocks is countercyclical (see also Kehrig (2015) and Bloom (2014)). Bachmann et al. (2013) proxy for aggregate uncertainty with forecaster disagreement and find that the latter is higher in downturns. Hassan et al. (2019) and Baker et al. (2016) develop a measure of uncertainty using textual analysis focusing on political risk and economic policy uncertainty.[5] We refer the reader to a comprehensive review of the literature to Datta et al. (2017) and Fernández-Villaverde and Guerrón-Quintana (2020).

[5]In a similar vein of research, Caldara et al. (2020) use textual analysis to explore the quantitative implications of trade policy uncertainty. Handley and Limão (2017) quantify the effects of trade policy uncertainty for the U.S. and Chinese economies using a general equilibrium model.

2 Data: Subjective Firm-Level Expectations

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

2.1 Data Sources

We obtained our data set by combining different sources. We first construct our measure of uncertainty using data on firm-level expectations from INVIND. INVIND is an annual business survey conducted between February and April of every year by the Bank of Italy on a representative sample of firms operating in industrial sectors (manufacturing, energy, and extractive industries), construction, and nonfinancial private services, with the 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 INVIND. Industry-specific price deflators are obtained from the Italian National Institute of Statistics. The sample period extends over 20 years, from 1996 to 2019. The matched data set includes about 25,000 firm-year observations from an average of more than 900 firms per year. We note that the number of firm-year observations in INVIND depends on the variable of interest and includes more than 35,000 observations. However, not all of the observations can be matched with balance sheet data in Cerved, reducing the sample to about 25,000 observations. Next, we report statistics using the available data and accounting for each firm's share in the population of Italian firms. We refer the reader to

Appendix A for more details.

2.2 Firm-Level Expectations: Variables Description

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

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

Shaped by firm-specific, sectoral, and aggregate factors, these variables allow us to directly observe the *first moment* of the probability distribution of the expected growth rate of sales and the *range* of subjective uncertainty around this point. We emphasize that we do not directly observe the probability mass over the support except for the 2005 and 2017 waves. We overcome this limitation in Section 3 by showing that there is a near-deterministic relationship between the range and the standard deviation, or *second moment*, of the probability distribution of expected sales at the firm level. We connect the range with the dispersion in future sales exploiting the 2005 and 2017 waves of the survey that elicit the entire probability distribution, asking firms to provide a quantitative assessment of their business prospects. Using the same data, we also establish that the minimum and the maximum proxy for the part of the variance of expected sales accounted for by outcomes below mean, or downside uncertainty, and the remaining part accounted for by outcomes above mean, or upside uncertainty. We now describe the statistical properties of $s^e_{avg,f,t}$, $s^e_{min,f,t}$, and $s^e_{max,f,t}$.

2.3 Firm-Level Expectations: Statistical Properties

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

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

Regarding $s^e_{min,f,t}$ and $s^e_{max,f,t}$, the median firm expects the worst-case scenario to result in a decrease of sales of about 2 percentage points and the best-case scenario in an expansion of 5. Also, for both variables, the interquartile range ($P_{75} - P_{25}$) is about 10 percentage points. The interval between best- and worst-case scenario is informative about the uncertainty faced by each firm as realized sales one year ahead fall within the max–min range in about 75 percent of the observations. Through the lens of this metric, the max–min range can be interpreted, on average, as firms reporting the 10-90 percentile of expected outcomes. Regarding the correlation of $s^e_{min,f,t}$ and $s^e_{max,f,t}$, with GDP, as shown in Table 1, the $s^e_{avg,f,t}$, $s^e_{min,f,t}$, and $s^e_{max,f,t}$ are as procyclical as actual sales.

The statistical properties of expectations display sizable differences conditioning on firms' size, age, and the sector in which they operate. based on firms' size, small and medium-sized firms (defined as firms employing between 20 and 50 workers) display an expected growth rate in the worst-case scenario of negative 5 percent, lower than negative 1 percent for large firms (with more than 50 employees).[6] This property shows despite a similar expected average and maximum growth rate, $s^e_{avg,f,t}$ and $s^e_{max,f,t}$.

Small and medium-sized firms do not perfectly overlap with the definition of young firms. Young firms (less than five years) tend to expect higher growth both on average and in the best-case scenario than mature and old ones (more than five years) by about 3 percentage points. 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 (4.28 percent) than those in the service sector (2.55 percent). This result reflects the faster growth rate of sales experienced by the manufacturing sector that we conjecture is being driven by the higher degree of international openness relative to the service sector. We refer the reader to Table $A.1$ in Appendix B for the full set of results.

3 Firm-Level Uncertainty and Subjective Expectations

We now describe how we use INVIND expectations to construct a time-varying measure of individual firms' subjective uncertainty and provide a set of stylized facts on firm-level uncertainty. In Section 3.1, we show that there is a near equivalence in the range between the maximum and minimum future expected sales (or the best- and worst-case scenario, $s^e_{max,f,t} - s^e_{min,f,t}$) and the dispersion (or second moment) of future expected sales. Moreover, the minimum and the maximum expected sales proxy the downside and upside components of overall uncertainty. Exploiting these results, we use the max–min range and its components as measures 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. Finally, we analyze how firm-specific and aggregate variables covary with

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

uncertainty in Section 3.3 and conclude by showing that uncertainty is a persistent process that does not abate quickly in Section 3.4.

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

INVIND provides us with the range between the best- and the worst-case scenario about the expected growth rate of sales one period ahead. We now show that this range, denoted by $\sigma_{max-min,f,t}$, measures the second moment of the probability distribution of expected outcomes. In addition, we decompose overall uncertainty into its upside and downside components and show that $s^{e}_{max,f,t}$ and $s^{e}_{min,f,t}$ proxy for upside and downside uncertainty, respectively. To obtain these results, we use data from the 2005 and 2017 waves of INVIND. Unlike other years in our sample, these waves elicited the full probability distribution of expected sales over a discretized support of intervals ranging from less than negative 10 percent to more than 10 percent.[7]

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 bin, the midpoint of the respective interval and its associated probability.[8] As we observe the probability distribution of future sales, we do not need to impose any distributional assumption. We regress each moment of the subjective distribution on $\sigma_{max-min,f}$, $s^{e}_{min,f}$ and $s^{e}_{max,f}$ pooling the 2005 and 2017 waves of INVIND.

The first result in Column 1 of Table 2 is the near equivalence between $\sigma_{max-min,f}$ and the

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

[8] For firms that report positive probability mass in the bins $\leq$-10 percent and $\geq$10 percent, we need to assume a lower and and upper bound to compute the midpoint of the interval. We choose -20 and 20 as these values represent the 10^{th} and 90^{th} percentiles of the actual sales distribution, see Table 1. Alternatively, we consider -25 and 25 percent, the same percentiles of a pooled distribution of realized sales in the year before, on, and after the survey was elicited.

true standard deviation of the probability distribution $St.Dev._f$. The max–min range measures the second moment of the probability distribution of future sales: firms with higher dispersion in expected outcomes also display a wider range of $\sigma_{max-min,f}$. The coefficient on $\sigma_{max-min,f}$ is statistically significant and the R^2 close to one indicates that the range accounts for almost the total variance of the dependent variable. Column 2 rules out that the range captures the skewness, as $\sigma_{max-min,f}$ is virtually orthogonal to the third moment.

The second result is that $s^e_{f,min}$ and $s^e_{f,max}$ proxy for overall uncertainty and its components. The equality in absolute terms of the coefficients in Column 3 shows that both extremes of the max–min range account for the bulk of the variance in overall uncertainty: a deterioration in $s^e_{min,f}$ or an equally sized improvement in the $s^e_{max,f}$ symmetrically increase the max–min range. [9] Columns 4 and 5 show that $s^e_{min,f}$ and $s^e_{max,f}$ proxy for downside ($St.Dev.Down_f$) and upside uncertainty ($St.Dev.Up_f$), respectively. We define downside (upside) uncertainty as the part of the variance accounted by outcomes below (above) mean so that $Std.Dev^2 = Std.Dev.Down^2 + Std.Dev.Up^2$. $Std.Dev.Down^2$ is equal to $\sum_{i=1}^{I} p_{i,f} \times \left(s^e_{i,f} - s^e_{avg,f}\right)^2 \times \left(s^e_{i,f} \leq s^e_{avg,f}\right)$ and $Std.Dev.Up^2$ is equal to $\sum_{i=1}^{I} p_{i,f} \times \left(s^e_{i,f} - s^e_{avg,f}\right)^2 \times \left(s^e_{i,f} > s^e_{avg,f}\right)$, where $p_{i,f}$ represents the subjective probability that each firm f attaches to a specific sales interval i, $s^e_{i,f}$ is the mid-point of each interval; s^e_{avg} denotes the first moment of the subjective distribution of future sales calculated as $s^e_{avg,f} = \sum_{i=1}^{I} p_{i,f} \times s^e_{i,f}$; and $\left(s^e_{i,f} \leq s^e_{avg,f}\right)$ is an indicator equal to one when the condition in brackets is verified.

Results in Column 4 indicate that $s^e_{min,f}$ is the main determinant of downside uncertainty: a lower $s^e_{min,f}$ increases downside uncertainty about four times more that an equally-sized deterioration in $s^e_{max,f}$. By the same logic, Column 5 shows that $s^e_{max,f}$ is the main deter-

[9] The equality in absolute terms of the estimated coefficients mirrors the results from the variance decomposition of $\sigma_{max-min,f,t}$ into $s^e_{min,f,t}$ and $s^e_{max,f,t}$. After computing a standard variance decomposition using data for every firm, we pool the results to construct the unconditional distribution across firms. For every firm f, we compute the shares of the variance attributed to $s^e_{max,f,t}$ and $s^e_{min,f,t}$ as $\beta_{cov,s^e_{min,f,t}} \equiv \frac{cov(s^e_{min,f,t},\sigma_{max-min,f,t})}{var(\sigma_{max-min,f,t})}$ and $\beta_{cov,s^e_{max,f,t}} \equiv \frac{cov(s^e_{max,f,t},\sigma_{max-min,f,t})}{var(\sigma_{max-min,f,t})}$.

minant of upside uncertainty. As the specifications in Columns 4 and 5 include the mean of expected future sales $s^e_{avg,f}$, our results are not driven by the indirect effect of $s^e_{min,f}$ and $s^e_{max,f}$ on the mean $s^e_{avg,f}$.

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

Our measure of firm-level uncertainty has three advantages. First, $\sigma_{max-min,f,t}$ is an ex ante measure of the uncertainty perceived by firms about future outcomes. Second, $\sigma_{max-min,f,t}$ reflects the managers' expectations—that is, the decision makers of the firm. Third, $\sigma_{max-min,f,t}$ can be easily interpreted as it relates to economic outcomes.

In our sample, uncertainty around managers' average expected future sales is 9.81 percentage points; the median uncertainty is instead 8. $\sigma_{max-min,f,t}$ is virtually acyclical with a correlation with the contemporaneous growth rate of real GDP of negative 0.07 (negative 0.03 and 0.00 with the first lag and the first lead of real GDP, respectively). This result reflects the similar comovement of $s^e_{min,f,t}$ and $s^e_{max,f,t}$ with contemporaneous economic activity.

The data indicate that firms' uncertainty correlates with firms' characteristics such as age, size, and the sector in which they operate. As shown in the first column of Figure 1, uncertainty is negatively correlated with size and age. Young firms (less than five years) and small and medium-sized firms (defined here as having less than 50 employees), on average, perceive a higher level of uncertainty (13 percentage points). Interestingly, $\sigma_{max-min,f,t}$ is acyclical, except for young firms and small and medium-sized firms that display a negative correlation with real GDP equal to negative 0.11 and negative 0.22, respectively.

As shown in the middle and right columns of Figure 1, the extremes of the max–min range, $s^e_{max,f,t}$ and $s^e_{min,f,t}$, display different correlations with size and age. $s^e_{max,f,t}$ is negatively correlated with size and age, with $s^e_{max,f,t}$ lower for older and small firms. Young firms expect, on average, a higher growth rate in the best-case scenario, $s^e_{max,f,t}$. The sales growth rate in the worst-case scenario is instead negatively correlated with size and positively correlated with age.

The max–min range reported by large firms is about 50 percent less than the uncertainty perceived by smaller and medium firms, consistent with life-cycle dynamics suggesting that they have already reached their optimal size or achieved a better knowledge of the market in which they operate. Finally, firms in the service sector face, on average, a similar level of uncertainty with those in the manufacturing sector. Old firms (with age equal to more than five years) and manufacturing firms drive the full sample results as they account for a significant fraction of it. We refer the reader to Table *A*.2 in Appendix C for the full set of descriptive statistics.

3.3 Covariates of Firm-Level Uncertainty

This section analyzes more formally whether measures of uncertainty correlate with past and future business prospects as well as past forecast errors. We focus on this specific subset of variables to connect our work with other studies in the literature; see, for instance, Bachmann et al. (2018) and Altig et al. (2022). Toward this goal, we regress $s^e_{min,f,t}$, $s^e_{max,f,t}$, and $\sigma_{max-min,f,t}$ on measures of past and future business prospects for the firm (proxied by the realized growth rate of sales $\Delta Sales_{t-1,t-2}$ and $s^e_{avg,f,t}$, respectively) as well as on firm's past forecast errors, controlling for the firm's number of employees, cohort effects (age of the firm), and firm-specific, industry, and year effects. Table 3 reports our estimates.

Starting from future business conditions, we find a positive correlation between the average expected growth rate of sales ($s^e_{avg,f,t}$) and firm-level uncertainty ($\sigma_{max-min,f,t}$). This result indicates that, at the firm level, fluctuations in uncertainty are positively correlated with movements in the mean of the probability distribution of expected outcomes. As shown in Columns 2 and 3, the positive correlation results from $s^e_{max,f,t}$ being more correlated to $s^e_{avg,f,t}$ than $s^e_{min,f,t}$.

Perceived uncertainty increases with firms' past forecast errors: a standard deviation increase in *Abs.Forec.Error* predicts larger firm's uncertainty by about one half of a percentage point. As shown in Columns 2 and 3, larger forecast errors prompt firms to widen the range of expected outcomes, reducing $s^e_{min,f,t}$ and increasing $s^e_{max,f,t}$. In a separate regression (not shown), we also regress future forecast errors on current uncertainty, finding a positive and significant relationship (0.23 with a p-value lower than 0.01), suggesting that higher uncertainty ex ante predicted realized risk ex post.[10]

We also analyze the impact of past realized sales growth on uncertainty and expectations. Following the approach in Bachmann et al. (2018), we let the relationship between past sales growth and uncertainty to be nonmonotonic, allowing coefficients on past sales growth to differ between past episodes of positive ($\Delta Sales_{f,t-1} > 0$) and negative ($\Delta Sales_{f,t-1} \leq 0$) realized sales growth. Our estimates indicate that there is an asymmetric V-shape relationship between uncertainty and past sales, in line with results in Bachmann et al. (2018) and Altig et al. (2022). Uncertainty is more responsive to negative sales than positive ones by a factor of five, with the latter close to but not statistically significant. A one standard deviation reduction to a negative growth rate of sales is associated with an increase in $\sigma_{max-min,f,t}$ equal to one half of a percentage point. The lack of significance of positive sales on $\sigma_{max-min,f,t}$ stems from not significant correlation between $s^e_{min,f,t}$ and past positive sales. $s^e_{max,f,t}$ increases with more positive sales and more negative sales rising, ceteris paribus, $\sigma_{max-min,f,t}$. Instead, $s^e_{min,f,t}$ becomes more negative only with more negative sales, creating the one-sided response of $\sigma_{max-min,f,t}$ to negative sales.

As shown by the R^2 of 0.44 in Column 1, more than half of the variance of firm-level uncertainty $\sigma_{max-min,f,t}$ is unexplained and not accounted for by firm-specific observables or sector-specific or aggregate factors.

[10] Our specification controls for firm-specific effects as well as sectoral and year dummies.

3.4 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. To establish this result, we fit an autoregressive process of order one to $\sigma_{max-min,f,t}$, $s^e_{min,f,t}$, and $s^e_{max,f,t}$, and exploit the 2017 wave of INVIND that elicits the full probability distribution of expected sales one year and three years ahead. This strategy allows us to study how uncertainty about sales growth in 2020 evolved from 2017 to 2019, using the max–min range of three years and one year ahead.

Fitting an autoregressive process of order one to $\sigma_{max-min,f,t}$ yields an estimated coefficient of 0.38 (statistically significant at 1 percent). As estimating persistence in a panel with a limited number of periods results in biased-down estimates of persistence, see Nickell (1981), we interpret this estimate as a lower bound.

Regressing the one year ahead max–min range in 2019 on the three year ahead max –min range in 2017 yields a coefficient of 0.54 (statistically significant at 5 percent), implying an autoregressive coefficient of roughly 0.74 ($0.54^{1/2}$). This strategy provides a clean test of the persistence of uncertainty, but, at the same time, the evidence is obtained for a specific time period. To be conservative, we interpret 0.74 as an upper bound of the persistence of the max-min range.

In light of our considerations on the strengths of each approach, we consider 0.56, the mid-point of our estimates, as the best estimate and conclude that uncertainty is a persistent process that does not abate quickly with the half-life of a shock to be about one and a half years. Results are similar for downside and upside uncertainty.

We estimate an autoregressive coefficient of 0.31 for $s^e_{max,f,t}$ and 0.27 for $s^e_{min,f,t}$. Instead, looking at three-year uncertainty, we estimate a coefficient of 0.71 (statistically significant at 5 percent) yielding an implied autoregressive coefficient of about 0.8 for downside uncertainty. The same estimates for upside uncertainty yield an estimate coefficient of 0.54 (statistically significant at 10 percent) and an implied autoregressive coefficient of about 0.74. $s^e_{min,f,t}$ and $s^e_{max,f,t}$, on average, display a persistence similar to the max-min range. In short, our estimates indicate that uncertainty and its components persist for a few years.

4 Measuring the Effects of Firm-Level Uncertainty

We now study the economic effects of uncertainty by tracing the dynamic responses of a large set of real and financial variables, broadening the analysis's scope relative to most of the existing literature. In Section 4.1, we describe in detail our empirical approach. In Section 4.2, we show that fluctuations in uncertainty are associated with sizable effects not only on investment but also on labor variables and cash holdings.

4.1 Empirical Methodology

To estimate the economic effects of fluctuations in uncertainty our strategy relies on the local projection technique, discussed in Jordà (2005). To trace the dynamic economic effects of uncertainty fluctuations over a broad range of outcomes we project firm-level real and financial variables at different horizons on contemporaneous uncertainty $\sigma_{max-min,f,t}$ and its components $s^e_{min,f,t}$ and $s^e_{max,f,t}$, while controlling for potentially confounding factors shown as

$$Y_{f,t+h} = \sum_{f=1}^{F} \alpha_{f,h} + \beta_{max-min,h} \times \sigma_{max-min,f,t} + \sum_{s=1}^{S} \times \eta_{s,h} Controls_{s,t} + \epsilon_{f,t+h}; \tag{1}$$

and,

$$Y_{f,t+h} = \sum_{f=1}^{F} \alpha_{f,h} + \beta_{min,h} \times s^e_{min,f,t} + \beta_{max,h} \times s^e_{max,f,t} + \sum_{s=1}^{S} \eta_{s,h} \times Controls_{s,t} + \epsilon_{f,t+h}; \tag{2}$$
$$for\ h = 0...4,$$

where $Y_{f,t+h}$ includes the set of real and financial outcomes: the log of investment, the log of total hours (distinguishing between the number of workers and hours-per-worker), the capacity utilization rate, and the growth rate of liquid assets, or cash, held by the firm.

The coefficient $\beta_{max-min,h}$ measures the economic effects of overall uncertainty, while $\beta_{min,h}$ and $\beta_{max,h}$ quantify the role of each component. To tease out confounding firm-level, sectoral, or aggregate factors, Equations 1 and 2 include a set of controls. To isolate fluctuations in uncertainty from correlated changes in current or *future* business conditions, the set of $Controls_{s,t}$ includes the growth rate of sales realized at time t ($\Delta Sales_{f,t}$) and the expected growth rate of sales one year ahead ($s^e_{avg,f,t}$). Observing $s^e_{avg,f,t}$ allows us to control for forecast errors, or "sales surprises" defined as the difference between the growth rate of sales at time t expected at time *t-1* ($s^e_{avg,f,t-1}$) and the sales realized at time t. To account for the impact of financial factors on firm's hiring and investment decisions, we also include book leverage at time *t-1*.

The panel structure of our data allows us to control for time-invariant factors specific to each firm, $\alpha_{f,h}$, ruling out that our results are driven by the correlation between the mean of $\sigma_{max-min,f,t}$ and the ones of dependent variables. Finally, the set of $Controls$ features sector, and year dummies to account for unobserved industry-specific characteristics or aggregate factors, potentially related to policy changes or business cycle fluctuations. In sum, to estimate the economic effects of uncertainty we exploit fluctuations of real and financial outcomes around firm- and sector-specific means while simultaneously netting out common movements of uncertainty across firms (through time effects).

4.2 Real and Financial Effects of Uncertainty

Our findings indicate that the economic effects of uncertainty are not limited to investment but extend to the labor market and the firm's financial structure. Table 4 reports the dynamic response of firm-level variables following a 1 percentage point increase in firm-level uncertainty. Entries are expressed in percent.

Fluctuations in uncertainty predict economic effects that are statistically and economically significant. Notably, these effects do not abate quickly and last for a few years. This result reflects both the persistence of firms' perceived changes in uncertainty (as shown in Section 3.4) 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 behavior that anticipates reducing investment. We discuss these results in turn.

On the real side, after an increase in perceived uncertainty equal to one standard deviation (5.63 is the standard deviation of $\sigma_{max-min,f,t}$ for the median firm), the firm reduces its capacity utilization rate and total hours by about 0.5 and 0.8 percent, respectively, equivalent to about 70 percent of one standard deviation of both variables. Also, a reduction in employed workers, smaller than that of hours, signals that the intensive margin of labor is adjusted more swiftly. Over the same period, on the financial side, firms also increase the growth rate of cash holdings, before reverting in year 2. After one year, the firm starts cutting on investment, by more than 2 percent in each of the following two years (or about one investment standard deviation). As the increase in uncertainty is reabsorbed, investment overshoots its steady-state level before converging, but the effect is not statistically significant.

To gauge the magnitude of the estimated effects it is instructive to compare our results with existing studies that create measures of uncertainty (or risk) at the firm level. We estimate the cumulative effects of uncertainty are larger than what we typically found in the existing literature and play out at longer horizons. A study similar to our work is Alfaro et al. (2017), which employs measures of financial volatility to proxy for firm-level uncertainty in the United States and studies its effect one year out on investment, employment, and cash holdings. Relative to Alfaro et al. (2017), the effects of uncertainty are twice as large one year out, while employment is comparable with total hours in magnitude, consistent with the intensive margin being more important in European labor markets than in the United States. The response of cash holdings in our sample is about half of their estimates. Overall, the cumulative effects on real activity are larger given our focus at longer horizons. Larger estimated effects are found also relative to studies that employ textual analysis to disentangle sources of uncertainty, or risk, such as political risk in Hassan et al. (2019) and in Caldara et al. (2020) for trade policy uncertainty.[11]

5 Effects of Uncertainty through "Downside Uncertainty"

We now study whether the economic effects of uncertainty depend on the source driving the increase in dispersion of future expected sales—that is, whether it comes from downside or upside uncertainty. Typically, the existing literature does not distinguish between the source of fluctuations in uncertainty, mostly because of the limitation imposed by existing data.[12] Understanding this issue is important for at least two reasons. From an empirical standpoint, the source of the increase in uncertainty may predict its economic effects. For instance, higher uncertainty may display sizable economic effects only if driven by dispersion in positive or upside (negative or downside) outcomes. From a theoretical standpoint, measuring the effects of downside and upside uncertainty provides overidentifying restrictions against which to test competing models aimed at quantifying the aggregate effects of uncertainty. (We return to this issue in Section 6.) To quantify the economic effects of downside and upside uncertainty, we estimate Equation 2 that relaxes the implicit assumption imposed in Section 4.2 that forced the coefficients of $s^e_{max,f,t}$ and $s^e_{min,f,t}$ to be the same in

[11] In Caldara et al. (2020) investment drops about one and a half percent for a year, about three times as much as the contemporaneous drop in Hassan et al. (2019) due to political risk.

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

absolute terms.

The main takeaway is that firms respond to fluctuations in uncertainty only if it originates with downside uncertainty. Table 5 reports the full set of estimates. Our findings indicate that only an increase in downside uncertainty induces negative economic effects. Instead, an increase in upside uncertainty does not result in statistically significant economic effects (except for total hours). The propagation mechanism of fluctuations in downside uncertainty (or equivalently an increase in uncertainty driven by a deterioration in the worst-case scenario) is similar to the one discussed in Section 4.2. As shown in Figure 2, which reports the impulse responses following an increase in overall and downside uncertainty with associated 90 percent confidence bands, firms first reduce capacity utilization and total hours and then investment.[13] Over time, as the initial effect of the shock wanes, the dynamics are reverted. From a quantitative standpoint, the effects of uncertainty are somewhat larger than the one of overall uncertainty, especially for investment.

Disentangling the individual contribution of upside and downside uncertainty sheds light on the dynamics induced by an increase in $\sigma_{max-min,f,t}$. The estimated effects of an increase in uncertainty confound the significant sensitivity of firms' decisions to the rise in downside uncertainty and its unresponsiveness to upside uncertainty. Dynamics associated with fluctuations in downside uncertainty are statistically and economically significant. As shown in Appendix D, our results are robust when downside uncertainty is proxied by $s^e_{avg,f,t} - s^e_{min,f,t}$, and upside uncertainty by $s^e_{max,f,t} - s^e_{avg,f,t}$.

6 Implications for Macroeconomic Modeling

Firm-level uncertainty results in a persistent drop in employment, hours per worker, capital as well as an increase in cash holdings only when it originates from downside uncer-

[13] As the standard deviation of $\sigma_{max-min,f,t}$ and $s^e_{min,f,t}$ is similar (5.63 and 6.15, respectively), we pick the same shock equal to 5.63 for total and downside uncertainty to highlight the differences in the estimated coefficients.

tainty. While most of the existing literature has focused on investment, the immediate and persistent drop in hours in response to higher uncertainty suggests that labor behaves more like a durable input similar to capital rather than being determined purely by contemporaneous considerations. How does our evidence discipline existing theories of uncertainty, and what are the implications for macroeconomic models? To reproduce the negative effects of uncertainty, macroeconomic frameworks rely on models of "real options" or models that emphasize financial frictions, or models featuring robust control and ambiguity aversion.[14]

To obtain the negative effects both on capital and employment as well as cash hoarding, theories of real options emphasize "wait and see" motives because of the presence of adjustment costs that give firms the option to delay investment and hiring in the presence of uncertainty and make reversing decisions costly; see, for instance, Alfaro et al. (2017). With input irreversibility due to firm specificity or the absence of secondary markets, Bernanke's Bad News Principle applies with firms responding only to fluctuations in downside uncertainty. This choice increases firm's profits in low future productivity states in which the irreversibility constraint is binding and the firm cannot downsize capital or employment. More generally, our evidence supports theories of real options delivering an asymmetric adjustment cost function, in which downsizing capital or employment is costly.

Another approach in the literature emphasizes financial considerations with higher downside uncertainty about future sales potentially increasing the firm's likelihood of facing financial constraints, leading to a drop in investment and hiring. In Christiano et al. (2014) and Chugh (2016), an increase in risk about the realizations of idiosyncratic productivity in converting raw to productive capital results in lower credit extended to firms, that, in turn, acquire less capital and labor.

[14]On theoretical grounds, it is well known that the economic effects of uncertainty are, in general, ambiguous and depend on the assumptions about the production technology, competition in product markets, the shape of adjustment costs, and management attitudes toward uncertainty. Uncertainty can potentially have positive effects; see, for instance, the discussion in Guiso and Parigi (1999) and Bloom (2014).

Another strand of the literature emphasizes robust control and ambiguity aversion in Hansen et al. (1999), Ilut and Schneider (2014), and Ilut and Saijo (2021), where the negative effects of uncertainty are driven by loss of confidence about future outcomes. Ambiguity averse agents act as if they evaluate plans using a worst case probability drawn from a set of multiple beliefs. A loss of confidence makes the "worst case" mean worse, and agents act as if they have received bad news about the future prompting them to substitute away from uncertainty and reducing current hours worked. Assuming that the minimum of future sales is a summary statistic for the probability distribution under the worst-case scenario, our evidence is also consistent with this class of models as agents respond to a deterioration in the worst-case scenario while being insensitive to improvements in the best-case scenario. Confidence as a driver of fluctuations with shocks driving "wedges" in beliefs is also the focus of Angeletos et al. (2018) and Angeletos and Lian (2021).

7 A New Measure of Aggregate Uncertainty

We now construct an economy-wide measure of uncertainty, denoted by $\sigma_{max-min,agg,t}$ based on an aggregation of the max–min range at the firm level. Aggregate uncertainty $\sigma_{max-min,agg,t}$ is a summary statistic of total firm-level uncertainty perceived by each firm, reflecting aggregate, sector- and firm-specific factors. Our bottom-up microeconomic approach provides a unicum in the literature, as it covers multiple business cycles. Similarly, Altig et al. (2020) and Altig et al. (2022) use survey data to construct an aggregate proxy of aggregate uncertainty. Still, data availability limits the length of their series extending (albeit a monthly rather than yearly frequency) to the past six years. Alternative strategies are presented in Bloom (2009) and Bloom et al. (2018), which proxy aggregate uncertainty using dispersion in realized outcomes, and in Bachmann et al. (2013), which construct uncertainty measures based on both ex ante disagreement and ex post forecast error about future outcomes. Jurado et al. (2015) adopted a latent-variable approach to extract a measure of the common variation in uncertainty across more than 100 macroeconomic series.

Our aggregate measure, $\sigma_{max-min,agg,t}$, is constructed averaging firm-level uncertainty, with the weight on each firm being the product between their sales and the statistical weight representing the share of each firm in the entire population of firms. The mean and the standard deviation of $\sigma_{max-min,agg,t}$ are 8.53 and 1.60 percentage points, respectively. Similarly, we construct a measure of the aggregate minimum $s^e_{min,agg,t}$ (mean -2.10 with a standard deviation of 3.25) and the aggregate maximum $s^e_{max,agg,t}$ (mean of 6.24 and a standard deviation of 2.35). Unsurprisingly, the volatility of the series is smaller than its firm-level counterpart. Unlike firm-level uncertainty, aggregate uncertainty is negatively correlated with real GDP growth (-0.58), see Table 6. The countercyclicality of $\sigma_{max-min,agg,t}$ results from compositional effects with i) $\sigma_{max-min,f,t}$ being countercyclical for small and medium firms and ii) small and medium firms' sales being less countercyclical than large firms. As a result, in bad times the aggregate measure weighs more small and medium firms that, in turn, perceive higher uncertainty. Both factors yield a countercyclical $\sigma_{max-min,agg,t}$. In addition, $\sigma_{max-min,agg,t}$ is negatively correlated with $s^e_{agg,avg,t}$, an economy-wide measure of mean expectation about future sales, constructed using the same weights. The aggregation of the minimum, denoted by $s^e_{min,agg,t}$, and the aggregate maximum, denoted by $s^e_{max,agg,t}$, are strongly procyclical, with a correlation with the growth rate of real GDP of 0.91 and 0.84, respectively. As the minimum decreases, downside uncertainty rises.

While the countercyclicality of proxies of aggregate uncertainty is typically obtained in the literature, we emphasize that the correlation of our measure of ex ante aggregate uncertainty, $\sigma_{max-min,agg,t}$, with measures of cross-sectional dispersion of sales, hours, or capacity utilization is close to zero or slightly negative.

As shown in Section 3.3, firm-level ex ante uncertainty $\sigma_{max-min,f,t}$ is linked with realized ex post uncertainty: $\sigma_{max-min,f,t}$ increases with larger past forecast errors and predicts larger future forecast errors, validating that indeed the max–min range is connected with realized ex post risk. The statistically significant link appears to be quantitatively tenuous: an increase of a standard deviation in the forecast error is associated to an increase in the max–min range equal to about one sixth of its standard deviation. Through the lens of this metric, the lack of correlation between $\sigma_{max-min,agg,t}$ and measures of cross-sectional dispersion suggests that an increase in aggregate uncertainty does not necessarily lead to an increase in cross-sectional dispersion and much of the variation in the cross-sectional proxies is not driven by ex-ante uncertainty. Our evidence supports models in which shocks that can generate responses to uncertainty that are not necessarily connected to later realized changes in risk; see, for instance, Ilut and Schneider (2014) and Angeletos et al. (2018).

Figure 3 plots our measure $\sigma_{max-min,agg,t}$ together with the growth rate of real GDP. (The series for aggregate $\sigma_{max-min,agg,t}$ is demeaned.) Excluding the current spike due to the COVID-19 pandemic, uncertainty peaked in the 2009 Global Financial Crisis (GFC) and rose, although to a lesser extent, in 2012 during the sovereign debt crisis (SDC). During the GFC and SDC, uncertainty increased more in the manufacturing sector relative to the service sector. In contrast, in 2020 at the peak of the COVID-19 pandemic, uncertainty nearly doubled in the service sector, and it increased by 50 percent in the manufacturing sector.

Beyond business cycle effects, our measure was also affected by political considerations in 2019, reaching levels comparable with the SDC due to elevated political uncertainty. The time-series profile of selected percentiles of the cross-sectional uncertainty distribution offers more insight into what firms accounted for the increase in aggregate uncertainty. The GFC increased uncertainty more for large firms. The average size of firms in the fourth quartile (pool of high uncertainty, above the 75th percentile of uncertainty in a given year) reached about 430 employees, a jump of 30 percent from 2008. Similarly, the political uncertainty in

2019, the average size in the pool of high uncertainty increased by 50 percent. In contrast, the SDC appears to have affected more significantly smaller firms, a narrative in line with the struggle of the banking sector to cope with the crisis of sovereign debt and provide credit to smaller firms. Compositional effects did not play a role during Covid-19 as the distribution shifted with tiny changes in average size across quartiles.

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, showing that firm-level uncertainty is a persistent process. 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 only when driven by an increase in the downside component of uncertainty. In this sense, not all uncertainties are alike, and the source of uncertainty matters, with only its downside component resulting in meaningful economic effects. Our evidence provides a practical set of overidentifying restrictions against which to test competing macroeconomic models.

We construct a bottom-up measure of ex ante aggregate uncertainty. The lack of correlation between our bottom-up proxy and measures of cross-sectional dispersion suggest that much of the variation in cross-sectional dispersion is not driven by uncertainty. At the aggregate level, our results support modelling of uncertainty in which an increase in perceived uncertainty is not necessarily connected to later realized changes in risk.

References

Alfaro, I., Bloom, N., Lin, X., 2017. The Finance-Uncertainty Multiplier. Mimeo .

Altig, D., Baker, S., Barrero, J.M., Bloom, N., Bunn, P., Chen, S., Davis, S.J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N.a., 2020. Economic uncertainty before and during the COVID-19 pandemic. Journal of Public Economics 191.

Altig, D., Barrero, J.M., Bloom, N., Davis, S.J., Meyer, B., Parker, N., 2022. Surveying business uncertainty. Journal of Econometrics 231, 282–303. Annals Issue: Subjective Expectations & Probabilities in Economics.

Angeletos, G., Collard, F., Dellas, H., 2018. Quantifying Confidence. Econometrica 86, 1689–1726.

Angeletos, G.M., Lian, C., 2021. Confidence and the Propagation of Demand Shocks. The Review of Economic Studies 89, 1085–1119.

Armantier, O., de Bruin, W.B., Topa, G., Klaauw, W., Zafar, B., 2015. Inflation Expectations and Behavior: Do Survey Respondents Act on Their Beliefs? International Economic Review 56, 505–536.

Bachmann, R., Carstensen, K., Lautenbacher, S., Schneider, M., 2018. Uncertainty and Change: Survey Evidence of Firms' Subjective Beliefs. Working Paper .

Bachmann, R., Carstensen, K., Lautenbacher, S., Schneider, M., 2020. Uncertainty Is More Than Risk – Survey Evidence on Knightian and Bayesian Firms. Working Paper .

Bachmann, R., Elstner, S., Hristov, A., 2017. Surprise, surprise–measuring firm-level investment innovations. Journal of Economic Dynamics and Control 83, 107–148.

Bachmann, R., Elstner, S., Sims, E.R., 2013. Uncertainty and Economic Activity: Evidence from Business Survey Data. American Economic Journal: Macroeconomics 5, 217–249.

Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. The Quarterly Journal of Economics 131, 1593–1636.

Ben-David, I., Graham, J.R., 2013. Managerial Miscalibration. The Quarterly Journal of Economics 128, 1547–1584.

Bernanke, B.S., 1983. Irreversibility, Uncertainty, and Cyclical Investment. The Quarterly Journal of Economics 98, 85–106.

Bloom, N., 2009. The Impact of Uncertainty Shocks. Econometrica 77, 623–685.

Bloom, N., 2014. Fluctuations in uncertainty. Journal of Economic Perspectives 28, 153–76.

Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. The Review of Economic Studies 74, 391–415.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., Terry, S.J., 2018. Really Uncertain Business Cycles. Econometrica 86, 1031–1065.

Bontempi, M.E., Golinelli, R., Parigi, G., 2010. Why demand uncertainty curbs investment: Evidence from a panel of italian manufacturing firms. Journal of Macroeconomics 32, 218–238.

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., Raffo, A., 2020. The economic effects of trade policy uncertainty. Journal of Monetary Economics 109, 38 – 59. Special Issue: April 2019 Carnegie-Rochester-NYU Conference.

Christiano, L.J., Motto, R., Rostagno, M., 2014. Risk Shocks. American Economic Review 104, 27–65.

Chugh, S.K., 2016. Firm risk and leverage-based business cycles. Review of Economic Dynamics 20, 111–131.

Datta, D., Londono, J.M., Sun, B., Beltran, D.O., Ferreira, T.T., Iacoviello, M., Jahan-Parvar, M., Li, C., Rodriguez, M., Rogers, J.H., 2017. Taxonomy of Global Risk, Uncertainty, and Volatility Measures. International Finance Discussion Papers. Board of Governors of the Federal Reserve System (U.S.).

Dominitz, J., Manski, C.F., 1994. Using Expectations Data to Study Subjective Income Expectations. NBER Working Papers 4937. National Bureau of Economic Research, Inc.

Dominitz, J., Manski, C.F., 2004. How Should We Measure Consumer Confidence? Journal of Economic Perspectives 18, 51–66.

Fernández-Villaverde, J., Guerrón-Quintana, P.A., 2020. Uncertainty shocks and business cycle research. Review of Economic Dynamics 37, S118–S146. The Twenty-Fifth Anniversary of "Frontiers of Business Cycle Research".

Gennaioli, N., Ma, Y., Shleifer, A., 2016. Expectations and Investment. NBER Macroeconomics Annual 30, 379–431.

Guiso, L., Jappelli, T., Pistaferri, L., 2002. An Empirical Analysis of Earnings and Employment Risk. Journal of Business & Economic Statistics 20, 241–253.

Guiso, L., Jappelli, T., Terlizzese, D., 1992. Earnings Uncertainty and Precautionary Saving. Journal of Monetary Economics 30, 307–337.

Guiso, L., Parigi, G., 1999. Investment and demand uncertainty. The Quarterly Journal of Economics 114, 185–227.

Gulen, H., Ion, M., 2016. Policy uncertainty and corporate investment. The Review of Financial Studies 29, 523–564.

Handley, K., Limão, N., 2017. Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States. American Economic Review 107, 2731–2783.

Hansen, L.P., Sargent, T.J., Tallarini, T.D., 1999. Robust Permanent Income and Pricing. Review of Economic Studies 66, 873–907.

Hassan, T.A., Hollander, S., van Lent, L., Tahoun, A., 2019. Firm-Level Political Risk: Measurement and Effects. The Quarterly Journal of Economics 134, 2135–2202.

Holzmeister, F., Huber, J., Kirchler, M., Lindner, F., Weitzel, U., Zeisberger, S., 2020. What Drives Risk Perception? A Global Survey with Financial Professionals and Laypeople. Management Science 66, 3977–4002.

Hurd, M.D., McGarry, K., 2002. The Predictive Validity of Subjective Probabilities of Survival. Economic Journal 112, 966–985.

Ilut, C., Saijo, H., 2021. Learning, confidence, and business cycles. Journal of Monetary Economics 117, 354–376.

Ilut, C.L., Schneider, M., 2014. Ambiguous business cycles. American Economic Review 104, 2368–99.

Jordà, O., 2005. Estimation and Inference of Impulse Responses by Local Projections. American Economic Review 95, 161–182.

Jurado, K., Ludvigson, S.C., Ng, S., 2015. Measuring uncertainty. American Economic Review 105, 1177–1216.

Kehrig, M., 2015. The cyclical nature of the productivity distribution. US Census Bureau Center for Economic Studies Paper No. CES-WP-11-15 .

Leahy, J.V., Whited, T.M., 1996. The Effect of Uncertainty on Investment: Some Stylized Facts. Journal of Money, Credit and Banking 28, 64–83.

Massenot, B., Pettinicchi, Y., 2018. Can firms see into the future? survey evidence from germany. Journal of Economic Behavior & Organization 145, 66 – 79.

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

Nickell, S.J., 1981. Biases in Dynamic Models with Fixed Effects. Econometrica 49, 1417–1426.

Segal, G., Shaliastovich, I., Yaron, A., 2015. Good and bad uncertainty: Macroeconomic and financial market implications. Journal of Financial Economics 117, 369 – 397.

Senga, T., 2015. A New Look at Uncertainty Shocks: Imperfect Information and Misallocation. Technical Report. Working Paper.

Stein, L.C., Stone, E., 2013. The effect of uncertainty on investment, hiring, and r&d: Causal evidence from equity options. Working Paper .

Table 1: Firm-Level Expectations: Descriptive Statistics

	No. of Obs.	Mean	Std. Dev.	P_{10}	P_{25}	P_{50}	P_{75}	P_{90}	Corr w. $\Delta_{GDP_{t,t-1}}$
$s^e_{avg,f,t}$	49674	3.56	11.30	-7.20	0.00	2.60	7.20	14.30	0.25
$s^e_{min,f,t}$	30958	-3.89	9.91	-12.00	-10.00	-2.00	1.00	5.00	0.28
$s^e_{max,f,t}$	30976	7.07	9.82	0.00	2.00	5.00	12.00	15.00	0.18
$\Delta Sales_{t,t-1}$	41934	0.93	18.70	-19.90	-7.51	1.76	10.40	21.10	0.28

Note: Statistics are computed over the sample period from 1996 to 2019, taking into account the INVIND sample weight represented by each firm in the entire population of firms. 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). $s^e_{avg,f,t}$, $s^e_{min,f,t}$, $s^e_{max,f,t}$ denote the *average*, *minimum*, and *maximum* expected growth rates of sales one year ahead, respectively, while $\Delta Sales_{t,t-1}$ and $\Delta GDP_{t,t-1}$ reports the growth rate of *realized* sales and the growth rate of GDP between time *t* and *t-1*, respectively. P_X reports the X^{th} percentile of the distribution.

Table 2: $\sigma_{max-min}$ and Moments of the Subjective Probability Distribution

Year 2005 and 2017	$St.Dev._f$ (1)	$Skew._f$ (2)	$St.Dev._f$ (3)	$St.Dev.Down_f$ (4)	$St.Dev.Up_f$ (5)
$\sigma_{max-min,f}$	0.28***	-0.25			
	(0.00)	(0.21)			
$s^e_{min,f}$			-0.28***	-0.30***	-0.09***
			(0.00)	(0.00)	(0.00)
$s^e_{max,f}$			0.28***	0.08***	0.29***
			(0.00)	(0.00)	(0.01)
R^2	0.84	0.00	0.84	0.83	0.84
Observations	2047	2047	2047	2047	2047

Note: Each equation is estimated with ordinary least squares using the 2005 and 2017 waves of INVIND. P-values are shown 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 variables are reported on columns. $St.Dev._f$ is the second moment and $Skew._f$ is the third-moment of the firm-specific probability distribution of expected sales for the year 2005 and 2017, respectively. $St.Dev.Down_f$ and $St.Dev.Up_f$ denote the downside and upside components of overall uncertainty, respectively. For every firm f, $\sigma_{max-min,f}$ denotes the difference between $s^e_{max,f}$, and $s^e_{min,f}$, the maximum and minimum expected growth rate of sales one year ahead.

Table 3: Uncertainty Covariates

	$\sigma_{max-min,f,t}$	$s^e_{min,f,t}$	$s^e_{max,f,t}$
	(1)	(2)	(3)
$s^e_{avg,f,t}$	0.09***	0.67***	0.76***
	(0.00)	(0.00)	(0.00)
$Abs.Forec.Error_{f,t-1}$	0.04***	-0.02***	0.01**
	(0.00)	(0.00)	(0.01)
$\Delta Sales_{f,t-1} > 0$	0.01	0.00	0.02***
	(0.13)	(0.55)	(0.00)
$\Delta Sales_{f,t-1} < 0$	-0.05***	0.02**	-0.03***
	(0.01)	(0.04)	(0.00)
Observations	7780	7784	7780
R^2	0.44	0.77	0.80

Note: Each regression is estimated by ordinary least squares over the sample period 1996 to 2019, and it also includes fixed effects, year- and industry-effects, and firms' age and size. $\sigma_{max-min,f,t}$ measures firm-level uncertainty; $s^e_{max,f,t}$, $s^e_{avg,f,t}$, and $s^e_{min,f,t}$ denote the maximum, average, and minimum one-year-ahead expected growth rates of sales, respectively.

Table 4: Real and Financial Effects of Firm-Level Uncertainty

	Increase in Uncertainty 1p.p.				
Horizon=h	0	1	2	3	4
Capacity Util. (t+h)	-0.096*	-0.054*	0.015	0.003	0.047
	(0.06)	(0.09)	(0.77)	(0.97)	(0.22)
Total Hours (t+h)	-0.143***	-0.110**	-0.063	-0.063	-0.013
	(0.00)	(0.05)	(0.42)	(0.41)	(0.79)
Hours-per-Worker (t+h)	-0.088***	-0.025	-0.025	-0.051	0.001
	(0.00)	(0.35)	(0.39)	(0.26)	(0.96)
No. of Employees (t+h)	-0.064	-0.093**	-0.058	0.002	-0.029
	(0.11)	(0.05)	(0.11)	(0.95)	(0.37)
Real Investment (t+h)	-0.039	-0.411*	-0.524**	0.201	0.443
	(0.65)	(0.10)	(0.02)	(0.54)	(0.13)
Growth Rate of Cash Holdings (t+h)	0.011*	-0.006	-0.008*	0.000	-0.003
	(0.05)	(0.22)	(0.09)	(0.95)	(0.62)

Note: The table reports ordinary least squares estimates of the coefficient β_h, the estimated coefficient on $\sigma_{max-min,f,t}$ in Equation 1. The sample period runs from 1996 to 2019. P-values are in parentheses. Stars denote the significance level of the coefficient they refer to: * p-value<0.10, ** p-value<0.05, and *** p-value<0.01. Standard errors are clustered by firm and year. Entries, except for cash holdings in percentage points, are expressed in percent.

Table 5: Real and Financial Effects of Firm-Level Uncertainty

Panel A - Increase in Downside Uncertainty 1p.p.

Horizon=h	0	1	2	3	4
Capacity Util. (t+h)	-0.150***	-0.075**	0.002	0.050	0.028
	(0.01)	(0.01)	(0.95)	(0.40)	(0.67)
Total Hours (t+h)	-0.185***	-0.136**	-0.108*	-0.134**	-0.038
	(0.00)	(0.01)	(0.07)	(0.03)	(0.31)
Hours-per-Worker (t+h)	-0.088***	-0.025	-0.025	-0.051	0.001
	(0.00)	(0.35)	(0.39)	(0.26)	(0.96)
No. of Employees (t+h)	-0.064	-0.093**	-0.058	0.002	-0.029
	(0.11)	(0.05)	(0.11)	(0.95)	(0.37)
Real Investment (t+h)	-0.099	-0.790**	-0.594*	-0.138	0.671**
	(0.39)	(0.02)	(0.06)	(0.73)	(0.06)
Growth Rate of Cash Holdings (t+h)	0.013**	0.007	0.005	-0.010*	0.001
	(0.02)	(0.35)	(0.25)	(0.05)	(0.80)

Panel B - Increase in Upside Uncertainty 1 p.p.

Horizon=h	0	1	2	3	4
Capacity Util. (t+h)	-0.029	-0.029	0.030	-0.051	0.073
	(0.45)	(0.63)	(0.68)	(0.44)	(0.56)
Total Hours (t+h)	-0.095*	-0.086	-0.024	0.015	0.012
	(0.07)	(0.18)	(0.82)	(0.90)	(0.88)
Hours-per-Worker (t+h)	-0.005	0.013	-0.003	-0.029	0.005
	(0.79)	(0.73)	(0.85)	(0.61)	(0.82)
No. of Employees (t+h)	-0.097	-0.088	-0.050	0.066	0.015
	(0.21)	(0.21)	(0.53)	(0.31)	(0.81)
Real Investment (t+h)	0.034	0.007	-0.428	0.655	0.117
	(0.72)	(0.97)	(0.21)	(0.23)	(0.37)
Growth Rate of Cash Holdings (t+h)	0.008	-0.005	-0.011	-0.010	-0.004
	(0.14)	(0.21)	(0.11)	(0.22)	(0.65)

Note: The table reports ordinary least squares estimates of the coefficient $\beta_{min,h}$ in Panel A and $\beta_{max,h}$ in Panel B in Equation 2. The sample period runs from 1996 to 2019. P-values are in parentheses. Stars denote the significance level of the coefficient they refer to: * p-value<0.10, ** p-value<0.05, and *** p-value<0.01. Standard errors are clustered by firm and year. Entries, except for cash holdings in percentage points, are expressed in percent. Panel A reports the response of each variable to a 1 percentage point *decrease* in $s^e_{min,f,t}$, or equivalently an increase in downside uncertainty. Panel B reports the response of each variable to a 1 percentage point *increase* in $s^e_{max,f,t}$, or, equivalently, an increase in upside uncertainty.

Table 6: Correlation between Ex Ante and Ex Post Uncertainty Measures

Contemporaneous Correlation	$\Delta GDP_{t,t-1}$	$\sigma_{max-min,agg,t}$
$\sigma_{max-min,agg,t}$	-0.58	1
$s^e_{avg,agg,t}$	0.82	-0.51
$XS\ Sales\ dispersion_t$	-0.30	-0.14
$XS\ Empl.\ dispersion_t$	-0.21	0.10
$XS\ Cap.\ Util.\ dispersion_t$	-0.46	0.04

Note: Each entry reports the contemporaneous correlation between the growth rate of real GDP $\Delta GDP_{t,t-1}$ and ex ante uncertainty $\sigma_{max-min,agg,t}$. The sample period is from 1997 to 2021.

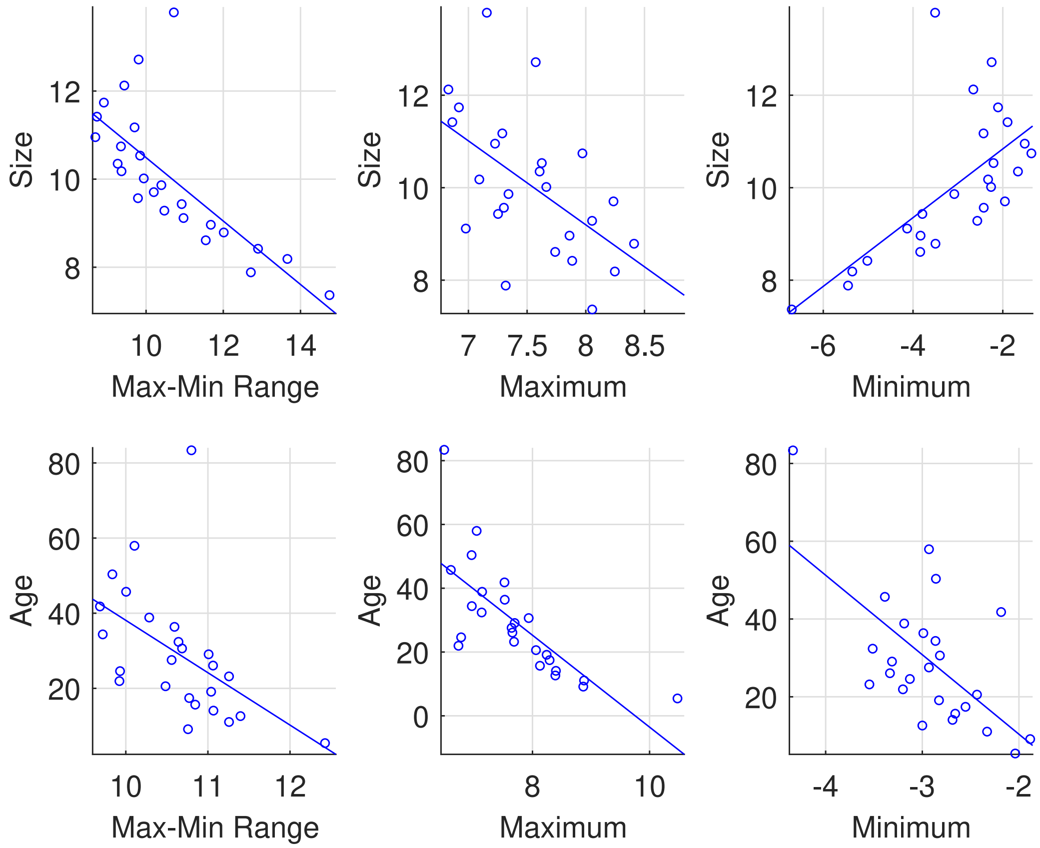

Figure 1: Uncertainty, Age, and Size

Note: Charts report the average sales (or age) and average max-min range for 25 quantiles, computed by pooling observations from 1996 to 2021.

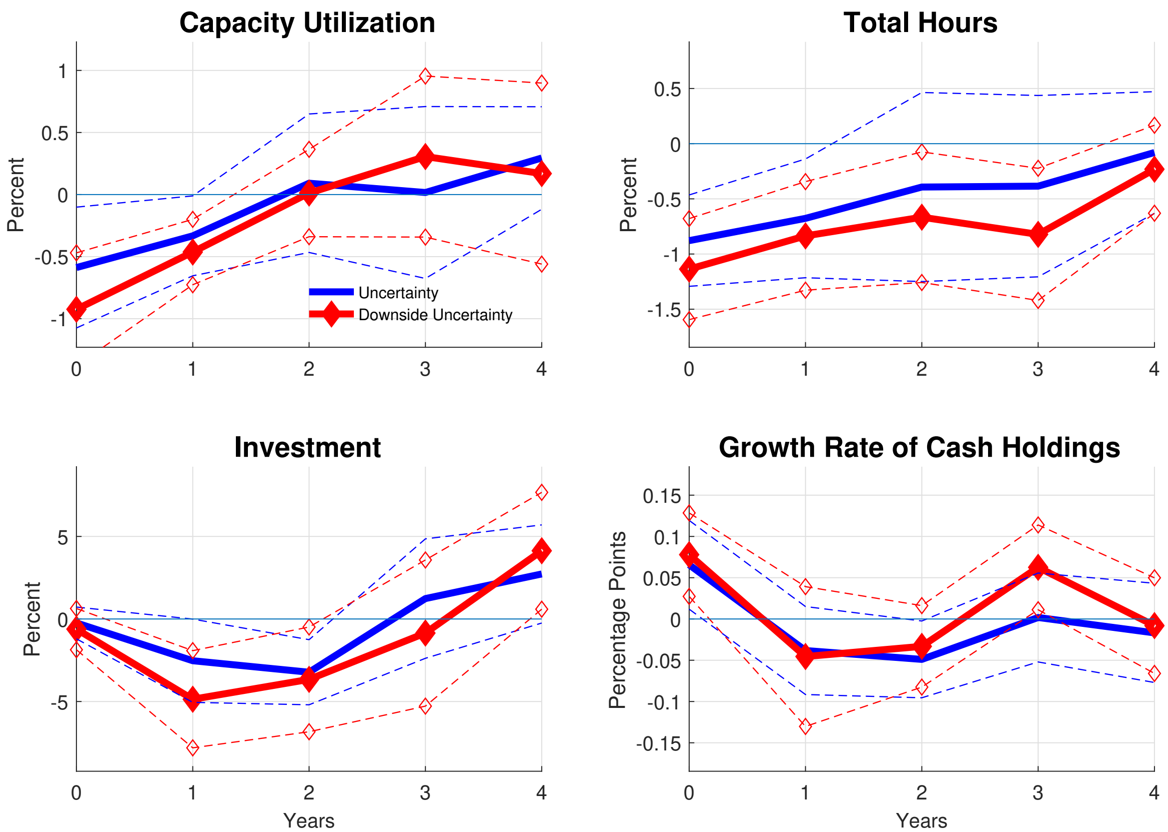

Figure 2: Uncertainty through Downside Uncertainty

Note: In each panel, solid lines report estimated impulse responses following a one standard deviation shock and using coefficients estimates in Tables 4 and 5. Dashed lines report 90 percent confidence intervals.

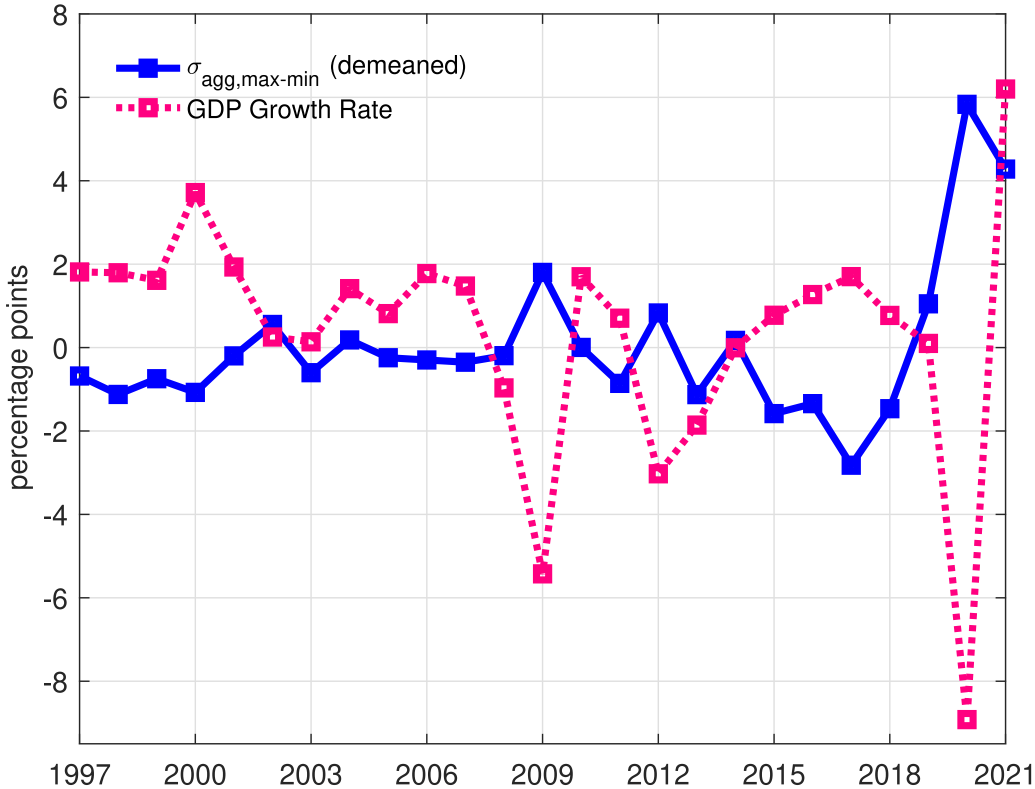

Figure 3: Uncertainty and GDP Growth

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

ONLINE APPENDIX NOT FOR PUBLICATION

A Data Sources

Our data on expected sales growth (the average, the minimum and the maximum) comes from the Survey of Industrial and Service Firms (INVIND), a large annual business survey conducted by the Bank of Italy on a representative sample of firms. Since 2002, the reference universe in INVIND consists of firms with at least 20 employees operating in industrial sectors (manufacturing, energy, and extractive industries) and non-financial private services, with administrative headquarters in Italy. The survey adopts a one-stage stratified sample design. The strata are combinations of the branch of activity (according to an 11-sector classification), size class (in terms of number of employees classified in 7 buckets), and region in which the firm's head office is located. In recent years, each wave has around 4,000 firms (3,000 industrial firms and 1,000 service firms). The data are collected by the Bank of Italy's local branches between February and April every year. The question between the minimum and maximum expected growth rate of sales (min—max gap) covers around 900 firms on average per year, from 1993 to 2007, and 1,677 firms on average per year from 2008 to 2021. The data set has a panel dimension. The firms observed in the previous edition of the survey are always contacted again if they are still part of the target population. In contrast, those no longer wishing to participate are replaced with others in the same branch of activity and size class. To limit the impact of outliers, we winsorize the 1% tails of the max-min range, the minimum, the maximum, the average expected sales, investment, hours, capacity utilization, and cash holdings.

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									
$s^e_{avg,f,t}$	49674	3.59	11.60	1.00	-7.10	0.00	2.70	7.10	14.50
$s^e_{min,f,t}$	30958	-3.57	10.40	-0.20	-12.00	-10.00	-2.00	1.00	5.00
$s^e_{max,f,t}$	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									
$s^e_{avg,f,t}$	3059	3.53	10.20	1.07	-4.80	0.00	2.40	5.90	14.30
$s^e_{min,f,t}$	5115	-5.97	10.60	-0.42	-14.00	-12.00	-5.00	0.00	4.00
$s^e_{max,f,t}$	5120	6.63	10.40	0.75	-2.00	1.00	5.10	12.00	12.70
Large Firms: Labor Force ≥ 50									
$s^e_{avg,f,t}$	46339	3.60	11.70	0.99	-7.40	0.00	2.80	7.30	14.60
$s^e_{min,f,t}$	25630	-2.14	10.00	-0.01	-12.00	-6.00	-1.00	2.00	7.00
$s^e_{max,f,t}$	25646	7.09	10.80	2.09	-1.00	2.00	5.00	12.00	16.20
Young Firms: Age ≤ 5									
$s^e_{avg,f,t}$	1367	6.27	14.90	1.20	-7.40	0.00	4.00	10.50	22.30
$s^e_{min,f,t}$	873	-3.60	11.60	0.66	-12.00	-12.00	-3.00	1.00	8.00
$s^e_{max,f,t}$	871	9.91	12.00	1.60	0.00	3.00	10.00	12.00	21.00
Old Firms: Age > 5									
$s^e_{avg,f,t}$	48307	3.54	11.50	0.98	-7.00	0.00	2.70	7.10	14.40
$s^e_{min,f,t}$	30085	-3.57	10.30	-0.23	-12.00	-10.00	-2.00	1.00	5.00
$s^e_{max,f,t}$	30105	6.85	10.60	1.62	-1.00	1.50	5.00	12.00	15.00
Manufacturing Sector									
$s^e_{avg,f,t}$	33873	4.28	12.20	0.83	-7.50	0.00	3.50	8.50	16.00
$s^e_{min,f,t}$	21592	-3.08	11.00	-0.26	-12.00	-10.00	-1.20	2.00	7.00
$s^e_{max,f,t}$	21607	7.48	11.20	1.41	-1.00	2.00	5.60	12.00	18.00
Service Sector									
$s^e_{avg,f,t}$	15801	2.55	10.40	1.30	-6.40	-0.10	1.80	5.10	11.30
$s^e_{min,f,t}$	9366	-4.25	9.43	-0.16	-12.00	-12.00	-2.00	0.20	4.00
$s^e_{max,f,t}$	9369	6.14	9.82	2.00	-1.00	1.00	5.00	12.00	12.00

Note: Statistics are computed over the sample period 1996 to 2019, taking into account the sample weight represented by each each firm in the entire population of firms. 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). $s^e_{avg,f,t}$, $s^e_{min,f,t}$, and $s^e_{max,f,t}$ denote the *average*, *minimum*, and *maximum* expected growth rates of sales one year ahead. P_X reports the X^{th} percentile of the distribution.

C Firm-Level Uncertainty

The table below reports descriptive statistics on firm-level uncertainty.

Table $A.2$: Firm-Level Uncertainty $\sigma_{max-min}$: Descriptive Statistics

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

Note: Statistics are computed over the sample period 1996 to 2019, weighting firm-specific observations based on their share of the entire population. The number of observations refers to the firms directly observed in the data. $\sigma_{max-min}$ denotes the difference between s^e_{max} and s^e_{min}, the maximum and minimum expected growth rates of sales one year ahead. P_X reports the X^{th} percentile of the distribution.

D Downside and Upside Uncertainty: Alternative Proxies

The table below reports descriptive statistics on alternative measure of firm-level downside, measured as $s^e_{avg,f,t} - s^e_{min,f,t}$, and, and upside uncertainty, measured as $s^e_{max,f,t} - s^e_{avg,f,t}$. We find that at the firm level $s^e_{avg,f} - s^e_{min,f}$ is acyclical with the correlation with the contemporaneous growth rate of real GDP equal to -0.03 and $s^e_{max,f} - s^e_{avg,f}$ slightly countercylical (-0.12).

Table A.3: Alternative Downside and Upside Uncertainty : Descriptive Statistics

	No. of Obs.	Mean	St. Dev.	Skew.	P_{10}	P_{25}	P_{50}	P_{75}	P_{90}
Full Sample									
$s^e_{avg,f,t} - s^e_{min,f,t}$	30735	5.77	6.33	0.50	2.00	4.10	7.40	12.10	
$s^e_{max,f,t} - s^e_{avg,f,t}$	30735	4.24	5.78	0.04	0.70	2.40	5.20	10.10	
Small and Medium Firms: $20 \leq$ Labor Force ≤ 50									
$s^e_{avg,f,t} - s^e_{min,f,t}$	5082	4.86	5.99	3.23	0.20	1.00	3.20	6.30	10.10
$s^e_{max,f,t} - s^e_{avg,f,t}$	5082	4.39	6.86	3.20	0.00	0.50	1.70	5.20	12.50
Large Firms: Labor Force > 50									
$s^e_{avg,f,t} - s^e_{min,f,t}$	25443	5.86	6.36	3.46	0.50	2.00	4.30	7.50	12.20
$s^e_{max,f,t} - s^e_{avg,f,t}$	25443	4.23	5.68	3.70	0.00	0.80	2.50	5.20	10.00
Young Firms: Age ≤ 5									
$s^e_{avg,f,t} - s^e_{min,f,t}$	866	7.11	9.01	3.71	0.70	2.69	5.00	7.60	16.00
$s^e_{max,f,t} - s^e_{avg,f,t}$	866	3.59	5.25	7.82	0.00	0.90	2.50	5.00	8.00
Mature and Old Firms: Age > 5									
$s^e_{avg,f,t} - s^e_{min,f,t}$	29869	5.75	6.27	3.39	0.50	2.00	4.10	7.40	12.10
$s^e_{max,f,t} - s^e_{avg,f,t}$	29869	4.26	5.78	3.60	0.00	0.70	2.40	5.20	10.20
Manufacturing Sector									
$s^e_{avg,f,t} - s^e_{min,f,t}$	21450	6.22	6.64	3.40	0.50	2.20	4.80	8.00	13.00
$s^e_{max,f,t} - s^e_{avg,f,t}$	21450	4.45	5.81	3.42	0.00	0.80	2.70	5.60	10.60
Service Sector									
$s^e_{avg,f,t} - s^e_{min,f,t}$	9285	4.85	5.54	3.46	0.40	1.50	3.20	6.00	10.60
$s^e_{max,f,t} - s^e_{avg,f,t}$	9285	3.81	5.68	4.20	0.00	0.60	2.00	4.80	9.30

Note: Statistics are computed over the sample period 1996 to 2019, 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. $s^e_{avg,f,t}$, $s^e_{max,f,t}$ and $s^e_{min,f,t}$ denote the average, maximum, and minimum expected growth rates of sales one year ahead. P_X reports the X^{th} percentile of the distribution.

Below we show the estimated effects of firm-level uncertainty when downside and upside uncertainty are proxied by $s^e_{avg,f,t} - s^e_{min,f,t}$ and $s^e_{max,f,t} - s^e_{avg,f,t}$, respectively. As discussed in Section 5, downside uncertainty drives the economic effects of total uncertainty. Upside uncertainty does not result in appreciable economic effects.

Table A.4: Alternative Proxies of Downside and Upside Uncertainty

Panel A - Increase in Alternative Downside Uncertainty 1 p.p.					
Horizon=h	0	1	2	3	4
Capacity Util. (t+h)	-0.169***	-0.054	0.043	0.123**	0.116
	(0.01)	(0.56)	(0.84)	(0.02)	(0.15)
Total Hours (t+h)	-0.157***	-0.105*	-0.130*	-0.171**	-0.030
	(0.00)	(0.10)	(0.11)	(0.03)	(0.32)
Real Investment (t+h)	-0.128	-0.120	-0.622*	-0.987	1.080*
	(0.71)	(0.98)	(0.09)	(0.27)	(0.10)
Growth Rate of Cash Holdings (t+h)	0.019*	0.007	0.005	-0.010*	0.001
	(0.10)	(0.81)	(0.32)	(0.05)	(0.80)
Panel B - Increase in Alternative Upside Uncertainty 1 p.p.					
Horizon=h	0	1	2	3	4
Capacity Util. (t+h)	-0.016	-0.004	0.048	-0.097	0.047
	(0.79)	(0.97)	(0.69)	(0.27)	(0.20)
Total Hours (t+h)	-0.096	-0.093	-0.046	0.077	0.051
	(0.13)	(0.15)	(0.53)	(0.51)	(0.44)
Real Investment (t+h)	0.399	-0.601	-0.367	0.571	0.596
	(0.48)	(0.40)	(0.32)	(0.29)	(0.26)
Growth Rate of Cash Holdings (t+h)	-0.008	-0.014	-0.001	-0.011	-0.007
	(0.33)	(0.06)	(0.91)	(0.27)	(0.48)

Note: The table reports ordinary least squares estimates of the coefficient $\beta_{avg-min,h}$ in Panel A and $\beta_{max-avg,h}$ in Panel B in Equation 2 with downside and upside uncertainty now proxied by $s^e_{avg,f,t} - s^e_{min,f,t}$ and $s^e_{min,f,t} - s^e_{avg,f,t}$, respectively. The sample period runs from 1996 to 2019. P-values are shown in parentheses. Stars denote the significance level of the coefficient they refer to: * p-value<0.10, ** p-value<0.05, and *** p-value<0.01. Standard errors clustered by firm and year. Entries, except for cash holdings in percentage points, are expressed in percent. Panel A reports the response of each variable to a 1 percentage point *increase* in $s^e_{avg,f,t} - s^e_{min,f,t}$, or equivalently an increase in downside uncertainty. Panel B reports the response of each variable to a 1 percentage point *increase* in $s^e_{max,f,t} - s^e_{avg,f,t}$, or, equivalently, an increase in upside uncertainty.