The Effect of Uncertainty on Investment, Hiring, and R&D:
Causal Evidence from Equity Options

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There is wide debate over the impact of uncertainty on firm behavior, due to the difficulty both of measuring uncertainty and of identifying causality. This paper takes three steps that attempt to address these challenges. First, we develop an instrumental variables strategy that exploits firms' differential exposure to energy and currency prices and volatility. For example, airlines are negatively affected by high oil prices while oil refiners benefit from them, but both are sensitive to oil price volatility; retailers, in comparison, are not particularly sensitive to either the level or volatility of oil prices. Second, we use the expected volatility of stock prices as implied by equity options to obtain forward-looking measures of uncertainty over firms' business conditions. Finally, we examine how uncertainty affects a range of outcomes: capital investment, hiring, research and development, and advertising. We find that uncertainty depresses capital investment, hiring, and advertising, but encourages R&D spending. This perhaps-surprising result for R&D is consistent with a theoretical literature emphasizing that long investment lags create valuable real put options which offset the effects of call options lost when projects are started. Aggregating across our panel of Compustat firms, we find that rising uncertainty accounts for roughly a third of the fall in capital investment and hiring that occurred in 2008–10.

1 Introduction

Firms face many sources of uncertainty, including demand and input market conditions, technological progress, the competitive environment, and financing availability. In the face of such uncertainty, these firms must choose investments that affect future profitability differently depending on how the uncertainty is resolved. These decisions involve investment not only in physical capital, but in the labor force, and in intangible factors through activities such as research, development, and advertising. In this paper, we use firm-level data to provide new empirical evidence on how uncertainty affects investment. Using a new instrumental variables strategy to econometrically identify uncertainty shocks, we find that uncertainty depresses capital investment, hiring, and advertising, but increases R&D spending.

Firms' investment is a key factor for the business cycle and other aggregate economic phenomena. To understand the effects of macroeconomic fluctuations in investment, however, it is valuable to examine the microeconomic decisions that firms make to build factories, buy equipment, research new ideas, and hire workers. For many years, theorists have argued that economic uncertainty can be an important determinant of investment levels and dynamics. Although understanding how uncertainty affects firms' decisions is important in macroeconomic analysis, economic theory offers only ambiguous predictions.

In particular, while adjustment costs and partial irreversibility may cause firms to delay investment in the face of heightened uncertainty (as in Dixit and Pindyck, 1994), other mechanisms— such as long times-to-build (as in Bar-Ilan and Strange, 1996), investment's ability to resolve technical uncertainty (as in Grossman and Shapiro, 1986; Pindyck, 1993b), the existence of complementary production factors (as in Oi, 1961; Hartman, 1972; Abel, 1983), and competitive dynamics (as in Kulatilaka and Perotti, 1998)—mean uncertainty may instead encourage investment. Empirical analysis is therefore necessary to assess both the direction and magnitude of uncertainty's effects.

This paper contributes to the empirical literature on investment under uncertainty in three

main ways. We view as our key contribution the use of a new instrumental variables strategy that relies on differential exposure to commodities markets to identify uncertainty fluctuations that are plausibly exogenous to firm behavior. While we are interested in the effect of uncertainty on investment, a causal relationship operating in the opposite direction is likely also present. For example, the decision to undertake a risky investment project may introduce heightened uncertainty over the firm's future returns. Latent factors may also affect both uncertainty and the attractiveness of investment, creating a non-causal correlation.[1] Prior literature typically attempts to deal with endogenous uncertainty by relying on "internal" instruments: lagged values of the dependent and explanatory variables (see for example Leahy and Whited, 1996; Bulan, 2005; Bloom, Bond, and Van Reenen, 2007). While these estimation techniques are attractive for their limited data requirements, their validity relies on strong assumptions about properties of the investment and uncertainty time series.

In contrast, our strategy relies on the fact that the effects of commodity fluctuations (including exchange rate) vary across industries in both degree and direction. Consider the effect of rising energy prices: these present good news for oil refiners, bad news for airlines, and relatively neutral news for retailers. Although energy prices affect positively and negatively sensitive firms in opposite directions, increased uncertainty in the energy market creates uncertainty for sensitive firms—both refiners and airlines—relative to insensitive ones. We estimate industry-level sensitivities using data on share price returns. Our instrumental variables exploit the differential effects of commodity price movements between positively and negatively sensitive firms to identify first-moment shocks, and the differential effects of commodity uncertainty movements between more and less sensitive firms to identify second-moment shocks.

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[1]Kothari, Laguerre, and Leone (2002) provide empirical evidence of reverse causation, showing that investment can lead to elevated uncertainty, and Minton and Schrand (1999) explicitly "recognize that volatility is a choice variable" chosen as one of several joint managerial decisions. Theoretical models describe mechanisms though which both investment and uncertainty could be affected by latent factors. For example, Brunnermeier and Sannikov (2010) show how shocks to credit conditions can affect both asset price volatility and firms' capital stocks, and Pastor and Veronesi (2011) build a model where bad economic news (that would presumably affect investment) increases uncertainty over future government policies.

An additional area of contribution is our use of an explicitly forward-looking proxy for firm-specific uncertainty that captures a broad range of potential sources of uncertainty: the expected volatility of firms' stock prices as implied by equity options. Rather than relying on econometric methods to generate a forecast of future stock price volatility, the implied volatility from equity options represents the market's own forecast.[2] In addition to being closer to the information available to managers at the time they make investment decisions, implied volatility may be less affected than measures estimated from realized returns by movements unattributable to changes in fundamentals ("stock price bubbles").[3]

Finally, we consider investment in a broad variety of long-lived production inputs. While prior microeconomic analyses have largely focused on capital investment, we also examine uncertainty's impact on hiring, research and development, and advertising. Among our most striking findings is that uncertainty actually encourages firms to engage in R&D spending, in contrast with its depressing effect on other forms of investment. This is consistent with R&D projects' high degree of technical uncertainty and long lags between investment and project completion.

Our analysis is based on 2001–11 data for 3,965 U.S. public companies with exchange-traded options, covering a wide variety of market environments including the recent period of economic turmoil. In Ordinary Least Squares specifications that naïvely fail to account for the endogeneity of uncertainty, we observe a negative covariance between uncertainty (as proxied by implied volatility) and capital investment, hiring, and advertising. Instrumental variables estimation finds that uncertainty has a negative and statistically significant effect on capital investment,

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[2]Although our use of firm-level option-implied volatility is new, analogous aggregate measures—mainly the VIX implied volatility from S&P 500 index options—have been used in empirical macroeconomic studies including Bloom (2009). Volatility forecasts derived from realized stock returns are used to proxy uncertainty in firm-level investment regressions by many authors starting with Leahy and Whited (1996). Various uncertainty measures used in the empirical literature—including volatilities of firm performance, exchange rates, and input and output prices, as well as measures derived from analysts' and managers' forecasts—are discussed in Section 3.

[3]Schwert (2002) shows that realized volatility is often much higher or lower than the market forecast, as evidenced by smoother series for implied volatility, and Christensen and Prabhala (1998) find that "implied volatility outperforms past volatility in forecasting future volatility and even subsumes the information content of past volatility…."

hiring, and advertising, but a significant positive effect on R&D.

The magnitudes of these effects are large. In the great recession, uncertainty (as proxied by option-implied volatilities) approximately doubled. Our estimates suggest that an uncertainty increase of this magnitude would cause the firms we analyze to decrease capital investment by about one sixth and drop net hiring nearly to zero. These effects represent approximately half of the total declines in investment and hiring observed in our sample in fiscal 2009, the year following the highest levels of uncertainty. They are also approximately one-third the size of the declines in total U.S. gross domestic business investment and net private hiring during that period.

The paper proceeds as follows: Sections 2 and 3 discuss the theoretical foundations for our analysis and briefly review the relevant empirical literature, respectively. We lay out our empirical strategy in Section 4. Section 5 describes our data sources and the construction of our sample. Estimation results are presented in Section 6, and Section 7 concludes.

2 Theoretical Foundations

In a benchmark linear model of firm decision-making, uncertainty has no effect on investment since the firm seeks only to maximize the expected value of an objective function that depends linearly on underlying stochastic processes. In order for uncertainty to matter, there must therefore be a nonlinearity in some element of the firm's problem. One way to characterize the diverse threads of the theoretical literature on investment under uncertainty is by dividing them according to the assumed source of curvature. These sources fall into three general categories: adjustment costs, the firm's profit function, and utility functions over profits.

The first group of models assumes adjustment costs (or in the extreme, irreversibility) that make the cost of achieving some desired input stock level a nonlinear function of that level. With adjustment costs, *not* investing allows the firm to maintain the option to invest only if future business conditions are sufficiently attractive; uncertainty increases the value of this call option.

In "real options" models such as that of Dixit and Pindyck (1994) and Abel and Eberly (1996), the combination of uncertainty and irreversibility in investment generates regions of inaction where firms prefer to "wait and see" rather than immediately invest. Greater uncertainty expands this region of inaction, generating a negative relationship between uncertainty and investment.[4] The strength of these effects is likely to be higher for inputs that are characterized by a high degree of adjustment costs.

The second group of models considers curvature in the firm's profit function, which can arise from a variety of underlying sources. For example, Oi (1961), Hartman (1972), and Abel (1983) show that with a nonlinear production function, the marginal revenue product of capital is a convex function of output prices as long as the firm can freely adjust some input (labor, in their models) after investment decisions have been made. As a result, heightened demand uncertainty raises the expected marginal revenue product of capital, creating a positive relationship between uncertainty and investment.[5] Lee and Shin (2000) show that these positive effects should be strongest when the complementary, flexible factor represents a greater share of the production technology.

Profit may also be a convex function of input stocks when there is some lag before new investments become productive. Without investment lags, the benefits of deferring investment accrue in an uncertain future while the costs are incurred in the certain present. A key intuition (as in Bernanke, 1983) underlying traditional real options models is that these expected benefits depend only on the possibility of "bad news," and hence increase with uncertainty. Bar-Ilan and Strange (1996) show that with investment lags, the *costs* of deferring investment (i.e., forgone profits from having the *ex post* wrong input stock) are incurred some time in the future. As

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[4]Irreversible investment models do not always predict a negative relationship between uncertainty and investment. Ingersoll and Ross (1992) note that the effect of interest rate uncertainty on investment is ambiguous because present values are convex functions of interest rates. The nature of the shock process is also relevant; for example, firms may be more responsive to a permanent or persistent shock than to a temporary one.

[5]However, as examined in a number of papers (such as Caballero, 1991; Pindyck, 1993a), this result relies on particular modeling assumptions regarding the revenue function and the nature of uncertainty. For example, the effect may be eliminated or reversed if uncertainty is modeled as demand shocks to quantity rather than price.

expected costs depend only on the possibility of "good news," higher uncertainty encourages investment in the presence of investment lags, and Bar-Ilan and Strange (1996) show numerically that these effects can dominate uncertainty's discouraging effects due to irreversibility.

Investment may also have nonlinear effects on profit when it affects things other than the stock of productive inputs. For example, investment may be required to learn about a project's uncertain costs. Grossman and Shapiro (1986) show that firms prefer projects with less certain effort requirements, and Pindyck (1993b) confirms that uncertainty over the difficulty of completing a project ("technical uncertainty," in contrast with uncertainty over project input costs) can encourage investment.[6] An additional channel through which investment can affect profits is if it allows strategic preemption in imperfectly competitive industries; Kulatilaka and Perotti (1998) show that if investment has a sufficient ability to discourage entry or competitors' investments, uncertainty is likely to encourage investment.

The final group of models assumes curvature in managers' or investors' utility functions. Managerial risk aversion (Panousi and Papanikolaou, 2012) and ambiguity aversion (Ilut and Schneider, 2012) can also create a negative relationship between uncertainty and investment. A risk-averse investor will be concerned with undiversifiable risk, and will therefore consider the covariance of firm and market returns rather than the uncertainty faced by any firm in isolation. An increase in the covariance of a firm's returns with market returns represents undiversifiable portfolio risk, increasing the required rate of return and thereby discouraging investment. These models predict a negative relationship between investment and uncertainty, although the underlying concept of uncertainty is very different from that treated by traditional real options models. We will be considering uncertainty as proxied by a variance of firm returns, and will therefore not speak directly to the predictions of these CAPM-style models.

Taken together, the range of theoretical models describing the relationship between invest-

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[6]A numerical analysis leads Pindyck (1993b) to conclude that "for many investments, and particularly for large industrial projects for which input costs fluctuate, increasing uncertainty is likely to depress investment. The opposite will be the case only for investments like R&D programs, for which technical uncertainty is far more important."

ment and uncertainty might be said to offer ambiguous predictions. Rather than testing a particular model, this paper attempts to identify the direction and size of the causal relationship between uncertainty and investment in the data.

3 Empirical Literature

There is an extensive empirical literature investigating the relationship between uncertainty and investment using data at a variety of levels of aggregation from national accounts down to individual projects. Along with the difficulty of measuring uncertainty, the key challenge faced by this literature is the causal identification of uncertainty's effects. While the use of more aggregated data perhaps mitigates some concern about reverse causation—for example, that uncertainty about the returns on investment projects means that these projects actually increase uncertainty—aggregation leaves the econometrician with less variation in uncertainty with which to identify its effects. Furthermore, any analysis needs to separate confounding factors that affect both uncertainty and investment, most notably the "first moment" effects associated with the business cycle.

Authors have investigated the relationship between aggregate capital investment and a variety of uncertainty measures. These include the realized volatilities of stock market returns and a variety of macroeconomic variables including interest rates, inflation rates, exchange rates, energy prices, real wages, and GDP.[7] Various methods are used to calculated measures of volatility from realized fluctuations, ranging from simple standard deviations of higher-frequency movements to ARCH- and GARCH-estimated conditional variances. Several other papers use more explicitly forward-looking measures of macroeconomic uncertainty generated from the term structure of interest rates (Ferderer, 1993) and business surveys (Bachmann, Elstner, and Sims, 2010). This literature is summarized in Carruth, Dickerson, and Henley (2000); the general consensus of

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[7]This large macroeconomic literature includes Pindyck (1986); Huizinga (1993); Goldberg (1993); Ferderer (1996); Servén (2003); Eisfeldt and Rampini (2006); Gilchrist, Sim, and Zakrajsek (2010); Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011).

these studies is a negative effect of uncertainty on aggregate capital investment.

Many papers have also examined the relationship between capital investment and uncertainty using industry- or firm-level data. These studies typically use measures similar to those of the aggregate studies, including the volatility of exchange rates (Campa, 1993; Goldberg, 1993; Campa and Goldberg, 1995); input and output prices (Huizinga, 1993; Ghosal and Loungani, 1996); stock returns (Leahy and Whited, 1996; Bulan, 2005; Shaanan, 2005; Bloom, Bond, and Van Reenen, 2007; Baum, Caglayan, and Talavera, 2008, 2010; Gilchrist, Sim, and Zakrajsek, 2010); and measures of firm performance (Minton and Schrand, 1999; Ghosal and Loungani, 2000). Authors have derived uncertainty measures from disagreement and errors in analysts' earnings forecasts (Bond and Cummins, 2004; Bond, Moessner, Mumtaz, and Syed, 2005) and managers' perceptions about future product demand (Guiso and Parigi, 1999). Compared with the aggregate studies, these papers report less conclusive evidence on the relationship between capital investment and uncertainty. While the relationship appears to be negative, it is often weak or not robust to the inclusion of controls that capture the effect of business conditions (such as Tobin's q).

Most of the empirical work assessing the effects of uncertainty has focused on capital investment, but several studies have considered its effect on other forms of investment.[8] Minton and Schrand (1999) use cross-sectional regressions to show that firms with more volatile cash flows invest less in capital, R&D, and advertising. In a cross-country panel, Goel and Ram (2001) find a negative correlation between inflation uncertainty and aggregate R&D, but no relationship with capital investment. A series of papers by Czarnitzki and Toole (2007, 2011, 2012) consider a panel of German manufacturing firms, finding that firms conduct less R&D when the sales of recently introduced products have been volatile. While the volatility of new product sales provides a useful measure of uncertainty over the returns on future R&D projects, the estimated

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[8]I am focused on analysis of business investment, but there is also a literature on uncertainty's effects on consumers. See for example Eberly (1994); Carroll and Dunn (1997); Foote, Hurst, and Leahy (2000); Bertola, Guiso, and Pistaferri (2005); Nakamura, Sergeyev, and Steinsson (2012).

effects may be driven by the omission of a controls for these projects' expected returns.

While the extensive literature on investment under uncertainty considers a variety of settings, much of the empirical work to date shares the common features of using realized variances to proxy for or forecast future uncertainty, and either reporting correlative evidence or relying on "internal" instruments for causal identification. These estimators—generally in the spirit of Arellano and Bond (1991) or Blundell and Bond (1998)—instrument uncertainty (and other regressors such as those designed to capture business conditions) with lagged levels and differences of the dependent and explanatory variables. Unfortunately, the identifying assumptions required to ensure these instruments' exogeneity are perhaps dubious, in particular that firms' investment growth rates are uncorrelated with the deviation from their "steady state" investment rates. In contrast, by using the expected volatility of stock prices as implied by equity options, our paper makes use of the market's own forecast of explicitly forward-looking uncertainty, and introduces an identification strategy that relies on instruments which are intuitively and fundamentally related to firm-level uncertainty.

4 Estimation Strategy

Our basic estimating equations are simple linear investment models of the form

$$\frac{F_{i,t}}{S_{i,t-1}} = \lambda_\sigma \cdot \sigma_{i,t-1} + \kappa_q \cdot q_{i,t-1} + f_i + g_t + \epsilon_{i,t}, \tag{1}$$

estimated on a panel of firms (i) over time (t), where F is an investment flow (capital investment, hiring, R&D, or advertising) and S is the corresponding end-of-period stock. We are mainly interested in the effects of forward-looking firm-specific uncertainty as measured at the end of the prior period ($\sigma_{i,t-1}$). Average Tobin's q is (approximately) a normalization of the firm's enterprise value at the end of the prior period, which controls for firm-specific variation in business conditions. Firm fixed effects (f_i) capture persistent, firm-specific differences in be-

havior. Finally, annual fixed effects (g_t) capture the effect of changes in the macroeconomic environment that have a homogeneous effect across firms.[9]

We use the implied volatility from equity options as an uncertainty proxy. This measure represents the market's forecast of future stock price volatility, and is calculated as the volatility consistent with the market price of an exchange-traded option (using an inversion of the Black-Scholes formula). It is an attractive measure of uncertainty because stock prices capture the impact of a broad range of future shocks; implied volatilities therefore capture the uncertainty over this same broad range. Given the market incentives faced by options traders to forecast volatility correctly, it is unsurprising that implied volatilities are highly predictive of future realized volatility, and therefore capture many of the types of uncertainty that should affect managerial decision-making.[10]

Measures of Tobin's q are popular "first moment" controls in investment equations partly because in some models, uncertainty's effects on capital investment are entirely captured by marginal Tobin's q (i.e., the ratio between the value and cost of an additional unit of capital).[11] Given the lack of a suitable empirical measure of marginal q, we adopt the common measure of *average* Tobin's q, calculated as a ratio of the market value of the firm's capital stock to the replacement cost of that capital).[12] Of course, neither the market nor replacement value of

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[9]Note that with time-varying volatility and risk-averse investors, option-implied volatility is the sum of expected volatility and a risk premium. Risk premia vary over time and tend to be countercyclical. In a regression of investment on option-implied volatility, a negative coefficient may therefore reflect firms' responses to high risk premia rather than to increases in uncertainty. Assuming the risk premium is a primarily macroeconomic variable, the inclusion of time fixed effects controls for the effect of changing risk premia on investment patterns.

[10]Leahy and Whited (1996) discuss the advantage of implied volatilities over the realized measure they used; while the necessary data were unavailable at that time, the enormous growth of the equity options markets over the past decade means we now have access to extensive, reliable options data. Sridharan (2012) summarizes the literature assessing options-implied volatility's ability to predict realized volatility, noting that while it does a good job, it is a somewhat biased forecast that fails to fully subsume all of the information contained in financial statements.

[11]This relationship is highlighted by Dixit and Pindyck (1994), who show that in the presence of investment irreversibility, uncertainty affects the threshold value of q at which firms choose to invest. In particular, a higher degree of uncertainty increases the threshold value of q above which investment occurs. Abel and Eberly (1994) develop a model that nests the model of Abel (1983) and an irreversible investment model, and note that marginal q is equivalent to the expected present value of the stream of marginal products of capital in a multiperiod model. They show that under general assumptions investment depends only on marginal q and the capital stock; that is, uncertainty affects investment only through marginal q.

[12]Perfect competition and constant returns to scale are necessary—though not sufficient—for average q and

capital are readily observable, so the firm's enterprise value is typically taken as the market value of capital. Average Tobin's q can therefore serve as an attractive proxy for "first-moment" business conditions as well as a measure of the expected return on capital investment. Without such a control, correlation between first- and second-moment shocks would cause our estimates of uncertainty's effects to suffer from serious omitted variable bias.[13]

In attempting to assess the effect of uncertainty on investment, it is also important to recognize that causation may run in both directions. Starting a new project may drive up measures of uncertainty given that project returns are unknown; Kothari, Laguerre, and Leone (2002) provide evidence for such mechanisms. On the other hand, uncertainty over what projects a firm might pursue might be resolved when it invests. Latent factors that affect both uncertainty and investment are another potential source of endogeneity. The exogeneity of Tobin's q is also unlikely. Given the endogeneity of both first- and second-moment shocks, an instrumental variables strategy is necessary. In contrast with the literature's typical use of lagged variable values as instruments, we suggest a "natural" instrument strategy that identifies plausibly exogenous shocks to firm uncertainty and value using industry-specific exposure to commodity price and volatility shocks.

In the spirit of Bartik (1991), our instruments are structured as the product of predetermined cross-sectional sensitivity to a particular commodity market (c) with time-varying commodity

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marginal q to be equal (see Hayashi, 1982 for the deterministic case and Abel and Eberly, 1994 for a stochastic model).

[13] Leahy and Whited (1996) find that capital investment has a a positive relationship with average Tobin's q and a negative relationship with uncertainty when each explanatory variable is considered separately; however, when both q and uncertainty are included in the regression specification, neither coefficient estimate is statistically significant. They interpret this finding as evidence that uncertainty operates through the first moment of returns, but such a conclusion is not technically possible using this empirical test. In a world with constant returns to scale and perfect competition, uncertainty has no effect on investment. As illustrated in Dixit and Pindyck (1994), without these conditions, uncertainty only affects investment through marginal q. In the absence of constant returns to scale or perfect competition, marginal q is not equal to average q. Therefore, an empirical specification using *average q* cannot conclusively test the theory's prediction that the effect of uncertainty on investment operates exclusively through *marginal q*.

prices and volatilities:

$$\text{PriceExposure}_{i,t}^c \equiv \text{Sensitivity}_i^c \cdot \text{Price}_t^c \tag{2a}$$

$$\text{VolatilityExposure}_{i,t}^c \equiv \left|\text{Sensitivity}_i^c\right| \cdot \text{Volatility}_t^c. \tag{2b}$$

The sensitivity of an industry to a commodity market c is a directional measure of the degree to which the value of that industry's firms comove with the commodity price. For example, when oil prices are high, the oil and gas field services industry tends to do well; it therefore has a high positive sensitivity to the energy market. In contrast, the airline industry tends to fare poorly when energy prices rise, which is represented by a highly negative sensitivity. An oil prices change will have opposite impacts on the two industries' price exposures, but an increase in oil volatility is likely to drive up uncertainty in both industries, which is reflected in the fact that only the magnitude of the sensitivity enters the volatility exposure equation.[14] An industry like general retail which is not significantly affected by oil prices will have a sensitivity close to zero, reflecting the idea that oil price fluctuations do not systematically affect firms' values, nor therefore should energy volatility affect the uncertainty those firms face.

Identification of price and volatility shocks comes from the combined effects of two sources of variation: industries vary in their level of sensitivity, and commodity markets fluctuate over time. Separate identification of the first- and second-moment shocks comes from the fact that both these sources of variation differ between price and volatility exposure. In the cross-section, this is because volatility sensitivities are a nonlinear function (the absolute value) of price sensitivities. In the time series, this is because commodity prices and volatility do not move together.

The sensitivities are estimated as the factor loadings on commodity price changes in a regression of firm stock returns on these commodity returns and market returns, and are held

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[14]To formalize this intuition slightly, note that holding sensitivity fixed, volatility exposure is the standard deviation of price exposure: $\sigma(\text{PriceExposure}_{i,t}^c) = \sigma(\text{Sensitivity}_i^c \cdot \text{Price}_t^c) = \left|\text{Sensitivity}_i^c\right| \cdot \sigma(\text{Price}_t^c) = \left|\text{Sensitivity}_i^c\right| \cdot \text{Volatility}_t^c = \text{VolatilityExposure}_{i,t}^c.$

constant across companies in the same three-digit SIC industry (for precision). That is, for firm i in industry j, Sensitivity$_i^c = \widehat{\beta}_j^c$ from an estimation of

$$r_{i,t} = \alpha_i + \beta_i \cdot r_t^{\text{SPX}} + \sum_c \beta_j^c \cdot r_t^c + \varepsilon_{i,t}, \tag{3}$$

where $r_{i,t}$ is the return on firm i (including dividends), r_t^{SPX} is a measure of market return, and r_t^c is the change in the price of commodity c. The sensitivities are estimated using daily data from the five years prior to the main estimation period (1996–2000). Estimating industry- rather than firm-level sensitivities helps address the fact that our sample is a highly unbalanced panel which includes many companies in the the main 2001–11 estimation period that did not exist in 1996–2000: we treat $\widehat{\beta}_j^c$ as the sensitivity for all firms in industry j, regardless of whether they were used to estimate it. We include changes in both oil prices and the exchange rates of the U.S. dollar with 16 currencies.[15]

5 Data and Measurement

In order to assess the impact of uncertainty on firm behavior, we rely on two principal data sources. Firm behavior is measured using cash flow, income, and balance sheet statements available through Compustat, and uncertainty measures come from OptionMetrics. In addition, our instrumental variables strategy relies on assessing companies' exposure to commodity price and volatility shocks. The resulting estimates therefore require data on stock markets (from CRSP), energy markets (from Bloomberg) and foreign exchange markets (from the Federal

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[15]Given the possibility of hedging, why do commodity markets have an effect on at all on firms? As discussed in Section 2, a variety of mechanisms can create convexity in the firm's profit function that mean the firm would not benefit from avoiding exposure. Markets are incomplete and instruments therefore do not exist such that firms can fully hedge against all risks; when hedging instruments are available, they may be sufficiently expensive that a firm prefers to bear some risk rather than pay to eliminate it. Finally if shareholders are able to diversify across a portfolio of assets, it may not be optimal for firms to hedge, even at modest cost. Guay and Kothari (2003) find that the hedging portfolios of non-financial firms are very modest relative to firm size (and operating and investing cash flows), concluding that "corporate derivatives use appears to be a small piece of non-financial firms' overall risk profile." Indeed, we find that share price returns are correlated with commodity price movements.

Reserve and Bloomberg). These data are discussed below, with additional detail provided in Appendix A.

Company financial data comes from Compustat, and is available for fiscal years ending June 1950 through July 2012. We rely on variables drawn from cash flow statements, income statements, and balance sheets as well as stock prices and firm identifying information. Because financial statements report the value of capital (K) at book rather than replacement value, and do not account for the values of accumulated R&D (G) or advertising (M), we construct measures of these values recursively using a perpetual-inventory method similar to that described in Salinger and Summers (1983). The perpetual-inventory capital stock is also used along with several other variables to calculate a measure of average Tobin's q:

$$q_{i,t} = \frac{\text{Market capitalization}_{i,t} + \text{Debt}_{i,t} - \text{Current Assets}_{i,t}}{K_{i,t} + \text{Inventory}_{i,t} + \text{Intangibles}_{i,t} + \text{Investments and advances}_{i,t}}.$$

The details of these calculations, as well as additional information about the Compustat data, are discussed in Appendix A.1.

OptionMetrics provides daily implied volatility data for an unbalanced panel of 7,579 underlying securities from January 1996 through January 2012. An implied volatility is the standard deviation of future stock returns that is consistent with the market price of an exchange-traded equity option, and is calculated using an inversion of the Black-Scholes formula. While data is available from a wide variety of options (both puts and calls with a variety of strike prices and expiration dates), we use as our principal uncertainty measure the implied volatility of 91-day, at-the-money-forward call options. These are options for which the strike price is equal to the stock's forward price—given current interest rates and the company's dividend payout schedule—on the option's expiration 91 days in the future.[16] Additional information about the OptionMetrics data is provided in Appendix A.2.

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[16]Our decision to focus on at-the-money-forward options should not be surprising. These are the baseline options included in the OptionMetrics data archive, and strike prices of all other options are expressed as deviations from this baseline.

We merge the Compustat and OptionMetrics data by 8-digit CUSIP code, which yields an unbalanced panel of 6,583 matched companies for fiscal years ending in 1996–2011. Our main analysis is further limited to 2001–11 observations with data on hiring, capital investment, and several lagged measures (as described in Appendix B), and requires companies to have non-zero capital investment in at least one year. This gives a sample of 3,965 companies averaging 5.4 annual observations each; summary statistics are reported in Table 1, along with comparisons to the 2001–11 Compustat and Compustat-OptionMetrics linked samples.

Note that inclusion in OptionMetrics requires a firm to have exchange-traded equity options, which is more typical for large, better established firms. Even compared to the average firm in Compustat, which is already strongly selected for size by virtue of being publicly-traded, firms in our sample have sales, capital, labor, R&D, and advertising two to three times as high. Given this, it is clear that our analysis will be focused on the effect of uncertainty on relatively large firms' behavior. However, as illustrated by the summary statistics, our sample retains substantial heterogeneity in firm size.

Figure 1 illustrates the distributions (pooled across both time series and cross section) of our key dependent variables: annual capital investment, hiring, R&D, and advertising rates. We observe very little capital disinvestment, and the mass of firms with zero investment in a given year is relatively small. The rarity of zero-investment episodes may seem to be at odds with theories of irreversible investment or fixed costs, but aggregation over time and across plants within a firm can help reconcile these (see Bloom, Bond, and Van Reenen, 2007). Another possibility is that the costs incurred to replace depreciated capital may be less than those incurred for the installation of new capital. As a result, we may observe small amounts of investment each period as firms replace depreciated capital.

As illustrated in Figure 2, uncertainty varies significantly across firms and time. Implied volatility is a measure of the annualized standard deviation of expected returns; the (pooled)

Table 1: Summary statistics: Compustat, Compustat-OptionMetrics merged, and analysis samples

	Compustat			Compustat + OptionMetrics			Analysis sample		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Sales ($M)	2,416	110	11,937	6,189	1,009	20,380	6,628	1,107	21,639
Investment ($M)	178	4	1,068	424	39	1,728	465	46	1,849
Capital stock ($M)	1,193	30	6,926	2,771	280	10,583	3,033	320	11,251
I_t/K_{t-1}	21.4%	13.0%	24.8%	23.0%	16.5%	21.1%	21.3%	15.8%	19.0%
Net hiring	149	1	4,588	442	39	7,045	425	37	7,320
Employees	8,111	500	37,442	17,610	3,300	56,221	19,145	3,826	59,935
$\Delta L/L_{t-1}$	5.3%	1.2%	27.0%	7.7%	3.5%	22.7%	5.8%	2.7%	21.7%
R&D ($M)	90	3	520	211	24	801	236	29	846
R&D stock ($M)	606	39	3,170	1,336	171	4,709	1,438	187	4,883
R_t/G_{t-1}	23.9%	20.0%	19.1%	27.6%	23.1%	18.2%	26.7%	22.7%	17.0%
Advertising ($M)	59	1	336	149	12	490	160	14	515
Ad stock ($M)	106	2	636	273	22	909	298	25	974
A_t/M_{t-1}	56.9%	52.8%	33.7%	61.0%	55.4%	30.3%	58.7%	54.2%	29.0%
N	120,735			28,352			21,598		
Firms	18,164			5,222			3,965		
Firms in 2011	10,055			3,383			2,424		

Note: Not all variables are available for all observations. "Compustat" includes fiscal years ending in 2001–11. "Compustat + OptionMetrics" includes fiscal years ending in 2001–11 with nonmissing end-of-year 91-day implied volatility. "Analysis sample" includes fiscal years ending in 2001–11 with nonmissing capital investment and employees; nonmissing lagged capital stock, employees, end-of year Tobin's q, end-of-year 91-day implied volatility, and end-of-year three-month realized volatility; and is limited to firms with nonzero capital investment in some fiscal year ending in 2001–11. Variables are calculated using Compustat data as described in Appendix A.1, including Winsorization of extreme values.

Figure 1: Distribution of capital investment, hiring, R&D, and advertising
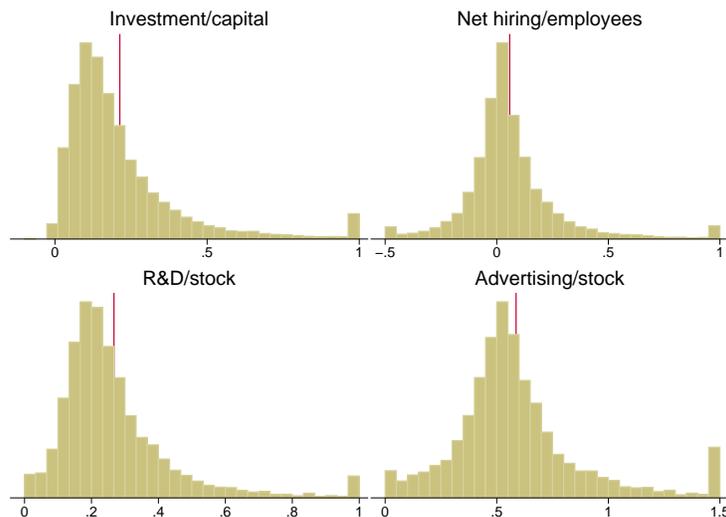
Note: Includes pooled (across firms and years) observations in the sample described in Appendix B. Variables are calculated using Compustat data as described in Appendix A.1, including Winsorization of extreme values.

mean observation of 52% corresponds to a daily expected standard deviation of 3.3%.[17] The episode of heightened uncertainty peaking in 2008–9 corresponded to an increase in the mean firm's implied volatility of approximately 40% (doubling from roughly 40% to 80%), and the typical cross-sectional interquartile range during our sample period was around 15%. These values provide useful context for interpreting the magnitude of our estimated effects. The figure also shows that while trends in implied volatility have generally tracked those of realized volatility (calculated as the standard deviation of daily stock returns as described in Appendix A.3), realized volatilities rose much higher during the great recession.

In order to estimate the commodity sensitivities necessary for our instrumental variables strategy, we utilize daily data on energy prices (from Bloomberg) and foreign exchange rates (from the Federal Reserve Board). Calculating the instruments requires this price data, along with measures of energy price and exchange rate uncertainty. We use the implied volatility of one month crude oil futures and three-month implied volatility for 16 foreign currencies from

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[17]Option traders sometimes refer to the "rule of 16": with approximately 252 trading days per year, an annual return volatility can be divided by $\sqrt{252} \approx 16$ to find the daily return volatility (expressed as the standard deviation of daily returns).

Figure 2: Volatility time series
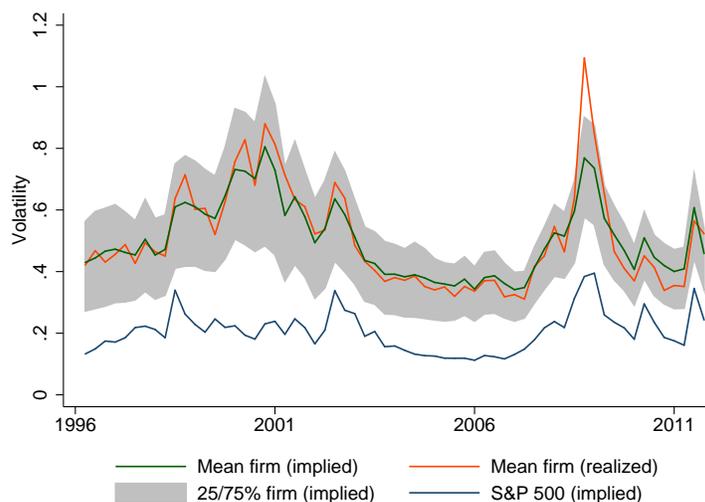
Note: Implied volatility is end-of-quarter 91-day implied volatility from at-the-money-forward call options as described in Appendix A.2, and is calculated identically for the S&P 500 index using index options. Realized volatility is the standard deviation of daily returns (including dividends) across all trading days in the last 90 days of the quarter as described in Appendix A.3. Means and interquartile range are calculated over fiscal quarters ending in the same calendar quarter. Includes fiscal quarters ending in 1996–2011 with nonmissing capital investment; nonmissing lagged capital stock, end-of-quarter Tobin's q, end-of-quarter 91-day implied volatility, and end-of-quarter three-month realized volatility; and is limited to firms with nonzero capital investment in some fiscal quarter ending 1996–2011.

Bloomberg. Additional information on the energy and currency data is provided in Appendices A.4 and A.5. The sensitivities are estimated (and matched to firms in the main sample) at the three-digit SIC level using Compustat's industrial classification, which is recorded as of the last time the firm appears in Compustat (i.e., as late as July 2012).

6 Results

The first step in executing our empirical strategy is estimating industry-level sensitivities as described in Equation 3. Table 2 lists the industries with the highest and lowest sensitivities to oil prices and to the exchange rate of the U.S. dollar with four major trade partners. Firms in industries at the top of each list tend to enjoy share price increases when oil prices rise or the dollar appreciates against the indicated currency, while those in industries at the bottom have the opposite relationship. These sensitivities are used together with the time series of oil prices/volatility, and currency exchange rates/volatility to form instruments as described in

Equation 2. (The oil and select currency time series are illustrated in Figures 6–7 in Appendix A.)

Table 3 reports estimates of the impact of uncertainty on capital investment. In column 1, we show the results of Ordinary Least Squares estimation of Equation 1 that (naïvely) fails to take into account the potential endogeneity of either second- or first-moment shocks as proxied by implied volatility and Tobin's q. As with all the estimation results we show, standard errors are two-way clustered by firm and year.[18] We observe highly statistically significant coefficients on implied volatility and q, showing that firms tend to invest more when their firm-specific uncertainty is low and when business conditions are good.

Subsequent specifications all use instrumental variables estimation to attempt to isolate the causal effects of uncertainty. Column 2 reports the results of our baseline specification, which instruments implied volatility and q with exposure to the price and volatility of oil and currency exchange rates as described in Section 4. In the last two rows we report F statistics on tests that in each first stage regression, the coefficients on the instruments are jointly zero; these test statistics are above the commonly referenced hurdle value of ten. We find a negative and strongly statistically significant coefficient estimate of -0.09 for uncertainty measured using implied volatility. Although statistically indistinguishable from our OLS estimate, we note that it is slightly more negative; this is consistent with the possibility that investment creates uncertainty, introducing a positive bias to OLS.

One way to assess the magnitude of our estimated effects is to note that the average firm in our sample saw its implied volatility rise during the great recession by approximately 0.4 (as was illustrated in Figure 2). That is, the annualized standard deviation of share price movements implied by option prices rose 40 percentage points. Multiplying this change by our coefficient estimate suggests that the increased uncertainty firms faced during the great recession was consistent with a 3.6 percentage point lower investment-to-capital ratio. Given the mean firm's 21.3% investment rate, this represents an economically significant 17% decline in capital investment.

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[18]Calculation of standard errors in financial panel data sets is discussed in Petersen (2009). Our estimation is implemented in Stata using the XTIVREG2 package.

Table 2: Highest- and lowest-sensitivity industries

Oil	Canada	Euro
Highest sensitivity	**Highest sensitivity**	**Highest sensitivity**
Oil and gas field svc. (138)	Medical offices (801)	Oil and gas field svc. (138)
Construction/mining equip. (353)	Nursing facilities (805)	Electronic components (367)
Crude petroleum and nat. gas (131)	Agricultural production (010)	Home health care (808)
Petroleum refining (291)	Variety stores (533)	Misc. fabric. metal prod. (349)
Gold and silver ores (104)	Retail stores, other (599)	Special industrial equip. (355)
Lowest sensitivity	**Lowest sensitivity**	**Lowest sensitivity**
Industrial inorganic chem. (281)	Groceries (514)	Miscellaneous stores (594)
Nursing facilities (805)	Consumer electronics stores (573)	Life insurance (631)
Hospitals (806)	R&D and testing services (873)	Furniture (251)
Drug and proprietary stores (591)	Electrical goods (506)	Mortgage banks/brokers (616)
Air transportation (451)	Gold and silver ores (104)	Commercial printing (275)

Japan	Mexico
Highest sensitivity	**Highest sensitivity**
Real estate agents and managers (653)	Groceries (514)
Variety stores (533)	Combined utility svcs. (493)
Miscellaneous stores (594)	Medical offices (801)
Drugs (512)	Mortgage banks/brokers (616)
Cable TV services (484)	Communications svcs., other (489)
Lowest sensitivity	**Lowest sensitivity**
Construction/mining equip. (353)	Home health care (808)
Personal credit institutions (614)	Paper mills (262)
Oil and gas field svc. (138)	Nonclassifiable (999)
Plastics etc. (282)	Oil and gas field svc. (138)
Gold and silver ores (104)	Consumer electronics stores (573)

Note: Sensitivities are coefficients $\widehat{\beta}_j$ from Equation 3 estimated on 1996–2000 data at three-digit SIC level using changes in the oil price and 16 foreign currency exchange rates. This table limited to industries where more than 20 firms were used to estimate sensitivities. Most positive sensitivity is listed first; most negative is listed last.

Table 3: IV estimates—Capital investment

	(1) OLS	(2) IV Baseline	(3) IV Real. vol	(4) IV Compustat	(5) IV Quarterly
Implied vol$_{t-1}$	-0.0523***	-0.0893***			-0.0691***
	(0.0181)	(0.0262)			(0.0194)
Realized vol$_{t-1}$			-0.0499***	-0.0395**	
			(0.0134)	(0.0198)	
Tobin's q_{t-1}	0.0170***	0.0279***	0.0266***	0.0213***	0.00957***
	(0.00146)	(0.00519)	(0.00559)	(0.00675)	(0.00163)
Observations	20789	20789	20789	46665	88684
F: vol first stg		32.6	507.2	13.9	9.1
F: q first stg		18.4	18.4	50.8	4.4

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in all regressions is I_t/K_{t-1}, and all include firm and time fixed effects (annual in columns 1–4, quarterly in column 5). Standard errors two-way clustered by period and year reported in parentheses.

Note: Estimation samples are as described in Appendix B: columns 1–3 use the main annual sample, column 4 does not require the availability of lagged implied volatility, and column 5 uses the quarterly sample. Variables are calculated as described in Appendix A. Instruments are energy/currency price and volatility exposures using sensitivities from 1996–2000 calculated at SIC3 level as described in Section 4.

From 2007 to 2009, U.S. aggregate gross domestic business investment fell 31%, suggesting that the uncertainty channel could explain approximately half of the aggregate fall.[19]

In order to slightly formalize this reasoning, we use our estimates to assess the following counterfactual: what would the rate of capital investment have been if uncertainty had remained at its low 2006 level? To do so, we first generate the fitted values associated with our instrumental variable estimates, considering only firms that were in the sample in 2007:

$$\widehat{I_{i,t}/K_{i,t-1}} \equiv \widehat{\lambda}_\sigma \cdot \sigma_{i,t-1} + \widehat{\kappa}_q \cdot q_{i,t-1} + \widehat{f}_i + \widehat{g}_t. \tag{4}$$

The average across firms of these fitted values (weighted by the previous period's capital stocks) gives the aggregate investment rate for our sample predicted by the model underlying our estimating equation. We then repeat these calculations, but rather than using the observed

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[19]The aggregate fall is calculated from NIPA table 5.1. The firms in our sample may of course not be typical of the overall economy, and a significant portion of their investment presumably takes place outside the U.S.

Figure 3: Fitted values for capital investment
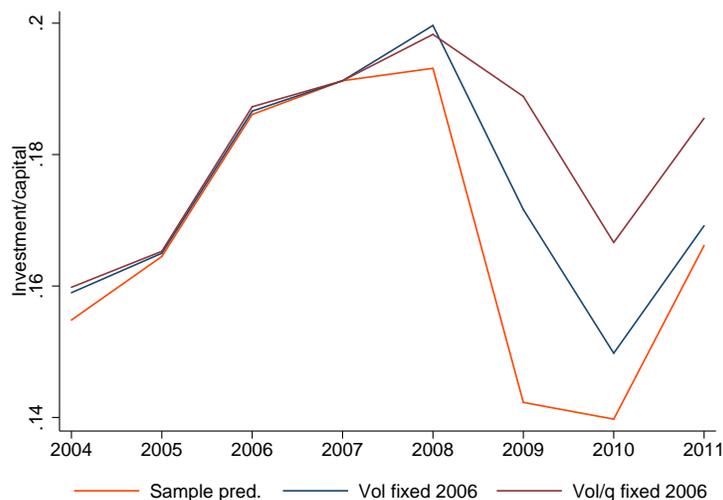
Note: Underlying estimates are from column 2 of Table 3. Aggregation across firms (and placement on horizontal axis) is based on the calendar year at fiscal year end. We restrict attention to firms in the sample in 2007, and calculate as follows: "Sample prediction" is the average across firms (weighted by previous year's capital stock) of the fitted values $\widehat{\lambda}_\sigma \cdot \sigma_{i,t-1} + \widehat{\kappa}_q \cdot q_{i,t-1} + \widehat{f}_i + \widehat{g}_t$. "Vol fixed 2006" is the weighted average of $\widehat{\lambda}_\sigma \cdot \sigma_{i,2006} + \widehat{\kappa}_q \cdot q_{i,t-1} + \widehat{f}_i + \widehat{g}_t$. "Vol/$q$ fixed 2006" is the weighted average of $\widehat{\lambda}_\sigma \cdot \sigma_{i,2006} + \widehat{\kappa}_q \cdot q_{i,2006} + \widehat{f}_i + \widehat{g}_t$.

implied volatilities $\sigma_{i,t}$, we use each firm's 2006 implied volatility $\sigma_{i,2006}$. Finally, we also calculate the aggregate investment rate predicted by the model if both uncertainty and Tobin's q had remained at their 2006 levels. These three series are shown in Figure 3, which illustrates that without increasing uncertainty, the drop in investment from 2008 would have been smaller by roughly a half (in 2009) to a quarter (in 2010).

One issue regarding interpretation of our estimates is that they are based only on firms with exchange-traded options. In columns 3–4 of Table 3 we aim to address this by using the realized volatility of stock returns as an alternate proxy for uncertainty. Column 3 maintains a consistent sample with our baseline specification, while column 4 includes all observations that would have been in our main sample except that they lack implied volatility data. Our estimates are roughly the same whether or not we limit the sample to firms with options. As was illustrated in Figure 2, realized volatilities rose in the great recession by almost twice as much as implied volatilities did; we might therefore expect (and indeed find) coefficients on realized volatility that are roughly half as big as those on implied volatility.

The final column of Table 3 reports estimates using quarterly data (for firms where it is available). Our instruments appear to be slightly weaker in this context, but we still find a significant negative effect of uncertainty on the next quarter's capital investment. Indeed the fact that the quarterly coefficient is nearly as large as the annual one suggests that uncertainty's depressing effect on investment operates fairly quickly.

In Table 4 and Figure 4 we present analogous results for the hiring rate. In line with our results on capital investment we find that uncertainty tends to discourage net hiring, and IV estimates a more negative effect than OLS (though not statistically distinguishably). As with capital investment, using realized volatility as a measure of uncertainty yields coefficient estimates approximately half the size as we get using implied volatility, and the effect of realized volatility is not much changed when we drop the restriction that firms have exchange-traded options. Column 5 shows that our baseline result is robust to replacing Tobin's q with an alternate first moment control that captures enterprise value per worker rather than per dollar of capital:

$$\text{``Labor } q\text{''}_{i,t} \equiv \frac{\text{Market capitalization}_{i,t} + \text{Debt}_{i,t} - \text{Current Assets}_{i,t}}{L_{i,t}}. \tag{5}$$

Following an increase in uncertainty of the size witnessed in the great recession (average implied volatility increasing by 0.4), our model predicts the net hiring rate to fall by 6.6 percentage points. This is close to the mean hiring rate in the sample, suggesting that uncertainty alone would have driven hiring near zero. This is illustrated in Figure 4, which compares the aggregate hiring rate for our sample calculated using actual implied volatilities with what our baseline specification would predict had firms' implied volatilities remained at their 2006 levels. Uncertainty explains about half of the fall in hiring by firms from 2007 to 2009.

In contrast with these results on capital investment and hiring, we find that uncertainty causes firms to spend *more* on research and development. These results are presented in Table 5 and Figure 5a (which are limited to firms that ever engage in R&D). The baseline instrumental

Table 4: IV estimates—Hiring

	(1) OLS	(2) IV Baseline	(3) IV Real. vol	(4) IV Compustat	(5) IV Alt q
Implied vol$_{t-1}$	-0.106*** (0.0201)	-0.165*** (0.0482)			-0.162*** (0.0573)
Realized vol$_{t-1}$			-0.0757*** (0.0264)	-0.0805** (0.0336)	
Tobin's q_{t-1}	0.0137*** (0.00102)	-0.000901 (0.00448)	-0.00323 (0.00474)	-0.000555 (0.00534)	
"Labor q"$_{t-1}$ (log)					0.00764 (0.0196)
Observations	20789	20789	20789	46665	20695
F: vol first stg		32.6	507.2	13.9	32.1
F: q first stg		18.4	18.4	50.8	160.4

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in all regressions is $(L_t - L_{t-1})/L_{t-1}$, and all include firm and annual fixed effects. Standard errors two-way clustered by year and year reported in parentheses.

Note: Estimation sample is as described in Appendix B, except that column 4 does not require the availability of lagged implied volatility. Variables are calculated as described in Appendix A. Instruments are energy/currency price and volatility exposures using sensitivities from 1996–2000 calculated at SIC3 level as described in Section 4.

Figure 4: Fitted values for net hiring
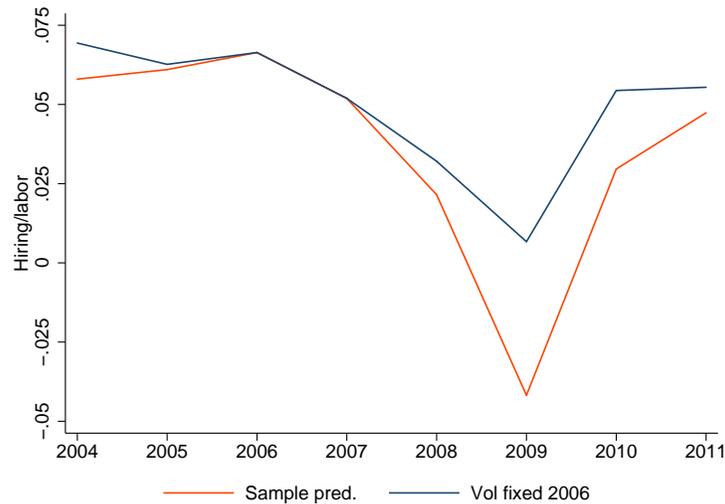
Note: Underlying estimates are from column 2 of Table 4. Aggregation across firms (and placement on horizontal axis) is based on the calendar year at fiscal year end. We restrict attention to firms in the sample in 2007, and calculate as follows: "Sample prediction" is the average across firms (weighted by previous year's employment) of the fitted values $\hat{\lambda}_\sigma \cdot \sigma_{i,t-1} + \hat{\kappa}_q \cdot q_{i,t-1} + \hat{f}_i + \hat{g}_t$. "Vol fixed 2006" is the weighted average of $\hat{\lambda}_\sigma \cdot \sigma_{i,2006} + \hat{\kappa}_q \cdot q_{i,t-1} + \hat{f}_i + \hat{g}_t$.

Table 5: IV estimates—Research and development

	(1) OLS	(2) IV Baseline	(3) IV Real. vol	(4) IV Compustat	(5) IV Alt q
Implied vol$_{t-1}$	-0.00168 (0.0200)	0.0961*** (0.0296)			0.142*** (0.0324)
Realized vol$_{t-1}$			0.0514*** (0.0193)	0.0772*** (0.0251)	
Tobin's q_{t-1}	0.00776*** (0.00125)	0.0218*** (0.00315)	0.0229*** (0.00325)	0.0261*** (0.00240)	
"R&D q"$_{t-1}$ (log)					0.0836*** (0.0105)
Observations	8810	8810	8810	17877	8748
F: vol first stg		56.5	9.9	23.5	86.1
F: q first stg		10.9	10.9	25.7	59.1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in all regressions is R_t/G_{t-1}, and all include firm and annual fixed effects. Standard errors two-way clustered by year and year reported in parentheses.

Note: Estimation sample is as described in Appendix B, but restricted to firms that report nonzero R&D in some fiscal year ending in 2001–11; column 4 does not require the availability of lagged implied volatility. R&D data is not available for all observations. Variables are calculated as described in Appendix A. Instruments are energy/currency price and volatility exposures using sensitivities from 1996–2000 calculated at SIC3 level as described in Section 4.

variables result is robust to the use of alternate first- and second-moment proxies, and the effect estimated using realized volatility is similar whether or not we restrict our sample to firms with options. ("R&D q" is calculated as in Equation 5, but with the knowledge stock G in the denominator). Our baseline estimates suggest that an increase in implied volatility of 0.4 elevates the R&D rate (for firms that ever engage in R&D) by 3.8 percentage points, or 14% of the average level in our sample.

Finally, we report results for advertising in Table 6 and Figure 5b, where we find that uncertainty has a strongly negative effect. (Note that advertising data is reported by relatively few firms.) Like intangible research outputs, advertising is characterized by a high degree of irreversibility. However, advertising can pay off very quickly, in contrast with the long lags required to reap benefits from many R&D projects. To the extent that investment lags create the positive effect of uncertainty on R&D, we should be unsurprised that we don't find a similar effect on advertising.

Figure 5: Fitted values for research and development and advertising
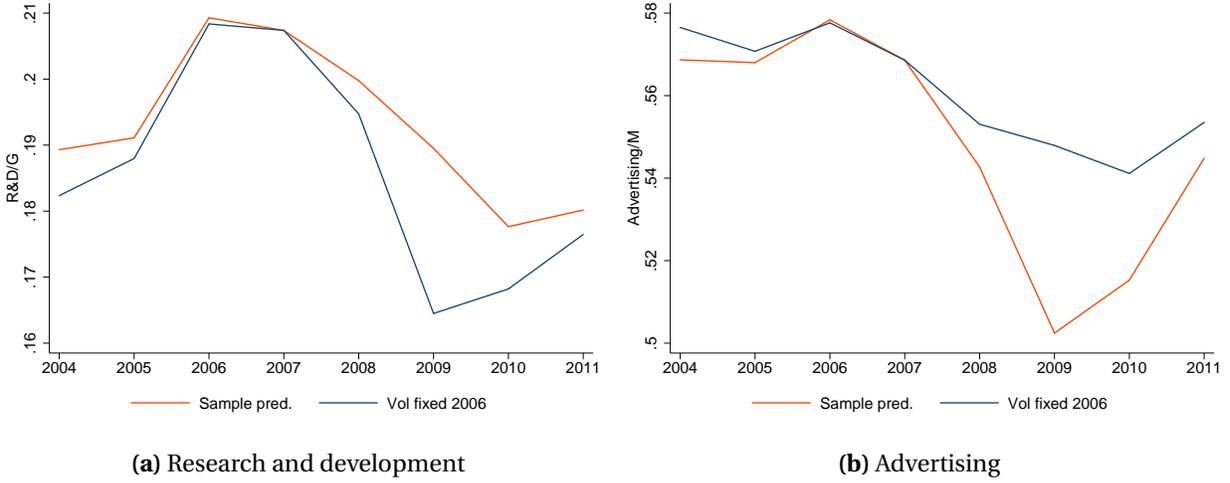
(a) Research and development

(b) Advertising

Note: Underlying estimates are from column 2 of Tables 5 (R&D) and 6 (advertising). Aggregation across firms (and placement on horizontal axes) is based on the calendar year at fiscal year end. We restrict attention to firms in the samples in 2007, and calculate as follows: "Sample prediction" is the average across firms (weighted by previous year's employment) of the fitted values $\widehat{\lambda}_\sigma \cdot \sigma_{i,t-1} + \widehat{\kappa}_q \cdot q_{i,t-1} + \widehat{f}_i + \widehat{g}_t$. "Vol fixed 2006" is the weighted average of $\widehat{\lambda}_\sigma \cdot \sigma_{i,2006} + \widehat{\kappa}_q \cdot q_{i,t-1} + \widehat{f}_i + \widehat{g}_t$.

Table 6: IV estimates—Advertising

	(1) OLS	(2) IV Baseline	(3) IV Real. vol	(4) IV Compustat	(5) IV Alt q
Implied vol$_{t-1}$	-0.139*** (0.0254)	-0.190*** (0.0508)			0.0666 (0.0934)
Realized vol$_{t-1}$			-0.113*** (0.0281)	-0.170*** (0.0394)	
Tobin's q_{t-1}	0.0151*** (0.00193)	0.0278*** (0.00715)	0.0247*** (0.00791)	0.0142* (0.00792)	
"Ad q"$_{t-1}$ (log)					0.133*** (0.0324)
Observations	5371	5371	5371	12545	5328
F: vol first stg		247.4	10.5	255.2	31.5
F: q first stg		19.5	19.5	18.2	12.0

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable in all regressions is A_t/M_{t-1}, and all include firm and annual fixed effects. Standard errors two-way clustered by year and year reported in parentheses.

Note: Estimation sample is as described in Appendix B, but restricted to firms that report nonzero advertising in some fiscal year ending in 2001–11; column 4 does not require the availability of lagged implied volatility. Advertising data is not available for all observations. Variables are calculated as described in Appendix A. Instruments are energy/currency price and volatility exposures using sensitivities from 1996–2000 calculated at SIC3 level as described in Section 4.

7 Conclusion

Theory offers only ambiguous predictions on the relationship between uncertainty and a firms' decisions to invest in various long-lived production inputs. Adjustment costs and partial irreversibility can cause firms to delay investment when their economic environment is more uncertain, but these mechanisms can be reversed by investment lags, informational considerations, competitive dynamics, or the existence of complementary production factors. Assessing the direction and the magnitude of uncertainty's effects therefore requires empirical analysis. The key challenge in the empirical literature is that isolating a causal relationship requires researchers to identify plausibly exogenous uncertainty shocks.

Macroeconomic fluctuations provide a natural source of exogenous variation. In this paper, we have introduced an instrumental variables strategy that estimates how sensitive various industries are to fluctuations in energy prices and currency exchange rates, and uses these differential sensitivities to identify variation in uncertainty across both firms and time. We use the same estimated sensitivities to identify variation in firm-specific business conditions. There are two reasons our strategy is able to separately identify first- and second-moment shocks: there is a nonlinear relationship between the sensitivity to commodity price and volatility fluctuations, and commodity prices and volatility do not consistently move together.

Differential exposure to commodity price and volatility movements creates identifying variation in firm-specific uncertainty, which we proxy both with the implied volatility from equity options and with the realized volatility of firm stock returns. The former measure is explicitly forward-looking and may be less subject to stock movements that are not driven by fundamentals relevant to managerial decision-making, but is available only for a limited and highly selected sample of firms. We find consistent effects across both measures, and—for the realized volatility measure—regardless of whether we limit the larger sample of publicly traded firms to those with exchange-traded options. Uncertainty tends to depress capital investment, hiring, and advertising, but encourage research and development spending.

7 Conclusion

The magnitude of these effects is significant. Uncertainty increased during the great recession, with the annualized standard deviation of stock returns implied by options approximately doubling for firms in our sample, and realized volatilities nearly tripling. Our estimates suggest that an uncertainty increase of this magnitude may have caused capital investment to fall by about one sixth and net hiring to fall nearly to zero. These represent approximately half of the total decline in investment and hiring in our sample in fiscal 2009, the year following the highest levels of uncertainty. We consider this strong circumstantial evidence that uncertainty played an important role in the great recession, which suggests the importance for the business cycle of assessing policies' effects on economic uncertainty.

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A Data

We use data from a variety of sources as described below. Merges of company data across sources were conducted using 8-digit CUSIP codes.

A.1 Company financial reports

We draw financial information from income statements, cash flow statements and balance sheets for the full universe of domestic publicly traded companies covered by Compustat. This yields an annual[20] unbalanced panel of 33,209 companies covering fiscal years ending June 1950 through July 2012. Values that have the data code "insignificant figure" are replaced with zeros. Furthermore, when a value is missing for a single period in the middle of a longer spell, it is replaced with zero if there is a zero immediately before or after, or else the average of the preceding and following (nonzero) values; these imputed values are used to calculate perpetual inventory stocks as described below, but are not included in estimation.

Because financial statements report capital at book rather than replacement value, we derive the capital stock $K_{i,t}$ recursively using a perpetual-inventory method similar to that described in Salinger and Summers (1983), starting from the earliest observation in each available company spell:

$$K_{i,0} = \text{PPE}_{i,0}$$
$$K_{i,t} = \frac{\pi_t^K}{\pi_{t-1}^K} \left(1 - \delta^K\right) K_{i,t-1} + I_{i,t}$$

where PPE is property, plant and equipment (Compustat variable PPENT); I is capital expenditure (CAPX); π^K is the price level (the Producer Price Index for Finished Capital Equipment Goods); and δ^K is the depreciation rate (assumed to be 10%). The capital stock is Winsorized to be

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[20]We exclude any observations dated less than twelve months before the same company's subsequent observation. These would typically be due to changing fiscal years.

nonnegative in each period.

In the same manner, we calculate perpetual-inventory "knowledge stocks" G using R&D (R, Compustat variable XRD) as the flow variable in place of investment. The added complication is that there is no analogue to the reported book value of property, plant, and equipment with which to initialize the stocks. We therefore focus on the first spell of available data for each company (of at least two years), assuming that the first year of reported R&D was consistent with growth of $g^G = 5\%$ net of depreciation $\delta^G = 15\%$ (as in Hall and Mairesse, 1995):

$$G_{i,0} = \frac{R_{i,0}}{\delta^G + g^G}.$$

It is difficult to estimate depreciation rates for the knowledge stock, but use of a 15% rate is identified by Hall, Mairesse, and Mohnen (2010) as being standard in the literature. The knowledge stock is deflated using the BEA's aggregate input price index for private business R&D investment.[21]

"Advertising stocks" M are calculated identically using XAD as a flow variable, $g^M = 5\%$ (as was used for R&D), $\delta^M = 50\%$ (estimated depreciation rates vary widely; Bagwell, 2007 surveys the literature and reports estimates from 15% to "80% and above"), and the Consumer Price Index.

Hiring is calculated as the change in the number of employees (EMP).

Investment ratios are Winsorized as follows: $I_t/K_{t-1} \in [-0.1, 1]$, $(L_t - L_{t-1})/L_{t-1} \in [-0.5, 1]$, $R_t/G_{t-1} \in [0, 1]$, and $A_t/M_{t-1} \in [0, 1.5]$.

Tobin's q is calculated as the ratio of the market value of capital to its replacement value:

$$q_{i,t} = \frac{\text{Market capitalization}_{i,t} + \text{Debt}_{i,t} - \text{Current Assets}_{i,t}}{K_{i,t} + \text{Inventory}_{i,t} + \text{Intangibles}_{i,t} + \text{Investments and advances}_{i,t}} \tag{6}$$

where market capitalization is the product of the number of outstanding common shares (CSHO)

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[21]This annual series is available in Table 4.1 of the BEA's "1959–2007 research and development data" release. For 2008 and subsequent years (where the BEA R&D deflator is not available), the knowledge stock is deflated using the Consumer Price Index.

and the final stock price (PRCC_F); K is the perpetual-inventory capital stock described above; and debt (LT), current assets (ACT), inventory (INVT), intangibles (INTAN), and investments and advances (INVAE plus INVAO) are all Winsorized to be nonnegative. The calculated values of q are Winsorized to lie in the range $[0.1, 20]$. We also define alternate first moment controls ("Labor q," "R&D q," and "Advertising q") analogous to q, with the same numerator as in Equation 6, but with either $L_{i,t}$, $G_{i,t}$, or $M_{i,t}$ as the denominator.

We also use analogous quarterly Compustat data on an unbalanced panel of 31,134 companies covering fiscal quarters ending March 1961 through January 2012. Cleaning and calculation steps are substantially the same as for annual data (although employment and advertising data are not available, and R&D is available quarterly for relatively few firms). Capital expenditure (CAPXY) is reported as year-to-date values, so investment is calculated as its first difference for fiscal quarters 2–4. Also, for some companies, certain variables are only available as semiannual or annual values; in these cases, reported values are allocated equally over the quarters covered for calculation of perpetual inventory stocks, but are not included when we conduct estimation. Quarterly investment ratios are Winsorized as follows: $I_t/K_{t-1} \in [-0.1, 0.4]$ and $R_t/G_{t-1} \in [0, 0.2]$. The quarterly analysis sample is described in Appendix B.

A.2 Implied volatility

OptionMetrics provides daily implied volatility data from January 1996 through January 2012 for companies with exchange-traded equity options. Each company has a corresponding series of call and put options which differ in their expiration dates and strike prices. For each of these options, OptionMetrics imputes an implied volatility for each trading day using the average of the end-of-day best bid and offer price quotes. Given an option price, duration, and strike price, along with interest rates, underlying stock price, and dividends, the Black-Scholes formula is used to back out implied volatility. This is an annualized measure representing the standard deviation of the expected change in the stock price. Note that this is not a directional measure,

but rather an expectation of absolute stock price movements regardless of their direction.

One of the advantages of using implied volatilities is that they can be measured across a variety of time horizons using options with different expiration dates. In particular, OptionMetrics calculates implied volatilities for durations ranging from 30 to 730 days.[22] We can use these implied volatility horizons to measure uncertainty over different forward-looking periods, although in this paper we focus only on 91-day implied volatility.

The calculations underlying our data are in fact somewhat more complicated. OptionMetrics builds an "implied volatility surface" for each underlying asset using options across a wide range of both expiration dates and strike prices. Although only a finite number of options trade for each asset, implied volatilities for arbitrary durations and strike prices can be calculated by interpolating the implied volatilities of "nearby" options. For instance, suppose we want the implied volatility for a Microsoft at-the-money call option expiring in 60 days when the current stock price is $51.50. Unfortunately, 60 days falls in between the expiration of listed March and June options. In addition, the March and June-expiry options are only listed for strikes of $50 and $52.50. In order to compute the 60-day at-the-money implied volatility, OptionMetrics interpolates using the available prices for March and June-expiry $50 and $52.50 strike options.

While implied volatility data is available for a variety of strike prices, we restrict our analysis to at-the-money-forward options; i.e., options for which the strike price is equal to the forward price of the underlying stock at the given expiration date. The forward (or expected future) price is calculated from the current stock price, the stock's dividend payout rate, and the interest rate yield curve. One possible extension of our analysis would consider implied volatility across a variety of strike prices, allowing richer measurement of asymmetric volatility expectations.

We further restrict our analysis to call options. Note that a call option and a put option on a given underlying asset with the same strike price and expiration date have the same implied

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[22]Specifically, the implied volatility horizons are 30, 60, 91, 122, 152, 182, 273, 365, 573 and 730 days. Not all are available for any given underlying asset; in particular, the longest-horizon implied volatilities are only calculated for underlying assets and periods when long-duration options exist and have exchange price quotes.

Table 7: Implied and realized volatility correlations

	Annual				Quarterly			
	Implied vol.		Realized vol.		Implied vol.		Realized vol.	
	t	$t-1$	t	$t-1$	t	$t-1$	t	$t-1$
Raw volatility series								
Implied vol$_t$	1.00				1.00			
Implied vol$_{t-1}$	0.54	1.00			0.80	1.00		
Realized vol$_t$	0.80	0.34	1.00		0.81	0.72	1.00	
Realized vol$_{t-1}$	0.38	0.84	0.24	1.00	0.71	0.82	0.71	1.00
Residuals after controlling for time and firm fixed effects								
Implied vol$_t$	1.00				1.00			
Implied vol$_{t-1}$	0.07	1.00			0.50	1.00		
Realized vol$_t$	0.63	0.06	1.00		0.57	0.47	1.00	
Realized vol$_{t-1}$	0.07	0.69	-0.02	1.00	0.43	0.60	0.43	1.00

Note: The annual and quarterly samples are as described in Appendix B. End-of-period implied volatility is from 91-day at-the-money-forward call options as described in Appendix A.2. Realized volatility is the standard deviation of daily returns (including dividends) across all trading days in the last 90 days of the period as described in Appendix A.3. Both implied and realized volatilities are Winsorized to lie below 200%.

volatilities; the difference in their prices comes from the fact that interest rates and dividends affect the value of call and put options in opposite directions. An analysis that attempted to separately measure upside and downside risk would benefit from including both puts and calls, since extreme strike prices are likely only to be available as one or the other. Here we consider only at-the-money-forward options, for which both puts and calls are available. To make this point clear, suppose instead we wanted to use implied volatilities for strike prices 50% below the current stock price. It is likely that the only options listed with such low exercise prices would be put options and we would therefore need to include them in the data sample.

Our principal proxy for uncertainty is 91-day implied volatility of at-the-money-forward call options, Winsorized to be no greater than 200%. The annual and quarterly autocorrelations of implied volatility are shown in Table 7.

A.3 Stock returns and realized volatility

To estimate firm-specific relationships between stock and commodity returns, we rely on daily returns data (including dividends; variable RET) from CRSP for individual firms and the S&P 500 Index, together with the energy price and exchange rate data discussed below. We also use these daily returns to calculate a measure of realized volatility for each firm: the standard deviation of daily returns across all trading days in the last 90 days of the period. This daily standard deviation is annualized (making its units comparable with the implied volatilities described above) by multiplying by $\sqrt{252}$. As with implied volatility, realized volatility is Winsorized to lie in $[0, 200\%]$. The correlation between implied and realized volatilities, as well as the autocorrelations for each, are shown in Table 7.
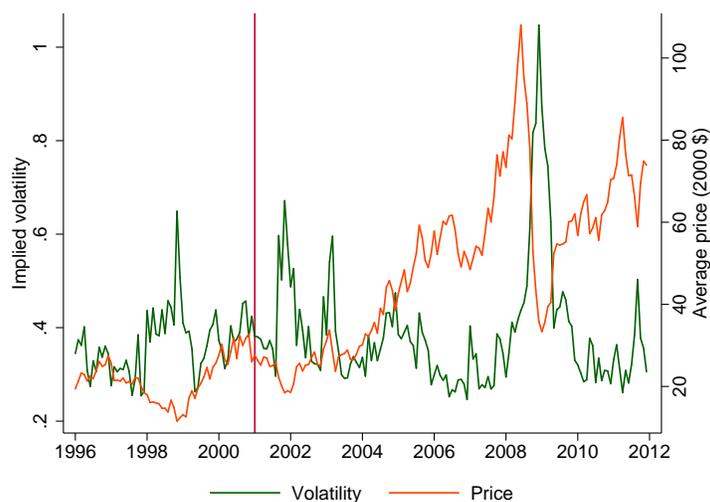
A.4 Energy prices and implied volatility

Bloomberg provides price and 30-day implied volatility data for one-month crude oil futures. Specifically, we use data on the New York Mercantile Exchange Division's light, sweet crude oil futures contract (Bloomberg CL1). This contract is the world's most liquid, largest-volume futures contract on a physical commodity. The contract size is 1,000 U.S. barrels and delivery occurs in Cushing, Oklahoma. Figure 6 illustrates the time-series variation in energy prices and volatility over the sample period, and indicates the first five years of data which were used to estimate commodity sensitivities.

A.5 Currency exchange rates and implied volatility

We use data from the Federal Reserve Board on daily exchange rates between the U.S. dollar and 16 currencies: five main currencies (Canada, Mexico, China, Euro, and Japan) and eleven additional ones (Australia, Hong Kong, Korea, New Zealand, Norway, South Africa, Sweden,

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**Figure 6:** Energy price and implied volatility

Note: Monthly end-of month data on crude oil prices and implied volatility are from Bloomberg as described in Appendix A.4.

Switzerland, Taiwan, Thailand, and the United Kingdom).[23] Prior to the Euro's introduction in January, 1999, its exchange rate is proxied by the FRB's "ec" rate, based on a basket of European currencies. Daily data on three-month implied exchange rate volatilities for these currency pairs were extracted using Bloomberg's VOLC function. Figure 7 illustrates the time-series variation in exchange rates and volatility over the sample period, and indicates the first five years of data which were used to estimate commodity sensitivities.

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[23]FRB currency data is available for 23 currencies, but implied volatility is not consistently available during our sample period for seven of these: Brazil, Denmark, India, Malaysia, Singapore, Sri Lanka, and Venezuela.

Figure 7: Currency exchange rates and implied volatilities

(a) Exchange rates

(b) Implied volatilities
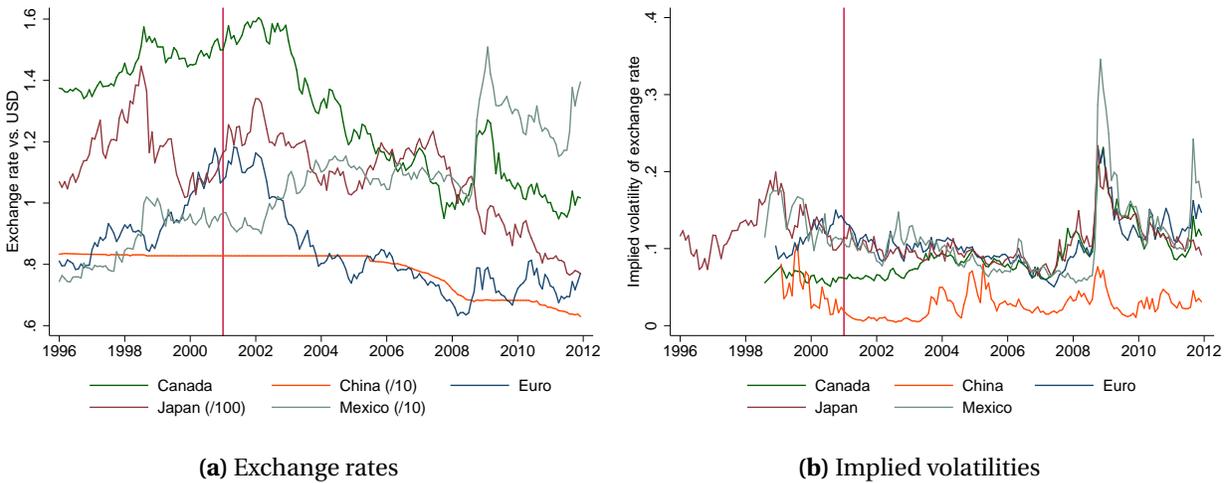
Note: Monthly end-of month data are from the FRB (rates) and Bloomberg (three-month implied volatilities) as described in Appendix A.5.

B Analysis Sample

Our main analysis sample includes observations from fiscal years ending in 2001–11 with non-missing capital investment and employees; nonmissing lagged capital stock, employees, end-of year Tobin's q, end-of-year 91-day implied volatility, and end-of-year three-month realized volatility; and is limited to firms with nonzero capital investment in some fiscal year ending in 2001–11. Summary statistics for the sample are reported in Table 1 in the main text.

Our quarterly analysis sample includes fiscal quarters ending in 2001–11 with nonmissing capital investment; nonmissing lagged capital stock, end-of quarter Tobin's q, end-of-quarter 91-day implied volatility, and end-of-quarter three-month realized volatility; and is limited to firms with nonzero capital investment in some fiscal quarter ending in 2001–11. Summary statistics for this sample are reported in Table 8, together with comparable statistics for the 2001–11 quarterly Compustat and Compustat-OptionMetrics linked samples.

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Table 8: Summary statistics: Compustat, Compustat-OptionMetrics merged, and analysis samples (quarterly)

	Compustat			Compustat + OptionMetrics			Analysis sample		
	Mean	Median	Std. dev.	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Sales ($M)	589	26	2,969	1,555	257	5,143	1,411	260	4,745
Investment ($M)	43	1	271	106	9	441	95	10	395
Capital stock ($M)	1,134	28	6,526	2,653	271	9,972	2,421	283	9,209
I_t/K_{t-1}	5.2%	2.8%	7.6%	5.3%	3.8%	5.8%	5.2%	3.7%	5.6%
R&D ($M)	22	1	133	54	6	209	53	7	203
R&D stock ($M)	577	37	3,006	1,347	168	4,562	1,290	172	4,402
R_t/G_{t-1}	5.6%	5.0%	4.0%	6.5%	5.7%	3.6%	6.3%	5.6%	3.5%
N	476,884			112,961			90,367		
Firms	18,788			5,571			4,455		
Firms in 2011	10,370			3,702			2,859		

Note: Not all variables are available for all observations. "Compustat" includes fiscal quarters ending in 2001–11 with nonmissing end-of-quarter 91-day implied volatility. "Compustat + OptionMetrics" includes fiscal quarters ending in 2001–11 with nonmissing capital investment; nonmissing lagged capital stock, end-of-quarter Tobin's q, end-of-quarter 91-day implied volatility, and end-of-quarter three-month realized volatility; and is limited to firms with nonzero capital investment in some fiscal quarter ending in 2001–11. Variables are calculated using Compustat data as described in Appendix A.1, including Winsorization of extreme values.