

Really Uncertain Business Cycles

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Abstract

We propose uncertainty shocks as an additional impulse driving business cycles. First, we demonstrate that uncertainty, measured by a number of proxies, appears to be strongly countercyclical. When uncertainty is included in a standard vector autoregression, increases in uncertainty lead to a large drop and subsequent rebound in economic activity. Second, we build a dynamic stochastic general equilibrium model that extends the benchmark neoclassical growth model along two dimensions. It allows for the existence of heterogeneous firms with non-convex adjustment costs in both capital and labor, as well as time-variation in uncertainty that is modeled as a change in the variance of innovations to productivity. We find that increases in uncertainty lead to large drops in economic activity. This occurs because a rise in uncertainty makes firms cautious, leading them to pause hiring and investment, and reduces the reallocation of capital and labor across firms, leading to a large fall in productivity growth. Finally, we show that uncertainty significantly reduces the response of the economy to stimulative policy, relative to its response during low uncertainty periods. This implies that in order for policy during high uncertainty periods to have the same effect it would as under low uncertainty periods, the policy impulse should be significantly larger and temporary.

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1 Introduction

In this paper we study the implications of variations in the level of uncertainty, or second-moment shocks, for business cycles. The idea to link uncertainty to the business cycle is not new. John Maynard Keynes (1936) argued that changes in investor sentiments, the so-called *animal spirits*, could lead to economic downturns. While this can be interpreted as an argument for the role of uncertainty, it has not traditionally played a large role in modern studies of business cycle fluctuations.

This paper attempts to fill this gap by taking two distinct steps. First, we address the empirical behavior of uncertainty over the business cycle. Evidence on the time series variation in uncertainty is scarce, as no measure of uncertainty is directly observable. To circumvent this difficulty, we use various proxies for uncertainty that include measures of cross-firm and cross-industry dispersion, time series variation of aggregate data, as well as measures of forecaster disagreement. We find that all of our uncertainty proxies are strongly countercyclical, and when combined into a single uncertainty index, we find that this index increases by 48% during recessions.¹ We then investigate the conditional association of uncertainty and the business cycle by including the uncertainty index in a standard vector autoregression (VAR), and find that an increase in uncertainty is associated with a large drop and subsequent rebound in economic activity.

Since it is hard to argue that our uncertainty index is completely exogenous, we use the second part of the paper to theoretically investigate the role of fluctuations in uncertainty since we can, by assumption within our model, assure the exogeneity of uncertainty shocks. Specifically, we study a dynamic stochastic general equilibrium model that allows for shocks to both the level of technology (the first moment) as well as uncertainty (the second moment), where the latter are modeled as variation in the standard deviation of the innovations to productivity. Various features of the model are specified to conform as closely as possible to the standard frictionless neoclassical growth model. The main deviation from this frictionless benchmark model lies in assuming that heterogeneous firms incur convex and non-convex adjustment costs in both capital and labor. The non-convexities imply that firms become more cautious in investing and hiring when uncertainty increases due to the option value of waiting, which increases when uncertainty is high since it is expensive for firms to invest and then disinvest or to hire and then fire. The time-varying option value implies that, in the presence of higher aggregate macro uncertainty, aggregate investment and employment levels fall as it becomes optimal for each individual firm to wait. In addition, we show that time-varying uncertainty reduces productivity growth during times of high uncertainty because it lowers the extent of reallocation in the economy; when uncertainty

¹This index is constructed as a simple average of our seven proxies after re-scaling each of them to an average of one in non-recession periods.

rises, productive firms expand less and unproductive firms contract less.² It is important to emphasize that we do not claim that other mechanisms that cause fluctuations in uncertainty and that can affect economic activity are irrelevant. Rather, we emphasize a specific mechanism in a model that encompasses the standard perfect competition, real business cycle (RBC) model, as this greatly simplifies comparison with existing work.

We then build on our theoretical model to investigate the effects of uncertainty on policy effectiveness. We use a simple illustrative example to show the presence significantly dampens the effect of an expansionary policy.

Our work is related to several strands in the literature. First, we add to the extensive literature building on the RBC framework by studying the role of productivity (TFP) shocks in causing business cycles. In the standard RBC literature, recessions are caused by large negative technology shocks.³ The reliance on negative technology shocks has proven to be controversial, as it suggests that recessions are times of technological regress. To quote King and Rebelo (1999): “If these shocks are large and important, why can’t we read about them in the Wall Street Journal?”⁴ As discussed above, our work provides a rationale for falls in measured productivity. Countercyclical increases in uncertainty lead to a freeze in economic activity, substantially lowering productivity growth during recessions. In our model, however, the drop in productivity is not causing the recession, but rather it is an artifact of a recession that was caused by an increase in uncertainty.

The paper also relates to the literature on investment under uncertainty. A growing body of work has shown that uncertainty can directly influence firm-level investment and employment in the presence of adjustment costs.⁵ The most relevant paper is Bloom (2009), which solves a partial equilibrium model with stochastic volatility and shows how uncertainty shocks lead to a drop in investment and hiring by firms. Our paper is different in that we are looking at the business cycle in a general equilibrium framework.

Finally, the paper is related to the literature studying macroeconomic models with micro-rigidities.⁶ The paper contributes to this literature by finding that in the presence

²In the actual U.S. economy, reallocation is a key factor driving aggregate productivity. See, for example, Foster, Haltiwanger and Krizan (2000, 2006), who report that reallocation, broadly defined to include entry and exit, accounts for around 50% of manufacturing and 80% of retail productivity growth in the US.

³See, for example, the discussion in Rebelo (2005): “Most RBC models require declines in TFP in order to replicate the declines in output observed in the data.”

⁴This reasoning has led many researchers to study models with other disturbances, which mostly focus on first-moment (level) shocks. A partial list of these alternative shocks includes oil shocks, investment specific shocks, monetary shocks, government expenditure shocks, news shocks, and terms-of-trade shocks. Yet, in most models, negative technology shocks continue to be an important driver of economic downturns.

⁵See, for example; Bernanke (1983), Pindyck (1988), Dixit (1990), Bertola and Bentolila (1990), Bertola and Caballero (1994), Dixit and Pindyck (1994), Abel and Eberly (1996), Hassler (1996), and Caballero and Engel (1999).

⁶See for example, Thomas (2002), Veracierto (2002), Kahn and Thomas (2006 and 2008), Bachman, Caballero and Engel (2008), and House (2008).

of time-varying uncertainty, micro-rigidities of the type considered here (i.e., non-convex adjustment costs) have important general equilibrium effects.

The remainder of this paper is organized as follows. Section 2 discusses the behavior of uncertainty over the business cycle. In Section 3 we formally present the model and define the recursive equilibrium. Since most of the business cycle literature has concentrated exclusively on first-moment shocks where the level of uncertainty is held constant, we depart from the standard log-linearization techniques and use non-linear methods instead. Specifically, section 3.4 presents our solution algorithm which builds on the work of Krusell and Smith (1998), Kahn and Thomas (2008) and Bachman, Caballero and Engel (2008). The model is calibrated and simulated in Section 4, where we study the role of uncertainty shocks in driving the business cycle. Section 5 studies the impact of policy shocks in the presence of time-varying uncertainty. Section 6 concludes.

2 The Rise in Uncertainty During Recessions

This section consists of two parts. The first part presents a range of proxies for uncertainty and their behavior over the business cycle. The second part provides evidence that time variation of our constructed uncertainty index is associated with a large drop and subsequent rebound in economic activity in a VAR that simultaneously controls for first-moment shocks.

2.1 Measuring Uncertainty Over the Business Cycle

In what follows, we present our seven proxies for uncertainty. Details of the construction of each measure are contained in Appendix A.

2.1.1 Cross-Firm and Cross-Industry Evidence

The first measure examines the cross-sectional spread of firm- and industry-level growth rates. The rationale for this is that uncertainty implies fatter tails in the distribution of productivity within the context of our model. Row (1) of Table 1 reveals that the cross-sectional spread of firm-level sales growth rates (as measured by the inter quartile range (IQR)) is 23.1% higher during quarters defined as recessionary by the NBER Business Cycle Dating Committee. This rise in the cross-sectional spread is also negatively correlated with real GDP growth, with a correlation of -0.466 .

One interpretation of this result is that it simply reflects differential responses of firms in different industries to a common macro shock. For example, an oil shock will have a large negative impact on firms in energy intensive industries like aluminum production,

but a positive effect on firms in energy producing industries like coal and gas production.⁷ To address this issue, we calculate the cross-sectional dispersion both within and across industries. We find the results to be practically identical. For example, recomputing this change in firm-level sales growth within each 2-digit SIC industry results in a rise in cross-sectional dispersion of 20.4% (standard error of 3.3%), very similar to the rise of 23.1% in the pooled data.⁸ This increase in the cross-sectional dispersion of sales growth is shown graphically in Figure 1, which plots the raw cross-sectional increase in sales dispersion (solid line) and the within-SIC2-industry increase in sales dispersion (dashed line). The same figure also includes gray bars meant to represent NBER recessions. Two features stand out. First, the two lines are extremely similar, indicating that the increase in cross-sectional variance over the business cycle is very similar within and across broad industry groups. Second, cross-sectional sales spreads appear to rise strongly during recessions, most notably during the 1974/75 and the 2001 recessions.

In an attempt to control for the fact that industries vary in their degree of procyclicality, we also calculated the IQR using the residuals from an industry by industry regressions of output growth on the quarterly NBER recessionary indicator. I.e., we ran 196 regressions of industry growth rates on the 1/0 indicator of an NBER recession and then used these residuals to calculate the quarterly IQR. The logic is that if certain industries always respond positively to recessions and others negatively, and this is the reason for the bigger dispersion in the IQR during recessions which was documented in Figure 1, then this residual IQR measure will be flat. If instead the bigger dispersion in industry growth rates during recessions is due to idiosyncratic industry level shocks the spread should be unchanged by taking out industry level measures of pro-cyclicality, which Figure 2 confirms is indeed the case.

The result in row (2) shows that the cross-sectional spread of firm-level stock returns is also countercyclical, rising by 22.4% during recessions. Again, this holds both within and across industries. For example, within 2-digit SIC industries, the rise in the spread of stock returns is 21.2% (standard error of 3.7%), again almost identical to the overall rise of 22.4%.⁹ This is shown graphically in Figure 3, which plots the raw cross-sectional spread of stock returns (solid line) and the within-SIC2-industry spread (dashed line). Figure 4 is

⁷This is essentially the critique Abrahams and Katz (1986) raised against Lillien (1982) who showed a strong correlation between cross-industry variation in unemployment and overall unemployment levels, arguing for a large role for structural unemployment during periods of rapid cross-industry movements of employment. Abrahams and Katz (1986) argued that it could instead be interpreted as a differential industry-level response to common negative macro shocks.

⁸All calculations were undertaken using 2-digit SIC cells with 25 or more firms, covering 24 2-digit SIC industries.

⁹All calculations were undertaken using 2-digit SIC cells with 25 or more firms, covering 27 2-digit SIC industries. Campbell et al. (2001) also report the result that the variance of cross-sectional stock returns is countercyclical.

constructed as Figure 2 but for the firm-level stock returns.

The results in row (3) of Table 1 reveal that the cross-sectional spread of industry-level output growth for manufacturing industries is also substantially higher during recessions, rising by 66.1% as compared to non-recessionary periods. This is shown in Figure 5, which reveals that cross-industry spread rose, especially during the recessions of the 1970s and 1980s, as well as during the 2008 recession. Figure 6 plots the evolution of different percentiles from the distribution of the growth rates of industrial production within each quarter, highlighting once again the increase in dispersion during recessionary periods. Note that recessions are characterized not only by a downward shift of the distribution of all firms, but also by a widening of the distribution. This is evident from the behavior of the 1st and 99th percentile.

2.1.2 Macroeconomic Measures of Uncertainty

An alternative approach uses high-frequency aggregate data to infer the underlying process for stochastic volatility. This captures the common macroeconomic component of uncertainty, in contrast to the idiosyncratic firm- and industry-level components discussed above. In row (4), we see that the conditional heteroskedasticity of output growth is 54.3% higher during recessions. This is estimated from a regression of monthly industrial production, including as many as twelve lags, with a GARCH(1,1) error process.¹⁰ In row (5) we look at an index of stock market volatility, and find that recessionary quarters are associated with a 39.1% higher volatility of stock market returns. Hence, output and stock market data both suggest macro uncertainty is substantially higher during recessions.¹¹ These two aggregate measures of uncertainty are plotted in Figures 7 and 8, and again these measures appear to be countercyclical.

2.1.3 Forecasting Evidence

Finally, we interpret the extent of disagreement between forecasters over future macroeconomic variables as a proxy for uncertainty. It is important to note that our model does not explicitly treat this issue and that theoretically, cross-sectional forecaster disagreement and uncertainty are not necessarily correlated.¹² However, there is an extensive empirical literature that argues in favor of using disagreement among macro forecasts — as measured

¹⁰ Longer lags in the GARCH process were not significant.

¹¹ Hamilton and Lin (1996) provide evidence similar to Schwert (1989) that stock market volatility is much higher during recessions. Engle and Rangel (2006) look at data from 48 countries (developed and developing) and find similar results for this panel (stock market volatility is significantly higher when GDP growth is low). Officer (1973) compiles stock market volatility data from about 1899 to 1960 and finds that the volatility of industrial productivity is correlated with stock market volatility (especially during the Great Depression).

¹² See, for example, Amador and Weill (2008).

by mean forecast error — as a proxy for uncertainty.¹³ In rows (6) and (7) we see that the dispersion of professional forecasts over future industrial production and unemployment increases substantially during recessions, rising by 60.1% and 71.5%, respectively. This supports the result from section (2.1.2) above, that macro uncertainty rises substantially during recessions. Again, this measure of macro uncertainty rises during recessions, and the two measures of forecaster disagreement are shown in Figures 9 and 10.

2.1.4 The Uncertainty Index Over the Business Cycle

In the final row of Table 1 we report an aggregated index of uncertainty, which is calculated as the average of the seven quarterly uncertainty proxies after normalizing all of them to an average of one during non-recessionary periods.¹⁴ The uncertainty index rises by 47.6% during recessions, and is strongly negatively correlated with real industrial production growth, with a correlation of -0.606 .¹⁵ Figure 11 plots this series over time, and it is obvious that recessions are periods of higher uncertainty. Interestingly, this relationship is stronger for the four recessions in the 1970s and 1980s, and weaker for the last two recessions in the early 1990s and 2000s. The 2008 recession coincides with another large uncertainty spike. Two other notable spikes in the graph occur in 1987Q4 and 1998Q3, which are the Black Monday and the Russia/LTCM stock market crashes, respectively. Both episodes generated large increases in both firm and aggregate stock return uncertainty measures, but did not coincide with recessions.

2.2 A VAR Analysis

The previous sub-section has extensively documented that there is a significant unconditional correlation between uncertainty — as measured by an array of proxies — and the business cycle. The remainder of Section 2 will provide some evidence that points to the existence of a conditional association.

At the macro level, it is obviously hard to identify causal effects because of the lack of exogenous variation in the variable of interest. Nevertheless, we estimate a (VAR) and study the impulse response functions for a realistically-calibrated increase in uncertainty. We intend to demonstrate that (i) uncertainty can lead to a sizable drop and subsequent rebound of economic activity, and that this holds even after controlling for TFP shocks.

¹³See, for example, Zarnowitz and Lambros (1987), Bomberger (1996), and Giordani and Soderlind (2004).

¹⁴Specifically, each one our seven measures is normalized over its full period of data availability. The aggregate index computed as non-missing in a specific quarter when at least 6 of the 7 measures are available.

¹⁵One alternative is to use the principal component factor method. Here, it loads relatively evenly on all of the indicators, with weights ranging from 0.17 to 0.27. This index is also strongly negatively correlated with real industrial production growth, with a correlation of -0.56 .

Specifically, the uncertainty index is added to an otherwise standard VAR. We employ the widely used specification of Christiano, Eichenbaum, and Evans (2005) (CEE).¹⁶

Of course, the resulting impulse response functions depend on the ordering of the variables, and thus we study two extreme cases. We begin by studying an ordering in which the uncertainty index is placed first and the remaining variables follow the order in CEE. This is based on the assumption that the second-moment shock (uncertainty) can contemporaneously influence all the other measures included in the VAR. Figure 12 depicts the Cholesky-orthogonalized impulse responses to a shock to uncertainty. The shock is calibrated to match the average increase of the uncertainty index during a recession (48%). The four panels of Figure 10 show the responses of GDP, total consumption, investment, and the uncertainty index. There is an immediate drop in GDP which keeps falling for one more quarter to reach a low of -1.6% . Output then rebounds to trend within four quarters of the initial shock. Consumption and investment behave very similarly to GDP. Figure 13 studies the other extreme, i.e., an ordering where the uncertainty index is placed last. As the figure suggests, similar results are obtained for this ordering. While the impact is smaller and shorter-lived with this ordering, the VAR estimates suggest a fall of more than 1% and 3% in GDP and investment, respectively.

In the same Figure 13 we add a control for TFP. Specifically, we use the log of the TFP measure from Basu, Fernald and Kimball (2006).¹⁷ The rationale is that by adding this variable, we add a control for a first-moment shock. We once add the uncertainty index first and the TFP measure second, and once place the uncertainty index last. As the figures suggest, we continue to find a large negative association between uncertainty and GDP growth even after controlling for TFP.

Finally, as an additional robustness check we include a measure of risk as proxied by the spread between AAA and BAA corporate bonds interest rates. Adding this as a control to the VAR does not alter the results of our estimation, suggesting that our uncertainty measure is not merely a proxy for risk.

3 The General Equilibrium Model

Directly measuring time variation in uncertainty is difficult. Moreover, while all the uncertainty proxies introduced above appear to be strongly countercyclical, each could potentially be interpreted as the result of a specific first-moment shock. A structural model with shocks to both the first and second moment can help in distinguishing first and second moment

¹⁶The order of the variables in CEE is as follows: real GDP, real consumption, the GDP deflator, real investment, real wage, labor productivity, the Federal Funds rate, real profits and the growth rate of M2. As in CEE, all of the variables besides the Federal Funds rate and money growth have been logged.

¹⁷We wish to thank John Fernald for providing this quarterly data.

shocks.

We thus proceed to analyze the potential role of variation in uncertainty within a dynamic stochastic general equilibrium model where heterogeneous firms are subject to both first and second moment shocks. In the model, each firm uses capital and labor to produce a final good. Firms that adjust their capital stock and employment incur non-convex adjustment costs. As is standard in the RBC literature, firms are subject to an exogenous process for productivity. We assume that the productivity process has an aggregate and an idiosyncratic component. In addition to these first-moment shocks, we allow the second moment of the innovations to productivity to vary over time. That is, shocks to productivity can be fairly small in normal times, but become potentially large when uncertainty is high.

3.1 Firms

3.1.1 Technology

The economy is populated by a large number of heterogeneous firms that employ capital and labor to produce a single final good. We assume that each firm operates a diminishing returns to scale production function with capital and labor as the variable inputs.¹⁸ Specifically, a firm indexed by j produces output according to

$$y_{j,t} = A_t z_{j,t} k_{j,t}^\alpha n_{j,t}^\nu, \quad \alpha + \nu < 1. \quad (1)$$

Each firm's productivity is a product of two separate processes: aggregate productivity, A_t , and an idiosyncratic component, $z_{j,t}$. Both the macro- and firm-level components of productivity follow autoregressive processes:

$$\log(A_t) = \rho^A \log(A_{t-1}) + \sigma_t^A \epsilon_t \quad (2)$$

$$\log(z_{j,t}) = \rho^Z \log(z_{j,t-1}) + \sigma_t^Z \epsilon_{j,t} \quad (3)$$

We depart from the benchmark RBC model in that we allow the variance of innovations to the productivity processes, σ_t^A and σ_t^Z , to vary over time, following two-point Markov process:

$$\sigma_t^A \in \{\sigma_L^A, \sigma_H^A\} \quad \text{where } Pr(\sigma_{t+1}^A = \sigma_j^A | \sigma_t^A = \sigma_k^A) = \pi_{k,j}^{\sigma^A} \quad (4)$$

$$\sigma_t^Z \in \{\sigma_L^Z, \sigma_H^Z\} \quad \text{where } Pr(\sigma_{t+1}^Z = \sigma_j^Z | \sigma_t^Z = \sigma_k^Z) = \pi_{k,j}^{\sigma^Z} \quad (5)$$

¹⁸An alternative model has a setup of monopolistically competitive firms in which each firm produces a differentiated good. Note that the assumption of decreasing returns to scale implies that there is a fixed factor of production that pins down firm size.

3.1.2 Capital and Labor Adjustment Costs

A firm's capital stock evolves according to the standard law of motion

$$\gamma k_{j,t+1} = (1 - \delta_k)k_{j,t} + i_{j,t}, \quad (6)$$

where the $\gamma - 1$ is the trend growth rate of output and δ_k is the capital rate of depreciation. We assume that adjusting the capital stock incurs a cost. Based on prior empirical evidence, we consider two types of adjustment costs.¹⁹ The first one involves a non-convexity — conditional on undertaking an investment, a fixed cost F^K is incurred independently of the scale of investment. The second capital adjustment cost we consider is a partial irreversibility; that is, the resale value of \$1 of capital is $\$S$, which is below the purchase price of capital, $1 > S > 0$.

We also assume that whenever the firm changes the number of employment hours, it faces an adjustment cost. Specifically, we assume that the law of motion for hours worked is governed by

$$n_{t,t} = (1 - \delta_n)n_{j,t-1} + s_{j,t}. \quad (7)$$

At each period a constant fraction, δ_n , of hours worked is exogenously destroyed due to retirement, illness, maternity leave, exogenous quits, etc. Whenever the firm chooses to increase/reduce its stock of hours relative to $(1 - \delta_n)n_{j,t-1}$, a fixed cost F^L is incurred independently of the size of the change in hours. The firm also has to pay a cost per worker hired, H , or fired, F , representing, for example, variable interviewing and training costs or severance packages.

3.1.3 The Firm's Value Function

We denote by $V(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$ the value function of a firm. The seven state variables are given by (1) a firm's capital stock k , (2) a firm's hours stock from the previous period n_{-1} , (3) the firm idiosyncratic productivity $z_{j,t}$, (4) aggregate productivity A_t , (5) macro uncertainty σ_t^A , (6) micro uncertainty σ_t^Z and (7) the joint distribution of idiosyncratic productivity and firm-level capital stocks and hours worked in the last period μ_t , which is defined for the product space $S = Z \times R_+ \times R_+$.

The dynamic problem of the firm consists of choosing investment and hours to maximize

¹⁹See the literature focused on estimating these labor and capital adjustment costs, including, Nickell (1986), Caballero and Engel (1999), Ramey and Shapiro (2002), Hall (2004), Cooper and Haltiwanger (2006), and Bloom (2009).

the present discounted value of future profit streams,

$$V(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) = \max_{i, n} \left\{ \begin{array}{l} y - w(A, \sigma^A, \sigma^Z, \mu)n - i \\ - AC^k(k, k') - AC^n(n_{-1}, n) \\ + \mathbb{E} [m(A, \sigma^A, \sigma^Z, \mu; A', \sigma^{A'}, \sigma^{Z'}, \mu') V(k', n, z'; A', \sigma^{A'}, \sigma^{Z'}, \mu')] \end{array} \right\} \quad (8)$$

given a law of motion for the joint distribution of idiosyncratic productivity, capital and hours,

$$\mu' = \Gamma(A, \sigma^A, \sigma^Z, \mu), \quad (9)$$

and the stochastic discount factor, m .

We denote by $AC^k(k, k')$ and $AC^n(n_{-1}, n)$ the capital and labor adjustment cost functions, respectively. $K(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$ and $N^d(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$ denote the policy rules associated with the firm's choice of capital for the next period and current demand for hours worked.

3.2 Households

The economy is populated by a large number of identical households that we normalize to a measure one. Households choose paths of consumption, labor supply, and investments in firm shares to maximize lifetime utility. We use the measure ϕ to denote the one-period shares in firms. The dynamic problem of the household is given by

$$W(\phi, A, \mu) = \max_{\{C, N, \phi'\}} \{U(C, N) + \beta \mathbb{E} [W(\phi', A', \mu')]\} \quad (10)$$

subject to the law of motion for μ and a sequential budget constraint

$$\begin{aligned} & C + \int q(k', n, z; A, \sigma^A, \sigma^Z, \mu) \phi'(dkdndz) \\ & \leq w(A, \sigma^A, \sigma^Z, \mu)N + \int \rho(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) \phi(dkdndz). \end{aligned} \quad (11)$$

The households receive labor income as well as the sum of dividends and the resale value of their investments, $V(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$. With these resources the household consumes and buys new shares at a price $q(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$ per share of the different firms in the economy.

We denote by $C(\phi, A, \mu)$, $N^s(\phi, A, \mu)$, $\Psi(k', n, z; A, \sigma^A, \sigma^Z, \mu)$ the policy rules determining current consumption, time worked, and quantities of shares purchased in firms that begin the next period with a capital stock that equals k' and who currently employ n hours,

respectively.

3.3 Recursive Competitive Equilibrium

A recursive competitive equilibrium in this economy is defined by a set of quantity functions $\{C, N^s, \Psi, K, N^d\}$, pricing functions $\{w, q, \rho, m\}$, and lifetime utility and value of the firm functions $\{W, V\}$, such that:

1. V and $\{K, N^d\}$, are the value function and policy functions, respectively, solving (8).
2. W and $\{C, N^s, \Psi\}$ are the value function and policy functions, respectively, solving (10).
3. Asset markets clear

$$\Psi(k', n, z; A, \sigma^A, \sigma^Z, \mu) = \mu(z, k', n) \text{ for every triplet } (z, k', n) \in S$$

4. Goods markets clear

$$\begin{aligned} & C(\phi, A, \mu) \\ = & \int_S \left[\begin{aligned} & Azk^\alpha N^\nu(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)^\nu - (K(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) - (1 - \delta_k)k) \\ & - AC^k(k, K(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)) - AC^n(n_{-1}, N(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)) \end{aligned} \right] \\ & \mu(dkdndz) \end{aligned}$$

5. Labor markets clear

$$N^s(\phi, A, \mu) = \int_S \left[N^d(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) \right] \mu(dkdndz)$$

6. The evolution of the joint distribution of z, k and n is consistent. That is, $\Gamma(A, \sigma^A, \sigma^Z, \mu)$ is generated by $K(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$, $N^d(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu)$, and the exogenous stochastic evolution of A, z, σ^Z and σ^A with the appropriate summation of firms' optimal choices of capital and hours worked given current state variables.

3.4 Sketch of the Numerical Solution

The model can be simplified substantially if we combine the firm and household problems into a single dynamic optimization problem as in Kahn and Thomas (2008). From the

household problem one can derive

$$w = -\frac{U_N(C, N)}{U_C(C, N)} \quad (12)$$

$$m = \beta \frac{U_C(C', N')}{U_C(C, N)} \quad (13)$$

where equation (12) is the standard optimality condition for labor supply and equation (13) is the standard expression for the stochastic discount factor. To ease the burden of computation it is useful to assume that the momentary utility function for the household can be specified as follows

$$U(C_t, N_t) = \frac{C_t^{1-\eta}}{1-\eta} - \theta \frac{N_t^\chi}{\chi}, \quad (14)$$

implying that the wage rate is a function of the marginal utility of consumption,

$$w_t = \phi N_t^{\chi-1} \frac{\theta}{C_t^{-\eta}}. \quad ((\text{wage}))$$

Kahn and Thomas (2003, 2008) and Bachmann, Caballero and Engel (2008) define the intertemporal price of consumption goods as $p(A, \sigma_z, \sigma^A, \mu) \equiv U_C(C, N)$. Using this approach, we can redefine the firm problem in terms of marginal utility, denoting the new value function as $\tilde{V} \equiv pV$. The firm problem can be expressed as

$$\tilde{V}(k, n_{-1}, z; A, \sigma^A, \sigma^Z, \mu) = \max_{\{i, n\}} \left\{ p(A, \sigma^A, \sigma^Z, \mu) (y - w(A, \sigma^A, \sigma^Z, \mu)n - i - AC^k(k, k') - AC^n(n_{-1}, n)) + \beta \mathbb{E} \left[\tilde{V}(k', n, z'; A', \sigma^{A'}, \sigma^{Z'}, \mu') \right] \right\} \quad (15)$$

We employ non-linear techniques to solve for the optimal policy functions instead of log-linearizing the model as is standard in the RBC literature.²⁰ Our solution uses a variation of the algorithm proposed by Krusell and Smith (1998). We reduce the large state vector of the model to include only the aggregate states (A, σ^A, σ^Z) and a small set of moments of the firm distribution which we will denote by Ω .²¹ The solution algorithm then works as follows (full details in Appendix B). In iteration l , perform the following steps.

1. Forecast the intertemporal price \hat{p} and next period's moments $\hat{\Omega}'$ as functions of the

²⁰In a log-linearized model, there is by construction no role for time varying second moments.

²¹The simplest example would be to use the average capital stock employed by all firms, but the set of moments can easily be extended to include, for instance, the standard deviation of firm specific capital holdings. In our benchmark calibration we use the average capital stock as the single moment in Ω .

current aggregate state:

$$\begin{aligned}\hat{p} &= f_1^{(l)}(z, A, \sigma^A, \sigma^Z, \Omega) \\ \hat{\Omega}' &= f_2^{(l)}(z, A, \sigma^A, \sigma^Z, \Omega)\end{aligned}$$

2. Assuming that $\chi = 1$, we get, for a given forecast of \hat{p} , the current period wage w from (??).²² We can then find the value function \tilde{V}^l associated with those forecasting functions by solving (15) substituting the approximated state Ω for the joint distribution μ and $f_2^{(l)}$ for the law of motion Γ .
3. Simulate the economy for T periods. Here, the forecasting rule for the intertemporal price is not used. Instead, in each period the market clearing price p_t is calculated as the price that combines firm optimization and goods market clearing. For a given price, the simplified firm optimization problem becomes

$$\max_{\{i, n\}} \left\{ p \left(y - wn - i - AC^k(k, k') - AC^n(n_{-1}, n) \right) + \beta \mathbb{E} \left[\tilde{V}^l(k', n, z'; A', \sigma^{A'}, \sigma^{Z'}, \hat{\Omega}') \right] \right\}$$

which uses the value function calculated in step 2 and the moment forecasting function from step 1. Market clearing is achieved when aggregation of the optimal policies from this problem yield market clearing in the goods market

$$C = \int \left(y + i - AC^k - AC^n \right) \mu(dkdndz).$$

This simulation yields sequences of prices $\{p_t\}$ and moments $\{\Omega_t\}$.

4. Update the forecasting functions $f_1^{(l+1)}$ and $f_2^{(l+1)}$ from the observed moments and equilibrium prices. Restart the algorithm at step 1 and iterate until the forecasting functions converge.^{23,24}

4 Simulation

This section motivates the choice of parameter values used in the simulations (see Table 2) and also presents simulation results for our preferred specification.

²² Assuming $\chi > 1$ would require the forecasting of an additional function in step 1 above. This would substantially complicate the numerical solution.

²³ For the forecasting functions, we use the first moments of the distribution over capital and labor as well as the aggregate uncertainty state. Interestingly, this provides a very good fit and an R2 of above 0.99.

²⁴ For the forecasting functions, we use the first moments of the distribution over capital and labor as well as the aggregate uncertainty state. Interestingly, this provides a very good fit and an R2 of above 0.99.

4.1 Calibration

4.1.1 Frequency and Preferences

We set the time period to equal a quarter. The household's discount rate, β , is calibrated to 0.985, while η is set equal to one implying that the momentary utility function features an elasticity of intertemporal substitution of one. As discussed above, we assume an infinite Frisch labor supply elasticity, or indivisible labor, corresponding to $\chi = 1$. We set the parameter θ such that households spend a third of their time working in the non-stochastic steady state. The trend growth rate of per capita output is set to equal 1.6% annually.

4.1.2 Production Function, Depreciation, and Adjustment Costs

The capital depreciation rate is set to match the average annual depreciation rate of 10%, leading us to set $\delta_k = 0.025$. The annual exogenous quit rate of labor is a key parameter, and is set to 15%. This estimate is based on the quit rate reported in the Bureau of Labor Statistic JOLTS data.²⁵

We set the firm's production function elasticity with respect to its capital stock, $\alpha = 0.25$ and $\nu = 0.5$, consistent with a capital cost share of 1/3 and a 25% markup when the firm faces an iso-elastic demand curve.

The existing literature provides a wide range of estimates for capital and labor adjustment costs.²⁶ We set our adjustment cost parameters to match Bloom (2009), which is the only paper we are aware of that jointly estimates capital and labor convex and non-convex adjustment costs. Fixed costs of capital adjustment are set to 1.5% of annual sales, and the resale loss of capital amounts to 40%. The fixed cost of adjusting hours, is set to 2.1% of annual wages, and the hiring and firing costs equal 1.8% of annual wages.

4.1.3 Aggregate and Idiosyncratic TFP Processes

We approximate the autoregressive processes (2) and (3) with Markov chains. The supports for the processes are set to include three standard deviations on either side of the mean. For idiosyncratic TFP, we increase this range to three times the standard deviation on either side. The parameters of the processes are taken from Khan and Thomas (2008) and

²⁵JOLTS stands for Job Openings and Labor Turnover Data, which the BLS has been collecting since January 2001. Hence, this data spans two NBER defined recessions. It distinguishes between quits, layoffs, and other separations. Our figures are seasonally adjusted for total private employment. In JOLTS, the monthly quit figure varies between 1.6% and 2.4%, with the lowest value occurring in November 2008 during the depths of the 2008 recession. Annualizing the November 2008 quit rate we get a value of 19.2%. Our calibration using a lower value of 15% is thus a conservative calibration.

²⁶See, for example, Hayashi (1982), Nickel (1986), Shapiro (1986), Caballero and Engel (1999), Ramey and Shapiro (2001), Hall (2004), Cooper, Haltiwanger and Willis (2004), Cooper and Haltiwanger (2006) as well as Mertz and Yashiv (2007).

adjusted to the quarterly frequency. Hence, ρ^A and ρ^Z are set to yield an annual persistence parameter of 0.859, whereas the standard deviation of innovations to the aggregate and idiosyncratic productivity process are set to yield an annual equivalent of 0.014 and 0.022, respectively.

4.1.4 The Calibrated Process for Uncertainty

We assume for simplicity that the stochastic volatility processes σ_t^A and σ_t^Z follow two-point Markov chains. In the benchmark calibration we assume that the values of aggregate and idiosyncratic uncertainty are driven by just one exogenous process that determines whether the economy is in the normal or uncertain regime. Moreover, in the benchmark calibration, the uncertainty process is assumed to be completely independent of the first-moment shocks. This implies that we are not artificially creating the drop in economic activity following a second-moment shock by correlating it with the first-moment shock.

The stochastic process of uncertainty in the model is only indirectly related to the uncertainty index we have created in Section 2. Therefore, we proceed by disciplining our uncertainty process. The model generates a time series for the IQR of cross-firm sales growth rates and the IQR of cross-firms stock returns which are observed in the data. We thus calibrate the uncertainty process such that the serial autocorrelation and the variance of the mean of those processes match their observable counterparts in the data. By setting the increase of σ_t^A and σ_t^Z in the high uncertainty state to a factor of 2.03 and using the following Markov transition matrix we can match the two aforementioned time series:

	<i>normal</i>	<i>uncertain</i>
<i>normal</i>	0.956	0.044
<i>uncertain</i>	0.208	0.792

This matrix implies that the economy resides in the low uncertainty state 82% of the time.

4.2 The Effects of an Uncertainty Shock

We first study the effects of an isolated increase in uncertainty. We simulate many economies and let each run for 500 periods to initialize the distribution over z , k and n , while forcing all economies to remain in the low uncertainty state. At period zero, all economies are subject to an uncertainty shock. That is, agents learn that, starting in period one, the distribution of productivities fans out.²⁷ The expected duration of the processes is governed by the transition matrix. This leads to an increase in the dispersion of cross-sectional firm sales

²⁷The magnitude of the shock is such that the standard deviation of the innovations to idiosyncratic and aggregate productivity increase by factors slightly larger than two as outlined in the calibration.

growth rates and stock returns of about 25%, matching the real data discussed in Section 2.

Figure 14 plots the fraction of economies that are in the high uncertainty state in each quarter, while Figure 15 show that the average firm productivity does not change in this experiment. Thus, the baseline simulation results are driven entirely by changes in uncertainty. In what follows we report the behavior of the variables of interest as the average over these economies.

The time profile of hours worked is shown in Figure 16. In period zero, once uncertainty rises, firms defer most hiring decisions, leading to a fall of about 2% in hours worked. Hours continue to fall until quarter three, by when uncertainty falls enough and productivity fans out sufficiently so that firms with high productivity draws start to increase hours. By quarter five, the economy has reverted back to the initial trend.

Labor use actually rises above its long-run value for a few more quarters before returning to this long-run level. The reason for such overshooting is that within the economy, many firms are bunched near the hiring threshold due to labor attrition. Small increases in productivity will cause firms to hire more workers, while small decreases in productivity will simply move them towards the interior of their (S, s) bands. As a result, the increased variance of the productivity shock induced by higher uncertainty increases aggregate medium-run hiring. Firms that have received positive productivity shocks hit their (S, s) bands and hire. Firms that receive a negative shock move to the interior of the (S, s) bands and do nothing. Since at period zero each firm's capital stock is given, the fall in aggregate hours worked manifests itself into a drop in aggregate output, as can be seen in Figure 17. Overall, output falls recovers by the fourth quarter and follows the overshooting of labor. Inter

The uncertainty shock also induces a drop and subsequent rebound in investment, as shown in Figure 18. As uncertainty rises in period zero, investment expenditure sharply falls due to postponed investment decisions. Substantial capital adjustment costs lead many firms to defer new investment expenditure until after uncertainty has subsided. Investment recovers by the third quarter as uncertainty has fallen sufficiently enough to lead firms start to addressing their pent-up demand for investment.

Figure 19 plots the time profile of consumption. When the uncertainty shock occurs in period zero, consumption jumps up immediately and then falls below trend for about five quarters. The reason for the initial spike in consumption is that the freeze in investment and hiring reduces the resources spent on capital and labor adjustment. Since the interest rate drops upon impact of the shock, consumers are signaled that consumption is cheap, which leads to an increase in consumption in period zero. In other words, even though consumers know they face higher uncertainty in the future and they would like to save

more, they do not increase savings in the first period because the returns to saving have become (temporarily) low and very risky.²⁸

Finally, Figure 20 plots the value for the aggregate Solow residual, defined as $Y_t/K_t^\alpha N_t^\nu$. The Solow residual also has a clear drop and subsequent rebound after the uncertainty shock, despite the fact that the average micro and macro productivity shocks were unchanged, as shown in Figure 15. The reason is that uncertainty freezes the reallocation of capital and labor from low- to high-productivity firms. In normal times, unproductive firms contract and productive firms expand, helping to maintain high productivity levels. When uncertainty is high, firms reduce expansion and contraction, shutting off much of this productivity-enhancing reallocation, leading to a fall in productivity growth rates. When uncertainty reverts back to normal, firms rapidly address their pent-up demand for reallocation so that productivity returns to its long-run trend.

Therefore, a second-moment shock induces a fall in investment, hours, and output. Intriguingly, the Solow residual also falls even though this is an effect rather than a cause of the drop in economic activity. Consumption also exhibits a fall from quarter two onwards, although there is an initial one-period jump in the basic model.

4.3 Model Simulations

We have shown that our model can generate expansions and contractions in response to an increase in uncertainty. One natural question is whether this success comes at a cost of the model's ability to generate empirically recognizable business fluctuations. That is, can the model, when calibrated with the same parameters used in the experiments discussed so far, generate co-movement, and volatility of macroeconomic aggregates that are empirically plausible? To answer this question, we simulate our model and compute the standard set of business cycle statistics.

As Panel A in Table 3 reports, the benchmark calibration generates second-moment statistics that closely match the empirical counterparts in the U.S. data. Investment is more volatile than output, while consumption is less volatile. Investment and hours commove with output. Similarly to many variants of the RBC model, hours are not as volatile relative to output as in the data.

²⁸This logic suggests that if we extended the model to allow for some alternative savings technology – for example, inventories or savings abroad – this initial spike in consumption would disappear as the representative consumer would just increase savings through this channel when the uncertainty shock hit to reduce the subsequent drop in consumption. Due to computational constraints we cannot increase the state space of the model.

4.4 Robustness Checks

To highlight the role of the adjustment costs in generating the effects of uncertainty shocks as those reported in Figures 15-20, we depict in Figures 21 and 22 the impact of an uncertainty when (i) there are only capital adjustment costs (Figure 21), and (ii) when there are no adjustment costs at all.

As Figure 21 shows, when the uncertainty shocks hits the economy and there are only capital adjustment costs output does not react. This is not surprising as on impact capital is a state variable and hence labor does not react. Since at period zero investment falls, starting in period 1 capital falls as hence output falls below trend and later recovers. Figure 22 shows that when there are no adjustment costs of any type in the economy, economic activity actually increases following an uncertainty shock. The reason for this result is related to the Hartman-Abel effect.²⁹

4.5 Uncertainty Shocks as a Magnification Mechanism

We have assumed so far that the uncertainty process is completely independent of the first-moment shocks. In this subsection we relax this assumption.

[To be completed].

5 Policy in the Presence of Uncertainty

In this section, we analyze the effects of a policy that tries to increase investment in an economy that is faced with shocks to uncertainty. As we argue below, uncertainty widens firms' (S, s) bands for investment and hiring, thereby reducing the impact response of any given policy. Figure 23 plots the evolution of the cross-sectional distribution of the ratio of firm TFP to capital in the model.³⁰ The uncertainty shock occurs in period zero. Note how, on impact, the investment and disinvestment threshold fan out. Slowly over time, as firms begin drawing their new high (low) productivity shocks, the distribution of firm-level TFP fans out towards the thresholds. For example, assume that a normal policy moves the threshold downward by 5%. Such a policy would have pushed about 50% of the firms over the investment threshold in normal times (i.e. periods -4,-3,-2,-1). But, the same policy

²⁹ Panes B-F in Table 3 report the second-moment statistics for different robustness checks relative to the benchmark model. Specifically, we consider five robustness checks: (i) No adjustment costs of any type (Panel B), (ii) only macro uncertainty (Panel C), (iii) only micro uncertainty (Panel D), (iv) a high dispersion of macro shocks relative to micro shocks (Panel E), and (v) a high dispersion of micro shocks relative to macro shocks (Panel F). As Table 3 shows, the second-moment statistics in all of these experiments closely resemble those in Panel A. This similarity is not surprising as all of these economies are subject to the first-moment shocks.

³⁰ In order to be able to draw the distribution, we look at the values of TFP/k for given capital and labor values.

would have had zero impact time zero, when the uncertainty shock occurs, since such a move in the threshold would have no effect on firms!

To substantiate these claims, we conduct a policy experiment. Specifically, we analyze the case of a 1% surprise investment credit for one quarter and we evaluate its effect during a normal period and after an uncertainty shock.^{31,32} Figure 24 shows the response of output to such a policy, that takes place at period zero in two cases. The line with squares shows the response of output to such a policy in the case of low uncertainty. The line with triangles shows the behavior of output in response to an uncertainty shock, while the line with circles shows the response of this economy with a tax credit. The difference between the second and the third line is the impact of policy during high uncertainty times. Figure 25, shows the differential effects of the policy in the two economies (line 1 versus the difference between lines 2 and 3 from Figure 24). As is clear from the figure, the presence of uncertainty mitigates the effects of such a policy relative to an economy that is in the normal, or low uncertainty, state.

Two messages that arise from this experiment are that in order for such a policy to have any effect on investment in the presence of uncertainty, it has to be both larger (in order to move the investment threshold down) and shorter-lived (in order to avoid overshooting once uncertainty falls) than the policy that would be implemented during normal times.

6 Conclusions

This paper proposes time variation in uncertainty as an additional impulse driving business cycles. First, we demonstrate that uncertainty, measured by a number of proxies, appears to be strongly countercyclical. When added to a standard VAR, increases in uncertainty lead to a large drop and subsequent rebound in economic activity. This result holds even after controlling for first-moment effects.

Second, we study a dynamic stochastic general equilibrium model that allows for shocks to both the level of technology (the first moment) as well as uncertainty (the second moment). More specifically, we model shocks to uncertainty as variation in the standard deviation of the innovations to productivity. We find that increases in uncertainty lead to large drops in employment and investment. This occurs because uncertainty makes firms cautious, leading them to pause hiring and investment. This freezing in activity also reduces the reallocation of capital and labor across firms, leading to a large fall in productivity

³¹We assume this credit comes "from Mars" and abstract from general equilibrium balanced budget considerations.

³²Note that this tax credit is not optimal. The optimal policy is to do exactly nothing in this setup. We are thus analyzing this policy experiment merely as a way to summarize the potential effects of policy in the presence of uncertainty.

growth. Taken together, the freeze in hiring, investment and productivity growth leads to a business-cycle-sized drop and rebound in output following a rise in uncertainty.

We then conclude by using our model to investigate the effects of uncertainty on policy effectiveness. We use a simple illustrative example to show the presence significantly dampens the effect of an expansionary policy.

References

- Abel, A.B. and Eberly, J.C. (1996), "Optimal Investment with Costly Reversibility", *Review of Economic Studies*, 63(4), 581-593.
- Abraham, K.G. and Katz, L.F. (1986), "Cyclical Unemployment: Sectoral Shifts or Aggregate Disturbances?", *Journal of Political Economy*, 9(3), 507-522.
- Aghion, P., Angeletos, G., Banerjee, A. and Manova, K. (2005), "Volatility and Growth: Credit Constraints and Productivity-Enhancing Investment", NBER WP 11349.
- Amador, M. and Weill, P.-O. (2008), "Learning from Private and Public Observations of Others' Actions", Stanford mimeo.
- Bachman, R., Caballero, R.J. and Engel, E.M.R.A. (2008), "Aggregate Implications of Lumpy Investment: New Evidence and a DSGE Model", Yale mimeo.
- Bartelsman, E., Becker, R. and Gray, W. (2000), "NBER Productivity Database", www.nber.org.
- Barlevy, G. (2004), "The Cost of Business Cycles Under Endogenous Growth", *American Economic Review*, 94(4), 964-990.
- Basu, S., Fernald, J. and Kimball, M.S. (2006), "Are Technology Improvements Contractionary?", *American Economic Review*, 96(5), 1418-1448.
- Bernanke, B. (1983), "Irreversibility, Uncertainty and Cyclical Investment", *Quarterly Journal of Economics*, 98, 85-106.
- Bentolila, S. and Bertola, G. (1990), "Firing Costs and Labor Demand: How Bad is Euroclerosis", *Review of Economic Studies*, 57(3), 381-402.
- Bernard, A., Redding, S. and Schott, P. (2006), "Multi-Product Firms and Product Switching", NBER WP 12293.
- Bertola, G. and Caballero, R.J. (1994), "Irreversibility and Aggregate Investment", *Review of Economic Studies*, 61, 223-246.
- Bloom, N. (2009), "The Impact of Uncertainty Shocks", forthcoming *Econometrica*.
- Bloom, N. (2007), "Uncertainty and the Dynamics of R&D", *American Economic Review Papers and Proceedings*, 97(2), 250-255.
- Bomberger, W. A. (1996), "Disagreement as a Measure of Uncertainty", *Journal of Money, Credit and Banking*, 28(3), 381-392.
- Caballero, R.J. and Engel, E.M.R.A (1999), "Explaining Investment Dynamics in U.S. Manufacturing: a Generalized (S,s) Approach", *Econometrica*, 67(4), 783-826.
- Caballero, R.J. and Leahy, J. (1996), "Fixed costs: the demise of marginal Q", NBER WP 5508.
- Campbell, J., Lettau, M., Malkiel B. and Xu, Y. (2001), "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk", *Journal of Finance*, 56(1), 1-43.
- Christiano, L.J., Eichenbaum, M. and Evans, C.L. (2005), "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy", *Journal of Political Economy*, 113(1), 1-45.

- Davis, S.J. and Haltiwanger, J. (1992), "Gross Job Creation, Gross Job Destruction, and Employment Reallocation", *Quarterly Journal of Economics*, 107, 819-863.
- Davis, S.J., Haltiwanger, J., Jarmin, R. and Miranda, J. (2006), "Volatility and Dispersion in Business Growth Rates: Publicly Traded Versus Privately Held Firms", NBER WP 12354.
- Dixit, A.K. and Pindyck, R.S. (1994), "Investment Under Uncertainty", Princeton University Press, Princeton.
- Engle, R.F. and Rangel, J.G. (2008), "The Spline-GARCH Model for Low-Frequency Volatility and Its Global Macroeconomic Causes", *Review of Financial Studies*, 21(3), 1187-1222.
- Faggio, G., Salvanes K.G. and Van Reenen, J. (2007), "Understanding Wage and Productivity Dispersion in the United Kingdom", mimeo.
- Foster, L., Haltiwanger, J. and Krizan, C.J. (2000), "Aggregate Productivity Growth: Lessons from Microeconomic Evidence", *New Developments in Productivity Analysis*, NBER, University of Chicago Press.
- Foster, L., Haltiwanger, J. and Krizan, C.J. (2006), "Market Selection, Reallocation and Restructuring in the U.S. Retail: Trade Sector in the 1990s", *Review of Economics and Statistics*, 88, 748-758.
- Koren, M. and Tenreyro, S. (2007), "Volatility and Development", *Quarterly Journal of Economics*, 122(1), 243-287.
- Gilchrist, S. and Williams, J.C. (2005), "Investment, Capacity, and Uncertainty: A Putty-Clay Approach", *Review of Economic Dynamics*, 8(1), 1-27.
- Giordani, P. and Soderlind, P. (2004), "Inflation Forecast Uncertainty", *European Economic Review*, 47(6), 1037-1059.
- Hall, R.E. (2004), "Measuring Factor Adjustment Costs", *Quarterly Journal of Economics*, 119, 899-927.
- Hamilton, J.D. and Lin, G. (1996), "Stock Market Volatility and the Business Cycle", *Journal of Applied Econometrics*, 11(5), 573-593.
- Hammermesh, D. (1989), "Labor demand and the structure of adjustment costs", *American Economic Review*, 79, 674-89.
- Hassler, J. (1996), "Variations in Risk and Fluctuations in Demand - a Theoretical Model", *Journal of Economic Dynamics and Control*, 20, 1115-1143.
- House, C.L. (2008), "Fixed Costs and Long-Lived Investments", NBER WP 14402.
- Jaimovich, N. and Siu, H. (2008), "The Young, the Old, and the Restless: Demographics and Business Cycle Volatility", forthcoming *American Economic Review*.
- Keynes, J.M. (1936), "The General Theory of Employment, Interest and Money", Macmillan, London.
- Lillien, D.M. (1982), "Sectoral Shifts and Cyclical Unemployment", *Journal of Political Economy*, 90(4), 777-793.

- Khan, A. and Thomas, J.K. (2003), "Nonconvex Factor Adjustments in Equilibrium Business Cycle Models: Do Nonlinearities Matter?", *Journal of Monetary Economics*, 50, 331-360.
- Khan, A. and Thomas, J.K. (2008), "Idiosyncratic Shocks and the Role of Nonconvexities in Plant and Aggregate Investment Dynamics", *Econometrica*, 76(2), 395-436.
- King, R.G. and Rebelo, S.T. (1999), "Resuscitating Real Business Cycles", in *Handbook of Macroeconomics*, John B. Taylor and Michael Woodford (eds.), Elsevier.
- Krusell, P and Smith, A.A. (1998), "Income and Wealth Heterogeneity in the Macroeconomy", *Journal of Political Economy*, 106(5), 867-896.
- Mele, A. (2007), "Asymmetric Stock Market Volatility and the Cyclical Behavior of Expected Returns", *Journal of Financial Economics*, 86, 446-478.
- Merz, M. and Yashiv, E. (2007), "Labor and the Market Value of the Firm", *American Economic Review*, 97(4), 1419-1431.
- Nickell, S.J. (1986), "Dynamic Models of Labor Demand", in O. Ashenfelter and R. Layard (eds.), *Handbook of Labor Economics*, North-Holland, Amsterdam.
- Officer, R. (1973), "The Variability of the Market Factor of the New York Stock Exchange", *Journal of Business*, 46, 434-453.
- Pindyck, R.S. (1988), "Irreversible Investment, Capacity Choice, and the Value of the Firm", *American Economic Review*, 78(5), 969-985.
- Ramey, V.A. and Ramey, G. (1994), "Cross-Country Evidence on the Link between Volatility and Growth", *American Economic Review*, 85, 1138-1151.
- Ramey, V.A. and Shapiro, M.D. (2001) "Displaced Capital: A Study of Aerospace Plant Closings", *Journal of Political Economy*, 109, 605-622.
- Rebelo, S.T. (2005), "Real Business Cycle Models: Past, Present, and Future", *Scandinavian Journal of Economics*, 107(2), 217-238.
- Schwert, G.W. (1989), "Why Does Stock Market Volatility Change Over Time?", *Journal of Finance*, 44, 1115-1153.
- Storesletten, K., Telmer, C.I. and Yaron, A. (2004), "Cyclical Dynamics in Idiosyncratic Labor-Market Risk", *Journal of Political Economy*, 112(3), 695-717.
- Thomas, J.K. (2002), "Is Lumpy Investment Relevant for the Business Cycle?", *Journal of Political Economy*, 110(3), 508-534.
- Veracierto, M.L. (2002), "Plant Level Irreversible Investment and Equilibrium Business Cycles", *American Economic Review*, 92(1), 181-197.
- Zarnowitz, V. and Lambros, L.A. (1987), "Consensus and Uncertainty in Economic Prediction", *Journal of Political Economy*, 95(3), 591-621.

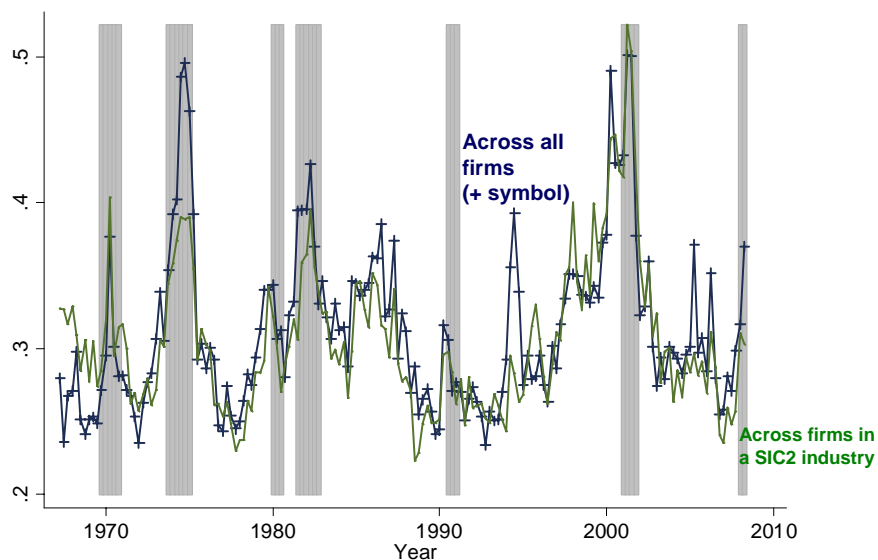
A Appendix: Uncertainty Data

To be added.

B Appendix: Numerical Solution Method

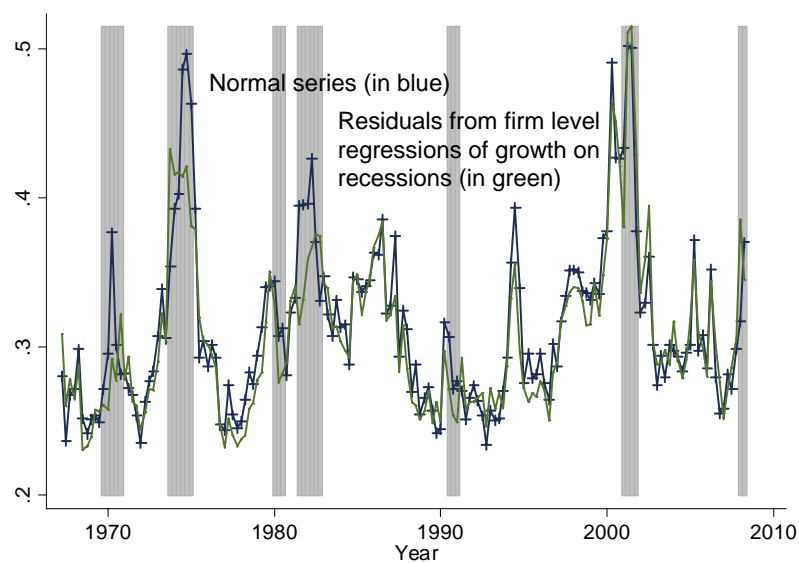
To be added.

Fig 1: Cross firm sales growth spread



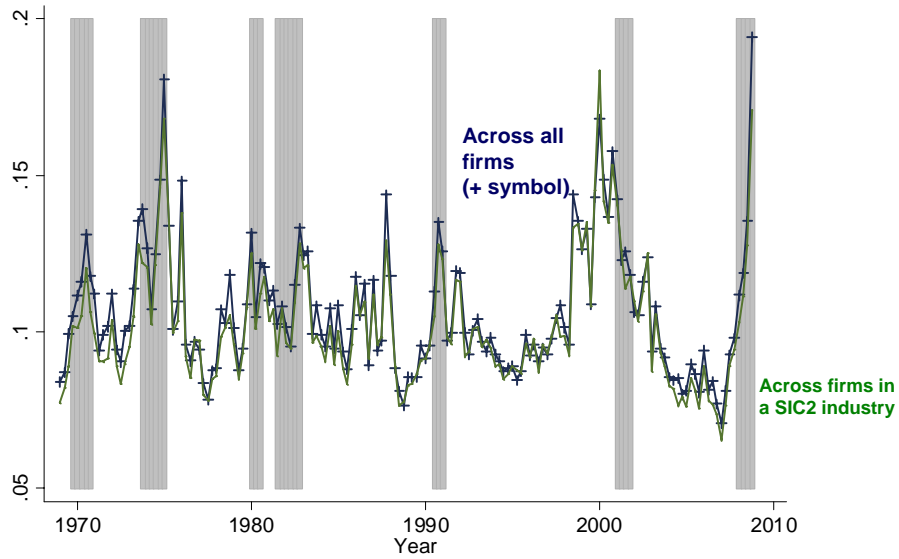
Interquartile range of sales growth (Compustat firms). Only firms with 25+ years of accounts, and quarters with 500+ observations. SIC2 only cells with 25+ obs.

Fig 2: Cross firm sales growth spread



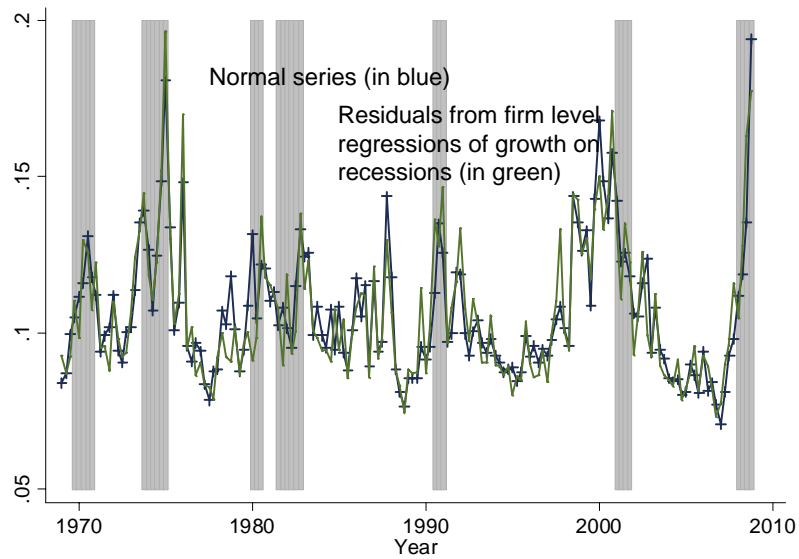
Interquartile range of sales growth (Compustat firms). Only firms with 25+ years of accounts, and quarters with 500+ observations. SIC2 only cells with 25+ obs.

Fig 3: Cross firm stock returns spread



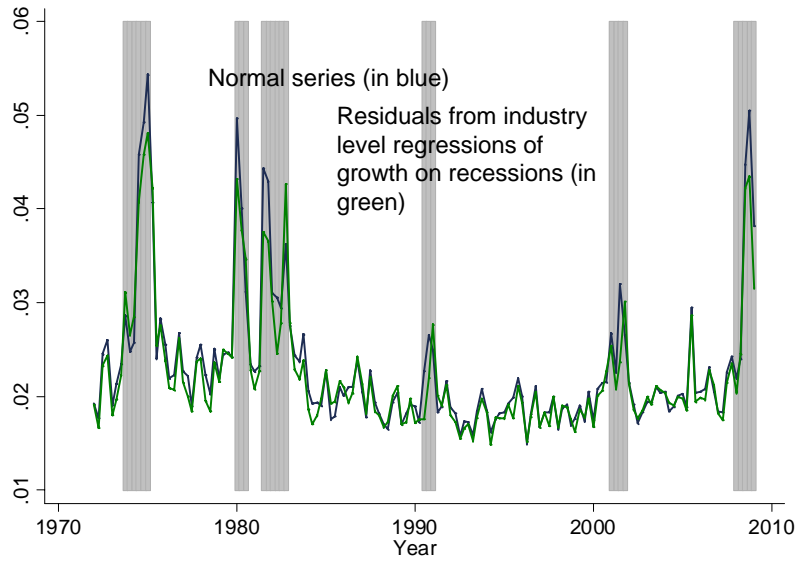
Interquartile range of stock returns (CRSP firms). Only firms with 25+ years of accounts, and quarters with 500+ observations. SIC2 only cells with 25+ obs.

Fig 4: Cross firm stock returns spread



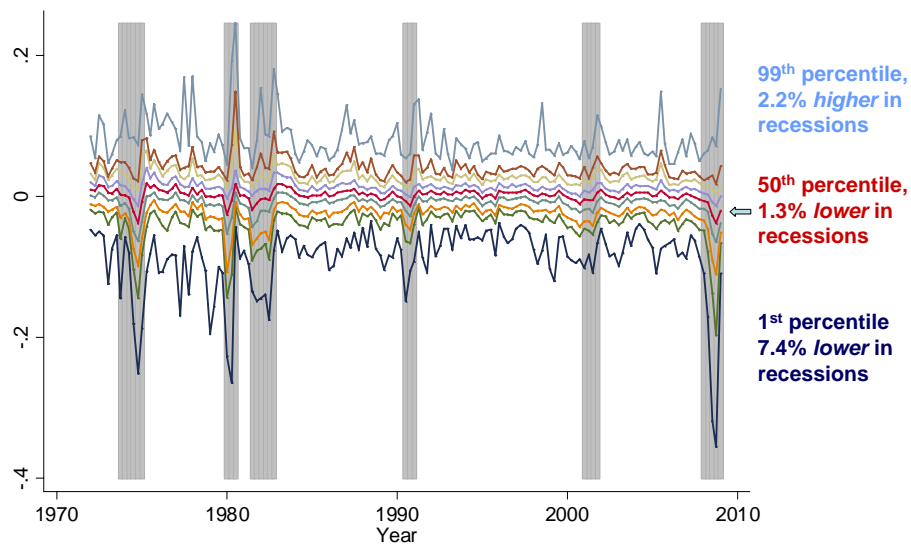
Interquartile range of stock returns (CRSP firms). Only firms with 25+ years of accounts, and quarters with 500+ observations. SIC2 only cells with 25+ obs.

Fig 5: Cross industry output growth spread



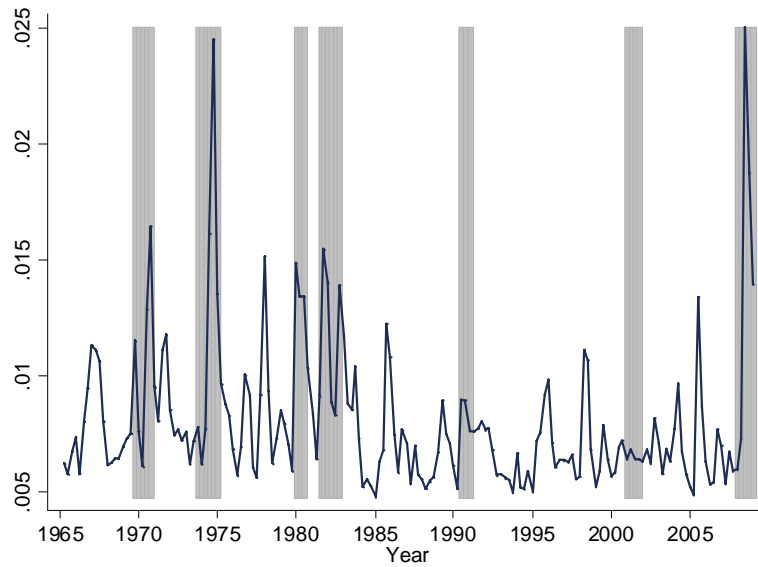
Inter-quartile range of the 3-month growth rates of industrial production. Covers all 196 manufacturing NAICS sectors in the Federal Reserve Board database.

Fig 6: Cross industry output growth distribution



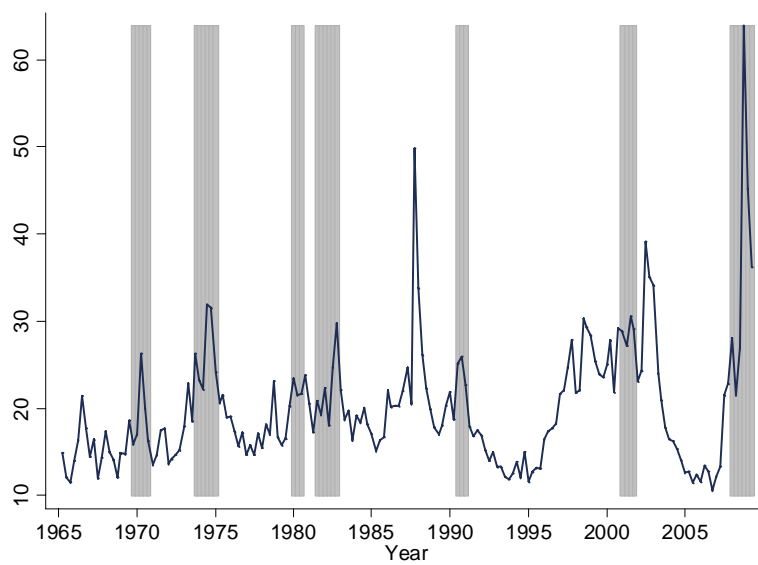
1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th and 99th percentiles of 3-month growth rates of industrial production within each quarter. All 196 manufacturing NAICS sectors in the Federal Reserve Board database.

Fig 7: Industrial production growth volatility



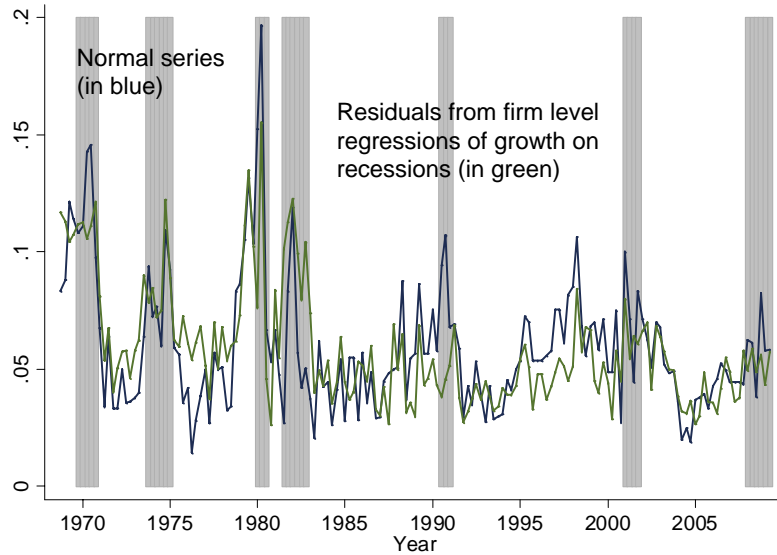
Monthly industrial production conditional heteroskedasticity, from a GARCH(1,1) auto-regression with 12 lags.

Fig 8: Stock market volatility



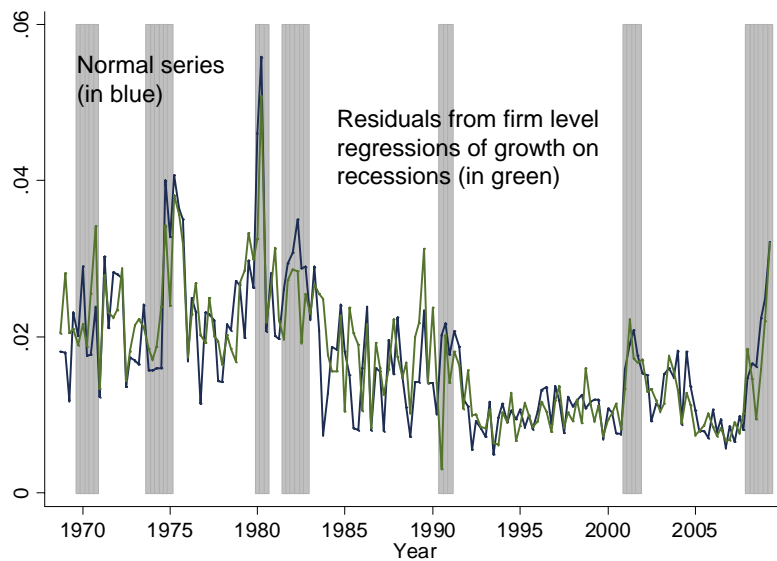
S&P 100 implied volatility (the VXO, which is very similar to VIX) from 1987, and normalized realized volatility of actual S&P100 daily stock returns prior to 1986.

Fig 9: Forecaster dispersion for unemployment



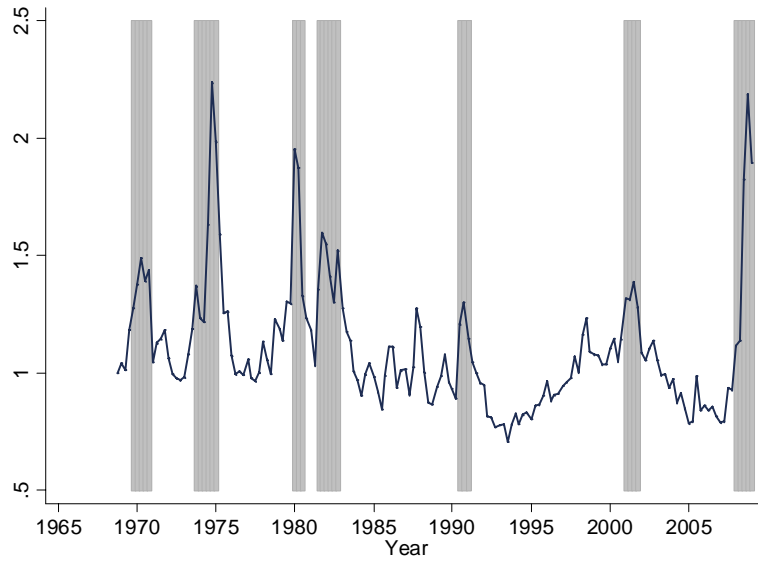
Interquartile range of year ahead unemployment rates / mean unemployment rates. From Survey of Professional Forecasters. Average of 41 forecasts per quarter.

Fig 10: Forecaster dispersion for ind production



Interquartile range of year ahead production/mean production. From Survey of Professional Forecasters. Average of 41 forecasts per quarter.

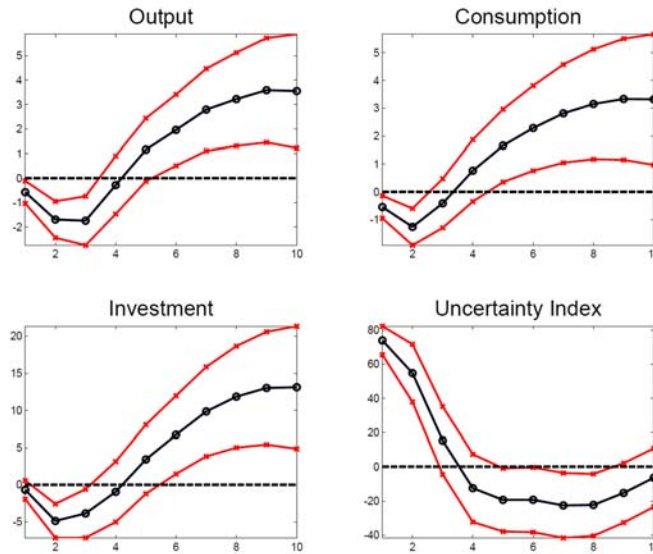
Fig 11: Uncertainty index



Mean of the 7 prior indicators after they have all been normalized to an average of 1 during non-recessionary quarters. Only reported when 6+ indicators present.

Fig 12: VAR analysis – uncertainty first

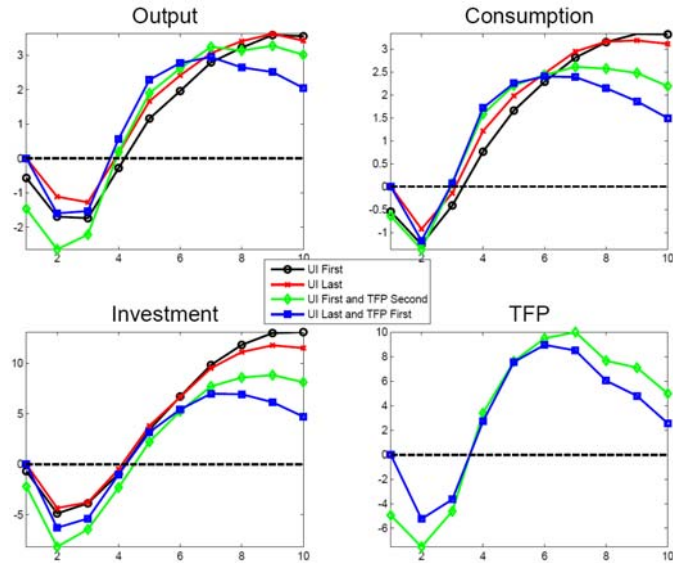
Shock calibrated to increase uncertainty 48% during recessions



Cholesky orthogonalized on quarterly data from 1968:4 to 2006:4 using 4 lags. Dotted lines are 95% confidence intervals

Fig 13: VAR analysis – different experiments

Shock calibrated to increase uncertainty 48% during recessions



Cholesky orthogonalized on quarterly data from 1968:4 to 2006:4 using 4 lags. Dotted lines are 95% confidence intervals

Fig 14: % of economies in the high uncertainty state

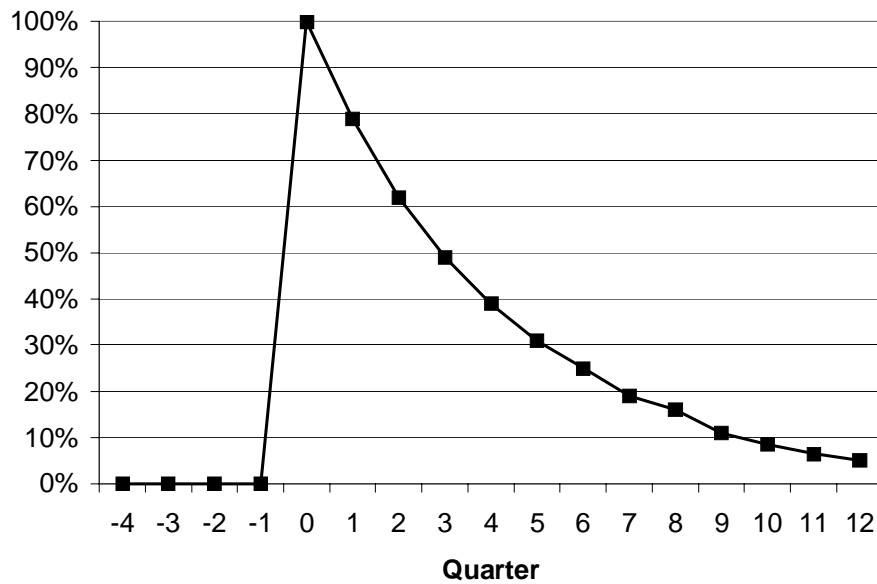


Fig 15: No first moment shock: average productivity

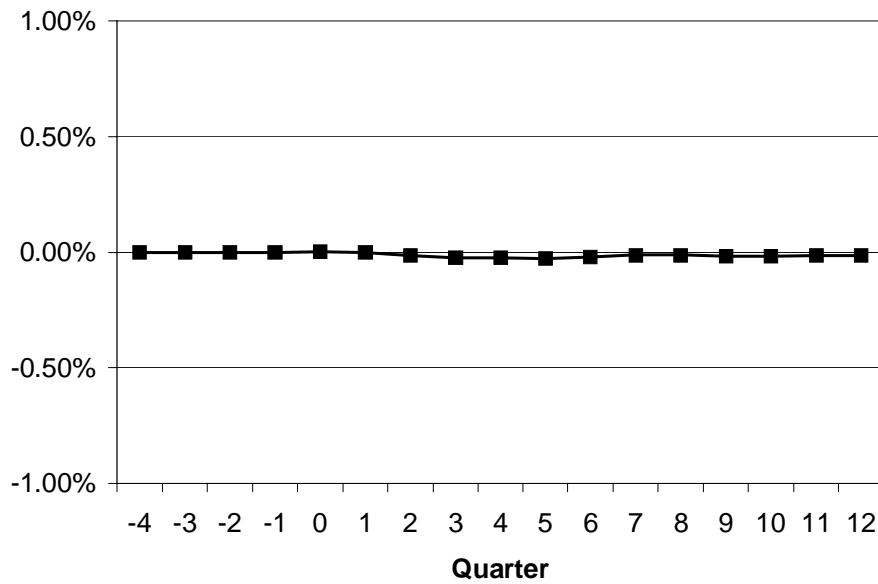


Fig 16: Effects of a rise in uncertainty on employment

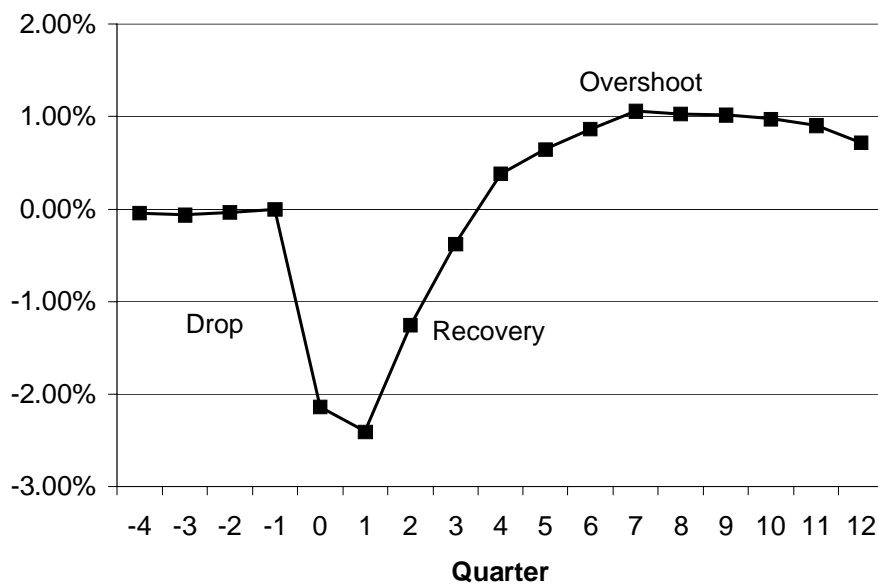


Fig 17: Effects of a rise in uncertainty on output

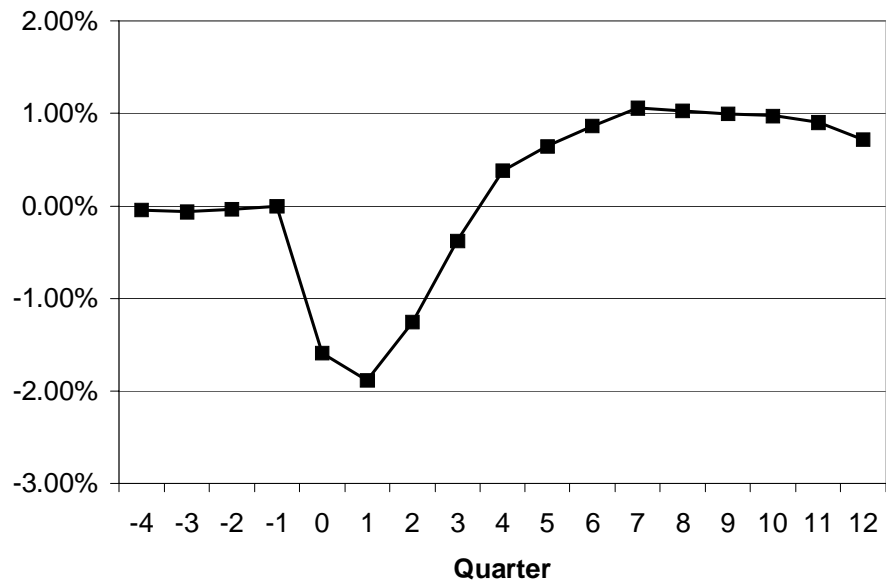


Fig 18: Effects of a rise in uncertainty on investment

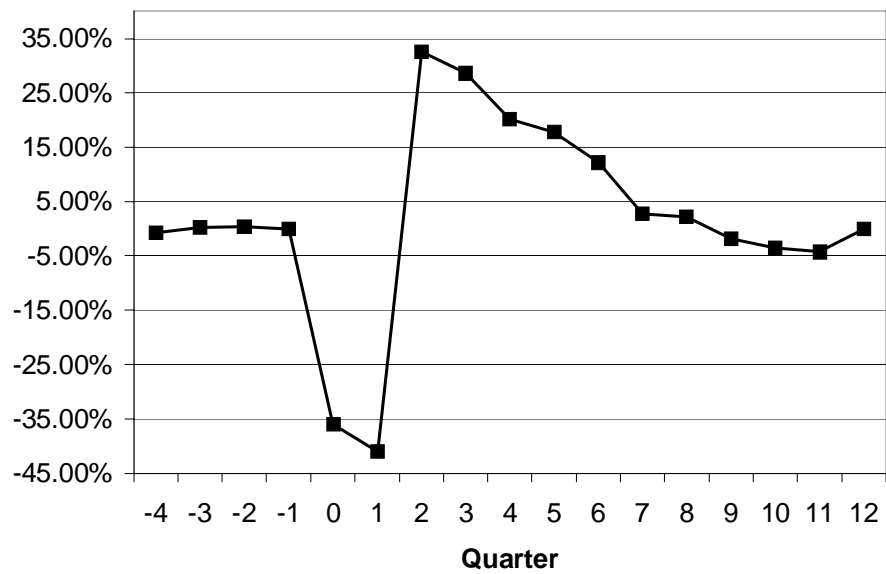


Fig 19: Effects of a rise in uncertainty on consumption

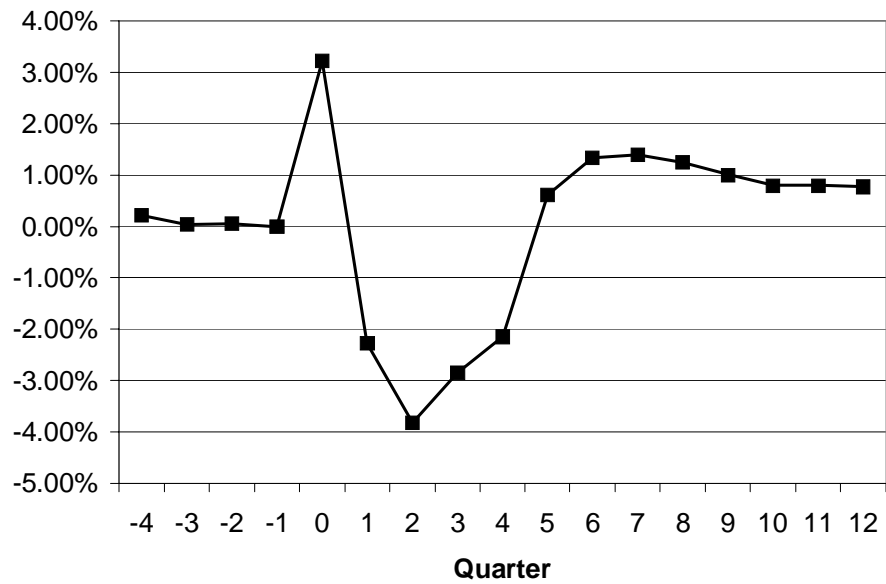


Fig 20: Effects of a rise in uncertainty on TFP

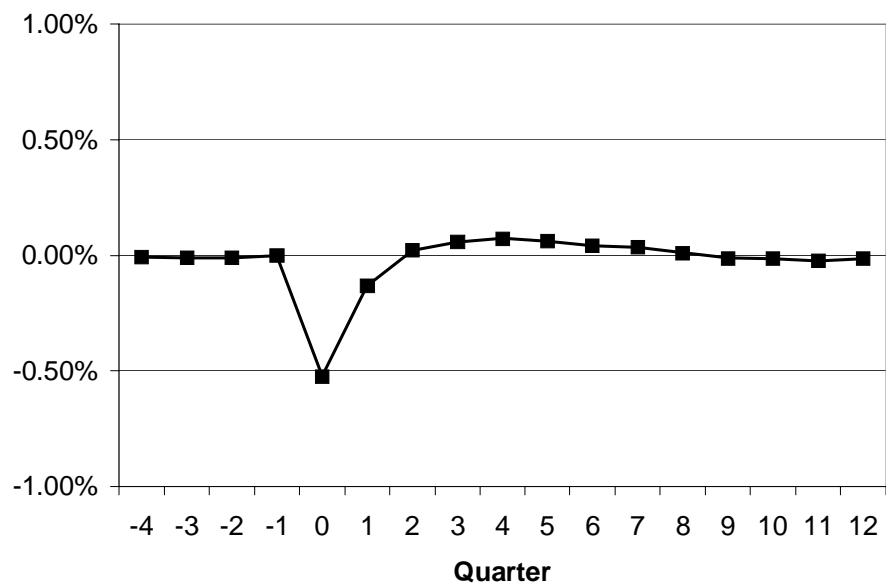


Fig 21: Only K AC: Output response to an uncertainty shock

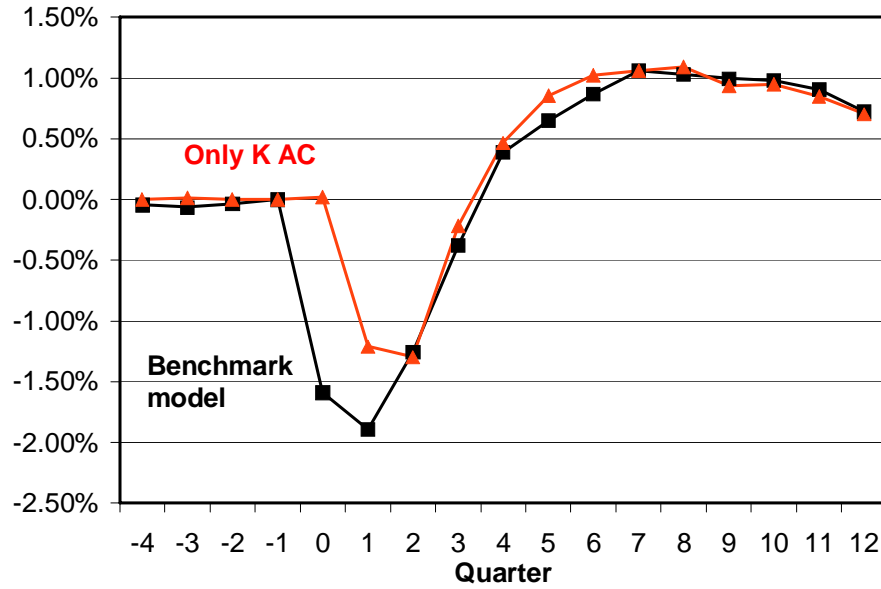


Fig 22: Effects of a rise in uncertainty: No AC

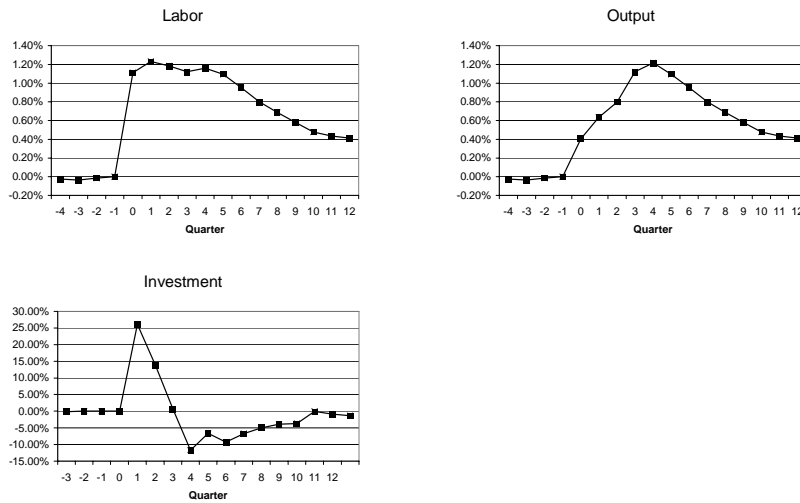


Fig 23: Cross-sectional distribution of firm TFP/capital

Thresholds & percentiles of firm distribution over z (for fixed k & l)

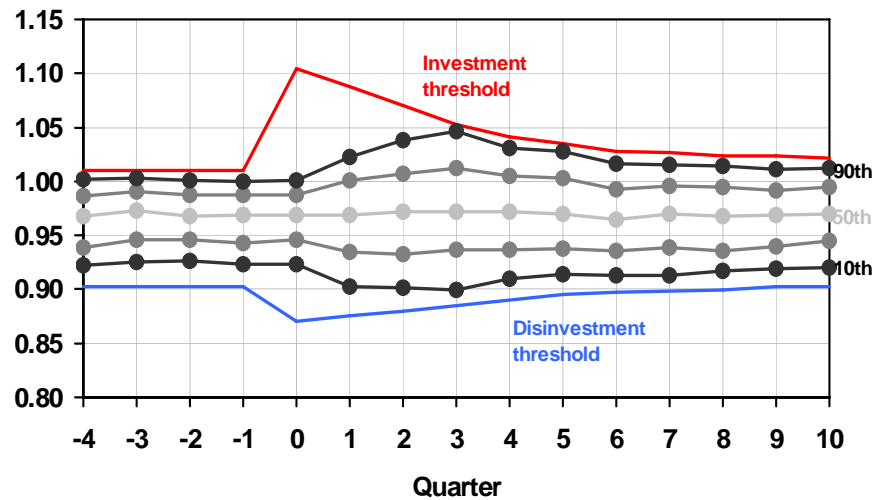


Fig 24: Impact of 1% investment credit

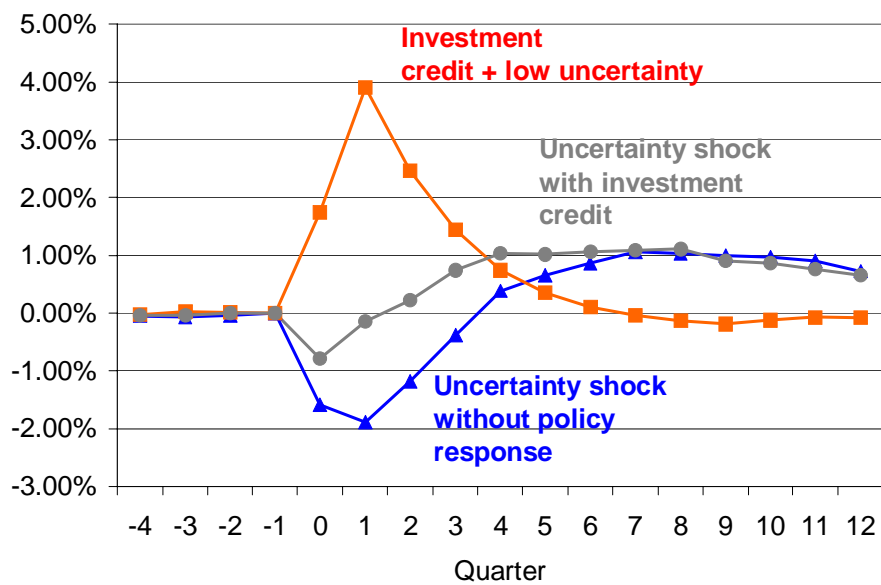


Fig 25: Impact of 1% investment credit

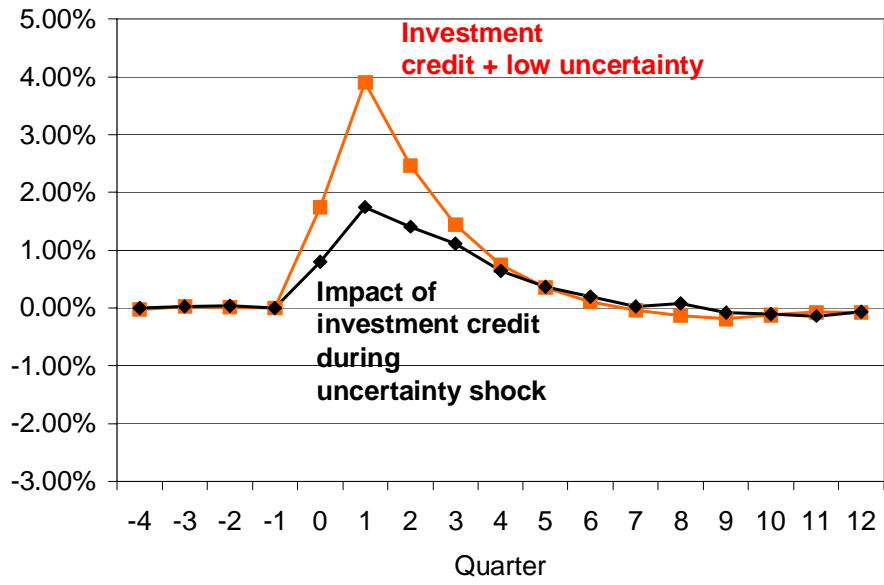


Table 1: Uncertainty and the Recession

	% increase during recessions, mean (<i>standard deviation</i>)	correlation with quart. ind. production growth	period covered
(1) Firm sales growth spread (quarterly cross-sectional interquartile range)	23.1 (3.4)	-0.471	67Q2 to 08Q2
(2) Firm stock returns spread (quarterly cross-sectional interquartile range)	22.4 (3.6)	-0.367	69Q1 to 08Q4
(3) Industry output growth spread (quarterly cross-sectional interquartile range)	66.5 (5.4)	-0.603	72Q1 to 09Q1
(4) Macro output growth volatility (quarterly average conditional standard deviation)	57.6 (13.1)	-0.409	62Q1 to 09Q1
(5) Macro stock returns volatility (quarterly standard deviation of daily stock returns)	44.2 (6.8)	-0.470	63Q1 to 09Q2
(6) Forecaster predicted industrial production spread (quarterly interquartile range / mean)	62.5 (9.3)	-0.282	68Q4 to 09Q2
(7) Forecaster predicted unemployment spread (quarterly interquartile range / mean)	70.4 (6.9)	-0.535	68Q4 to 09Q2
(8) Uncertainty index (average of normalized individual measures)	47.3 (3.6)	-0.621	68Q4 to 08Q4

Table 2: Calibration

Parameter	(Quarterly) Value	Rationale (also see the text)
β	0.985	Annual interest rate of 4%.
η	1	Elasticity of intertemporal substitution set to 1.
θ	1.813	Households spend one third of their time working in steady state.
γ	0.004	Annual trend growth rate in per capita consumption set to 1.6%.
α	0.25	Constant-returns-to-scale production function, 25% markup with iso-elastic
ν	0.50	demand curve, capital share of one third and labor share of two thirds.
δ_k	$1 - (1 - 0.10)^{25}$	Annual depreciation of 10%.
δ_n	$1 - (1 - 0.15)^{25}$	Annual exogenous quit rate of 15% (JOLTS).
F^K	1.5%	Fixed cost of changing the capital stock is 1.5% of annual sales (Bloom (2009)).
S	33.9%	Resale loss of capital of 33.9% (Bloom (2009)).
F^L	2.1%	Fixed cost of changing the number of hours is 2.1% of annual wage bill (Bloom (2009)).
H	1.8%	Per hour hiring cost of 1.8% of annual wage (Bloom (2009)).
F	1.8%	Per hour firing cost of 1.8% of annual wage (Bloom (2009)).
ρ^A	0.859	Persistence of aggregate productivity (Khan and Thomas (2008)).
ρ^Z	0.859	Persistence of idiosyncratic productivity (Khan and Thomas (2008)).
σ_{normal}^A	0.014	Std. of innovations to aggregate productivity in normal state.
σ_{normal}^Z	0.028	Std. of innovations to idiosyncratic productivity in normal state.
$\sigma_{uncertain}$	$2.03 * \sigma_{normal}$	Last three parameters set to match the serial correlation and variance of ...
$\pi_{L,H}^\sigma$	0.044	... the persistence and variance of firm sales growth rates and stock returns ...
$\pi_{H,H}^\sigma$	0.792	in the data presented in section 2

Table 3: Second moment statistics

Panel A				Panel B			
	Benchmark Model				NO AC		
	SD(X)	SD/SD(Y)	Corr(X,Y)		SD(X)	SD/SD(Y)	Corr(X,Y)
Y	1.80	1.00	1.00	Y	1.80	1.00	1.00
I	9.54	5.30	0.87	I	9.18	5.10	0.89
C	1.04	0.58	0.56	C	0.95	0.53	0.60
N	1.24	0.69	0.97	N	1.21	0.67	0.96

Panel C				Panel D			
	Only Macro UNC				Only Micro UNC		
	SD(X)	SD/SD(Y)	Corr(X,Y)		SD(X)	SD/SD(Y)	Corr(X,Y)
Y	2.10	1.00	1.00	Y	1.60	1.00	1.00
I	10.92	5.20	0.83	I	7.84	4.90	0.82
C	1.34	0.64	0.57	C	1.07	0.67	0.61
N	1.41	0.67	0.96	N	1.02	0.64	0.97

Panel E				Panel F			
	High Macro Dispersion				High Micro Dispersion		
	SD(X)	SD/SD(Y)	Corr(X,Y)		SD(X)	SD/SD(Y)	Corr(X,Y)
Y	1.80	1.00	1.00	Y	1.80	1.00	1.00
I	8.82	4.90	0.95	I	8.82	4.90	0.72
C	0.79	0.44	0.76	C	0.79	0.44	0.43
N	1.26	0.70	0.95	N	1.26	0.70	0.96