Short and Long Run Uncertainty

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Abstract

Uncertainty appears to have both a short-run and a long-run component, which we measure using firm and macro implied volatility data from equity options of 30 days to 5 years duration. We ask what may be driving uncertainty over these different time horizons, finding that policy uncertainty, interest rate volatility, and currency volatility are particularly associated with long-run uncertainty, while oil price volatility and CEO turnover appear to impact short- and long-run uncertainty about equally. Examining a panel of over 4,000 firms from 1996 to 2016 we find that investment is relatively more sensitive to long-run uncertainty than hiring, and about as sensitive to long-run uncertainty as R&D. Investment is also more sensitive to the overall level of uncertainty than both R&D and hiring, holding fixed the relative magnitude of short- versus long-run uncertainty. We investigate the channels underlying these different sensitivities to short- versus long-run uncertainty, and show empirically and in simulations that lower depreciation rates and higher adjustment costs explain why investment is more sensitive to longer-run uncertainty. Collectively, these results suggest that recent events that have raised long-run policy uncertainty may be particularly damaging to growth by reducing investment and R&D.

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1 Introduction

Uncertainty has received substantial attention as a potential factor shaping aggregate economic outcomes. For example, the Federal Open Market Committee minutes repeatedly emphasize uncertainty as a key factor driving the 2001 and 2007-2009 recessions, while Stock and Watson (2012) state that "the main contributions to the decline in output and employment during the [2007-2009] recession are estimated to come from financial and uncertainty shocks."

In the summer of 2016 the world economy was rocked with one such uncertainty shock when the United Kingdom voted to leave the European Union. But the Brexit vote generated no uncertainty about the economic policies or fundamentals in place during the weeks and months immediately following the vote. Instead, the referendum results created huge questions about the future of the UK's trading relationships, the long-run immigration status of European Union citizens living in the UK and vice versa, and more broadly about the long-run outlook of the British, European, and global economies. Similarly, the election of Donald Trump to the US Presidency in November 2016 produced a dramatic rise in policy uncertainty, particularly over longer-run policies regarding trade, immigration, taxation and healthcare reform.

This paper seeks to investigate whether short- and long-run uncertainty impact the economy equally by exploiting information about the time profile of uncertainty embedded in equity options of different durations. Equity options are issued at a range of durations from 30 days to 2 years for individual equities and 30 days to 10 years for the overall S&P 500 index, yielding firm-specific and macro implied volatility curves. The well-known VIX is a measure of the 30-day implied volatility of the S&P 500, but it is possible to apply the formula of the VIX to options with longer expiration horizons to obtain measures of longer-run stock market volatility. In Figure 1 we show how at a given point in time this "generalized VIX" varies with the maximum expiration of the options used to calculate that implied volatility, tracing out the time profile of uncertainty.

We begin by documenting that two principal components, roughly corresponding to "level" and "slope", account for up to 99 percent of the total variance in both the macro and firm-specific volatility curves. In effect, this result means that volatility curves are approximately linear, which we can already see in Figure 1. We argue that the changing level and slope of volatility curves reflects fluctuations in the time profile of uncertainty that could influence different firm decisions whose payoffs have different horizons. For example, investment and R&D as longer-run decisions may respond more strongly to long-run uncertainty than hiring.

Before going further, we ask what might drive flucturations in short- versus long-run implied volatility at the firm level. Examining five factors that vary at the firm-quarter level - the price of oil, interest rate exposure (via leverage), exchange rates, policy uncertainty, and CEO turnover - we find that policy uncertainty has a larger impact on long-run versus short-run uncertainty. This result is perhaps not very surprising given the longer-run focus of many of the major policy debates of recent years, including discussions about the US debt ceiling, health-care, immigration reform and involvement in foreign wars. Exposure to interest rate volatility also co-moves strongly with longer-run uncertainty, perhaps reflecting the impact of interest rates on longer-run, forward-looking activity like investment and R&D. We also find that exposure to currency volatility is predictive of movements in the levels of longer-run implied volatility. By contrast, we find oil price volatility and CEO turnover appear to impact both short-run and long-run uncertainty about equally.

To investigate the hypothesis that different firm policies react differently to short- versus long-run uncertainty, we build a panel dataset of over 4,000 firms from 1996 to 2016 combining data on firm-specific option implied volatiliies across across a range of horizons and standard data on real and financial variables from US publicly-traded companies. We find that investment, R&D activity, and employment are all significantly reduced by uncertainty, but investment and R&D are significantly more responsive to long-run uncertainty than employment. Investment is also more sensitive to the overall level of uncertainty, holding fixed the slope of the uncertainty profile.

Observing these relationships, we conjecture that the differential sensitivity to short- and long-run uncertainty across different types of investments is a result of differences in adjustability and durability. To test this conjecture we collect data at the industry-year level on the rate of depreciation of physical capital, and the share of structures versus equipment in the total physical capital owned by businesses in each industry and year. We find that the differential sensitivity of investment to long-run uncertainty relative to hiring is comes entirely from the sub-sample of our data with above-median share of structures, or below-median depreciation. This finding is consistent with our intuition that greater adjustment costs and lower depreciation make capital investment longer lived, and therefore more sensitive to long-run uncertainty.

Finally, we use simulations from a model with short- and long-run uncertainty processes to verify quantitatively that differences in durability and adjustability can jointly explain why investment drops more than hiring under long-run uncertainty. The firms in the model produce using two factors - capital and labor - which, again, are distinguished by capital having higher adjustment costs and lower depreciation rates. Consistent with our empirical results, the greater adjustment costs and (more importantly) greater durability of capital make it more responsive to long-run uncertainty than hiring in the model.

Our findings in this paper highlight how factor inputs with low depreciation rates (like buildings and longer-lived equipment) and those with high adjustment costs (like intangibles and organizational capital) are going to be particularly sensitive to long-run uncertainty. As such, the recent increases in policy uncertainty in the US - which, again, is a key driver of long-run uncertainty - may play a role in explaining the puzzlingly low level of aggregate investment (noted, for example, by Gutiérrez and Philippon (2016)), and low TFP growth rates (given the importance of intangible investment and R&D for TFP growth) in recent years. Similarly, we predict that the United Kingdom might face depressed investment and growth in the years following the Brexit vote as long as there is outstanding uncertainty about the longer-run future of British economic policy and trading relationships.

Our paper relates most obviously to the empirical literature focused on the impact of uncertainty for investment (and to a lesser extent hiring) - for example, Bernanke (1983), Dixit and Pindyck (1994), Caballero et al. (1995) and Abel and Eberly (1996). It is also related to the empirical literature that studies the impact of real frictions on investment dynamics. For example, Leahy and Whited (1996), Guiso and Parigi (1999) and Bloom, Bond, and Van Reenen (2007) all provide evidence suggesting that firm-level uncertainty shocks reduce firms' investment and hiring, while Romer (1990), Ramey and Ramey (1995), Bloom (2009), Fernández-Villaverde et al. (2011) provide evidence suggesting macro uncertainty shocks appear to drive business cycle fluctuations[1]. However, none of this literature focuses on the difference between short-run and long-run uncertainty. Perhaps closer to our paper is the asset pricing literature examining the volatility curve , including Bekaert and Hoerova (2014) and Dew-Becker et al. (2015). In a closely related paper Berger et al. (2017) study whether aggregate realized volatility or expectations of future volatility are associated with contractionary movements in macro variables, finding that expectations about future macro volatility have a hard time explaining contractions after accounting for current realized volatility. Our approach differs from theirs in that we focus on how real activity at the firm level is linked to fluctuations in the *idiosyncratic* rather than macro volatility curve, finding strong associations between the time profile of volatility and investment, hiring, and R&D growth.

We proceed by describing our data and providing more details about how we measure short- versus long-run uncertainty in Section 2. Then we asking what drives short- versus long-run uncertainty in section 3. In Section 4 we present the main empirical results on the response of investment, R&D, and hiring to uncertainty, while Section 5 we develop our model and simulation results. Section 6 concludes.

2 Data and Measurement

2.1 Measuring Short- and Long-run Uncertainty

We use data on option implied volatilities as our empirical measures of short- and long-run uncertainty at the macro and firm levels. Formally, an implied volatility measures the expected risk-neutral volatility in the price of the underlying asset over the horizon covered by the maturity of the option. Implied volatilities are often considered forward-looking measures of uncertainty, precisely because they reflect market-based expectations about returns on the

[1]See also Kehrig (2011)'s paper on countercyclical productivity dispersion; Christiano et al. (2014)'s, Arellano et al. (2012)'s and Gilchrist et al. (2014)'s papers on uncertainty shocks in models with financial constraints; work by Gilchrist and Williams (2005) on uncertainty, investment and capacity; Basu and Bundick (2012)'s paper on uncertainty shocks in a new-Keynesian model; Fernández-Villaverde et al. (2015)'s paper on fiscal policy uncertainty; Knotek II et al. (2011)'s paper on durable consumption and uncertainty; and Bachmann and Bayer (2013)'s paper on microeconomic level uncertainty with capital adjustment costs.

underlying security. The VIX, published by the Chicago Board of Options Exchange, is a well-known index of the 30-day implied volatility of the S&P 500, and is often used as a proxy for measuring short-run US macro uncertainty.

We argue that implied volatilities estimated using options of different horizons can be used to measure uncertainty about a particular firm or the aggregate economy looking ahead over different horizons. In Figure 2 we show that there is strong comovement between option implied volatilities of the stock market for a specific horizon and survey-based measures of subjective uncertainty about GDP growth looking ahead to that same horizon. The measures of subjective uncertainty come from the European Central Bank's quarterly Survey of Professional Forecasters (SPF), which asks respondents to provide subjective probability densities for the Eurozone's rate of real GDP growth looking one, two, and five years forward[23]. In Figure 2a we show that subjective uncertainty about GDP growth looking one year ahead is highly correlated with both the 1-year (generalized) VIX, and the 1-year VSTOXX, the latter which applies the methodology of the VIX to options on the Euro STOXX 50 index of major Eurozone publicly-traded companies. In Figure 2b we show there is also strong comovement between the 5-year VIX and 5-year subjective uncertainty[4]. Also in Figure 2c we show that the difference or slope between 5-year and 1-year GDP uncertainty is also well-tracked by the difference between the 5-year and 1-year VIX, so the "slope" as well as the "level" of the volatility curve reflect their analoges in the time profile of uncertainty. Based on this correspondence, we proceed using implied volatility to measure both short- and long-run uncertainty in the rest of the paper.

In our empirical results we focus our attention on firm-specific implied volatility, which

[2] We thank the authors of Kenny and Melo Fernandes (2017) for graciously sharing these series on subjective uncertainty. They fit a unimodal Beta distribution to each SPF respondent's subjective probability distribution for GDP growth looking one, two, or five years ahead from the latest data release, and use the implied standard deviation to measure uncertainty. See Appendix Figure 1 for a screenshot of the relevant survey questions.

[3] We do not use data from the US SPF because we find it to be less well suited for the exercise at hand. For instance, the US SPF has few questions about longer run forecasts. It asks respondents for forecasts of the current and next calendar years, which is problematic because the horizon of the forecast changes over time. Additionally, respondents to the US SPF provide probability densities for the "year-over-year growth of the annual average level" of real GDP. By contrast, the ECB's SPF clearly asks for the respondent's subjective probability density for the Eurozone's real GDP growth looking one, two, and five years ahead from the latest data release. We refer interested readers to the Philadelphia FRB and ECB's respective webpages for details on both surveys.

[4] We do not currently have data on a 5-year VSTOXX, so we use the VIX given the good fit in Figure 2a.

can also be estimated using options of any horizon, making it possible to measure expected uncertainty over a wide range of durations. We obtain individual firm implied volatility data from 1996 onwards from OptionMetrics, a database covering all exchange-listed options in the United States. They provide implied volatility figures for standardized options with horizons of 30, 60, 91, 152, 182, 273, 365, and 730 days, conditional on the firm having options trading at or beyond that maturity[5]. Throughout our empirical work we use the average of the put and call implied volatilities at each given duration, but our findings are robust to using either of the two instead, as the put and call implied volatility data are nearly identical. Because our data on firm financials is at an annual or quarterly frequency (see Section 2.3), we average daily implied volatility observations into a single uncertainty measure by firm-quarter or firm year. We link a firm's investment behavior in a given quarter with the implied volatility measured in the previous quarter, to mitigate reverse causality concerns and to exploit the fact that implied volatilities are forward-looking measures of uncertainty. Analogously, our baseline estimates link firm-level observations in a given fiscal year with the average implied volatility in the last quarter of the previous fiscal year.

2.2 Level and Slope of the Time Profile of Uncertainty are Sufficient Statistics

We document the stylized fact that volatility curves (the plot of implied volatility over different durations, measured at a point in time) are approximately linear, so we can approximate the entire volatility curve with two points, as is analogously done in finance with the term structure of interest rates, for example by Harvey (1988), Estrella and Hardouvelis (1991), and Ang and Piazzesi (2003). Our stylized fact is consistent with other papers in the the finance literature that focus on the term structure of variance swaps on the S&P 500, and expectations about future stock market volatility, including Ait-Sahalia et al. (2015), Egloff et al. (2010), and Berger et al. (2017).

In Table 1 we formally show that both the macro and firm-specific volatility curves are

[5]Option Metrics uses observed option trading data to provide information about theoretical "standardized" options, which are theoretical American put and call options with strike prices equal to at-the-money forward stock prices and fixed maturities. See Appendix B for more details.

well described by two principal components, roughly corresponding to "level" and "slope". First, we conduct a principal component analysis of daily observations of the generalized VIX between mid-2002 and mid-2016, showing the results in Table 1a. Running this exercise with our volatility in both levels and logs, we find that the first principal component loads positively and with a similar magnitude on each of the 30-day, 3-month, 6-month, 1-year, 2-year, 3-year, 5-year and 10-year generalized VIX. The second principal component, by contrast, loads negatively on the most short-run horizons, with the loading increasing monotonically for longer horizons, and is positive for horizons of two years or more. These results are consistent with the first principal component being associated with the overall level of the volatility curve, and the second component with the slope. Furthermore, these two components together account for 99 percent of the joint variance of the volatility curve. Although the first component on its own accounts for about 90 percent of the variation, fluctuations in the second still account for a sizeable 8 to 9 percent of the variation.

We verify that the above results also hold for our quarterly measures of firm-specific implied volatility in Table 1b. To restrict attention to idiosyncratic, within-firm variation the firm-specific volatility curves - which will be the variation we will use to identify our main empirical results in Sections 3 and 4 - we run our principal components exercise on residuals of firm-specific implied volatility after regressing on firm and date fixed effects. As with the daily macro volatility data, we find that the first principal component loads positively and about equally on each of the 30-day, 3-month, 6-month, 1-year, and 2-year implied volatility, whether we use levels of logs of volatility. We also find that the second component loads more negatively on shorter horizons and more positively on longer ones, and that the components toger account for 99 percent of the total within-firm variance of firm-specific volatility curves. Finally, we also find that 90 of that 99 percent is captured by the first "level" component, exactly as with the macro volatility curve.

We exploit the result that volatility curves are well described by their "level" and slope "components" to overcome the challenge that firm equity options with longer maturities (especially for one year and beyond) are traded less frequently, meaning that implied volatility data at these longer horizons is often missing. This lack of data both decreases sample size when these longer-run firm-level uncertainty measures, and also potentially raises issues about the selection of larger firms whose equity options trade at these longer horizons. Because we have documented that the level and slope of the volatility curve capture most of the variation, for most of our analysis below we use a firm's 30-day implied volatility to measure the level overall uncertainty, and the difference between a firm's 6-month and 30-day implied volatilities to measure the slope.

We verify the viability of this strategy in Table 2, even though our results in Table 1 suggested that restricting attention to level and slope would be sufficient. Starting with column (1) we show that the quarterly two-year firm-specific implied volatility (the longest duration at which firm equity options are commonly available) is well predicted by the corresponding level (30-day implied volatility) and slope (difference between the 6-month and 30-day volatilities) data, with an R-squared of 0.946. Hence, if we have data for the 30-day and 6-month implied volatilities for a firm - selecting the 30-day and 6-month durations as these are commonly traded - we can use them to proxy for the intercept and slope of the full (approximately linear) volatility curve. In columns (2) to (5) we repeat this exercise for daily observations of long-run macroeconomic uncertainty up to a five year horizon using the generalized VIX. Again we see consistent R-squared values above 0.9. This strong linearity is shown graphically in Figure 3 which plots the 2-year and 5-year VIX against their fitted values from the regressions of the 30-day and 6-month VIX in columns (2) and (4), where we see both the good overall fit and the fact this fit appears equally good at low, medium and high levels of implied volatility.

2.3 Matching our Implied Volatility Data with Compustat

We match our firm-specific implied volatility data to quarterly and annual accounting and financials data from Compustat, dropping firm-quarters and firm-years with negative book value of assets, negative sales or stockholders' equity, as well as those with missing capital expenditures. Our quarterly sample ranges from 1996Q2 to 2016Q2, while the annual sample covers 1997 to 2016. As is standard in the empirical literature on investment and uncertainty (e.g. Gulen and Ion (2015)), we exclude SIC codes corresponding to utilities and financials. The resulting matched dataset overrepresents large and fast-growing firms as these are the firms with a sufficient volume of equity option transactions for Option Metrics to provide implied volatility estimates. See Appendix Table 1 for summary statistics on the matched quarterly and annual samples, and Appendix Table 2 for some results on which firms have non-missing data on 30-day and 6-month implied volatility.

We measure investment as firms' capital investment rate (capital expenditures per existing unit of capital). Given our large firm sample we have no negative or zero investment rates so we take logs to reduce the influence of large outlier investment rates. To measure quarterly R&D activity we first impute quarterly R&D expenditures (XRD) to be zero whenever a firm's R&D expenditures are missing but were previously positive [6]. Then we construct R&D growth as our main measure of R&D activity. Similarly, we measure hiring as the growth in the reported number of employees across years. We construct standard first-moment controls in both our quarterly and annual datasets, including the ratio of cash flows (i.e. operating income) to assets, Tobin's q (the ratio of the firm's enterprise value to the book value of it's assets) and sales growth.

Following Davis, Haltiwanger and Schuh (1996), we measure all growth rates (in the number of employees, sales, or R&D expenditures) as the change in variable x_t between years $t-1$ and t, divided by the average of the two years (with two consecutive periods of zero given a zero growth rate). DHS growth rates are well-known to approximate the log-change for small growth rates, are symmetric around zero, and accommodate entry and exit with bounded values of plus and minus two. The latter property is especially important for R&D expenditures, where it is conceivable that even Compustat firms may go from having positive R&D to zero (and vice versa) from one quarter to the next.

3 What Drives Short- and Long-run Uncertainty?

In the preceding pages we have argued that variation in the level and slope of firm-specific volatility curves reflects the market's uncertainty about the firms' short- and long-run prospects.

[6] For example, if a firm did not report R&D until 2005, reported positive R&D from 2005 to 2010, and then stopped reporting R&D after 2010 we would impute zero R&D from 2011 onwards (but leave pre-2005 data as missing). This assumes that post 2010 this was a conscious decision not to report R&D but pre 2005 the data could genuinely have been missing. The reason for this approach is that the reporting of R&D expenditure by firms has been increasing over time due to more rigorous accounting standards and more generous tax treatment of R&D.

But what are the economic reasons leading market actors to perceive the volatility of firm equity to be high or low for any given horizon? In this section, we construct firm- and sector-specific measures of exposure to several sources of uncertainty, including economic policy, oil prices, interest rates, and changes in management. Then we ask whether these exposure measures are differentially associated with long-run uncertainty, shedding some light on what may drive fluctuations in the term structure of uncertainty.

3.1 Data on Uncertainty Drivers

We focus on a set of drivers of firm-level uncertainty that can be measured at a quarterly basis. In particular, we focus on oil and currency price volatility as suggested by Stein and Stone (2013) and Alfaro et al. (2017), economic policy uncertainty (EPU) as measured by Baker, Bloom, and Davis (2016), interest rate volatility, and CEO turnover as implied by Bertrand and Schoar (2003)'s work highlighting the importance of CEOs for company performance. We acknowledge that there are potentially many other factors driving idiosyncratic firm-level volatility, with our focus on these five driven by data availability. However, these five factors do capture a number of the key drivers of firm-level uncertainty, and also highlight their differential impacts on short- and long-run uncertainty.

We construct sector-level exposure to oil and currency price volatility using a two-step procedure. First, we estimate the sensitivity of individual stock returns to oil and currency price fluctuations by two-digit SIC industries, controlling for firm fixed effects and market returns. We estimate the following equation for the daily stock returns of firm i in sector j and date t :

$$r_{ijt} = \alpha_i + \beta_{jm} r_{mt} + \beta_{jo} r_{\text{oil}t} + \Sigma_k \beta_{jk} r_{kt} + \varepsilon_{it}.$$

Here r_{mt} are returns on the S&P 500, $r_{\text{oil}t}$ are oil price returns, and r_k are returns from holding currency k, while α_i is a vector of firm fixed effects. The data on stock returns comes from CRSP, and oil price and exchange rate data from Bloomberg. We use data from 7 currencies which the Federal Reserve Board has designated as "major" currencies and which it uses to construct the nominal and real trade-weighted U.S. Dollar Index of Major

Currencies[7]. Our coefficients of interest are β_{jo} and each of the β_{jk}'s (one for each particular currency), which capture the sensitivity of stock returns of firms in industry j to fluctuations in oil prices and exchange rates, respectively. We run this regression on a pre-sample period ranging from 1985 to 2004 and assume that the estimated sensitivities carry over to our main sample period from 2005 onwards[8]. This ensures that our estimated sensitivities are not dependent on the data in that main sample. In the baseline setup we estimate the sensitivities by SIC-2 industry, restricting attention to sectors that have data for at least 20 firms during the estimation period.

The second step in constructing volatility exposure to oil and currencies involves multiplying the absolute value of each industry's sensitivity by a measure of the volatility of the commodity or currency in question. We use the log of 30-day implied volatility for oil and each of our currencies (obtained from Bloomberg and averaged over a calendar quarter), and construct an overall measure of currency volatility exposure by adding up over the individual currencies:

$$\text{OilVolExposure}_{ijt} = |\hat{\beta}_{jo}^{weighted}| \cdot \log(\sigma_{ot}) \tag{1}$$

$$\text{CurrVolExposure}_{ijt} = \sum_{k} |\hat{\beta}_{jk}^{weighted}| \cdot \log(\sigma_{kt}). \tag{2}$$

In constructing these variables, we attempt to capture the fact that certain industries might be differentially exposed to fluctuations in exchange rates and commodity prices, having controlled for overall market and firm conditions. For example, the air travel and oil and gas sectors might be differentially exposed (respectively, negatively and positively) to oil price movements. When oil prices are more volatile, these more exposed sectors should perceive

[7] See https://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf. The seven currencies are Canadian Dollar, Japanese Yen, Euro (or European Currency Unit prior to 1999), Australian Dollar, Swedish Krona, Swiss Franc, British Pound. The same set of currencies is used in Alfaro et al. (2017).

[8] Although we have firm-level implied volatility data from 1996, we do not have implied volatility data for oil prior to 2005, meaning that we must restrict our attention to 2005 and later for this "drivers" exercise.

significant oil uncertainty, especially in comparison with other sectors that are less exposed to oil. We therefore multiply our measure of oil price uncertainty by the absolute value of the sensitivity. Firms in highly exposed sectors will be highly affected by oil price volatility regardless of whether they benefit from higher or lower oil prices. The same logic applies for firms in sectors that are exposed to one or another major foreign exchange market. For example, domestic atomobile manufacturing may be highly affected by fluctuations in the Japanese Yen due to significant competition from Japanese firms, and in our measure will be particularly exposed to volatility on the Yen-Dollar exchange rate.

To reduce the degree of measurement error induced by using estimated sensitivities as regressions, we weight each sensitivity by its relative degree of statistical significance within the industry before constructing these exposure variables. This approach follows the strategy in Alfaro et al. (2017). Namely, we define the weighted sensitivity of industry j's stock returns to oil as $\hat{\beta}_{jo}^{weighted} = \omega_{jo}\hat{\beta}_{jo}$ where $\omega_{jo} = |t_{jo}|/(|t_{jo}| + \sum_k |t_{jk}|)$ and t_{jl} is the t-statistic of estimated sensitivity β_{jl}. Analogously, for industry j and currency k, $\hat{\beta}_{jk}^{weighted} = \omega_{jk}\hat{\beta}_{jk}$ and $\omega_{jk} = |t_{jk}|/(|t_{jo}| + \sum_k |t_{jk}|)$.

Our data on quarterly firm-specific exposure to economic policy uncertainty (EPU) comes from Baker et al. (2016). This variable is constructed by first scaling an industry's share of revenues from Federal Government contracts by the aggregate news-based EPU index. Then, individual firms are assigned to an industry according to their firm-level line of sales data, so this results in a firm-by-quarter policy uncertainty index[9]. We refer interested readers to the original article for more details on this procedure.

We measure a firm's exposure to interest rate volatility in a given quarter based on its leverage and the option implied volatility on US Treasury yields. Namely, we multiply the ratio of a firm's total debt (short term plus long term liabilities) to total assets as reported in Compustat by the natural logarithm of the average level of the TYVIX index during the calendar quarter. The CBOE computes the TYVIX by applying the methodology of the VIX to 30-day futures on 10-year Treasury Notes; thus, the TYVIX serves as a measure of interest rate volatility. By interacting this volatility series with the firm's leverage, we aim to

[9]Following Baker et al. (2016) when we use EPU exposure as a right-hand-side variable, we also include a control that interacts federal spending as percent of GDP with firm's exposure to government purchases (again, based on line-of-business data) to control for the direct effect of fiscal policy changes on volatility.

capture differential exposure to uncertainty about monetary policy and interest rates across firms with different balance sheet positions.

Our data on executive turnover comes from Execucomp, a database containing information on top executives in Compustat firms, in particular listing the dates during which CEOs held office. This is a simple way of capturing an idiosyncratic event with potentially significant repercussions to the firm's future, and potentially affecting the market's uncertainty about the firm. In our baseline measure we flag all firm-quarters in which Execucomp records a CEO leaving office, but we find similar results if we restrict to cases in which the cited reason for the CEO's departure is not retirement.

3.2 Drivers Results

We study how oil, currency, and interest rate volatility, economic policy uncertainty, and CEO turnover are associated with short- and long-run uncertainty at the firm level by regressing quarterly measures of firm implied volatility on each of these drivers, including firm and date fixed effects. We display the results in Table 3, splitting them into four panels across two pages.

Starting with the top panel focusing on short-run 30-day implied volatility we see individually in columns (1) to (5) and jointly in column (6) that all of our candidate drivers are positively correlated with firm-specific uncertainty, and all but currencies are are statistically significant . In particular, oil-price exposure is highly significant, and has an extremely large (and robust) coefficient. Economic policy uncertainty and exposure to interest rate volatility are also highly significant and larger in magnitude than currency exposure and CEO churn. In the second panel we look at each of the drivers' association with the longer-run (6 month) implied volatility and again see that individually each of economic policy uncertainty, oil, currency and CEO turnover is positively associated with longer-run uncertainty, with quantitatively similar results in the joint specification of column (6). Now the oil volatility exposure is about 25 percent smaller in magnitude in comparison with the top-panel, while the policy-uncertainty measure is still highly significant and slightly larger in magnitude in both the individual joint specifications.

In the bottom panels of Table 3 we ask which of the drivers are still predictive 6-month implied volatility after controlling for the overall level of the vol curve, namely by adding 30-day volatility as an additional regressor. We argue that drivers differentially associated with long-run uncertainty should have predictive power over 6-month implied volatility even after adding this control[10]. Our results show that economic policy uncertainty and interest rate volatility exposure are still positive and significant in the individual and joint specifications, even though their magnitudes are smaller than in the second panel from the top. These smaller magnitudes probably reflect the fact that the slope component of the firm-specific volatility curve accounts for only about 9 percent of the total variance, with the rest largely attributable to the level component, as we say in Table 1. Currency volatility, while insignificant in the top panels is now significant, apparently able to explain relative movements in 6-month versus 30-day volatility although not their level. Oil price volatility and CEO turnover experience even larger drops in magnitude, effectively dropping out of the regressions, with similar results in the joint specification in column (6). These patterns suggest that policy uncertainty, interest rate volatility, and - perhaps to a lesser degree - currencies are drivers of long-run uncertainty. CEO turnover and oil prices, by contrast are at best associated with movements in the level but not the slope of the volatility curve.

Overall our results are intuitive, suggesting that slow-moving and potentially more radical drivers of uncertainty like economic policy and capital structure are linked to long-run uncertainty. It will be useful to keep these results in mind later in the paper when we explore why investment, hiring, and R&D might react differently to movements in short- versus long-run uncertainty.

4 Investment and Hiring under Short-Run and Long-run Uncertainty

In this section we document our main empirical finding that the investment, R&D activity, and hiring behavior of large, publicly-traded firms in the US is negatively impacted by both

[10]This exercise controls flexibly for the strong (but perhaps imperfect) comovement across different parts of the volatility curve. In previous versions of this paper we instead used the slope of the vol curve, namely the log difference between the 6-month and 30-day implied volatilities as a dependent variable with similar results.

short- and long-run uncertainty. The sensitivity of each of these activities to the profile of uncertainty differs, however. We document that capital investment is more sensitive to both short and long-run uncertainty than hiring, while R&D activity is about equally sensitive to long-run uncertainty than hiring, but less sensitive to short-run uncertainty. Finally we document that this response to long-run uncertainty is mainly driven by more highly-levered firms. Replication files for all the empirical results are available online at this link.

4.1 Specification and Identification

We study the empirical relationship between investment, hiring and R&D growth against short- versus long-run uncertainty by estimating equations of the form

$$\begin{aligned} Y_{i,t} \quad = \quad & \alpha_i \; + \; \gamma_t \; + \; \beta_1 \log(30dIVOL_{i,t}) \; + \; \beta_2(\log(6mIVOL_{i,t}) \; - \; \log(30dIVOL_{i,t})) \\ & + \delta_1 Q_{i,t-1} + \delta_2 CF_{i,t}/A_{i,t-1} + \delta_3 G_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where i indexes firms and t indexes quarters or years depending the specification; $Y_{i,t}$ is one of our outcome variables, namely one of investment, net hiring, or growth in R&D expenditures; α_i is a vector of firm fixed effects; γ_t is a vector of date fixed effects; $30dIVOL_{it}$ and $6mIVOL_{it}$ are the 30-day and 6-month implied volatilities associated with firm i on date t. In turn, $Q_{i,t}$, $CF_{i,t}/A_{i,t-1}$, and G_{it} are Tobin's q, the ratio of current cash flows to book value of assets, and sales growth[11].

Formally, our results are conditional correlations between our outcome variables and short- and long-run uncertainty, shown in Table 4. In these OLS specifications we use lagged uncertainty to exploit the fact the implied volatility is a forward-looking measure of uncertainty. We also include Tobin's q, cash flow ratio, and sales growth, as well as a full set of firm and date fixed effects to attempt to control for first-moment determinants of investment, R&D growth, and hiring that might be correlated with uncertainty. We acknowledge that these variables cannot control for all unobserved first-moment determinants of investment

[11]Tobin's q is the ratio of the firm's full enterprise value (common and preferred stock capital plus current and long-term liabilities) over the book value of assets. We measure cash flow is measured as income from operating activities, and sales growth as the change in sales over the past four quarters from the previous four quarters, divided by the average over the past eight quarters.

that may be correlated with short- and long-run uncertainty, and they also cannot eliminate concerns about reverse causality so this remains a fairly descriptive exercise.

4.2 Main Empirical Results

In Table 4 column (1) we consider the link between quarterly investment – measured as the ratio in logs of quarterly capital expenditures (CAPX) per unit of lagged net property, plant, and equipment (PPENT) – on the level of uncertainty proxied by the log of 30 day implied volatility, and the slope of the volatility curve measured as the log difference between 30 day and 6 month implied volatility. The specification also includes all of our first moment controls and a full set of firm and date fixed effects. We see that both the level and slope coefficients are negative and highly significant, suggesting both short-run and long-run uncertainty are negatively associated with capital investment.

In column (2) we verify that this negative link between investment and the level and slope of the volatility curve is also present looking at annual data. We move on to look at hiring in column (3) and find that it is also negatively associated with the level and slope of the firm's volatility curve, but this link is smaller in magnitude and also in terms of statistical significance. We again see this finding that hiring declines less than investment when short- but particularly long-run uncertainty is relatively high in column (4) when we use the difference between annual investment and hiring as the outcome of interest.

Turning to column (5) we explore at the relationship between quarterly growth in R&D expenditures and short- and long-run uncertainty, finding now that R&D activity is quantitatively very responsive to long-run uncertainty, but not to the overall level of the volatility curve. This result speaks to a strong deceleration in the growth of R&D expenditures in the presence of long-run uncertainty, which is intuitive if we believe that there are flow adjustment costs to R&D, say, because it is hard to fire scientists or scale down the costs associated with running laboratories, and the payout of this R&D materializes slowly. Then, high long-run uncertainty makes it undesirable to commit to high levels of R&D spending that cannot be easily scaled down even in the far-off future. We find that R&D growth is about as strongly associated with long-run uncertainty as investment, as we see in column (6) where we use the difference between the two as the dependent variable. So firms seem to decelerate their R&D expenditure growth about as strongly as they adjust their investment rates during times of high long-run uncertainty, but investment drops more strongly when the overal level of uncertainty is hight (holding the slope constant), as suggested by the positive and significant coefficient on 30-day implied vol in column (6) [12].

Our results suggests that there is something like a a hierarchy in terms of the relationship between short- versus long-run uncertainty and real activity, with the largest responses to long-run uncertainty in R&D growth and investment, and the smallest decline in hiring. Increases in the level of uncertainty - holding the slope constant - are also linked to declines in investment, and to a lesser degre hiring, but we find no significant deceleration of R&D in these cases. As we discussed in the introduction, the current low levels of investment in the US could be due in part to the high levels of policy uncertainty, which as we saw in Section 3 is linked to both short- and long-run uncertainty, and somewhat more closely to long-run uncertainty. Our result that R&D responds about as as investment to short- and long-run uncertainty furthermore suggests that these high levels of policy uncertainty and long-run uncertainty could have particularly detrimental effects on innovation and aggregate productivity growth in the longer term.

We devote most of the rest of this paper to further exploring what aspects of different types of investment decisions result in the patterns uncovered in this section. In the next section we explore empirically the role of adjustment costs (as proxied roughly by the share of structures versus equipment in industry-level capital) and depreciation rates in explaining why investment might react more than hiring in the face of both short- and long-run uncertainty. Our simulation exercises in Section 5 are an attemp to show more formally that adjustment costs versus depreciation parameters generate differential sensitivity to long- versus short-lived uncertainty shocks in an otherwise standard real options model of investment.

[12] Interestingly, Stein and Stone (2013) find a positive relationship for R&D on uncertainty, but they examine the *level* rather than the *growth* rate of R&D expenditure. We think the growth rate is the correct variable for symmetry with the change in the capital shock and employees, and because this focuses on the short-run response of factor inputs to increased uncertainty as the literature has focused on, following the early theory and empirical papers like Dixit and Pindyck (1994) and Leahy and Whited (1996).

4.3 Robustness Checks

Before turning our attention to what mechanisms are responsible for differential sensitvity of investment, hiring, and R&D growth to short- and long-run uncertainty we show in Table 5 that our baseline results about quarterly investment are robust to small modifications in the specifications.

To begin, we reproduce this baseline specification from column (1) of Table 4. In column (2) we include lagged investment as an additional control to capture the fact that capital expenditures in the current quarter may have been planned for some time, meaning that lagged investment is predictive of current investment and potentially correlated with our (also lagged) measures of short- and long-run uncertainty. However, upon examination it is clear that this is not driving our result that investment responds strongly to both the level and slope of the volatility curve.

In columns (3) and (4) we test the validity of using 6-month implied volatility to proxy for long-run uncertainty, instead using 1-year and 2-year implied volatility. The latter is the longest horizon for which we have implied volatility for individual firms' equity. The point estimates in both columns (3) and (4) are similar to the baseline specification despite having about one-third and one-fifth the sample size, respectively.

Finally, in columns (5) and (6) we consider whether our baseline result changes depending on whether we use firm-specific volatilities from put versus call options. Recall that our firm-specific implied volatility data comes from OptionMetrics, who back out these implied volatility using theoretical, standardized options with fixed maturities like 30 days and 6 months. An observation in this raw data is the implied volatility for a particular firm, horizon, day, and position (put or call). For our baseline analysis we average across puts and calls within a firm-maturity-day triple, before averaging across days within a calendar quarter. In columns (5) and (6) we show that our results are robust to using the implied volatility from either put or call options. In fact, examining the data from puts and calls, we find that they are nearly perfectly correlated.

4.4 The Role of Structures, Equipment and Depreciation

Our basic intuition for why particular forms of forward-looking activity, namely investment in physical capital and R&D growth, are more responsive to long-run uncertainty than others like hiring has to do with the natural horizon of different types of investment. Under this intuition, longer-lived, less reversible or adjustable investments should be particularly sensitive to long-run uncertainty.

To test our intuition empirically we collect data from the Bureau of Economic Analysis on: (1) the share of structures versus equipment in the total amount of physical capital across two-digit NAICS industries and years since 1996; and (2) the rate of economic depreciation of physical fixed assets by industry and year[13]. We map these data onto our merged OptionMetrics-Compustat datasets and ask whether our results look different for firm-years with above- or below-median share of structures and physical depreciation. We view this exercise as a rough look at the role of adjustment costs and depreciation, with the share of structures in an industry's total physical capital serving as a rough proxy for the severity of adjustment costs in the industry, and depreciation directly looking at the life length of capital investments in the same industry [14].

In Table 6 we show that capital's strong relationship long-run uncertainty, and its differential sensitivity to both short- and long-run uncertainty relative to hiring is driven by the subsample of firm-years in industries with above-median share of structures in total industry capital. In column (1) we reproduce our basic result from column (2) of Table 4, but restricting attention to firms and years for which we have data on the share of structures. In column (2), looking at the subsample with below-median share of structures in the industry, we find investment drops less when the level of uncertainty, is higher. Investment also barely drops

[13]To be specific, we downloaded the BEA's data tables for the current cost net stock of private equipment and structures, and their data on the current cost depreciation of private non-residential fixed assets, also broken down by industry. We would ideally use firm-specific measures of equipment and structures, but unfortunately these are not available in Compustat for our sample period. Additionally, we would prefer measures of economic rather than accounting depreciation, so we opt to use the industry-level data from the BEA for that as well.

[14]We also collect data on the rate of depreciation of intellectual property (intangible) assets from the BEA. In Appendix Table 3, we show that the sensitivity of R&D growth to long-run uncertainty comes from the subsample of industry years with above-median intangibles depreciation. Similarly, we show that investment's stronger link to the level of uncertainty relative to R&D growth comes from firm-years with high intangibles depreciation.

with increases in slope of the volatility/uncertainty profile for this subsample. By contrast, in column (3) we find strong declines in investment with the level and slope of uncertainty. In columns (4) to (6) we repeat the exercise focusing now on hiring as an outcome variable.

We find no empirical relationship between hiring and short- or long-run uncertainty from firm-years in industries with low shares of structures, and a statistically significant - though small- relationship between hiring and both the level and slope of the volatility curve in column (6). We interpret the result from column (6) as a product of complementarities between labor and capital that lead labor to respond when capital's adjustment costs are higher. In columns (7) to (9), furthermore, we find that investment's differential sensitivity to long-run uncertainty is attributable to firm-years with a high share of structures in their total capital.

The exercise in Table 7 reveals, in turn, that investment's strong sensitivity to long-run uncertainty arises from the subsample of firm-years in industries that experience low depreciation of physical capital, as seen in columns (1) to (3). Similarly, in columns (4) to (6), hiring declines with long-run uncertainty only in industries that experience low depreciation, and in columns (7) to (9) it is clear that the investment doesn't drop significantly more than hiring in industries where capital investments depreciate quickly, and therefore are more short-lived.

Undoubtedly, our current proxies for adjustment costs and asset life are positively correlated. Specifically, structures are both more long-lived than equipment, and harder to adjust than equipment, so in Section 5 we use simulations to examine whethere there both adjustment costs and depreciation play a role in our resultsl.

5 Simulation

We develop a firm-level partial equilibrium model to help interpret our prior results on the differential sensitivity of R&D, investment, and employment to short- and long-run uncertainty. The model is based on a canonical setup like that considered in Chapter 8 of Adda and Cooper (2003), but features two input factors - capital and labor -, rich adjustment costs, and time-varying uncertainty. Moreover, we allow this firm-specific uncertainty to have both a short-run and a long-run component. We do not include R&D in this baseline model because of the complexity of having three input factors with three investment decisions alongside a first moment driving process plus short and long-run uncertainty, but the implications from the comparison of investment and hiring will naturally carry over to the R&D case.

Solving the model numerically for data-calibrated parameters, we investigate the impact of short- and long-run uncertainty on firm activity on a panel of simulated data. Consistent with the empirical results from Section 4, firms stop investing and hiring in reaction to both short- and long-run uncertainty, but investment drops relatively more than hiring in reaction to long-run uncertainty. We show that the longer life and greater irreversibility of capital in the model are responsible for these patterns. Replication files are available online at this link.

5.1 A Two-Factor Model: Capital versus Labor

Firms are assumed to consist of a number of production units, each making the intertemporal decision to invest and hire workers. On date t each production unit has access to a reduced-form supermodular revenue-generation function based on an underlying Cobb-Douglas physical production function, assuming that other inputs (e.g. materials) are optimized out statically:

$$R(A_t, K_t, L_t) = A_t K_t^{\alpha_k} L_t^{\alpha_l}$$

A_t is a stochastic Hicks-neutral shock to revenue-generating capacity, which we assume to be log-normal and follow an $AR(1)$ process with stochastic volatility:

$$\log A_t = \rho_A \log A_{t-1} + \sigma_t \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0,1) \tag{4}$$

We introduce short- and long-run uncertainty to the model by letting σ_t^2, the variance of innovations to $\log A$, to be the sum of a short-run and a long-run component:

$$\sigma_t^2 = \sigma_{s,t}^2 + \sigma_{l,t}^2 \tag{5}$$

The two volatility components, σ_s and σ_l, follow independent, symmetric Markov chains on two points (i.e. a high and a low state), with the persistence of σ_l being higher than for σ_s. In the simulation we assume production units within a firm have a common volatility process, while innovations to $\log A$, are drawn independently across units within a firm.

Production units choose to invest in new capital and hire workers, both of which become immediately available for production. Capital depreciates at a rate δ_k and workers quit at a rate δ_l, yielding the following laws-of-motion for K and L:

$$\begin{aligned} K_t &= (1-\delta_k)K_{t-1} + I_t \\ L_t &= (1-\delta_l)L_{t-1} + H_t \end{aligned}$$

We assume that $\delta_l \geq \delta_k$, making K longer-lived than L. Investment and hiring are both subject to adjustment costs due to partial irreversibility (capital resale and layoffs result in a loss of $1-\gamma_k, 1-\gamma_l$, respectively of the value of K and L), and are also subject to fixed adjustment costs denoted F_k and F_l. By assumption, K has also higher adjustment costs than L, i.e. $\gamma_k \geq \gamma_l$, and $F_k \geq F_l$. These differences in the life of potential investments, as well as the cost of (especially, downward) adjustability are the key elements of the model that drive firms' different reactions to short- versus long-run uncertainty.

Production units decide every period how much to invest in each of K and L so as to maximize the net present value of cash flows, bearing in mind their current first-moment state A, latest stock of $K$and L, and the current state of the persistent and transitory volatility processes σ_s and σ_l. The complete recursive problem can be stated as follows:

$$
\begin{aligned}
V(A_t, K_{t-1}, L_{t-1}, \sigma_{s,t}, \sigma_{l,t}) &= \max_{I_t, H_t} \left\{ \begin{array}{c} A(K_{t-1}(1-\delta_k)+I_t)^{\alpha_k}(L_{t-1}(1-\delta_l)+H_t)^{\alpha_l} \\ -C(I_t, H_t, K_{t-1}, L_{t-1}; \gamma_k, \gamma_l, F_k, F_l) \\ +\frac{1}{1+r}\mathbb{E}_t[V(A_{t+1}, K_{t-1}(1-\delta_k)+I_t, L_{t-1}(1-\delta_l)+H_t, \sigma_{s,t+1}, \sigma_{l,t+1})] \end{array} \right\} \\
& s.t. \\
K_t &= (1-\delta_k)K_{t-1} + I_t \\
L_t &= (1-\delta_l)L_{t-1} + H_t \\
\log A_{t+1} &= \rho_A \log A_t + \sigma_{t+1}\varepsilon_{t+1} \\
\sigma_t^2 &= \sigma_{s,t}^2 + \sigma_{l,t}^2 \\
\sigma_{s,t+1} &= \Pi_s(\sigma_{s,t}) \\
\sigma_{;,t+1} &= \Pi_l(\sigma_{l,t})
\end{aligned}
$$

5.2 Calibration, Numerical Solution and Simulation

We calibrate the model taking standard parameter values from the literature, when possible, and trying to choose reasonable ones when there is no consensus. We make the revenue elasticities of K and L both equal to 0.4 in the model, consistent with constant returns to scale in the physical production function, equal coefficients on K and L, and 25% markups. We make the revenue elasticity of both inputs equal in order to focus on how the differential adjustability and long-livedness of each generate differential sensitivity to short- and long-run uncertainty. The capital and labor depreciation/attrition rates δ_k and δ_l are set to 20% and 45% on an annual basis respectively, noting that given the stationary nature of the TFP process this also needs to account for output growth. The irreversibility on K is set to 25%, with L being twice as downward adjustable. The full parameterization is in Appendix Table 4, with the model period set to be one month to allow for within quarter variation.

The recursive optimization problem is fairly standard, so we solve it via conventional policy iteration on a state space for $(A, K, L, \sigma_s, \sigma_l)$ of $(5, 42, 42, 2, 2)$. Having found the optimal investment policy for each element of the state space, we simulate a panel of 5,000 firms, each consisting of 25 production units that face the investment decision every month. The choice of 25 units per firm should be interpreted as a stand-in for some large number of divisions, offices, etc. within a firm. Again, each unit experiences idiosyncratic shocks to revenue-generating ability A, but the volatility σ_t of first moment shocks is common across units within a firm. The simulation is run for 360 months (30 years), but we discard the first 300 (25 years) to remove the influence of initial conditions. Then we aggregate monthly firm-level figures into quarterly and annual data, measuring stock variables like K and L as the sum across all units of the firm at the end of the period. For flow variables like gross investment and cash flow we take the sum across units and across months within a year or quarter. As a last step in generating our simulated dataset, we add 5% measurement error to all of the simulated data to proxy for the noise in real data.

To measure short- and long-run uncertainty for each firm-month in the simulation, we use the average expected volatility $\hat{\sigma}$ over the next S or L months, respectively:

$$\hat{\sigma}_{S,t} = \mathbb{E}_t[\frac{1}{S}\sum_{m=1}^{S}\sigma_{t+m}] \qquad \text{and } \hat{\sigma}_{L,t} = \mathbb{E}_t[\frac{1}{L}\sum_{m=1}^{L}\sigma_{t+m}], \qquad \text{where} \qquad \sigma_t = \sqrt{\sigma_{s,t}^2 + \sigma_{l,t}^2}.$$

We choose to measure uncertainty in this manner for analogy with option implied volatility, our uncertainty proxy in the empirical sections of the paper. Implied volatility captures the expected future uncertainty about the value of an asset over a given horizon that depends on the maturity of the options used to calculate the implied volatility (see section 2.1). Our baseline choices for S and L are 1 and 24 months, respectively, but our analysis is robust to using 1 and 6 months, which are the implied volatility horizons we consider in the empirical sections of the paper. As with the rest of the simulated data we average monthly uncertainty measures by quarter, but we take a firm's level of short- and long-run uncertainty in year t with the average $\hat{\sigma}_{s,t}$ and $\hat{\sigma}_{l,t}$ during last quarter in the year. This is analogous to our treatment of the empirical implied volatility data (again, see Section 2 for details).

5.3 Simulation Results

The model generates a tight negative relationship between capital investment and both short- and long-run uncertainty. In Table 8 we regress the quarterly net investment rate on lagged expected volatility (in logs) using 30-day, 6-month, and 2-year horizons, including first moment controls and firm and date fixed effects[15]. Columns (1) through (3) document that our simulated investment series is negatively linked to uncertainty at all three horizons. In columns (4) and (5), we again regress logged investment on both the level of short-run (30-day) expected uncertainty, and the slope uncertainty time profile, alternatively using 6 months or 2 years as the long-run horizon. The results indicate strong negative links between investment and both the level and slope, suggesting that firms invest less intensively when the overall level of uncertainty is high, and also when uncertainty over longer horizons is higher than in the short run. Qualitatively, whether we take 6 months or 2 years as the long-run uncertainty horizon makes little difference, so henceforth we focus on 6 months as the long-run horizon, for analogy with the empirical work. Including additional first-moment determinants of investment, specifically ones that mirror those used in the empirical section, does not qualitatively change the results.

In Table 9 we investigate how uncertainty impacts investment in capital versus hiring. We focus on differences in net investment versus net hiring in the presence of short- and long-run uncertainty. All specifications in Table 5 include firm and date fixed effects and the first moment controls we use in the empirical section, namely the simulation counterparts to Tobin's q (value/assets), cash flow (operating profits), and sales (output) growth. The results in columns (1) and (2) document negative relationships between investment and hiring and both short- and long-run uncertainty. The magnitudes of the coefficients, however, suggest that investments in K decline more strongly when long-run uncertainty is high relative to short-run uncertainty. Hiring, by contrast, seems mostly sensitive to the level uncertainty, but not significantly linked to the degree of long- versus and short-run uncertainty.

In columns (3) to (5) we look more closely at this hypothesis by using relative capital investment less hiring as an outcome variable, and investigating what feature of the model is responsible by modifying the calibration. Starting with column (3), we see that in our baseline calibration investment and hiring seem to decline about equally with the level of short-run uncertainty, as the 30-day coefficient is small and insignificant. However, the negative coefficient on the slope term confirms that investment responds particularly negatively

[15] We define net investment as the growth rate of the firms' capital measured following Davis et al. (1996) as the difference across periods divided by the average. Our simulation results are all similar whether we use "gross" or "net" investment as an outcome variable.

when long-run uncertainty is high relative to short-run uncertainty, but hiring does not. In column (4) we set the adjustment costs for labor equal to those for capital ($\gamma_l = \gamma_k$) and find that the long-run effect falls by about half, with some offsetting short-run impact. So the greater irreversibility in investment relative to hiring contributes to investment's sensitivity to long-run uncertainty. Finally, in column (5) we equalize both durability and adjustability, setting the depreciation rate equal to the quit rate ($\delta_k = \delta_l$), and confirm that both short- and long-run uncertainty are about equally linked to investment in both assets.

Overall, these experiments indicate that both the long-livedness of K relative to L and its higher adjustment cost contribute to the baseline result that K investments seem particularly affected by higher long-run uncertainty. These insights imply that long-lived, costly to adjust assets - like buildings, long-lived equipment and R&D - will likely be particular sensitive to long-run uncertainty. So these investments are going to be most acutely reduced, for example, by spikes in policy uncertainty.

6 Conclusion

Uncertainty appears to have both a short-run and a long-run component. To measure the time profile of uncertainty we use firm and macro implied volatility data from 30 days to 10 years duration for a panel of over 4,000 US firms. We document that two principal components, the level and slope of implied volatility curves by horizon capture nearly all of the variation in the time profile of uncertainty. Empirically, we find that firms' long-run volatility is more closely linked with slow-moving and radical risks like those inherent to policy uncertainty and exposure to interest rate volatility via higher leverage. Moreover, there are other sources of firm-level uncertainty like CEO turnover, which are associated with both short- and long-run uncertainty about equally.

We find that R&D growth and investment are particularly sensitive to long-run uncertainty, while employment responds more equally to short- and long-run uncertainty. To investigate the channels responsible for these phenomena, we split our sample according to the share of structures in physical capital, and rate of depreciation in physical capital, finding that industries with relatively more structures - and therefore higher adjustment costs

- and lower depreciation - meaning longer-lived capital - account for investment's higher sensitivity to uncertainty than employment. To disentangle the roles of adjustment costs and depreciation, we consider a model of investment and hiring and find that both aspects are important explaining why investment is more sensitive to longer-run uncertainty than hiring.

Our findings are significant in the wake of recent events like Britain's vote to leave the European Union and Donald Trump's assumption of the US Presidency, which have generated considerable uncertainty over future economic policy around the world. As we have shown, such policy uncertainty is particularly linked with long-run uncertainty and in turn with low rates of investment and R&D that can have significant consequences for the global economic outlook in years to come.

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A Simulation Appendix

A.1 Details on Model Solution and Simulation

We build the simulation model in MATLAB and run it on Stanford's HPC clusters. The firms' dynamic optimization problem is solved using discretization[16] and a standard policy iteration algorithm, which we illustrate below. First we make an initial guess $V_0(A, k, l, \sigma_s, \sigma_l)$ for the value function and find initial optimal policies $k_1(A, k, l, \sigma_s, \sigma_l)$ and $l_1(A, k, l, \sigma_s, \sigma_l)$ to maximize the firm's current revenue and expected continuation value under the assumption that the value function is V_0. Then we obtain the next guess for the value function, V_1, as the value that would arise from following policies k_1 and l_1. In practice we approximate V_1 by iterating on our current guess of the policies 300 times. That is we define

$$V_{0,n+1}(A, k, l, \sigma_s, \sigma_l) = \begin{array}{c} R(A, k, k_1(A, k, l, \sigma_s, \sigma_l), l, l_1(A, k, l, \sigma_s, \sigma_l), \sigma_s, \sigma_l) + \\ \mathbf{E}[V_{0,n}(A', k_1(A, k, l, \sigma_s, \sigma_l), l_1(A, k, l, \sigma_s, \sigma_l), \sigma_s', \sigma_l') | A, k, l, \sigma_s, \sigma_l] \end{array}$$

where $R(\cdot)$ denotes the flow returns function containing revenues minus investment and hiring costs, and $\mathbf{E}[\cdot]$ is the conditional expectations operator based on the current state $(A, k, l, \sigma_s, \sigma_l)$, and let $V_1 = V_{0,300}$. We then obtain our second guesses for the policy functions k_2 and l_2 via maximization under the new guess V_1 and take the absolute distance $d = \max_{A,k,l,\sigma_s,\sigma_l} |k_2 - k_1|$. If d is below a pre-determined tolerance level, we conclude that V_1, k_2, and l_2 solve the firm's dynamic program. Otherwise, we repeat the above procedure by iterating on policy functions k_2 and l_2 to obtain $V_2 = V_{1,300}$ and new candidate policy functions k_3 and l_3. The algorithm continues until convergence, which comes a lot faster under this procedure than with standard value function iteration, as is well known in the computational literature.

To simulate data from the model we use Monte Carlo simulation, in order to accommodate the fact that the firms in our simulation dataset consist of 25 investment units, each making optimal investments according to the value function problem formulated in section

[16] We use full discretization of the state space to accommodate the "sharp" adjustment costs in the model, which may lead the value function to be non-differentiable in certain regions of the state space. Similarly, we refrain from using interpolation at any point during the solution procedure to avoid interpolating within these regions of non-differentiability.

5. The investment units within a firm have independent first-moment shocks but common uncertainty shocks. For each firm-month in the simulation, we first obtain σ_s and σ_l states for the firm, then draw new first-moment shocks A for all of the units within the firm, then record investment and hiring choices by unit. Finally, we aggregate the unit-level data to the firm level by adding up K and L across units within a firm-month. We run the simulation for 360 months, dropping data from the first 300 months for ergodicity.

We transfer the simulated data to Stata, where we aggregate the monthly simulation data to quarterly and annual frequencies and run the empirical analysis of the simulated data, as described in the main text.

A.2 Simulation Parameters

Appendix Table 4 displays the parameters used in the baseline calibration for the two-factor model with capital and labor. We discuss most of our choices in Section 5.2, and list sources as appropriate in the parameterization tables.

B Data Appendix

B.1 Construction of the Firm-level Implied Volatility Dataset

We obtain our implied volatility data from the OptionMetrics database. OptionMetrics uses observed option trading data to provide information about theoretical "standardized" options, which are theoretical American put and call options with strike prices equal to at-the-money forward stock prices and fixed maturities of 30, 60, 91, 152, 182, 273, 365, and 730 days. They obtain these standardized options by using all available options on the same security and weighting them by vega, maturity, delta, and exercise style. They generate a volatility surface using a normal kernel weighting function and choosing bandwidth empirically, and calculate standardized option prices and implied volatilities from this surface. Details of this procedure are available at http://www.optionmetrics.com/. Options must have vegas greater than 0.5 and time to maturity greater than 10 days to be input into the standardization process. Note these are integrated volatilities rather than spot volatilities -

so for example $\sigma^2_{6-month} = \int_0^{6-months} \sigma_t^2 dt$ and cited in annualized units. An observation in the raw data is a firm-day.

To construct the implied volatility dataset we first obtain a single measure of implied volatility for each horizon by firm-day by averaging implied volatility across puts and calls. Put and call data are nearly identical, with correlations close to .99, so using either puts or calls made little difference to the empirical results. Then we compute quarterly measures of implied volatility by horizon by averaging the daily implied variance of the standardized options. That is, the implied volatility of a firm i during quarter $t$is $\sigma_{it} = \sqrt{\frac{1}{N_t}\sum_{\tau=1}^{N_t} s_{i\tau}^2}$ where $s_{i\tau}$ is a daily observation of implied volatility for the firm and N_t is the number of days in quarter $t$for which we have nonmissing volatility observations. Our empirical specifications in exploit variation in the level and slope of firm-specific volatility curves. These curves plot a firm's implied volatility by horizon, and thus capture the degree of uncertainty the firm faces in the short and long run.

B.2 Matching Implied Volatility Data to Compustat

We match the quarterly dataset to quarterly and annual firm-level data from Compustat North America. In constructing the annual matched dataset we take the implied volatility for a firm-year to be that of the last quarter of the year. This is useful to obtain less noisy implied volatility measures at an annual frequency and allows us to exploit the forward-looking nature of implied volatility. Since many of our regressions in section 4 use lagged volatility, we effectively regress an annual outcome variable on the implied volatility in final months of the previous fiscal year, which reflects the market's uncertainty about the firm looking forward to the year in question. For the quarterly matched dataset we simply match by quarter.

See Appendix Table 1 for summary statistics on the samples defined by the baseline regressions in Table 4.

Selection into our matched sample is largely based on the availability of accounting data from Compustat and implied volatility data from OptionMetrics, specifically selecting firms with options of durations of at least six months. We test for selection into this sample in Appendix Table 2, where we run linear probability models to predict whether a Compustat firm has non-missing 30-day and 6-month implied volatility in a particular month. This exercise suggests that larger, faster growing, and less volatile firms are more likely to have non-missing implied volatility data at both horizons.

B.3 Additional Details on Testing for Drivers of Short- and Long-run Uncertainty

See section 3 for an outline of how we construct the matched firm-quarter dataset containing implied volatility and drivers data.

During our estimation of the sector-level sensitivities of equity returns to market, oil, and currency returns we restrict attention to SIC-2 sectors that featured at least 20 distinct firms during the estimation period of 1985-2004. When we restricted attention to sectors that included 15 or 25 firms the results did not change very much.

All of our uncertainty regressions in Table 3 are weighted by employment, as is standard in this line of literature (e.g. Baker et al., 2016). Also following Baker et al. (2016) whenever we have the firm-specific economic policy uncertainty index as a regressor we include a control consisting of federal spending as a fraction of GDP multiplied by firm-level exposure to government purchases.

In our baseline regressions in in Table 3 we define CEO turnover as an indicator for firm-quarters during which Execucomp records a CEO stepping down. In the data, only 78% of these CEO departures have a new CEO taking office within the same calendar quarter, but our regressions are robust to defining CEO turnover as an indicator for firm-quarters with a new CEO coming in. The same is true if we define turnover to indicate any change in the identity of the CEO within the quarter, regardless of whether the CEO is replaced during the quarter, the post becomes vacant and is unfilled within the calendar quarter, or a new CEO takes over a vacancy that began in a previous quarter. We also find similar results if we restrict attention to cases in which the reason cited for the CEO's departure is explicitly given as something other than retirement.

C Depreciation of Intangible Capital and Short- vs. Long-run Uncertainty

In addition to figures on physical capital stocks and depreciation, the Bureau of Economic Analysis publishes its estimates of intellectual property assets depreciation by industry and year. Here we repeat the exercise from Section 4.4, but focusing on differences across investment and R&D growth in their sensitivity to short- and long-run uncertainty and how those differences depend on the rate of depreciation of intangible assets. See Appendix Table 3 for our results.

In columns (1) to (3) we show that investment's sensitivity to both the level and slope of the uncertainty profile is concentrated almost entirely among firm-quarters belonging to industries with above-median intangibles depreciation, perhaps because industries with longer-lived intangible assets are less dependent on physical capital.. Analogously, in columns (4) to (6) the link between R&D growth and the slope of the uncertainty profile originates entirely among the subsample with short-lived intangibles. We believe the intuition for this result is a consequence of adjustment costs on the level of R&D expenditures (a flow variable), rather than on the firm's knowledge stock. When intangile capital depreciates quickly, firms may be particularly reluctant to commit to higher levels of R&D spending in the longer-run, highly uncertain future, given that the payoff to those R&D investments will mostly vanish in the short- to medium-term.

In Columns (7) to (9) we additionally document that investment's strong sensitivity to the overall level of uncertianty is also concentrated among sectors with high intangibles depreciation.

Table 1: Principal Components of Macro and Firm-specific Implied Volatility

a. Macro Volatility

	Levels		Logs	
Horizon	**1st**	**2nd**	**1st**	**2nd**
30 days	0.332	-0.526	0.333	-0.538
3 months	0.352	-0.386	0.352	-0.388
6 months	0.364	-0.234	0.363	-0.230
1 year	0.369	-0.068	0.367	-0.062
2 years	0.368	0.104	0.366	0.109
3 years	0.365	0.200	0.363	0.203
5 years	0.357	0.334	0.356	0.333
10 years	0.319	0.594	0.326	0.582
Cumulative Variance:	0.908	0.990	0.919	0.990

Notes: First and second principal component loadings across horizons for levels *(left)* and logs *(right)* of the generalized VIX, measured at a daily frequency between July 1, 2002 and July 29, 2016.

b. Firm-specific Volatility

	Levels		Logs	
Horizon	**1st**	**2nd**	**1st**	**2nd**
30 days	0.447	-0.441	0.447	-0.446
3 months	0.457	-0.356	0.457	-0.351
6 months	0.459	-0.241	0.459	-0.243
1 year	0.446	0.420	0.446	0.426
2 years	0.426	0.666	0.426	0.661
Cumulative Variance:	0.908	0.978	0.910	0.980

Notes: First and second principal component loadings across horizons for levels *(left)* and logs *(right)* of firm-specific implied volatility, measured at a quarterly frequency. Prior to obtaining principal components, we remove firm and date fixed effects from this data to focus on firm-specific variation in short- and long-run implied volatility. We measure the implied volatility of a given firm in a given quarter for a given horizon as the average across all daily implied volatility observations for that quarter and that horizon. Our daily implied volatility data comes from OptionMetrics.

Table 2: Predicting Long-run Implied Volatility

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	2-year Firm Implied Vol.	1-year VIX	2-year VIX	3-year VIX	5-year VIX
30-day Implied Vol.	0.878***	0.942***	0.866***	0.818***	0.735***
	(0.006)	(0.012)	(0.027)	(0.033)	(0.047)
6-month - 30-day Vol.	1.196***	1.233***	1.347***	1.369***	1.336***
	(0.038)	(0.033)	(0.073)	(0.092)	(0.125)
Constant	4.308***	1.423***	3.522***	5.067***	7.844***
	(0.200)	(0.303)	(0.689)	(0.842)	(1.139)
Observations	22,794	3,585	3,585	3,585	3,585
R-squared	0.944	0.993	0.971	0.948	0.901

Notes: Column (1) regresses quarterly firm-level 2-year implied volatility (source: Optionmetrics) on 30-day and 6-month minus 30-day implied volatility. Columns (2) to (6) regress the daily generalized VIX for the specified horizon on the contemporaneous 30-day and 6-month minus 30-day generalized VIX (source: Goldman Sachs). Column (1) standard errors clustered by firm. Columns (2) to (6) report Newey-West standard errors, assuming autocorrelation up to 250 trading days. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Drivers of Short- and Long-run Uncertainty

Top Panels

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			log(30-day IVOL)			
Economic Policy Unc. Exposure	0.239***					0.223***
	(0.053)					(0.044)
Oil Vol. Exposure		1.266**				1.305**
		(0.596)				(0.560)
Currency Vol. Exposure			0.017			0.012
			(0.045)			(0.039)
CEO Turnover				0.019**		0.018**
				(0.007)		(0.007)
Interest Rate Vol. Exposure					0.207***	0.207***
					(0.033)	(0.033)
Dependent Variable			log(6-month IVOL)			
Economic Policy Unc. Exposure	0.267***					0.253***
	(0.063)					(0.041)
Oil Vol. Exposure		0.999**				0.981**
		(0.399)				(0.387)
Currency Vol. Exposure			0.032			0.029
			(0.035)			(0.030)
CEO Turnover				0.015**		0.014**
				(0.006)		(0.006)
Interest Rate Vol. Exposure					0.192***	0.192***
					(0.031)	(0.030)
Observations	68,424	68,424	68,424	68,424	68,424	68,424
Clusters	60	60	60	60	60	60

Bottom Panel

Dependent Variable	log(6-month IVOL)					
log(30-day IVOL)	0.776***	0.776***	0.776***	0.776***	0.772***	0.772***
	(0.024)	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)
Economic Policy Unc. Exposure	0.082**					0.081***
	(0.031)					(0.026)
Oil Vol. Exposure		0.016				-0.026
		(0.120)				(0.097)
Currency Vol. Exposure			0.019***			0.020***
			(0.005)			(0.005)
CEO Turnover				0.000		0.000
				(0.005)		(0.005)
Interest Rate Vol. Exposure					0.032***	0.032***
					(0.008)	(0.008)
Observations	68,424	68,424	68,424	68,424	68,424	68,424
Clusters	60	60	60	60	60	60

Notes: All columns include a full set of time and firm fixed effects, with variables measured at a quarterly frequency. Robust standard errors in parentheses, clustered by 2-digit sector. One observation is a firm-quarter. Implied volatility data are from OptionMetrics. Firm-specific exposure to Economic Policy Uncertainty by month is from Baker et al (2016). We construct sectoral exposure to oil and currencies using CRSP data on stock returns, Bloomberg data on oil prices and exchange rates from 1985-2004, and quarterly averages of implied volatility data for oil and currencies covering 2005-2016.We consider exchange rates for the USD against CAD, JPY, EUR, AUD, SEK, CHF, GBP. CEO Turnover is from Execucomp, constructed as an indicator for whether the CEO was stepping down during the quarter. Interest rate volatility exposure is the product of a firm's leverage in a given quarter and the natural logarithm of the average level of the TYVIX during the quarter. We measure leverage as the ratio of short plus long term debt over total assets, and the TYVIX is the CBOE's 30-day volatility index on 10-year US Treasury yields. Regressions are weighted by employment. *** p<0.01, ** p<0.05, * p<0.1, +p<.15

Table 4: Investment, R&D Activity, and Hiring under Short- and Long-run Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Investment**	**Investment**	**Hiring**	**Investment - Hiring**	**R&D Growth**	**R&D Growth - Investment**
Frequency	Q	A	A	A	Q	Q
Lag log(30-day IVOL)	-0.229***	-0.229***	-0.019*	-0.202***	-0.016	0.164***
	(0.037)	(0.036)	(0.010)	(0.035)	(0.017)	(0.046)
Lag log(30-day IVOL) - log(6-month IVOL)	-0.202***	-0.261***	-0.024	-0.228***	-0.181**	-0.029
	(0.060)	(0.071)	(0.023)	(0.067)	(0.072)	(0.108)
Lag Tobin's Q	0.118***	0.113***	0.013***	0.101***	0.001	-0.110***
	(0.010)	(0.010)	(0.002)	(0.009)	(0.004)	(0.011)
Cash Flow / Assets	0.979***	0.758***	0.141***	0.603***	2.483***	1.762***
	(0.147)	(0.142)	(0.051)	(0.142)	(0.757)	(0.648)
Sales Growth	0.388***	0.663***	0.497***	0.163***	0.007	-0.401***
	(0.034)	(0.039)	(0.022)	(0.035)	(0.015)	(0.040)
Observations	114,765	30,939	30,848	30,790	77,224	76,018
R-squared	0.576	0.683	0.444	0.652	0.147	0.299
Clusters	4642	3976	3970	3962	3115	3093

Notes: Regressions are quarterly (Q) in columns (1), (5), and (6) and annual (A) in columns (2) to (4). All columns include a full set of firm and date fixed effects and are weighted by employment. Robust standard errors in parentheses, clustered by firm. Data is from Compustat for accounting variables matched to data on implied volatility of standardized options taken from OptionMetrics. Investment is measured as the log of capital expenditure (CAPEX) over lagged net plant property and equipment (PPENT). R&D growth is measured as the change across periods in R&D expense (XRD) divided by the average, and imputed to zero if both current and lagged values are both zero. R&D expense is imputed to zero if missing but the firm previously reported positive R&D expense. Hiring is measured as the change in the stock of employees across fiscal years, divided by the average between the current and previous year. Tobin's Q is measured as the sum of market value, preferred stock capital, current and long-term liabilities, all divided by the book value of assets. Cash flow is defined as operating income. In annual specifications, the implied volatility for a given fiscal year is taken to be the average implied volatility during the last quarter of the year, while it is taken as the average for the quarter in quarterly specifications. In the regressions, implied volatility is lagged by 1 or 4 quarters depending on whether the frequency is quarterly or annual. All variables are winsorized at the 1st and 99th percentiles. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Investment Under Short- and Long-run Uncertainty, Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			**Investment**			
Lag log(30d IVOL)	-0.229***	-0.146***	-0.292***	-0.241***	-0.232***	-0.217***
	(0.037)	(0.023)	(0.061)	(0.064)	(0.037)	(0.036)
Lag log(6m IVOL) - log(30d IVOL)	-0.202***	-0.177***			-0.206***	-0.163***
	(0.060)	(0.041)			(0.057)	(0.052)
Lag log(1-year IVOL) - log(30d IVOL)			-0.296***			
			(0.099)			
Lag log(2y IVOL) - log(30d IVOL)				-0.219***		
				(0.084)		
Lag Investment		0.425***				
		(0.018)				
Lag Tobin's Q	0.118***	0.074***	0.106***	0.095***	0.118***	0.118***
	(0.010)	(0.007)	(0.014)	(0.014)	(0.010)	(0.010)
Cash Flow / Assets	0.979***	1.108***	0.875***	0.747***	0.977***	0.983***
	(0.147)	(0.167)	(0.243)	(0.253)	(0.147)	(0.147)
Sales Growth	0.388***	0.227***	0.354***	0.421***	0.387***	0.388***
	(0.034)	(0.024)	(0.049)	(0.056)	(0.034)	(0.034)
Implied Volatility from Puts and Calls	Y	Y	Y	Y		
Implied Volatility from Puts Only					Y	
Implied Volatility from Calls Only						Y
Observations	114,765	106,725	31,391	21,493	114,765	114,765
R-squared	0.576	0.660	0.613	0.619	0.577	0.576
Clusters	4642	4341	1436	1299	4642	4642

Notes: All columns are quarterly OLS regressions weighted by employment and include a full set of firm and date fixed effects. Robust standard errors in parentheses, clustered by firm. Data are from Compustat for accounting variables matched to data on implied volatility of standardized options taken from OptionMetrics. Investment is measured as the log of capital expenditure (CAPEX) over lagged net plant, property, and equipment (PPENT). Tobin's Q is measured as the sum of market value, preferred stock capital, current, and long-term liabilities, all divided by the book value of assets. Cash flow is defined as operating income. Implied volatilities measured as the average for the quarter and lagged. We measure a firm's implied volatility for a given horizon in a given quarter as the average daily implied volatility in the quarter. In columns (1) through (4) we average the implied volatility of standardized put and call options within a day before averaging across days in a calendar quarter. In columns (5) to (6) we use data only from puts and calls, respectively. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Structures, Equipment and Short- vs. Long-run Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable		**Investment**			**Hiring**			**Investment - Hiring**	
Sample	All	Low Structures/ Capital	High Structures/ Capital	All	Low Structures/ Capital	High Structures/ Capital	All	Low Structures/ Capital	High Structures/ Capital
Lag log(30d IVOL)	-0.221***	-0.166***	-0.304***	-0.022**	-0.008	-0.033**	-0.194***	-0.155***	-0.264***
	(0.036)	(0.045)	(0.051)	(0.011)	(0.012)	(0.016)	(0.035)	(0.047)	(0.048)
Lag log(6m IVOL) - log(30d IVOL)	-0.241***	-0.027	-0.419***	-0.033	0.004	-0.062**	-0.202***	-0.025	-0.351***
	(0.071)	(0.100)	(0.094)	(0.024)	(0.036)	(0.031)	(0.067)	(0.097)	(0.089)
Lag Tobin's Q	0.114***	0.114***	0.113***	0.013***	0.011***	0.014***	0.101***	0.102***	0.100***
	(0.010)	(0.014)	(0.015)	(0.002)	(0.003)	(0.003)	(0.009)	(0.012)	(0.013)
Cash Flow / Assets	0.722***	0.426***	0.920***	0.142***	0.116**	0.150*	0.569***	0.307**	0.753***
	(0.140)	(0.143)	(0.212)	(0.051)	(0.046)	(0.081)	(0.138)	(0.134)	(0.213)
Sales Growth	0.663***	0.689***	0.650***	0.499***	0.470***	0.534***	0.162***	0.216***	0.113**
	(0.040)	(0.047)	(0.063)	(0.023)	(0.023)	(0.038)	(0.035)	(0.042)	(0.055)
Observations	30,513	15,733	14,742	30,513	15,733	14,742	30,513	15,733	14,742
R-squared	0.685	0.677	0.705	0.444	0.451	0.453	0.654	0.647	0.673
Firms	3926	2001	2009	3926	2001	2009	3926	2001	2009

Notes: All columns are annual OLS regressions at the firm level. All columns include a full set of firm and date fixed effects, and are weighted by employment. Columns (1), (4), and (7) contain the baseline estimates for all firm-years for which we have industry-level data from the BEA on the share of structures in physical capital. Columns (2), (5), and (8) show results for observations belonging to industry-years below the median share of structures; (3), (6), and (9) do the same for observations in industry-years with above-median share of structures. Data are accounting information from Compustat matched to data on implied volatility of standardized options taken from OptionMetrics. Robust standard errors in parentheses, clustered by firm. Investment is the log of capital expenditure (CAPEX) over lagged net plant property and equipment (PPENT). Hiring is the change in employment (EMP) across years divided by the average employment in the two years. Tobin's Q is measured as the sum of market value, preferred stock capital, current and long-term liabilities, all divided by the book value of assets. Cash flow is defined as operating income. Implied volatility is measured as the average for the last quarter of the fiscal year in the annual specifications. We obtained data on the total replacement cost of physical fixed assets (structures and equipment) by NAICS 2-digit industry from the BEA. All variables are winsorized at the 1st and 99th percentiles. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Depreciation of Physical Capital and Short- vs. Long-run Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable		**Investment**			**Hiring**			**Investment - Hiring**	
Sample	All	Low Depreciation	High Depreciation	All	Low Depreciation	High Depreciation	All	Low Depreciation	High Depreciation
Lag log(30d IVOL)	-0.221***	-0.261***	-0.195***	-0.022**	-0.030**	-0.003	-0.194***	-0.223***	-0.190***
	(0.036)	(0.051)	(0.044)	(0.011)	(0.015)	(0.013)	(0.035)	(0.049)	(0.044)
Lag log(6m IVOL) - log(30d IVOL)	-0.241***	-0.349***	-0.153	-0.033	-0.070**	0.011	-0.202***	-0.272***	-0.160
	(0.071)	(0.093)	(0.108)	(0.024)	(0.032)	(0.034)	(0.067)	(0.090)	(0.099)
Lag Tobin's Q	0.114***	0.119***	0.111***	0.013***	0.013***	0.014***	0.101***	0.106***	0.097***
	(0.010)	(0.015)	(0.012)	(0.002)	(0.003)	(0.003)	(0.009)	(0.014)	(0.011)
Cash Flow / Assets	0.722***	0.912***	0.414***	0.142***	0.205***	0.033	0.569***	0.692***	0.376***
	(0.140)	(0.216)	(0.155)	(0.051)	(0.079)	(0.054)	(0.138)	(0.216)	(0.145)
Sales Growth	0.663***	0.714***	0.632***	0.499***	0.560***	0.441***	0.162***	0.149***	0.188***
	(0.040)	(0.053)	(0.068)	(0.023)	(0.034)	(0.028)	(0.035)	(0.053)	(0.054)
Observations	30,513	15,532	14,631	30,513	15,532	14,631	30,513	15,532	14,631
R-squared	0.685	0.703	0.688	0.444	0.475	0.448	0.654	0.669	0.659
Firms	3926	2416	2254	3926	2416	2254	3926	2416	2254

Notes: All columns are annual OLS regressions at the firm level. All columns include a full set of firm and date fixed effects and are weighted by employment. Columns (1), (4), and (7) contain the baseline estimates for all firm-years for which we have industry-level data on depreciation from the BEAl. Columns (2), (5), and (8) show results for observations belonging to industry-years with physical depreciation below the median; (3), (6), and (9) do the same for observations in industry-years with above-median depreciation. Data are accounting information from Compustat matched to data on implied volatility of standardized options taken from OptionMetrics. Robust standard errors in parentheses, clustered by firm. Investment is the log of capital expenditure (CAPEX) over lagged net plant property and equipment (PPENT). Hiring is the change in employment (EMP) across years divided by the average employment in the two years. Tobin's Q is measured as the sum of market value, preferred stock capital, current and long-term liabilities, all divided by the book value of assets. Cash flow is defined as operating income. Implied volatility is measured as the average for the last quarter of the fiscal year in the annual specifications. All variables are winsorized at the 1st and 99th percentiles. We obtained data on the value of economic depreciation and physical fixed assets (structures and equipment) from the BEA by NAICS 2-digit industries. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Simulation Quarterly Capital Investment Under Short- and Long-run Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable				**Net Investment**			
Lag log(30d Expected Vol.)	-0.053***			-0.217***	-0.114***	-0.211***	-0.125***
	(0.004)			(0.022)	(0.009)	(0.020)	(0.008)
Lag log(2y Expected Vol.)		-0.205***					
		(0.013)					
Lag log(6m Expected Vol.)			-0.091***				
			(0.006)				
Lag log(2y Expected Vol.) - log(30d Expected Vol.)				-0.223***		-0.193***	
				(0.029)		(0.026)	
Lag log(6m Expected Vol.) - log(30d Expected Vol.)					-0.164***		-0.153***
					(0.020)		(0.019)
Lag Tobin's Q	0.079***	0.079***	0.079***	0.079***	0.079***	0.044***	0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cash Flow/(K+L)						3.245***	3.246***
						(0.017)	(0.017)
Sales Growth						0.019***	0.019***
						(0.003)	(0.003)
Observations	95,000	95,000	95,000	95,000	95,000	65,000	65,000
R-squared	0.120	0.121	0.121	0.121	0.121	0.504	0.504
Firms	5000	5000	5000	5000	5000	5000	5000

Notes: The dependent variable is net investment measured as the DHS growth rate in the capital stock. All columns include a full set of firm and date fixed effects. Robust standard errors in parentheses, clustered by firm. Each observation is a firm-quarter from a 5,000 firm simulation panel. Each firm consists of 25 production units making investment decisions and independent first moment shocks common uncertainty shocks. The model is solved and simulated at a monthly frequency and aggregated to quarterly data. Short- and long-run uncertainty are measured as the average expected volatility of shocks to revenue-generation over the horizon indicated. Tobin's Q is measured as firm value divided by the stock of K and L. Cash flow is defined as revenue. Sales growth is measured as the revenue over the past four quarters, minus that over the previous four quarters, divided by the average of the two. All variables are winsorized at the 1st and 99th percentiles. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Simulation Annual Net Investment and Hiring Under Short- and Long-run Uncertainty

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	**Net Investment**	**Hiring**	**Net Investment – Hiring**		
Calibration	Baseline	Baseline	Baseline	Equal AC	Equal Dep & AC
Lag log(30d Expected Vol.)	-0.130***	-0.106***	-0.023	0.150***	-0.012
	(0.020)	(0.026)	(0.026)	(0.017)	(0.012)
Lag log(6m Expected Vol.) - log(30d Expected Vol.)	-0.221***	-0.034	-0.183***	-0.083*	-0.044
	(0.050)	(0.065)	(0.065)	(0.043)	(0.030)
Lagged Tobin's Q	0.081***	0.136***	-0.054***	-0.023***	-0.000
	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Cash Flow / (K + L)	1.385***	1.412***	-0.027	0.134***	-0.001
	(0.018)	(0.025)	(0.024)	(0.017)	(0.006)
Proportional Sales Growth	-0.043***	-0.053***	0.011	-0.066***	0.008*
	(0.009)	(0.013)	(0.012)	(0.008)	(0.004)
Observations	20,000	20,000	20,000	20,000	20,000
R-squared	0.746	0.670	0.097	0.104	0.061
Firms	5000	5000	5000	5000	5000
Calibration Parameters:					
K effective depreciation	0.2	0.2	0.2	0.2	**0.45**
L effective depreciation	0.45	0.45	0.45	0.45	0.45
K resale loss	0.25	0.25	0.25	0.25	0.25
L resale loss	0.125	0.125	0.125	**0.25**	**0.25**

Notes: The dependent variables are net investment and hiring, defined as the (DHS) growth rates of capital and labor. Column (5) has equal adjustment costs on capital and labor, and column (6) additionally has equal depreciation. All columns have a full set of firm and time fixed-effects. Robust standard errors in parentheses, clustered by firm. Each observation is a firm-year from a 5,000 firm simulation panel. Each firm consists of 25 production units making investment decisions subject to independent first moment shocks and common uncertainty shocks. The model is solved and simulated at a monthly frequency and aggregated to annual data. Short- and long-run uncertainty are measured on the monthly data as the average expected volatility of first moment shocks over the next 30 days and 6 months, respectively. When aggregating to annual data, we take for a given year the average short- and long-run uncertainty over the last quarter of the year. Tobin's Q is measured as firm value divided by the stock of K and L. Cash flow is defined as revenue. All growth variables are constructed as the current value minus the previous year's value, divided by the average of the two. All variables are winsorized at the 1st and 99th percentiles. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 1: Summary Statistics

ANNUAL SAMPLE			QUARTERLY SAMPLE		
	Mean	**SD**		**Mean**	**SD**
Total Assets ($M)	5,265	10,496	**Total Assets ($M)**	4,523	9,276
Capital Expenditures ($M)	287.6	641.3	**Capital Expenditures ($M)**	61.26	138.8
Sales ($M)	4,401	8,730	**Sales ($M)**	1,005	2,068
Cash Flow / Assets	0.0896	0.1517	**Cash Flow / Assets**	0.0210	0.0474
PPENT ($M)	1,644	3,738	**PPENT ($M)**	1,398	3,299
Lagged Tobin's Q	2.034	1.857	**Lagged Tobin's Q**	2.032	1.868
Sales Growth	0.0880	0.3044	**Sales Growth**	.1175	0.2938
Lagged log(30day IVOL)	3.864	0.4503	**Lagged log(30day IVOL)**	3.835	0.4379
Lagged log(6m IVOL)	3.820	0.4272	**Lagged log(6m IVOL)**	3.788	0.4195
CAPX/PPENT	0.3500	0.4286	**CAPX/PPENT**	0.0810	0.0902
Employment Growth	0.0535	0.2207	**R&D Expense ($M)**	34.62	95.32
Employees ('000s)	16.28	30.73	**R&D Growth**	.0109	.6536
N	30,280		**N**	112,772	
Date Range: 1997-2016			Date Range: 1996Q2 – 2016Q2		

Notes: Summary statistics for the baseline regressions, columns (1) and (4) of Table 3, respectively for the annual and quarterly samples. Data is from Compustat North America Fundamentals Quarterly and Annual matched with implied volatility data from Option Metrics. Cash flow is defined as operating income. Tobin's Q is measured as the sum of market value, preferred stock capital, current liabilities and long term debt, all divided by the book value of assets. All growth variables measured as the change between the value in the current and the previous year, divided by the average of the two. Implied volatility by horizon is measured as the average for a firm-quarter, where in the annual sample we identify the implied volatility in a given fiscal year with the average of the last quarter. All variables are winsorized at the 1st and 99th percentiles.

Appendix Table 2: What types of firms have non-missing implied volatility? (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**1(30-day Implied Volatitility Nonmissing)**					
log(Quarterly Sales)	0.0163***			0.0136***	0.0146***	0.0149***
	(0.00151)			(0.00155)	(0.00196)	(0.00209)
Sales Growth		0.0119**		0.0250***	0.0395***	0.0258***
		(0.00569)		(0.00589)	(0.00844)	(0.00268)
Lagged log(91-day Realized Vol.)			-0.0583***	-0.0338***	-0.0951***	-0.0218***
			(0.00561)	(0.00535)	(0.00870)	(0.00310)
Date Fixed Effects	N	N	N	N	N	Y
Firm Fixed Effects	N	N	N	N	N	Y
Years in Sample	2012	2012	2012	2012	2002	2000-2013
Standard Errors	Robust	Robust	Robust	Robust	Robust	Clustered by Firm
R-squared	0.039	0.001	0.025	0.050	0.101	0.560
Observations	7,715	7,715	7,715	7,715	5,864	109,973
Dependent Variable	**1(6-month Implied Volatility Nonmissing)**					
log(Quarterly Sales)	0.0181***			0.0160***	0.0190***	0.0175***
	(0.00157)			(0.00165)	(0.00221)	(0.00248)
Sales Growth		0.0108		0.0247***	0.0447***	0.0327***
		(0.00694)		(0.00708)	(0.00919)	(0.00313)
Lagged log(91-day Realized Vol.)			-0.0577***	-0.0283***	-0.109***	-0.0169***
			(0.00585)	(0.00595)	(0.00999)	(0.00384)
Date Fixed Effects	N	N	N	N	N	Y
Firm Fixed Effects	N	N	N	N	N	Y
Years in Sample	2012	2012	2012	2012	2002	2000-2013
Standard Errors	Robust	Robust	Robust	Robust	Robust	Clustered by Firm
R-squared	0.039	0.001	0.020	0.046	0.104	0.516
Observations	7,715	7,715	7,715	7,715	5,864	109,973

Notes: OLS regressions on an indicator for nonmissing 30-day or 6-month implied volatility based on firm characteristics.An observation is a firm-quarter. Financial information is from Compustat, and quarterly average implied and realized volatility of firm equity taken from Optionmetrics. Sales growth is measured as the sum of sales over the past four quarters minus that of the previous four quarters, divided by the average of the two. All variables are winsorized at the 1st and 99th percentiles. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3: Depreciation of Intangible Capital and Short- vs. Long-run Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable		**Investment**			**R&D Growth**			**R&D Growth - Investment**	
Sample	All	Low Depreciation	High Depreciation	All	Low Depreciation	High Depreciation	All	Low Depreciation	High Depreciation
Lag log(30d IVOL)	-0.195***	-0.063	-0.242***	-0.020	-0.034	-0.010	0.168***	0.029	0.222***
	(0.046)	(0.051)	(0.062)	(0.018)	(0.032)	(0.028)	(0.047)	(0.058)	(0.064)
Lag log(6m IVOL) - log(30d IVOL)	-0.179**	0.120	-0.364***	-0.193**	0.021	-0.347***	-0.022	-0.095	0.004
	(0.077)	(0.103)	(0.104)	(0.079)	(0.126)	(0.105)	(0.112)	(0.152)	(0.152)
Lag Tobin's Q	0.111***	0.083***	0.140***	0.000	-0.018**	0.010**	-0.110***	-0.100***	-0.129***
	(0.012)	(0.015)	(0.014)	(0.004)	(0.007)	(0.005)	(0.011)	(0.015)	(0.013)
Cash Flow / Assets	0.716***	1.484***	0.552**	2.573***	5.397***	1.745**	1.845***	3.879***	1.185*
	(0.206)	(0.259)	(0.229)	(0.765)	(1.067)	(0.728)	(0.647)	(1.020)	(0.611)
Sales Growth	0.428***	0.304***	0.456***	0.019	0.045	0.008	-0.399***	-0.252***	-0.435***
	(0.038)	(0.045)	(0.056)	(0.015)	(0.030)	(0.024)	(0.041)	(0.051)	(0.061)
Observations	75,423	38,716	36,648	75,423	38,716	36,648	75,423	38,716	36,648
R-squared	0.586	0.617	0.600	0.142	0.247	0.086	0.301	0.313	0.343
Firms	3067	2418	1606	3067	2418	1606	3067	2418	1606

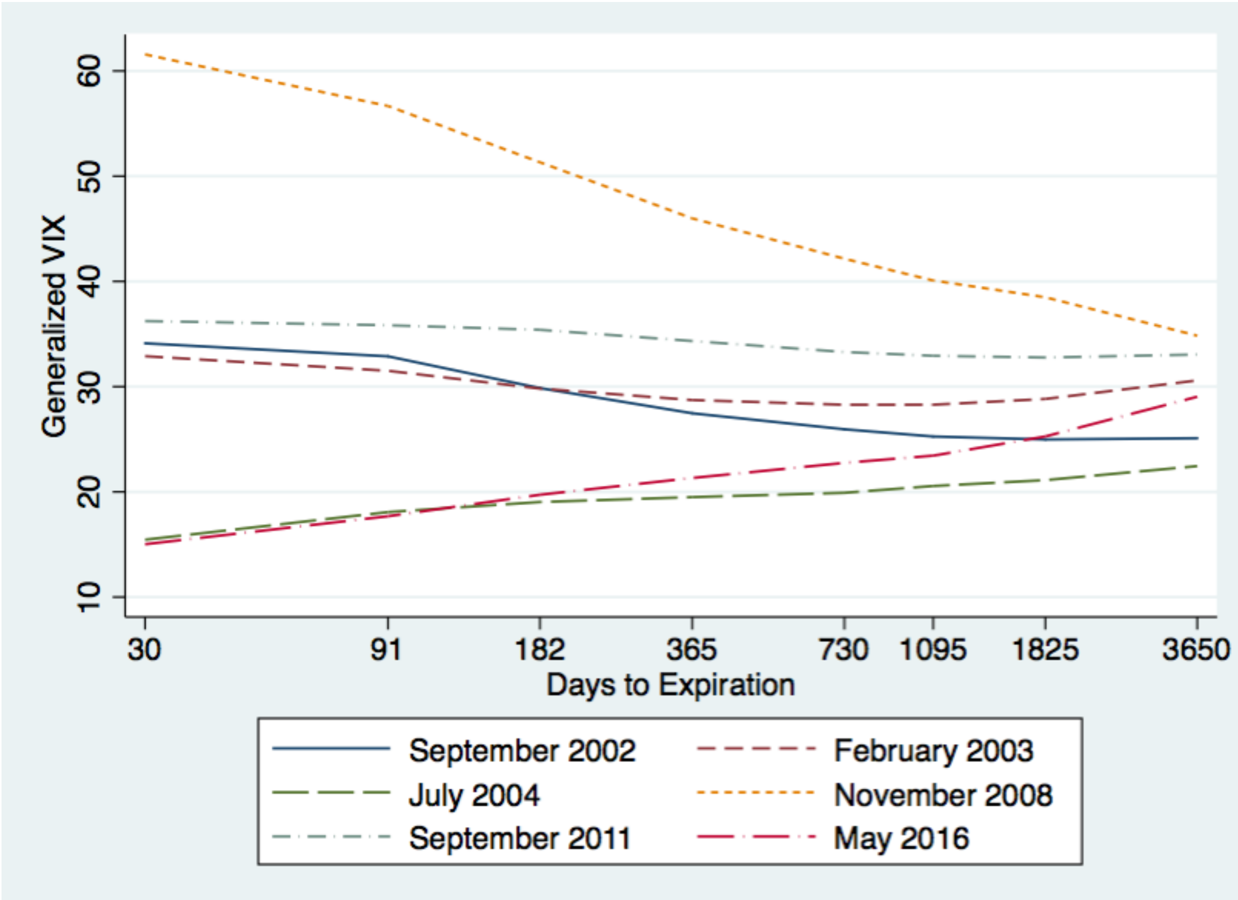
Notes: All columns are annual OLS regressions at the firm level. All columns include a full set of firm and date fixed effects, and are weighted by employment. Columns (1), (4), and (7) contain the baseline estimates for all firm-years for which we have industry-level data on depreciation from the BEA. Columns (2), (5), and (8) show results for observations belonging to industry-years with intangibles depreciation below the median; (3), (6), and (9) do the same for observations in industry-years with above-median depreciation. Data are accounting information from Compustat matched to data on implied volatility of standardized options taken from OptionMetrics. Robust standard errors in parentheses, clustered by firm. Investment is the log of capital expenditure (CAPEX) over lagged net plant property and equipment (PPENT). R&D Growth is the change in R&D expenditures (XRD) across years divided by the average R&D speding across the two years. Tobin's Q is measured as the sum of market value, preferred stock capital, current and long-term liabilities, all divided by the book value of assets. Cash flow is defined as operating income. Implied volatility is measured as the average for the last quarter of the fiscal year in the annual specifications. All variables are winsorized at the 1st and 99th percentiles. We obtained data on the value of economic depreciation of intangibles and estimates of the knowledge stock by NAICS 2-digit industry from the BEA. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 4: Baseline Calibration

Parameter	Description	Value	Notes
$1/(1+r)$	discount rate	.996	r = 0.05, annually
α_k , α_l	revenue elasticity of K , L	.4	CRS and 25% markups
σ_{sl} , σ_{ll}	low volatility state for σ_s and σ_l	.24	33% monthly in LL state
σ_{sh} , σ_{lh}	high volatility state for σ_s and σ_l	.46	66% monthly in HH state
ρ_s	monthly persistence of σ_s	.85	annual autocorrelation .15
ρ_l	monthly persistence of σ_l	.95	annual autocorrelation .49
δ_k	K effective monthly depreciation	.018	20% annual depreciation
δ_l	L effective monthly depreciation	.035	45% annual depreciation
γ_k	K resale loss	.25	25% resale loss, conventional value
γ_l	L resale loss	.125	$0.5\gamma_k$
F_k	fixed K adjustment costs	.01	N/A
F_l	fixed L adjustment costs	.01	N/A
ρ_A	monthly autocorrelation of log(A)	.983	.95 quarterly, Khan & Thomas (2008)

Notes: Parameters used in the baseline calibration of the two-factor simulation model analyzed in Section 5.

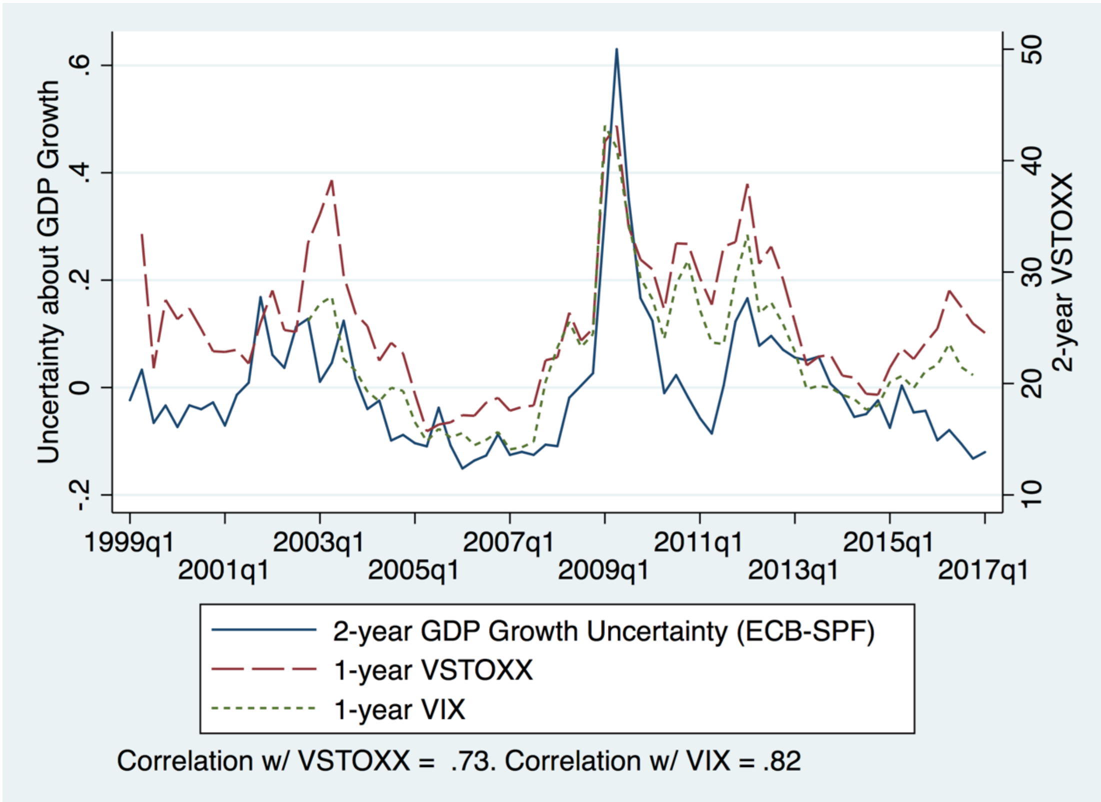
Figure 1: Fluctuations in the VIX



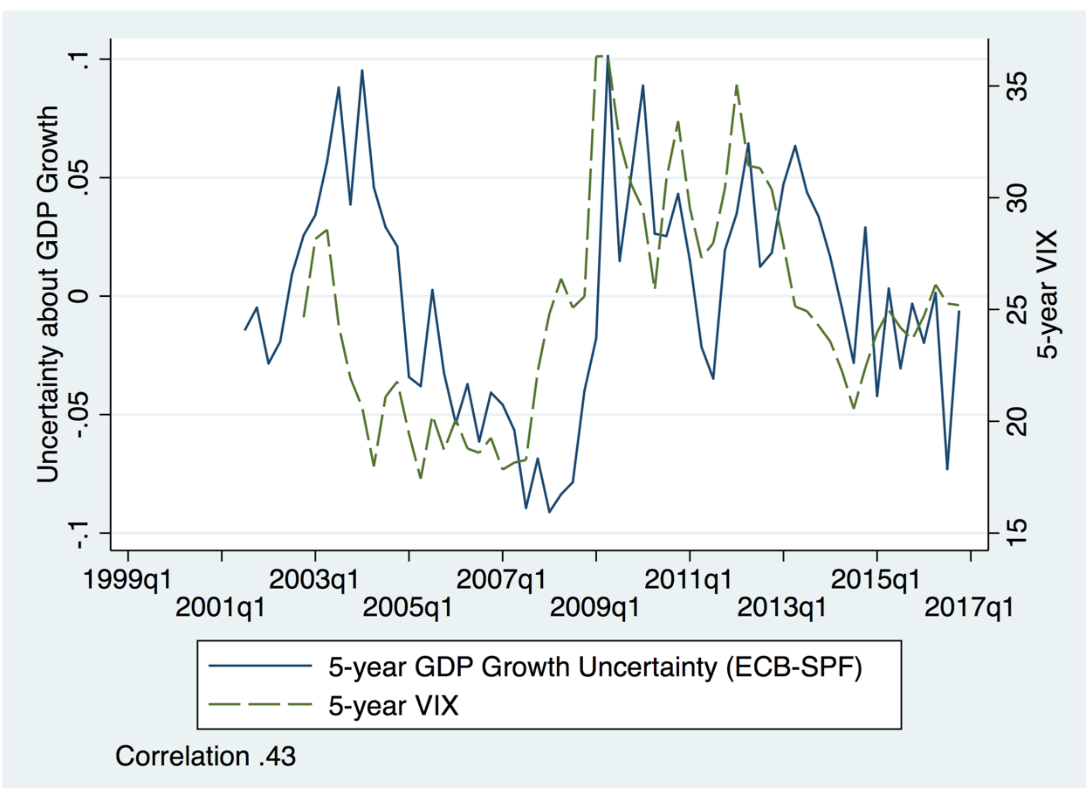
Notes: Average of the generalized VIX for the indicated month, by days to expiration measured on a logarithmic scale. The generalized VIX uses the formula used for the "true" VIX (a model-free measure of the 30-day implied variance on the S&P 500) for horizons other than the standard 30 days. Source: Goldman Sachs.

Figure 2: Short- and Long-run Uncertainty vs. Short- and Long-run Implied Volatility

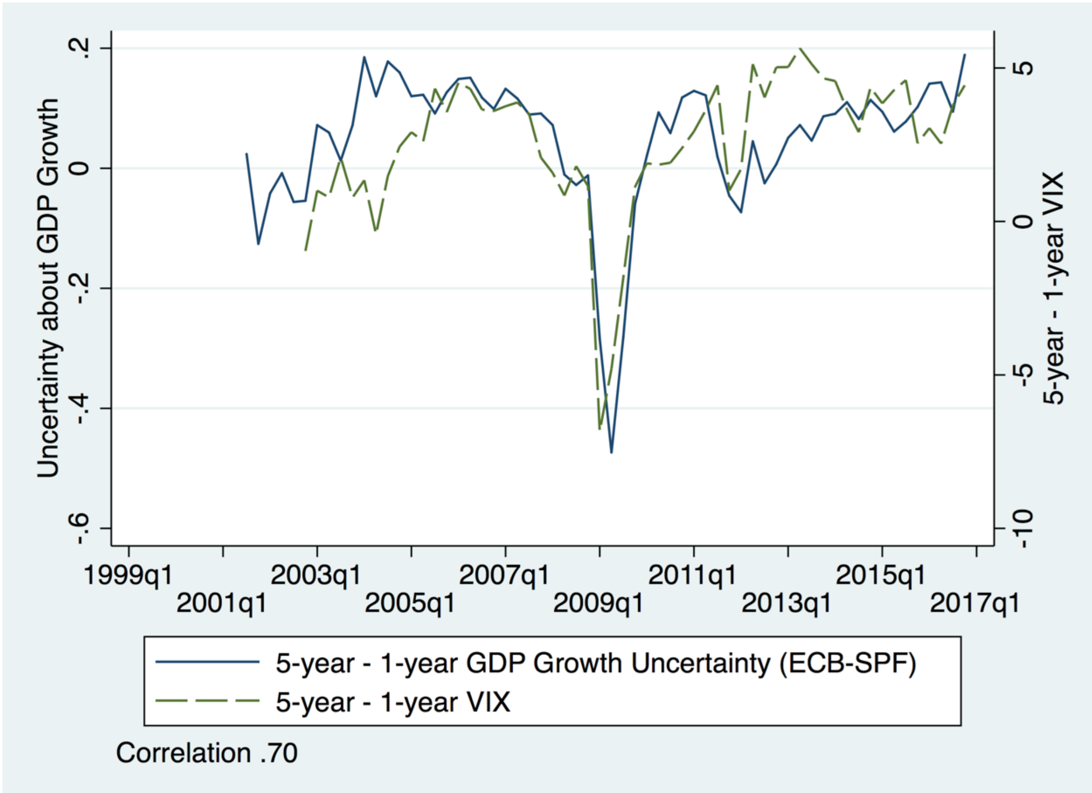
a. One-year Horizon



b. Five-year Horizon



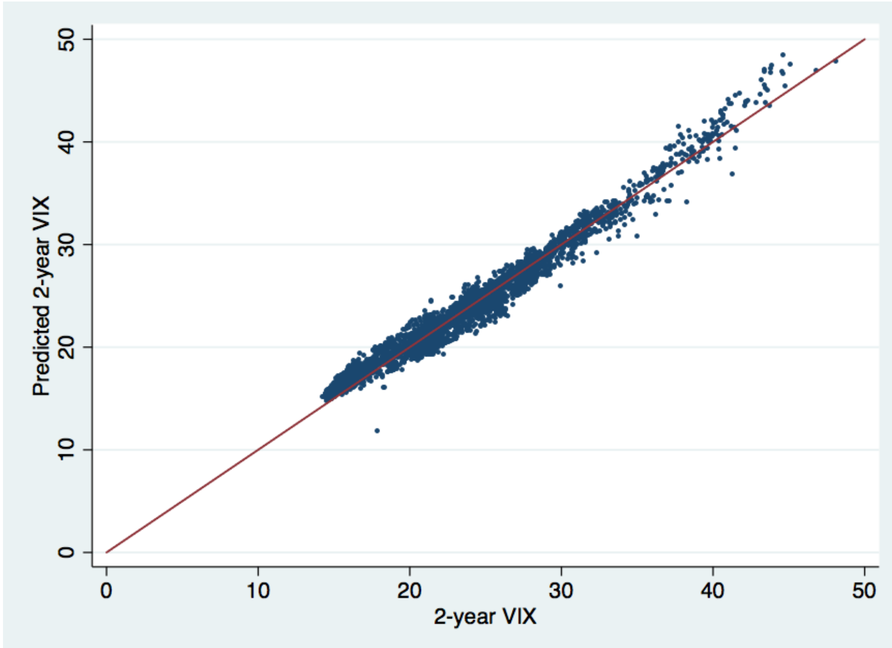
c. Slope: Five-year minus One-year Uncertainty and Volatility



Notes: Quarterly data on GDP Growth Uncertainty from the ECB Survey of Professional Forecasters was generously provided by the authors Kenny and Melo Fernandes (2017). GDP Growth Uncertainty for a given forecaster is the implied subjective standard deviation from fitting a unimodal Beta distribution to the respondent's subjective probability distribution for GDP growth of the Euro Area looking 4 quarters ahead from the latest data release. We detrend this subjective uncertainty series before plotting. The generalized VIX uses the formula used for the "true" VIX (a model-free measure of the 30-day implied variance on the S&P 500) for horizons other than the standard 30 days, building one-, two-, or five-year VIX as necessary. We build quarterly observations of these longer-run VIX measures by averaging across the days in a calendar quarter. The one-year VSTOXX is the analogue to the one-year VIX, but uses options on the EURO STOXX 50 index of major publicly-traded companies based in the Euro Area. In each figure we lag the generalized VIX and VSTOXX by one quarter to account for the timing and horizon of the questions in the ECB's Survey of Professional Forecasters.

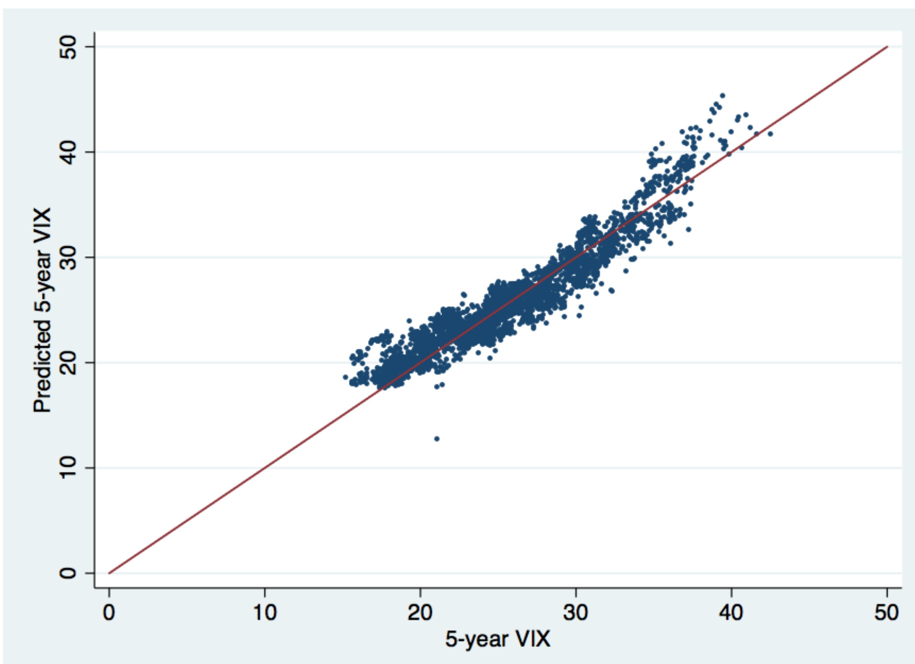
Figure 3: Predicting long-run VIX with 30-day and 6-month VIX

A. 2-year VIX



Notes: This figure plots the fitted values from a regression of daily observations of 2-year VIX on a constant, and the same day's 30-day and 6-month VIX. Data obtained from Goldman Sachs. R^2=.97

B. 5-year VIX



Notes: This figure plots the fitted values from a regression of daily observations of 2-year VIX on a constant, and the same day's 30-day and 6-month VIX. Data obtained from Goldman Sachs. R^2=.90

Appendix Figure 1: Forecaster's Subjective Probability Distributions for Euro Area GDP Growth:

	Probabilities of euro area real GDP growth* Year-on-year change					
	2013	**2014**	**2015**	**2013 Q3**	**2014 Q3**	**5 years ahead (2017)**
< -1.0%						
-1.0 to -0.6%						
-0.5 to -0.1%						
0.0-0.4%						
0.5-0.9%						
1.0-1.4%						
1.5-1.9%						
2.0-2.4%						
2.5-2.9%						
3.0-3.4%						
3.5-3.9%						
≥ 4.0%						
Total	100	100	100	100	100	100

* Standardised ESA definition. Probabilities should sum to 100%. Average of the period.

Notes: Kenny and Melo Fernandes (2017) measure subjective uncertainty at one-, two-, and five-year horizons using respondent's subjective probabilities about Euro Area GDP growth in the one, two, and five years following the latest data release. The figure above is from the ECB's sample questionnaire (available online at https://www.ecb.europa.eu/stats/pdf/spfquestionnaire.pdf) , which asked about year-on-year changes since the last data release, which would have been for 2012 Q3 in January 2013 when this survey was out in the field.