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

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Abstract

Using 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 below-mean outcomes. Economy-wide uncertainty, constructed by 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.

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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 of 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 subjective firm-level uncertainty, its economic effects, and the properties of aggregate uncertainty across business cycles.

First, we construct a measure of subjective 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.

[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.

Second, the detrimental effects of higher firm-level uncertainty over a broad set of real 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 and 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 subjective uncertainty for the Italian economy, aggregating firm-level data, and find it to be countercyclical. While this countercyclicality reproduces the literature's typical result, we note 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 subjective 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 minimum and maximum 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 subjective 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 complementary, 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. 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 estimates on the effects of uncertainty on investment are twice as large one year out and even more detrimental considering the full horizon of our estimates. We find smaller effects of uncertainty on cash holdings.

One caveat in the interpretation of our results is that the economic effects of the minimum and the irrelevance of the maximum are similar to those of downside and upside uncertainty. In our sample, after running a horse race between the two components, we find more support for downside uncertainty, but are cautious in fully dismissing the importance of the worst-case scenario as a driver of our results.

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 subjective uncertainty. Our bottom-up measure of aggregate uncertainty about future sales is countercyclical, increasing sharply during economic crises, such as the Global 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 subjective 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 subjective uncertainty and cross-sectional dispersion. Our evidence supports models in 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 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 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 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 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.

[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).

[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.

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 (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 a subjective 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 (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).

2 Data: Subjective Firm-Level Expectations

This section describes the data sources that constitute the basis for measuring subjective 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 subjective 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, 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.

[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.

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, growth rate of sales one year ahead, denoted by $s^e_{max,f,t}$.
3. The *minimum*, or worst-case scenario, 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 with 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 gap between the average and the minimum and between the maximum and the average 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.

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.

The median firm expects sales ($s^e_{avg,f,t}$) 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 year 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.

The median firm expects the worst-case scenario ($s^e_{min,f,t}$) to result in a decrease of sales of about 2 percentage points and the best-case scenario ($s^e_{max,f,t}$) in an expansion of 5. Also, for both variables, the interquartile range ($P_{75} - P_{25}$) is about 10 percentage points. The interval between the best- and worst-case scenario is informative about the uncertainty 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. 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 realized sales.

The statistical properties of expectations display sizable differences conditioning on firms' size, age, and the sector in which they operate. Based on firms' sizes, 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 Subjective Expectations and Firm-Level Uncertainty

We now construct a time-varying measure of individual firms' subjective uncertainty using INVIND expectations 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

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

the dispersion (or second moment) of future expected sales. Moreover, the gaps between the average and the minimum and the maximum and the average 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 firms' characteristics in Section 3.2. Finally, we analyze how firm-specific and aggregate variables covary with uncertainty in Section 3.3 and conclude by showing that uncertainty is a persistent process in Section 3.4.

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

INVIND provides us with the range between the maximum and the minimum 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. Also, we decompose overall uncertainty into its upside and downside components and show that $s^e_{max,f,t} - s^e_{avg,f,t}$ and $s^e_{avg,f,t} - s^e_{min,f,t}$ proxy for upside and downside uncertainty, respectively. These results obtain using the 2005 and 2017 waves of INVIND that, unlike other years in our sample, 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 apply standard formulas and use, for each bin, the midpoint of the respective interval and its associated probability.[8] As

[7] In 2005, the support of the probability distribution of expected sales x was discretized using 11 bins: ≤-10 percent, -10 percent<x≤-6 percent, -6 percent<x≤-4 percent, -4 percent<x≤-2 percent, -2 percent<x<0 percent, 0, 0 percent<x≤2 percent, 2 percent<x≤4 percent, 4 percent<x≤6 percent, 6 percent<x≤10 percent, ≥10 percent. In 2017, the grid between -6 percent and +6 percent was finer, with intervals of one percentage point rather than two. For the 2005 and 2017 waves, INVIND 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 ≤-10 percent and ≥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

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 $\sigma_{max-min,f}$, $s^e_{avg,f} - s^e_{min,f}$ and $s^e_{max,f} - s^e_{avg,f}$ 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 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 $s^e_{f,avg} - s^e_{f,min}$ and $s^e_{f,max} - s^e_{f,avg}$ proxy for overall uncertainty and its components. The equality in absolute terms of the coefficients in Column 3 shows that both components account for the bulk of the variance in overall uncertainty: an increase in $s^e_{avg,f} - s^e_{min,f}$ or in $s^e_{max,f} - s^e_{avg,f}$ symmetrically increases the max–min range. Columns 4 and 5 show that $s^e_{avg,f} - s^e_{min,f}$ and $s^e_{max,f} - s^e_{avg,f}$ 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; $s^e_{avg,F}$ 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.

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.

Results in Column 4 indicate that the average-minimum gap is the main determinant of downside uncertainty: a higher $s^e_{avg,f} - s^e_{min,f}$ increases downside uncertainty about three times more that an equally sized increase in $s^e_{max,f} - s^e_{avg,f}$. By the same logic, Column 5 shows that $s^e_{max,f} - s^e_{avg,f}$ is the main determinant of upside uncertainty.

3.2 Subjective 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 a measure of the subjective 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, $\sigma_{max-min,f,t}$ is easily interpretable as it relates to economic outcomes.

In our sample, the mean of uncertainty around managers' expected future sales is 11 percentage points; the median uncertainty is 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. Downside uncertainty is, on average, higher than upside uncertainty by about one percentage point and, as $\sigma_{max-min,f,t}$, is acyclical with a -0.03 correlation with GDP. Upside uncertainty is slightly countercyclical with a -0.12 correlation with GDP.

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

Figure 1, downside and upside uncertainty decrease with age and size, following the pattern displayed by the max–min range.

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 $s^e_{max,f,t}$ being 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; see Figure *A*.1 in Appendix C.

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 Subjective 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 $s^e_{min,f,t}$, $s^e_{max,f,t}$, $\sigma_{max-min,f,t}$, and its components 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 and its components by about 1/2 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.[9]

We also analyze the impact of past realized sales growth on uncertainty and expectations. Following 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 1/2

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

percentage point. The lack of significance of positive sales on $\sigma_{max-min,f,t}$ stems from the not significant correlation of $s^e_{min,f,t}$ and downside uncertainty with past positive sales. $s^e_{max,f,t}$ and upside uncertainty increase 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 in Columns 1, 4, and 5, more than half of the variance of firm-level uncertainty $\sigma_{max-min,f,t}$ and its components is unexplained and not accounted for by firm-specific observables or sector-specific or aggregate factors.

3.4 Subjective Firm-Level Uncertainty Persists for a Few Years

We now turn to study the persistence of subjective firm-level uncertainty. Our main takeaway is that, on average, firm-level uncertainty persists for a few years. To establish this result, we fit an autoregressive process of order one to expectations and measures of uncertainty 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 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 midpoint 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 about 0.25 for downside and upside uncertainty. Instead, looking at three-year uncertainty, the same statistic is about 0.65.[10] Overall, the downside and upside uncertainty, on average, display a persistence similar to the max-min range.

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

[10]Looking at the extremes of the max–min, the implied persistence is slightly higher and about 0.75.

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

and,

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

where $Y_{f,t+h}$ includes real and financial outcomes: the log of capacity utilization rate, total hours, and investment 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 $\beta_{avg-min,h}$ and $\beta_{max-avg,h}$ 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 and interest expenses 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 Subjective 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 our estimates. To facilitate the comparison across specifications, we standardized the max–min range so that $\beta_{max-min,f,t}$ reports the effects on firm-level variables following a 1 standard deviation increase in firm-level uncertainty. Entries are expressed in percent.

The economic effects of uncertainty are statistically and economically significant and, notably, last for a few years. This result reflects both the persistence of subjective 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 hoard cash, signaling a precautionary behavior that anticipates reducing investment. We discuss the results next.

On the real side, after an increase in perceived uncertainty, the firm reduces its capacity utilization rate and total hours by about 0.7 percent, respectively, equivalent to about 70 percent of one standard deviation of both variables. Also, firms adjust the labor input using the intensive and the extensive margin of labor. Over the same period, on the financial side, firms also increase the growth rate of cash holdings, before reverting in year two. After one year, the firm starts cutting on investment, by about 3 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.

To gauge the magnitude of the estimated effects it is instructive to compare our results with existing studies that use 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 overall twice as large, 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.[11]

5 Effects of Uncertainty through "Downside Uncertainty"

We now study whether the economic effects of subjective 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.) Table 5 reports the estimated

[11] 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. 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.

coefficients in Equation 2.

The main takeaway is that firms respond to fluctuations in uncertainty only if it originates with downside uncertainty. Instead, an increase in upside uncertainty does not result in statistically significant economic effects. The propagation mechanism of fluctuations in downside uncertainty is similar to the one discussed in Section 4.2. From a quantitative standpoint, the effects of uncertainty are somewhat larger than the one of overall uncertainty, except 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.

We also verify that downside uncertainty is not merely a stand-in for the worst-case scenario as captured by the minimum expected sales, $s^{e}_{min,f,t}$. Although the minimum is also correlated with downside uncertainty, as discussed in Section 3.1, an alternative interpretation calls for firms caring about the minimum per se rather than downside uncertainty. As shown in Table *A*.3 in Appendix D the asymmetry between the minimum and the maximum mirrors the one between downside and upside uncertainty. To disentangle whether downside uncertainty or the minimum drives our results, one would like to estimate the most general specification that, in addition to the full set of controls, includes average expected sales, measures of the components of uncertainty together with the minimum and the maximum. However, because of collinearity, we can include only three of the those five variables. As the focus is on $s_{avg,f,t} - s_{min,f,t}$ and $s_{min,f,t}$ we keep these variables. Then, following common practice, we drop $s_{avg,f,t}$ and $s_{max,f,t}$ because they are the variables more correlated with the other regressors. Specifically, the correlation of $s_{min,f,t}$ with $s_{avg,f,t}$ and

$s_{max,f,t}$ is 0.66 and 0.82, respectively.[13] The correlation among the remaining variables ranges between -0.33 and 0.13. Table A.4 shows that the negative effects of downside uncertainty survive the horse race with the minimum, while the minimum is not statistically significant. That said, given the econometric caveats due to collinearity, we cannot exclude completely the role of the worst-case scenario as a possible explanation of our results.

6 Implications for Macroeconomic Modeling

Firm-level uncertainty predicts a persistent drop in employment, hours per worker, and capital and an increase in cash holdings only when it originates from downside uncertainty. 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", models that emphasize financial frictions, and 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 uncer-

[13]Note that $s_{avg,f,t}$ can be obtained as a linear combination of $s_{avg,f,t} - s_{min,f,t}$ and $s_{min,f,t}$, while $s_{max,f,t}$ obtains as a linear combination of $s_{max,f,t} - s_{avg,f,t}$, $s_{avg,f,t} - s_{min,f,t}$, and $s_{min,f,t}$.

[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).

tainty. 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.

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. 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 constructs uncertainty measures based on both the ex ante disagreement and the 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 subjective 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, subjective firm-level 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 subjective uncertainty. Our evidence supports models in which the negative effects of uncertainty shocks do not necessarily lead to later realized changes in risk; see, for instance, Ilut and Schneider (2014) and Angeletos et al. (2018).

Figure 2 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 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 50 percent in the manufacturing sector.

Beyond business cycle effects, our measure was also affected by political instability in 2019, reaching levels comparable with the SDC.

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' characteristics, showing that firm-level uncertainty is a persistent process. Our empirical analysis finds that uncertainty fluctuations at the firm level predict significant 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.

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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)			
$s^e_{avg,f} - s^e_{min,f}$			0.28***	0.29***	0.09***
			(0.00)	(0.00)	(0.00)
$s^e_{max,f} - s^e_{avg,f}$			0.28***	0.10***	0.30***
			(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 dependent 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

	$\sigma_{max-min,f,t}$	$s^e_{min,f,t}$	$s^e_{max,f,t}$	$Down.Unc._{f,t}$	$Ups.Unc._{f,t}$
	(1)	(2)	(3)	(4)	(5)
$s^e_{avg,f,t}$	0.09***	0.67***	0.76***	0.29***	0.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Abs.Forec.Error_{f,t-1}$	0.04***	-0.02***	0.01**	0.05***	0.05***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
$\Delta Sales_{f,t-1} > 0$	0.01	0.00	0.02***	-0.00	-0.04***
	(0.13)	(0.55)	(0.00)	(0.51)	(0.00)
$\Delta Sales_{f,t-1} < 0$	-0.05***	0.02**	-0.03***	-0.02***	-0.04***
	(0.01)	(0.04)	(0.00)	(0.00)	(0.00)
Observations	7780	7784	7780	7464	5572
R^2	0.44	0.77	0.80	0.55	0.43

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. Downside uncertainty and upside uncertainty are defined as $s^e_{avg,f,t} - s^e_{min,f,t}$ and $s^e_{max,f,t} - s^e_{avg,f,t}$, respectively.

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

	Uncertainty: Estimated $\beta_{max-min,h}$				
Horizon=h	0	1	2	3	4
Capacity Utilization (t+h)	-0.722*	-0.410*	0.050	0.049	0.402
	(0.09)	(0.09)	(0.92)	(0.93)	(0.31)
Total Hours (t+h)	-0.700*	-0.749***	-0.395	-0.688	-0.005
	(0.06)	(0.01)	(0.38)	(0.11)	(0.99)
Hours-per-Worker (t+h)	-0.221*	-0.030	-0.208	-0.051	0.013
	(0.06)	(0.35)	(0.39)	(0.26)	(0.96)
Real Investment (t+h)	0.712	-3.728**	-2.225*	1.489	3.882*
	(0.45)	(0.02)	(0.08)	(0.23)	(0.06)
Growth Rate of Cash Holdings (t+h)	0.088*	-0.052	-0.068*	-0.008	-0.144
	(0.05)	(0.22)	(0.07)	(0.98)	(0.71)

Note: The table reports ordinary least squares estimates of $\beta_{max-min,h}$, the estimated coefficient on $\sigma_{max-min,f,t}$ in Equation 1. $\sigma_{max-min,f,t}$ is standardized so that $\beta_{max-min,h}$ is the economic effect predicted by a standard deviation increase in $\sigma_{max-min,f,t}$. 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. Variables of interest are standardized so that coefficients report the economic effects of an increase in uncertainty equal to one standard deviation.

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

Panel A - Downside Uncertainty: Estimated $\beta_{avg-min,f,t}$					
Horizon=h	0	1	2	3	4
Capacity Utilization (t+h)	-1.069**	-0.341	0.277	0.776**	0.718
	(0.01)	(0.57)	(0.85)	(0.02)	(0.15)
Total Hours (t+h)	-0.732*	-0.622*	-0.359	-1.063**	0.302
	(0.06)	(0.09)	(0.36)	(0.03)	(0.45)
Hours-per-Worker (t+h)	-0.479***	-0.586	-0.586*	-0.921	0.661***
	(0.01)	(0.12)	(0.09)	(0.23)	(0.001)
Real Investment (t+h)	0.285	-3.259*	-0.007	-3.050**	9.517***
	(0.88)	(0.07)	(0.99)	(0.04)	(0.01)
Growth Rate of Cash Holdings (t+h)	0.123*	-0.014	-0.059	0.109**	0.041
	(0.06)	(0.81)	(0.32)	(0.05)	(0.17)

Panel B - Upside Uncertainty: Estimated $\beta_{max-avg,f,t}$					
Horizon=h	0	1	2	3	4
Capacity Utilization (t+h)	-0.091	-0.023	0.270	-0.542	0.259
	(0.79)	(0.97)	(0.70)	(0.27)	(0.20)
Total Hours (t+h)	-0.453	-0.698	0.155	0.156	-0.276
	(0.38)	(0.17)	(0.74)	(0.86)	(0.78)
Hours-per-Worker (t+h)	-0.191	-0.328	0.052	-0.220	-0.269
	(0.45)	(0.39)	(0.90)	(0.47)	(0.61)
Real Investment (t+h)	1.146	-1.016	-1.219	4.399	1.435
	(0.61)	(0.67)	(0.67)	(0.21)	(0.39)
Growth Rate of Cash Holdings (t+h)	-0.045	-0.078*	-0.005	-0.063	-0.040
	(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. 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. Variables of interest are standardized so that coefficients report the economic effects of an increase in downside and upside uncertainty equal to one standard deviation.

Table 6: Correlation between Subjective and Realized 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 subjective uncertainty $\sigma_{max-min,agg,t}$. The sample period is from 1997 to 2021.

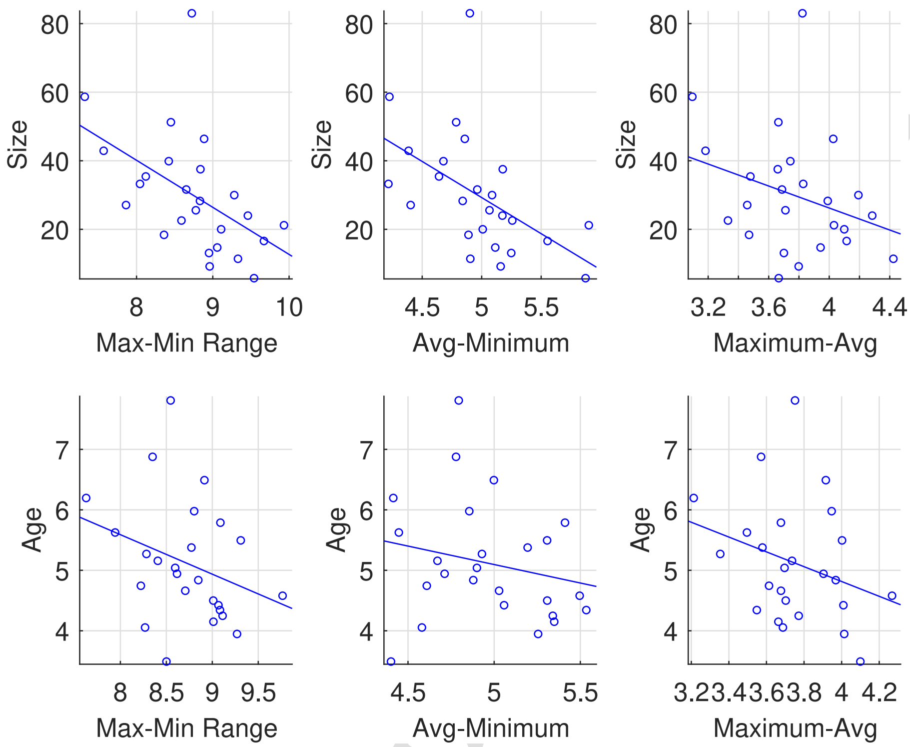

Figure 1: Components of Uncertainty, Age, and Size

Note: Charts report the max–min range, the average –minimum, and the maximum –average expected sales for 25 quantiles versus size and age, computed by pooling observations from 1996 to 2021.

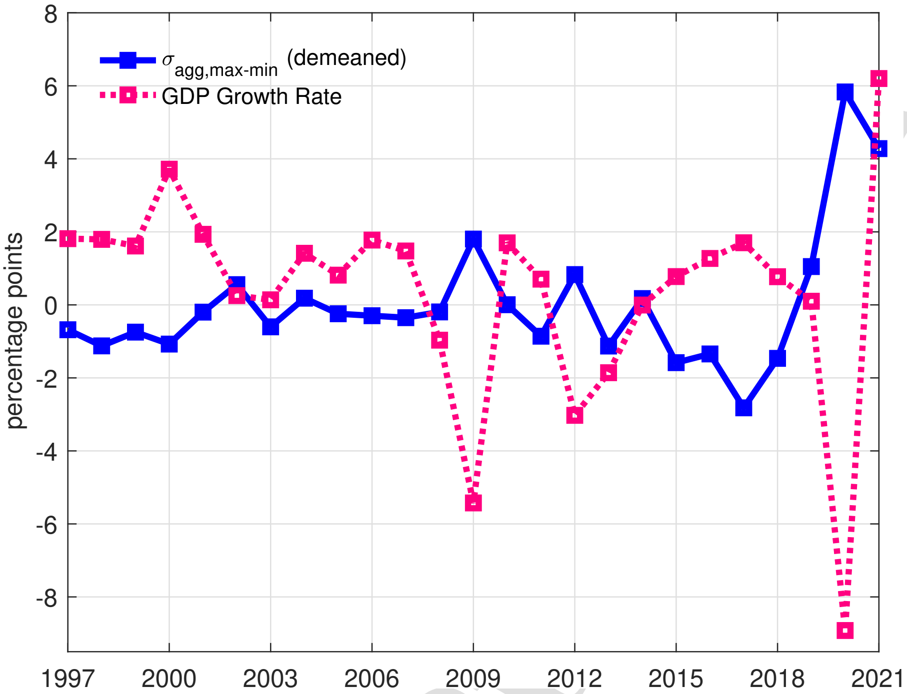

Figure 2: Uncertainty and GDP Growth

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.

Research Highlights for "The Economic Effects of Firm-Level Uncertainty: Evidence Using Subjective Expectations"

1. Use managers' expectations to construct measures of ex ante firm-level uncertainty
2. Firm-level uncertainty is a persistent process that lasts for a few years
3. Firm-level uncertainty reduces firms' hours, investment, and increases cash holdings
4. Negative effects of uncertainty only when it originates from downside uncertainty
5. Aggregate ex ante uncertainty countercyclical but uncorrelated with typical proxies