# Really Uncertain Business Cycles

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**Abstract**

A central question in macroeconomics is what causes recessions? In this project we claim that time variation in uncertainty plays an important role. We start by gathering evidence from aggregate, industry and firm-level datasets as well as forecasts and demonstrate that all those proxies for uncertainty are strongly counter-cyclical. Volatility and uncertainty appear to rise by about one third during recessions. We then show, using Vector Auto Regression (VAR) techniques, that an increase in uncertainty is associated with a rapid fall in output and employment. These empirical findings motivate us to address the importance of uncertainty shocks in a theoretical model. We construct a general equilibrium business-cycle model with time-varying uncertainty. The model's response to a first-moment (productivity) shock is similar to the response in standard real business cycle (RBC) models. However, there is also a large drop and rebound in activity in response to second-moment (uncertainty) shocks as firms become cautious and postpone decisions. Productivity growth falls since reallocation across production units pauses when uncertainty is high. Once uncertainty falls back down activity quickly resumes as firms address their pent-up demand.

The Census data will be used in two ways. First, we will construct more accurate time-series measures of uncertainty. This requires information on the cross-sectional spread of establishment-level employment, output and productivity growth. Second, the data will be used to evaluate the predictions of this new type of business cycle model. Specifically, we will look at the responsiveness of investment and other business decisions to productivity at different levels of uncertainty.

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# 1 Introduction

One of the most important questions in macroeconomics is what leads to recessions? In the standard Real-Business Cycle (RBC) literature recessions are caused by large negative technology shocks. With the exception of the oil price shocks, however, it is difficult to identify negative technology shocks that are large enough to cause recessions. As King and Rebelo (1999) ask in their seminal paper, "if these shocks are large and important, why can't we read about them in the Wall Street Journal?"An alternative explanation is put forward in Keynesian models of the business cycle, which suggest that recessions are mainly driven by monetary and fiscal policy shocks. Again, identifying these empirically has proven to be challenging. Hence, this major question remains fundamentally unanswered: Where are the shocks that drive the business cycle and, most importantly, where are the large negative shocks to technology that cause recessions?

This project investigates an additional mechanism: variations in the level of uncertainty. The general idea that links uncertainty to the business cycles is not new. John Maynard Keynes himself argued that changes in investor sentiment, 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 the theory of business cycles for two reasons. First, evidence on time series variation in uncertainty is scarce. The behavior of levels of variables over the business cycle (the first moment) is well documented, but the dispersion of these (the second moment) is much less well understood. Second, models with time varying uncertainty are theoretically challenging. In macroeconomics, the standard analytical and numerical solution techniques used in the RBC literature do not apply in this setup.[1] One exception is Bernanke (1983), who models a single firm deciding on investment in energy efficient capital in the presence of oil-price uncertainty. He finds that higher uncertainty reduces investment as firms become more cautious. However, this paper is based on a stylized single-firm economy in partial equilibrium.[2]

Recent work, however, has made progress on both issues. On the modeling side Bloom (2007) solves a model with heterogeneous firms and stochastic volatility and shows, in partial equilibrium, that high frequency fluctuations in uncertainty can cause large temporary drops and rebounds in aggregate output and employment. This occurs because higher uncertainty causes a large fraction of firms to temporarily pause their investment and hiring. The simulated impact of an uncertainty shock in this model compares favorably to vector-autoregressive estimations on US data, showing a

[1]For example, the standard solution method for RBC models involves log linearization around the steady state, which by construction rules out any direct role for uncertainty. Consequently, almost all business cycle models make the assumption that the level of uncertainty is constant.

[2]There is also a finance literature that explicitly models stochastic volatility, but this generally ignores the real side of the economy and interprets real economic variables as exogenous driving forces.

good match in both magnitude and timing. In this model, the pause in activity freezes the process of reallocation across units. Foster, Haltiwanger and Krizan (2000, 2006) show that reallocation can account for a significant fraction of aggregate total factor productivity (TFP) growth. This suggests that the effects of time variation in uncertainty could be large.

On measurement issues Schwert (1989) and Campbell et al. (2001) generate stock market measures of uncertainty show these are counter-cyclical. In this paper we gather evidence from aggregate, industry and firm-level datasets as well as forecasts and confirm this result for a much wider range of indicators. Volatility and uncertainty appear to rise strongly in recessions. One graphical demonstration of the greater volatility of output in recessions is Figure 1, which plots the quarterly growth rates of industrial production for 73 manufacturing industries for the period from 1962 to 2007 using data from the Federal Reserve Board Industrial Production Indices. The data is split into non-recession months (in black) and recession months (in grey). During a recession growth rates of industrial production are significantly lower on average (the first moment effect of recessions), and also significantly more dispersed (the second moment effect of recessions). In fact, the greater spread of industrial production during recessions is more striking at first sight than the difference in the means. This type of evidence suggests that this issue deserves further empirical investigation.

This project intends to build on the work cited above to answer the following research question: How large is the role of uncertainty in driving business cycles? To do this, the project is carrying out three interlinked pieces of analysis:

(A) Constructing accurate time-series measures of uncertainty to quantify the size and significance of rises in uncertainty during recessions. This will use a variety of data sets, including the Census data, to build time series measures of cross-sectional volatility on a quarterly and annual basis linking them to GDP growth, industrial production and NBER recession indicators.

(B) Building a general equilibrium model that allows for shocks to both the level of technology (the first moment) as well as uncertainty (the second moment). The model can then be used to evaluate the impact of empirically calibrated changes in uncertainty. This could answer the question if these shocks are large enough to generate recessions and recoveries.

(C) Evaluating the empirical performance of this new type of business cycle model using Census micro data, with a particular focus on reallocation across establishments. One of the key ideas behind the impact of uncertainty is that it shuts down the process of reallocation. Firms become more cautious with productive firms expanding by less and unproductive firms contracting by less. Particularly at high levels of uncertainty the hiring and investment behavior of establishments should be less sensitive to productivity and demand conditions.

This project should provide both academic and policy benefits. On the academic front, providing a mechanism that is potentially able to explain recessions in a neo-classical framework addresses a major research question. On a policymaking front, understanding the factors that drive business cycles is critical in terms coming up with an optimal response.

Section 2 provides empirical evidence that uncertainty rises during recessions. It also provides an outline of the potential use for Census data to improve upon the existing uncertainty measures. Section 3 briefly introduces the theoretical model that we use to evaluate the mechanism we want to stress. Section 4 describes how the Census data can used to test the model's predictions. Section 5 describes in detail the Census data sets that this project would use and comments on the risk for disclosure. Section 6 contains information on the Title 13 benefits. We discuss the proposed duration of the project as well as our sources for funding in Section 7. Section 8 concludes. Appendix A contains more detailed information on the data used in Section 2 and Appendix B provides a more rigorous definition of the model introduced in Section 3.

## 2 The Rise in Uncertainty During Recessions

Uncertainty is inherently unobservable. There does not exist a perfect way of deriving an exact measure of ex ante uncertainty from the observable outcomes of economic variables. We will argue in this section, however, that a wide array of uncertainty measures that we assembled all point in the same direction: uncertainty rises significantly during recessions. The firm, industry and aggregate indices of uncertainty and volatility, as well as the measures derived from forecaster disagreement, are strongly counter-cyclical, rising by about 20 to 60% during recessions.

Table 1 summarizes the evidence we provide. We show that all our measures increase significantly during recessions as defined by the NBER business cycle dating committee. Moreover, all measures are negatively correlated with quarterly real GDP growth. In the remainder of this section we will briefly describe the evidence provided by Table 1.[3] Thereafter, we will propose extensions of our analysis that require the use of Census data. For expositional simplicity we henceforth use the term measures of uncertainty (rather than volatility). In the stochastic volatility process that we use in the model in Section 3 uncertainty and volatility are closely linked together.

### 2.1 Firm and Industry Level Measures of Uncertainty

One approach to modelling time-series uncertainty is to examine the time variation in the cross sectional spread of firm and industry level growth rates. We find a significant increase of all our cross-sectional measures during recessions. This holds for sales, earnings and output measures,

[3]The data sources and construction of the individual measures will be discussed in detail in Appendix A.

and is not merely the effect of a differential reaction to aggregate shocks as we will argue in more detail below. Hence, we will interpret this finding as an increase in the idiosyncratic component of uncertainty during economic downturns.

Row (1) of Table 1 shows that the cross-sectional spread of firm-level sales growth rates is 23.8% higher during quarters that the US economy spends in a recession. This rise in the cross-sectional spread of firm-level sales growth is also negatively correlated with real GDP growth at -0.327. One interpretation of this results is that it simply reflects differential responses of industries to a common macro shock, rather than increase idiosyncratic volatility. For example, an oil shock will have a large negative impact on firms in energy intensive industries like aluminum production, but potentially a positive effect on firms in energy producing industries like coal and gas production.[4] However, we find that this increase in cross-sectional dispersion arises both within and between industries. We can, for example, recompute the spread in firm-level sales growth within each 3-digit SIC industry. The resulting increase during a recession is 20.7%, which is almost identical to the 23.8% we found in the pooled data.[5] Hence, there is strong evidence for an increase in the within industry spread of sales-growth during recessions. This suggests that our results are not driven primarily by the differential response of industries to common shocks.

The next three rows of the table further support our finding. The results in Row (2) show that the cross-sectional spread of firm-level stock returns is also counter-cyclical, rising by 21.7% during recessions. Again, this holds both within and across industries. For example, within 3-digit SIC industries the rise in the spread of stock returns is 21.9%.[6]

This rise in monthly cross-sectional spread of stock returns is also persistent within recessions, actually rising slightly over the course of these. For example, the cross-sectional spread is 12% higher in quarters 4 to 6 of a recession than in quarters 1 to 3. This is also inconsistent with the idea that recessions are differential responses to a common macro shock, since this would generate a large cross-sectional spread of returns in the first quarter but nothing from the second quarter onwards. The fact the cross-sectional stock-returns are persistently higher throughout recessions suggests that unexpected idiosyncratic shocks are continuing to arise throughout recessions.

[4]This is similar in spirit to the critique of Abrahams and Katz (1986) of the paper by Lilien (1982). Lilien shows a strong correlation between cross-industry variation in unemployment and overall unemployment levels, arguing that this was due to a rise in structural unemployment during periods of rapid cross-industry reallocation of employment. Abraham and Katz (1986) argue that this could instead be interpreted as differential industry level responses to common negative macro shocks.

[5]All calculations at the 3-digit SIC level are restricted to industries with 25 or more firms. This leaves us with a sample of 17 3-digit SIC industries covering 266 firms. If we use broader 2-digit SIC industries (again keeping observations with 25 or more firms) the increase in cross-sectional firm-level sales growth is 21.0% for a sample of 24 SIC 2-digit industries covering 519 firms.

[6]We again restrict the sample to industries with at least 25 firms. That leaves us with 15 3-digit SIC industries covering 652 firms and 25 2-digit SIC industries covering 1619 firms. If we calculate the rise in cross-sectional spread of firm-level stock returns at the 2-digit level the increase is 21.1%.

Row (3) reveals that the cross-sectional spread of industry level output growth for manufacturing industries is also substantially higher during recessions, rising by 58.7% compared to non-recessionary periods. The cross-sectional spread of industry-level productivity growth in manufacturing is also rising during recessions. Row (4) shows an increase by about 32.5% during years with all four quarters in recessions (and proportionally less for one, two or three quarters in recession). Hence, cross firm and industry spreads of sales growth, stock returns, production and productivity growth are all substantially higher during recessions.

## 2.2 Macro Measures of Uncertainty

A second approach to measuring uncertainty is to use aggregate time series data to infer estimates of the underlying stochastic volatility process. This is intended to capture the common macroeconomic component of uncertainty, in contrast to the idiosyncratic firm and industry level components discussed above. Again we construct measures using data both from financial markets and the real economy. Again, all measures point in the same direction.

In Row (5) we see that the volatility of output growth is 37.8% higher in recessions. This is estimated as the quarterly average of the conditional standard deviation of monthly industrial production.[7] In Row (6) we look at an index of stock market volatility and find that recessions are associated with a 31.4% higher implied volatility of market returns. Hence, output and stock market data suggest that macro uncertainty is substantially higher during recessions.

## 2.3 Forecaster Measures of Uncertainty

A third approach to measure uncertainty is to evaluate the extent of disagreement between professional forecasters over the future development of key macroeconomic variables. There is a large literature that uses the disagreement among macro forecasts as a proxy for uncertainty, typically finding a strong correlation with other measures of uncertainty like forecast errors (see, for example, Zarnowitz and Lambros (1987), Bomberger (1996), and Giordani and Soderlind, (2003)).

In Rows (7) and (8) we see that the disagreement over future GDP growth and unemployment forecasts increases substantially during recessions, rising by 55.6% and 51.3% respectively. This adds further support to our findings above: macro uncertainty rises substantially during recessions.

## 2.4 The Uncertainty Index over the Business Cycle

In the last row of Table 1 we report the results of using a combination of the uncertainty measures introduced above. This is the first factor of a principal component factor analysis of the seven

[7] This is estimated using a AR(12) regression with ARCH(2) errors.

quarterly uncertainty proxies. This uncertainty index rises by about 33.6% during recessions, and is strongly negatively correlated with GDP growth at -0.487. Figure 2 plots this series over time alongside an indicator for recessionary quarters (area shaded in grey). It is evident 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 in the early 1990s and 2000s. The other notable spikes in the graph are the Black Monday stock market crash in the fourth quarter of 1987 and the collapse of the LTCM hedge fund in the third quarter of 1998. Both generated large increases in both the firm-level and aggregate stock-return volatility measures without very large effects on the real economic variables. This rise in uncertainty is also larger for longer-lasting recessions. For example, the uncertainty index rises by 26.2% for recessions lasting 4 quarters of less, and by 38.0% for recessions lasting more than 4 quarters.

### 2.5 Proposed Census Measures of Uncertainty

We would rely on Census data to extend our analysis to the establishment-level. Building on the evidence presented above our hypothesis is that uncertainty is counter-cyclical at the establishment-level. To test this hypothesis we would construct additional measures of uncertainty using data from the Census:

I. Establishment-level annual interquartile range of employment growth rates, calculated for 1977 to 2005 using the full Longitudinal Business Database (LBD). This would cover a population of around 3 million establishments with at least 10 years of continuous data, providing extremely detailed statistics on the time series movement of cross-sectional employment growth.[8] Such a large sample would also enable us to look within SIC 4-digit industries, to fully control for the possibility that differential responses at the industry level to common macro shocks are driving the increased industry level spread.

II. Establishment-level annual interquartile range of output growth and 5-factor productivity growth rates, both calculated for 1974 to 2005 using the combined Annual Survey of Manufacturing and the Census of Manufacturing (CMF). This would provide a sample of around 10,000 establishments per year with at least 10 years of continuous data[9], enabling us again to calculate statistics on time series movements of the distribution.

In addition we would also investigate measures of uncertainty in capacity utilization by examining the Survey of Plant Capacity Utilization (PCU), and in research and development expenditures using

[8]See Jarmin and Miranda (2002) for some numbers on the panel structure of the LBD.
[9]See Doms and Dunne (1998) for some approximate number on the panel structure of the ASM.

the Survey of Industrial Research and Development (RAD).

The new uncertainty measures would then be used to investigate the proposed counter cyclicallity of uncertainty in a way that is exactly analogous to the procedure used for the annual productivity figures from the NBER-CES Manufacturing Industry Productivity Database in Row (4) of Table 1. We would first generate an annual variable, Recession Share, defined as the share of quarters that the economy is in a recession in a given year. This uses the timing as determined by the NBER recession dating committee. We would then simply regress the constructed annual uncertainty measures on a constant and this variable.

$$\mathsf{UncertaintyMeasure}_t = \beta_0 + \beta_1 \mathsf{RecessionShare}_t + \epsilon_t$$

The percentage rise in uncertainty during a full year in recession can then be calculated as the ratio of the estimated coefficient on the recession share variable and the constant:

$$\mathsf{PercentageRiseInUncertainty} = 100 \times \frac{\hat{\beta}_1}{\hat{\beta}_0}$$

Similarly, the standard error of this estimate can be calculated as 100 times the standard error on the coefficient $\hat{\beta}_1$ divided by the constant $\hat{\beta}_0$. These numbers and the correlations of the new measures with real GDP growth would be reported as additional rows in Table 1 to provide evidence on the change in uncertainty for establishments over the business cycle, alongside the similar estimates for firms, industries, forecaster disagreement and macro outcomes. We will now turn to the theoretical model we will use to evaluate the effect of uncertainty shocks on the business cycle.

## 3 Modelling Time Series Variations in Uncertainty

The traditional business cycle literature has focused almost completely on first moment shocks. Here, booms and busts in economic activity can be generated by moderate positive and negative productivity shocks. This literature has almost completely ignored fluctuations in the second moment of productivity. However, as previously discussed, uncertainty does appear to fluctuate strongly over time, in particular rising sharply during recessions. Hence, it is an open question whether fluctuations in uncertainty matter for business cycles.

The intuition for why uncertainty might matter is as follows. Increases in uncertainty generate an *option value* of waiting when firms face adjustment costs. For example, if it is expensive for firms to invest and then disinvest - because of resales losses on capital goods for example - firms will tend to act more cautiously when uncertainty is high. They will tend to delay making any investment or disinvestment decisions. Of course, if every firm in the economy becomes more cautious because of higher macro uncertainty, then investment levels will fall, generating a regression. When uncertainty falls back down again, firms will start to invest heavily to address pent-up demand from their previous period of caution, generating a rapid rebound. Thus, rises and falls in uncertainty can potentially generate recessions and then rebounds in economic activity.

Recent research using Census data suggests potentially large effects on productivity growth. As Foster, Haltiwanger and Krizan (2000 and 2006) show, about 70% to 80% of aggregate US productivity growth could be due to reallocation.[10] That is, productive firms expanding and gaining market share and unproductive firms shrinking and losing market share, appears to account for the majority of aggregate productivity growth. But if uncertainty rises and firms become cautious, productive firms will expand less and unproductive firms contract less. Hence, higher uncertainty could substantially reduce aggregate productivity growth.

To formally model these effects of uncertainty on the business cycle, we build a general equilibrium model with heterogeneous firms and both first and second moment shocks. In this section we will provide an extremely brief and nontechnical discussion of the model. A more rigorous definition of the model and the numerical solution techniques can be found in Appendix B.

We model an economy with a large number of firms that use capital and labor to produce a common final good. Adjusting employment is assumed costless in this simplified model, but firms that adjust their capital stock incur both convex and non-convex adjustment costs. The adjustment cost functions are just reduced form representations of a host of frictions that exit in practice. For instance, one could think of the effort that needs to be put into installing the capital, the disruption of current production when adding new machines or the relatively low resale value of machines that are specific to a certain plant. There is large literature on the size of capital adjustment costs. These have been estimated by, among others, Cooper and Haltiwanger (2006) and Bloom (2007). We will use the estimates provided by those authors and also provide a number of robustness checks.

As is standard in the RBC literature, firms are subject to an exogenous process of productivity that consists of two parts, an aggregate and an idiosyncratic component. We will depart from the standard setup by allowing 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. We will use nonlinear techniques to solve for the optimal decision rules of firms in this non-standard environment. Once we find those decision rules, it is possible to simulate the economy using realistically calibrated processes for the time-varying second moment. Here, the empirical evidence from Section 2 will become extremely valuable. Setting up the model will then

[10]Foster, Haltiwanger and Krizan (2000, 2006) report that reallocation, broadly defined to include entry and exit, accounts for around 50% of manufacturing and 90% of retail productivity growth. These figures will in fact understate the full contribution of reallocation as they miss the within establishment reallocation, which Bernard, Redding and Schott's (2006) results on product switching suggest could be important.

enable us to tackle two central research questions:

I. *Are the rises in uncertainty we observe during recessions large enough to account for these recessions*? If they are, this suggests that uncertainty fluctuations could potentially play an important part in driving the business cycle.

II. *Does the response of firms to monetary and fiscal policy fall during recessions*? A prediction of the model is that high uncertainty reduces the responsiveness of firms. In times of high uncertainty firms become cautious and react less to a given shock. We will be looking at the impulse responses predicted by the model for a realistically calibrated first moment shock in times of high uncertainty versus times of low uncertainty. This is obviously critical for analyzing the effects of monetary and fiscal policy, especially during a recession. If firms are unresponsive in recessions, larger changes in interest and tax rates will be needed to obtain the desired effect.

More generally, the combination of our model and the empirical evidence might also allow us to shed further light on the long-term downward trend in volatility that has been coined the *Great Moderation*. Since the mid-1980s it appears that a number of indicators of volatility in the US and many other G7 countries have been trending downward over time (see, for example, Blanchard and Simon (2001), Stock and Watson (2002) and Jaimovich and Siu (2007)). One major question in this literature is what the impact of these on US economic growth could be? Out model could help to address this question.

# 4 Testing the model

The model will be tested using both macro and micro data. The census data will be used for the micro data tests.

## 4.1 Macro tests of the model

One way to test the model is to examine whether variations in uncertainty appear to lead recessions. To evaluate this, we estimate a series of vector-auto regressions (VAR), controlling for other factors such as interest rates, prices and stock-market levels, to try and identify the impact of higher uncertainty. We estimate a range of VARs on quarterly data from 1968:4 to 2004:3. The variables in the estimation order are log(S&P500 stock market index), the uncertainty index, the Federal Funds rate, log(average hourly earnings), log(consumer price index), log(employment) and log(real GDP). This ordering is based on the assumptions that shocks instantaneously influence the stock market (levels and volatility), then prices (wages, the CPI and interest rates) and finally quantities (hours, employment and output). Including the stock market levels as the first variable in the VAR ensures the impact of stock-market levels - a proxy for first moment effects - is already controlled for when looking at the impact of volatility shocks.[11]

Figure 3 plots the impulse response function of real GDP (the solid line with plus symbols) to a 33% shock to the uncertainty index, calibrated to be the average increase of the uncertainty index during recessions. Following a shock to uncertainty GDP falls by about 1.5% within two quarters, and then returns to trend by the fourth quarter. The 95% confidence interval bands (dashed lines) are plotted around this, highlighting that this drop and rebound is statistically significant at the 5% level. In Figure 4 the response of employment to a 33% uncertainty shock is plotted, showing a slightly larger and more persistent impact, with unemployment falling by about 2.5% within two quarters, and returning to trend by the fifth quarter.[12]

Thus, overall the VAR results are consistent with the idea that fluctuations in uncertainty play an important role in driving the business cycle. Both the size and timing of the drop and rebound in GDP and employment after a shock to the uncertainty index are very similar to those of an average recession. Of course these results do not prove causality - it could be that higher uncertainty is an effect rather than a cause of recessions. To investigate this further, we will also use micro-tests of the model which deliver a further set of testable predictions consistent with an uncertainty driven recession.

### 4.2 Micro tests of the model

The model predicts that when uncertainty is high, firms will become more cautious because of the higher option value to waiting. This means firms will invest less in response to a positive productivity shock and disinvest less in response to a negative productivity shock. This fall in responsiveness can be denoted as $\partial^2 I_t/\partial \Delta A_t \partial \sigma_t < 0$, where $I_t$ is investment, $\Delta A_t$ the change in productivity and $\sigma_t$ uncertainty. Figure 5, which is taken from a simulation exercise in Bloom, Bond and Van Reenen (2007) illustrates this idea graphically. It plots the average annual investment response of firms to demand shocks at different percentiles of uncertainty. At very high levels of uncertainty (like the 90th percentile) firms are much less responsive to demand shocks than at very low levels of uncertainty (like the 10th percentile). Bloom, Bond and Van Reenen (2007) test the predictions of this model on a panel of UK annual firm-level data, and indeed find that firms are much less responsive to demand shocks at higher uncertainty.[13] The magnitudes of this cautionary effect of uncertainty are

[11] All variables are Hodrick Prescott (HP) detrended ($\lambda = 1600$) in the baseline estimations.

[12] Figures A1 and A2 in the Appendix confirm the robustness of these VAR results to a range of alternative approaches over variable ordering, variable timing and detrending.

[13] Guiso and Parigi (1999) also run a similar estimation exercise using a cross-section of Italian firms and some innovative survey based measures of uncertainty, and also find a large significant cautionary effect of uncertainty on

large, with the average response to demand shocks falling by 50% when going from the 25th to 75th percentiles of uncertainty, which is equivalent to the increase in uncertainty from a recession. We would aim to use the census data to directly test the impact of recessions on investment and employment responsiveness in US establishment level data. This would be carried out using both regression and graphical analysis.

**Regression Analysis:** We would estimate the responsiveness of establishments to productivity changes at different levels of the aggregate uncertainty index. That is, we would estimate regressions on the establishment panel of the following form:

$$I_{i,t} = \beta_0 + \beta_1 \Delta A_{i,t} + \beta_2 \sigma_t + \beta_3 \Delta A_{i,t} * \sigma_t + \beta_3 X_{i,t} + \epsilon_{i,t}$$

where $I_{i,t}$ is investment, $\Delta A_{i,t}$ is the growth of productivity, $\sigma_t$ is our uncertainty index plotted in Figure 2 (aggregated up to the annual level) and $X_{i,t}$ are other possible controls like SIC industry, size and age. The subscripts $i$ and $t$ index establishment and year respectively. The key term for testing the model is the coefficient $\beta_3$, where $\beta_3 < 0$ is consistent with the prediction that higher uncertainty retards the response of establishments to productivity shocks.

There are, of course, a number of variants of this specification that we will also investigate. These include: (i) using the change in employment and R&D as the dependent variables, to look at the response of labor and technology investment to productivity shocks at lower/higher uncertainty; (ii) using an indicator of the number of quarters in recession in the year instead of $\sigma_t$, to directly test if recessions reduce the responsiveness of firms to productivity shocks; (iii) using the growth rate of output rather than the growth rate of measured productivity, $\Delta A_{i,t}$, in the regression to test both if demand factors matter and to check for measurement error in the calculation of productivity numbers[14]; (iv) including higher order terms in the regression like $\Delta A_{i,t}^2$ and $\sigma_t^2$ to ensure the interaction term is not simply proxying for other omitted non-linear terms; and (v) using a variety of estimation approaches such as OLS, Within-groups and Blundell-Bond GMM to try and address issues like unobserved heterogeneity and endogeneity between investment and productivity growth.

**Graphical Analysis:** We would also graphically examine the slope the relationship between investment and productivity growth at various levels of uncertainty using Kernel, Lowess, spline and

firms investment response to demand shocks.

[14]There are at least three commonly used measures for constructing productivity, which we will experiment with. There is the cost-share approach, which weights factor inputs by costs-shares of factor inputs, typically using industry level cost-share numbers if the sample size is large enough. There is the OLS and/or GMM approach, which estimates the coefficients of output on factor inputs using different types of regression techniques, taking the residual as a measure of productivity. Finally, there is the Olley-Pakes approach, which uses investment rates as an indicator of productivity under an invertibility condition.

other non-parametric regression techniques. For example, we could split the sample into normal and recessionary years and plot the Lowess smoothed curves[15] of investment on productivity growth rates, in a similar manner to Figure 5. According to the model the non-recessionary line should be steeper than the recessionary line, indicating a lower responsiveness of investment to productivity during recessions. Point-wise standard errors can be obtained for non-parametric lines using bootstrapping approaches so that differences between slopes can also be statistically tested. As with the regression analysis there are a number of different variants this graphical analysis can take, including: (i) using employment or R&D rather than investment; (ii) splitting the sample by percentiles of the macro uncertainty indicator rather than recession/non-recession; (iii) using output growth rather than productivity growth; and (iv) running a semi-parametric estimation, with splines for example, so we can also include other controls for things like establishment industry, size and age.

# 5 Census Data Requirements

The Census data will be used in two distinct ways. First, we will construct more accurate time-series measures of uncertainty using very disaggregated data as outlined in Section 2. This requires information on the cross-sectional spread and standard deviations of establishment-level employment, output and calculated productivity growth. Second, the data will be used to evaluate the predictions of the model introduced in Section 3. In this regard we will look at the responsiveness of investment and other decisions to productivity at different levels of uncertainty and over the cycle as discussed in Section 4.2 above. In this section, we will list the Census and non-Census datasets that we would use in our analysis. Moreover, we will outline why the use of Census data is crucial for our analysis. Finally, we will discuss the risk of disclosure.

## 5.1 Datasets

**Census Datasets:** We propose to construct an annual panel datasets on manufacturing establishments from three primary datasets.

I. Longitudinal Business Database (LBD), 1976 to 2005

II. Annual Survey of Manufacturing (ASM), 1973 to 2005

III. Census of Manufactures (CMF), 1967 to 2007

[15] Lowess smoothing estimates a linear regression at each data point, using Cleveland's (1979) tricube weighting over a moving window of the data, to generate a non-parametrically smoothed data series. Lowess is similar to Kernel smoothing, but uses information on both the mean and the slope of the data and so is more efficient in estimating functions with continuous first derivatives.

The LBD would be used on its own, and the three datasets would also be linked together by establishment and year to produce a data panel on manufacturing establishments spanning 1973 to 2005 (this has previously been called Longitudinal Research Database (LRD)). It uses the ASM to fill in the 4 missing years between each CMF. Access to two other census data sets would be very useful again as described in Section 2:

IV. Survey of Plant Capacity Utilization (PCU), 1974 to 1999

V. Survey of Industrial Research and Development (RAD), 1972 to 2003

**Non-Census Datasets:** In addition to the datasets listed above we construct time series measures of uncertainty from the following non-census datasets as described in Section 2 and in much more detail in Appendix A:

I. Compustat Quarterly Accounts, 1967 to 2004

II. Federal Reserve Board of Governors, industrial production in manufacturing, 1962 to 2005

III. Chicago Board of Exchange, implied volatility (VXO), 1986 to 2007

IV. Center for Research in Security Prices (CRSP), daily equity returns, 1962 to 2007

V. Philadelphia Federal Reserve Bank, Survey of Professional Forecasters (SPF), 1950 to 2006

### 5.2 Advantages of the Census Datasets

Below we will highlight the three main advantages of using Census data. They are related to the sample size, the territorial coverage and the sample period that the Census data provide.

**Sample size:** The large size of the Census data samples - around 10,000 establishments for the ASM and three million for the LBD with at least 10 years of data - will enable us to generate accurate time series indicators of volatility over time. In comparison, Compustat firm level datasets only have around 1000 firms with at least 10 years of data. Generating time-series indicators of uncertainty requires very large sample sizes because of the sensitivity of variances to outliers.[16] The large sample sizes in the census datasets are also important is allowing us to remove SIC 4-digit industry and year effects. This will allow us to address the concern that the time-series variation in the cross sectional spreads might be due to differential industry level responses to common shocks rather than higher firm-level uncertainty.

[16]Formally, estimators of means converge in $L^2$ space while estimators of variance coverge in $L^4$ space, where the latter has a much slower rate of convergence.

**Territorial coverage:** The census data covers US based establishments, including all public and private, domestic and foreign establishments in the US. The Compustat database in contrast covers the complete global operations of firms which have a listing on a US based securities exchange. Hence, Compustat excludes all privately owned domestic US firms and foreign multinationals located in the US, but includes all overseas operations of US listed public companies. Since commercial activity is increasingly international, with current estimates that 50% of the employees of publicly listed US manufacturers are located abroad, the difference between the Census data coverage and Compustat is considerable. Because US monetary and fiscal policy is focused on national outcomes like employment, inflation and GDP, the Census data is much more closely aligned with the territorial coverage of policy interest.

**Time series:** The census has a consistent establishment level database for the LBD going back to 1976 and for the ASM going back to 1973, generating a long time-series of data. Having this long-run coverage is important given the infrequent nature of recessions, with only 5 since the early 1970s. The Compustat database does have coverage back to the mid 1960s, but only for a small sample of firms. Most firms in Compustat were added in two expansion waves in the mid 1970s and early 1980s. This leads to sample selection problems for the construction of any firm-level data panel using Compustat going back to before the early 1980s. Moreover, in Compustat a number of the quarterly accounts variables - like investment - are not available prior to 1983, again restricting the time period of analysis using Compustat data.

### 5.3 Risk of Disclosure

We believe our proposal presents no risk of disclosure for the Census data. The reason is that our analysis is entirely at the aggregate level given the macro focus of this research. Moreover, the necessity of using large samples for the uncertainty measures imply that we are aiming to use the largest possible sample sizes - around 10,000 establishments in the case of the ASM and three million in the case of the LBD. When we do industry-level analyses, these industry coefficients will not be reported - instead we will only report aggregate figures after controlling for industry effects. For example, we might want to report the average cross-sectional variance of establishment level sales growth relative to the 4-digit SIC mean, much as we reported both the absolute cross-sectional spread of firm-level sales growth and its level relative to 3-digit SIC controls in Section 2.

## 6 Title 13 Benefits

This project would provide considerable benefit to the Census Bureau under Title 13 of the U.S. Code. In particular, criterion 3, 5 and 6 seem to apply as outlined below.

**Criterion 3:** *Developing means of increasing the utility of Census Bureau data for analyzing public programs, public policy, and/or demographic, economic, or social conditions.*
The project would create more accurate measures of the spread of the growth rates of hiring, investment and productivity in manufacturing and study their cross-correlations. These measures would provide information on the change in low and high frequency distributions over time.

High-frequency changes in distributions are interesting from a monetary and fiscal policymaker perspective as they matter for the appropriate response to downturns in the business cycle. If, for example, recessions were associated with periods of much higher uncertainty then leading indicators of this gathered from industry sources by bodies such as the Federal Reserve Board would provide important forecasting information for monetary policy.

In addition to better forecasting ability, these measures would provide information regarding the extent to which individual industries are affected from rises in uncertainty. This might provide policy makers with information regarding the optimal targeting of measures in attempts to alleviate the impact of a recession.

**Criterion 5:** *Understanding and/or improving the quality of data produced through a Title 13, Chapter 5 survey, census of estimate.*
This project will construct measures of volatility from Census micro datasets and it would document the time series properties of the spread, standard deviations and cross-correlations in employment, investment, R&D expenditure and productivity growth across establishments. By cross comparing these with external datasets - as outlined in the section on data requirements above - we can evaluate the likely extent of measurement error in the Census datasets. This examination should lead to a better assessment of this aspect of data quality and to recommendations for improvement. For example, our eight quarterly and annual measures of uncertainty displayed in Table 1 are all strongly correlated with recessions. If it does not turn out to be true for Census measures of volatility, it could suggest some kind of cyclical selection/measurement bias in the Census data, that generates a cyclical bias in measured volatility. By directly comparing the Census data with the Compustat and industry level data constructed from sources like the Federal Reserve Board Industry statistics (which is independently collected by the Board directly from trade-associations) we would start to investigate the causes of any such discrepancies on an industry by industry basis.

Finally, by comparing the constructed statistics to a wide range of other measures of uncertainty, the project would significantly increase the value of the constructed aggregate series for other researchers.

**Criterion 6:** *Leading to a new or improved methodology to collect, measure or tabulate a Title 13, Chapter 5 survey, census or estimate.*
The analysis may show that establishment level data can be meaningfully displayed in both means and variances at higher frequency. The proposal would provide an interpretation of the higher moments at this high frequency by, for example, indicating the extent of volatility during a recession and its contribution to the course of the recession. Consequently, tabulations of high frequency changes in moments could be of interest for many researchers and policymakers.

# 7 Funding, Duration & Software

All funding for this research will be provided directly by Stanford University. We are also planning to apply for an NSF grant next year. The duration of the project would be for 5 years, with a desired start of Summer 2008. The intensity of RDC use would be 15 hours per week for the first year, 10 hours per week for the second year, and 5 hours per week for years 3, 4 and 5. All analysis would be run in Stata.

# 8 Conclusion

One of the most important questions in macroeconomics is what leads to recessions? In the standard Real-Business Cycle literature recessions are caused by negative technology shocks. However, it is very hard to find negative technology shocks in the data that are large enough to cause recessions. Alternative explanations that build on Keynesian models of the business cycle suggest that recessions are driven by monetary and fiscal policy shocks. Again, identifying these empirically has proven to be challenging. Hence, this major question remains fundamentally unanswered: Where are the shocks that drive the business cycle and, most importantly, where are the large negative shocks to technology that cause recessions?

In this paper we claim large increases in uncertainty play an important role. We start by gathering evidence from aggregate, industry and firm-level datasets as well as forecasts and demonstrate that all those proxies for uncertainty are strongly counter-cyclical. Volatility and uncertainty appear to rise by about one third during recessions. We then show, using VAR techniques, that an increase in uncertainty is associated with a rapid fall in output and employment. These empirical findings motivate us to address the importance of uncertainty shocks in a theoretical model.

We thus construct a general equilibrium business-cycle model with time-varying uncertainty. The model's response to a first-moment (productivity) shock is similar to the response in standard real business cycle (RBC) models. However, there is also a large drop and rebound in activity in response to second-moment (uncertainty) shocks as firms become cautious and postpone decisions. Productivity growth falls since reallocation across production units pauses when uncertainty is high. Once uncertainty falls back down, activity quickly resumes as firms address their pent-up demand. To test the model empirically, both macro and micro tests can be used. First, the model can be tested by showing that the simulated impact of uncertainty shocks is similar to the VAR results from shocks to measured uncertainty in the data. Second, micro data is needed to investigate whether uncertainty - as predicted by the model - also impedes reallocation across firms particularly during recessions.

The Census data will be used in two ways. First, the data will allow us to construct more accurate time-series measures of uncertainty. This requires information on the cross-sectional spread of establishment-level employment, output and productivity growth. Second, the data will be used to evaluate the predictions of this new type of business cycle model. Specifically, we will look at the responsiveness of investment and other business decisions to productivity at different levels of uncertainty.

# A Appendix: Existing Measures of Uncertainty

## A.1 Firm and Industry level Measures of Uncertainty

**Firm Sales Growth Spread:** The data on firm-level sales growth rates comes from the Compustat quarterly accounts. We restrict the sample to firms with at least 150 quarters of accounts to ensure sufficient sample size. We also use only quarters with at least 250 observations to reduce the impact of compositional changes. The sample ranges from 1965 to the second quarter of 2004. The sales growth rate is defined over a four quarter window in order to remove effects of the quarterly accounting cycle. Our definition of the growth rate is centered around the current quarter which provides desirable properties in terms of symmetry[17]

$$\mathsf{GrowthRate}_t = \frac{\mathsf{Sales}_{t+2} - \mathsf{Sales}_{t-2}}{0.5 \times (\mathsf{Sales}_{t+2} + \mathsf{Sales}_{t-2})}$$

As a measure of the cross-sectional spread in firm sales growth we calculate the interquartile range, i.e. the difference between the 75th and the 25 percentile. This prevents our results from being driven mainly by isolated events like mergers, acquisitions or disposals.

**Firm Stock Return Spread:** The CRSP database provides stock returns for individual firms from the 2nd quarter of 1962 until the second quarter of 2006. We limit the sample to quarters with at least 750 firms and to firms with at least 25 years of monthly returns. We calculate quarterly averages of the interquartile range of monthly stock returns.

**Industry Output Growth Spread:** We use data on the industrial production of 73 NAICS 3-digit manufacturing sectors for the period from 1972 to 2007. The data can be obtained from the Federal Reserve Board. We then calculate the quarterly average of the monthly interquartile range of sectoral growth rates.

**Industry Productivity Growth Spread:** The Manufacturing Industry Database is a joint effort between the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies (CES) and it contains annual industry-level data on output, employment, payroll and other input costs. The data is described in detail in Bartelsman, Becker and Gray (2000). We use the 5-factor TFP measure for all available 4-digit SIC manufacturing industries and all available years, i.e. 1962 to 1996. Again, we calculate the interquartile range to measure the cross-sectional dispersion. To calculate the increase of this annual measure during a recession we use the procedure

[17] This symetric growth measure is a modified version of the Davis and Haltiwanger (1992) measure of employment growth in establishments, which defined growth as $(E_t - E_{t-1})/(E_t + E_{t-1})$.

presented in Section 2. Hence, the number reported in Table 1 refers to the percentage increase in the spread for a year with all four quarters defined as recessionary, estimated by regressing the annual spread against an annual indicator reporting the fraction of quarters in a recession in that year.

### A.2 Macro Measures of Uncertainty

**Macro Output Growth Volatility:** This Measure uses the seasonally adjusted series of industrial production (final products and non-industrial supplies) from the Federal Reserve Board. We estimate an AR(12) process of the logarithm of industrial production with an ARCH(2) error term. Longer lags are not significant. Denoting industrial production by $x$ and assuming that $\epsilon_t \sim \mathcal{N}(0, \sigma_t)$ we estimate the following.

$$\begin{aligned} \log(x_t) &= \alpha_0 + \alpha_1 \log(x_{t-1}) + \cdots + \epsilon_t \\ \sigma_t^2 &= \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \nu_t \end{aligned}$$

Our measure for macro output growth volatility is then given by the quarterly average of the monthly conditional standard deviation of innovations $\hat{\sigma}_t^2$.

**Macro Stock Return Volatility:** We use the quarterly average of the CBOE's VXO index, i.e. the daily index of implied volatility that is derived from option prices on the S&P 100. The index is only available from 1987 onwards. Pre 1987 we use the standard deviation of daily returns on the S&P 500 which we normalize to the same mean and variance as the VXO for the period when the two series overlap (1987-2005). The daily return data is again taken from the CRSP database.

### A.3 Forecaster Measures of Uncertainty

**Forecaster Spread (GDP)** This measure uses the four quarter ahead forecast of nominal GDP growth from the Survey of Professional Forecasters. The forecasts are collected quarterly with an average of 41 responses per period. Our measure of disagreement uses the ratio of the standard deviation to the mean of forecasts within each period.

**Forecaster Spread (Unemployment)** The four quarter ahead forecast of the unemployment rate comes from the same source as the series above. The average number of responses here is 53.

### A.4 Uncertainty Index

The uncertainty index is defined as the first principal component factor of all the quarterly series above (i.e. rows (1) to (3) and (5) to (8) in Table 1). The factor loadings on the indicators are relatively even with weights of 0.197, 0174, 0.268, 0.221, 0.174, 0.191 and 0.224 on rows (1) to (3) and (5) to (8) respectively). From 1968:4 to 1971:4 the missing interquartile range of industrial output growth is forecasted using the remaining six indicators.

# B Appendix: The Model

## B.1 Technology

In what follows we will denote all production units as firms. The economy is populated by a large number of heterogeneous firms that employ capital and labor to produce a homogenous final good. We assume diminishing returns to variable the variable inputs, capital and labor. Denoting investment as $i$, the law of motion for capital is given by

$$k_{jt+1} = (1 - \delta_k)k_{jt} + i_{jt}$$

As in the standard RBC literature, there is an exogenous productivity process. Here, each firm's productivity is given by a multiplicative composite of two separate processes: aggregate productivity $A_t$ and an idiosyncratic component $z_{jt}$. Firm level output is then given by a standard Cobb-Douglas production function:

$$y_{jt} = A_t z_{jt} k_{jt}^{\alpha} n_{jt}^{\nu}$$

Both the macro and the firm level component of productivity follow an autoregressive process. We depart from the benchmark model in that we allow the variance of innovations to the productivity processes to vary over time. More specifically, we will assume for simplicity that the stochastic volatility processes follow two point Markov chains.

$$\begin{aligned} \log(A_t) &= \rho_A \log(A_{t-1}) + \sigma_{At}\epsilon_t \\ \log(z_{jt}) &= \rho \log(z_{jt-1}) + \sigma_{zt}\epsilon_{jt} \end{aligned}$$

It is useful to divide the state variables in two groups. The first concerns the economy wide state variables, aggregate productivity $A_t$, micro and macro uncertainty, $\sigma_{zt}$ and $\sigma_{At}$, as well as the joint distribution of idiosyncratic productivity and firm-level capital stocks $\mu_t$. The aggregate state is thus fully characterized by $(A_t, \sigma_{zt}, \sigma_{At}, \mu_t)$. In addition, each firm's state is described by its current capital stock $k_{jt}$ and its current idiosyncratic productivity $z_{jt}$. The law of motion for the joint distribution of idiosyncratic productivity and capital is defined as $\mu_{t+1} = \Gamma(A_t, \sigma_{zt}, \sigma_{At}, \mu_t)$.

The dynamic firm problem can thus be stated as follows. Given the current aggregate and idiosyncratic state variables and the laws of motion introduced above, the firm choses investment to maximize the present discounted value of future profit streams. The appropriate stochastic discount factor or pricing kernel $m$ will be discussed below.

$$\begin{aligned} &V(k, z; A, \sigma_A, \sigma, \mu) = \\ &\max_{i,n} \left\{ y - w(A, \sigma_A, \sigma, \mu)n - i - AC(k, k') + E_t \left[ mV(k', z'; A', \sigma'_A, \sigma'_z, \mu') \right] \right\} \end{aligned}$$

## B.2 Households

Let us now turn to the household problem. The economy is populated by a large number of identical households that we normalize to measure one. Households chose a path of consumption, labor supply and investments in firms to maximize lifetime utility. Households hold their wealth in one period shares in the firms for which we use the measure $\phi$. They receive labor income as well as the sum of dividends and the resale value of their investments, $V$. Denote the price of a share of an individual firm as $q$. The dynamic problem is then given in its functional form as

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

subject to the law of motion for $\mu$ and a sequential budget constraint

$$C + \int q(k, z; A, \sigma_z, \sigma_A, \mu)\phi'(dkdz) \leq w(A, \sigma_A, \sigma, \mu)N + \int V(k, z; A, \sigma_A, \sigma, \mu)\phi(dkdz).$$

## B.3 Recursive Competitive Equilibrium

[Define RCE]

## B.4 Simplify the Problem

We can simplify the model significantly by combining the firm and household problems into a single dynamic optimization problem. Starting with the household problem we can take first order conditions to get the standard optimality conditions: an Inter-Euler condition, an Intra-Euler condition and an asset pricing equation. We are for now only interested in the latter two: the second gives us an expression for the wage rate and the third pins down the stochastic discount factor that needs to be used in the firm problem.

$$\begin{aligned} w &= \frac{U_N(C,N)}{U_C(C,N)} \\ m &= \beta\frac{U_C(C',N')}{U_C(C,N)} \end{aligned}$$

The problem can be simplified further. Let us assume the following momentary utility function for the household. That allows us to express the wage rate as a function of the intertemporal price $p$.

$$\begin{aligned} U(C,N) &= \frac{C^{1-\gamma}}{1-\gamma} - \theta N \\ w &= \frac{\theta}{p} \end{aligned}$$

Following Kahn and Thomas (2003) and Bachmann, Caballero and Engel (2007), we will now define the intertemporal price of consumption goods as $p(A, \sigma_z, \sigma_A, \mu) \equiv U_C(C, N)$. We can then redefine the firm problem in terms of marginal utility, denoting the new value function as $\tilde{V} \equiv pV$. The firm problem simplifies nicely and can be expressed as follows where the state variables in the prices are suppressed to keep the notation tractable.

$$\begin{aligned} & \tilde{V}(k, z; A, \sigma_A, \sigma, \mu) = \\ & \max_{\{i\}} \left\{ \left(y - wn - i - AC(k, k')\right) p + \beta E_t \left[ V(k', z'; A', \sigma'_A, \sigma'_z, \mu') \right] \right\} \end{aligned} \tag{1}$$

Moreover, the firm's labor demand in the current period does not affect the following period's state. Hence, we can solve the static problem of optimal labor demand.

$$n = \left( \frac{\nu z A k^{\alpha}}{w} \right)^{\frac{1}{1-\nu}}$$

### B.5 Numerical Solution

This model was motivated by the inability of standard techniques to deal with time variation in the second moment. We will therefore employ nonlinear techniques to solve for the optimal policy functions instead of loglinearizing the model as is standard in the RBC literature. Our solution uses the algorithm proposed by Krusell and Smith (1998). That is, we reduce the large state vector of the model to include only the aggregate states $(A, \sigma_A, \sigma_z)$ and a number of moments of the distribution of firms which we will denote by $\Omega$. The simplest example would be to use simply the average capital stock employed by all firms and the average value of the idiosyncratic shock. In principle, the state space can easily be increased to include other moments as well. The solution algorithm then works as follows. In iteration $l$, perform the following steps.

I. Forecast the intertemporal price $p$ and next period's moments $\Omega'$ as functions of the current aggregate state:

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

II. For a given forecast of $p$ we know the current period wage $w$ and the optimal labor demand $n$. We can then find the optimal policy functions by solving (1) where we substitute the approximated state $\Omega$ for the joint distribution $\mu$ and $f_2^{(l)}$ for the law of motion $\Gamma$.

III. Using the optimal policies we can simulate the economy for $T$ periods. Note that we are not using a market clearing price, but instead the forecasted price $\hat{p}$. Given the decisions of all firms in period $t$, we find the market clearing price $p$ from the market clearing condition for the goods market.

$$C = \int (y + i - AC)\, \mu(dkdz)$$

IV. We can re-estimate the forecasting functions $f_1^{(l+1)}$ and $f_2^{(l+1)}$ from the observed moments and equilibrium prices. We then restart the algorithm at step 1 and iterate until the forecasting functions converge.

### Model Evaluation

Given the optimal policies and forecasting functions, we can easily simulate the economy for a given sequence of the exogenous driving forces. That allows us to simulate the effect of a shock to micro and or macro uncertainty that is realistically calibrated using the results from Section 2.

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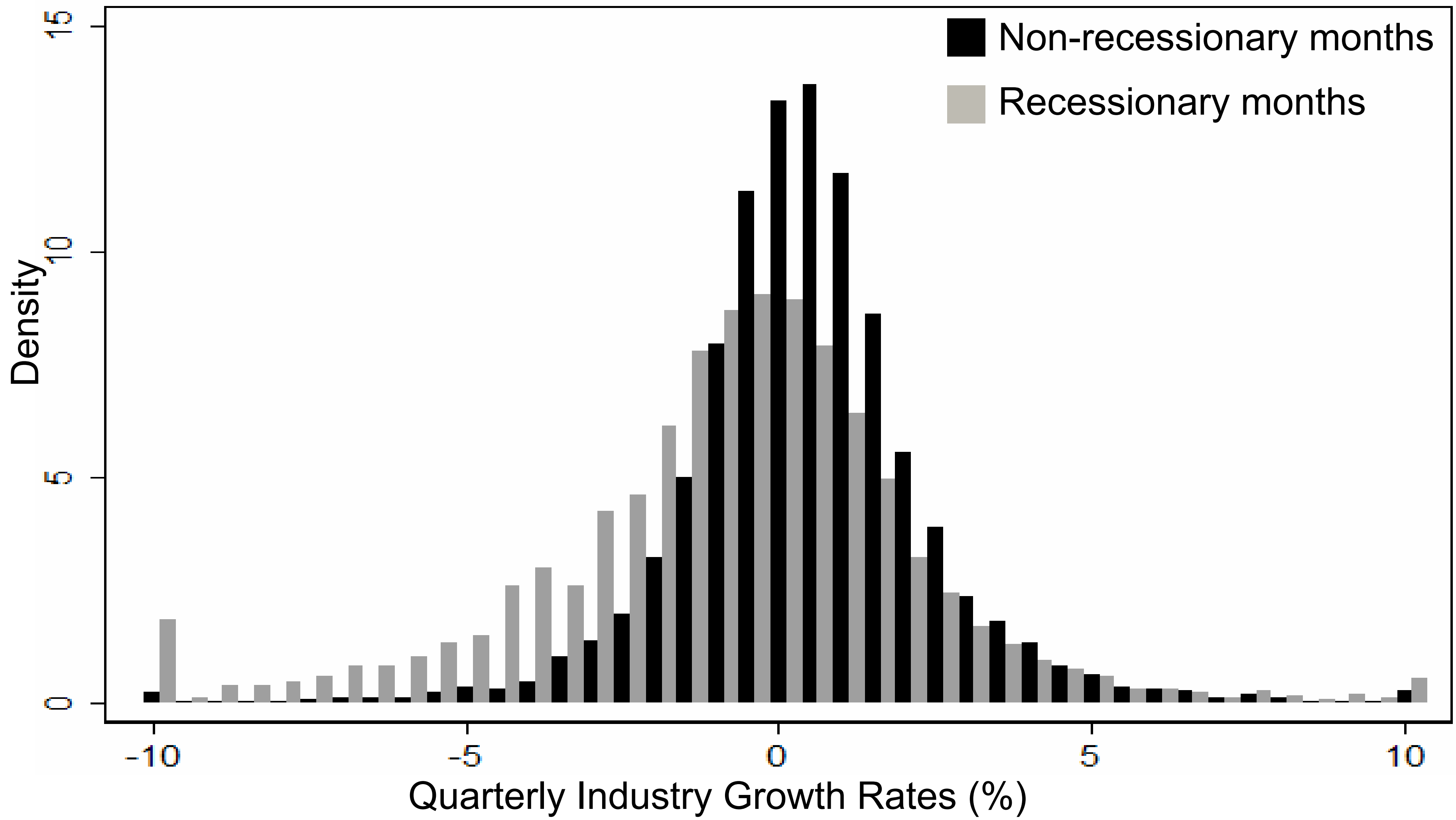
# Table 1: The Increase in Measures of Uncertainty During Recessions

| | | % increase during recessions, mean *(standard deviation)* | correlation with real quarterly GDP growth | period covered |
|---|---|---|---|---|
| (1) | **Firm sales growth spread** (quarterly cross-sectional interquartile range) | 23.8 *(4.0)* | -0.327 | 65Q1 to 04Q2 |
| (2) | **Firm stock returns spread** (quarterly cross-sectional interquartile range) | 21.7 *(3.8)* | -0.256 | 62Q2 to 06Q2 |
| (3) | **Industry output growth spread** (quarterly cross-sectional interquartile range) | 58.7 *(7.2)* | -0.396 | 72Q1 to 07Q1 |
| (4) | **Industry productivity growth spread** (annual cross-sectional interquartile range) | 32.5 (9.4) | -0.553 | 1962-1996 |
| (5) | **Macro output growth volatility** (quarterly average of abs. ARCH(2) errors on monthly AR(12)) | 37.8 *(3.5)* | -0.352 | 63Q1 to 06Q1 |
| (6) | **Macro stock return volatility** (quarterly standard deviation of daily stock returns) | 31.4 *(6.3)* | -0.238 | 62Q2 to 06Q1 |
| (7) | **Forecaster disagreement (GDP)** (quarterly standard deviation/mean) | 55.6 *(9.9)* | -0.444 | 68Q4 to 07Q1 |
| (8) | **Forecaster disagreement (unemployment)** (quarterly standard deviation/mean) | 51.3 *(5.9)* | -0.225 | 62Q4 to 06Q4 |
| (9) | **Uncertainty index** (principal component factor of quarterly measures) | 33.6 *(2.9)* | -0.487 | 68Q4 to 04Q2 |

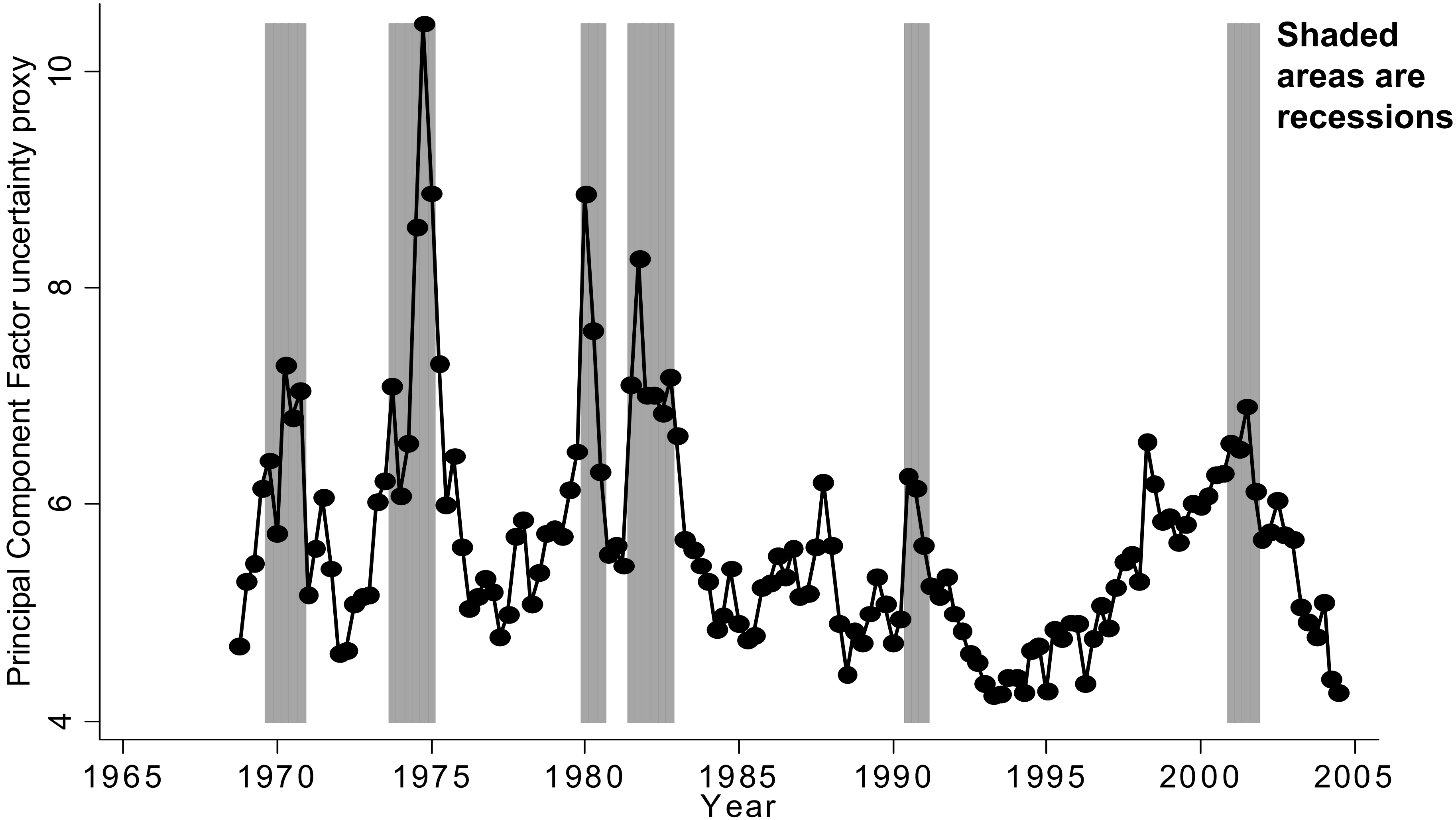
Notes: The first column reports the precentage increase of the variable during a recession, with standard errors in italics in ( ). So, for example, the first row reports that the interquartile range of quarterly firm-level sales growth is 23.8% higher during a recession, with a standard error of 4.0%. Business cycles defined using the NBER business cycle committee dates. The second column shows the correlation with quarterly real GDP growth measured using the BEA NIPA (all correlations are significant at the 1% level). The third column reports the period covered. The data sources and details on how our measures are constructed can be found in Appendix A. Row (1) contains the standard deviation of firm sales growth, defined as $(\text{sales}_{t+2} - \text{sales}_{t-2})/(0.5\times\text{sales}_{t+2} + 0.5\times\text{sales}_{t-2})$, where the 4-quarter window is used to remove quarterly accounting effects. This comes from Compustat quarterly accounts using firms with 150+ quarters of accounts, and quarters with 250+ observations. Row (2) contains the interquartile range of firm stock returns, measured using the monthly firm-level stock returns. This comes from CRSP, using firms with 25+ years of monthly returns data and quarters with at least 750 firms. Row (3 ) reports the quarterly average of the monthly interquartile range of growth rates of industrial production, covering the manufacturing sector broken down into 73 NAICS 3-digit sectors, obtained from the Federal Reserve Board. Row (4) reports the annual cross-sectional interquartile range of 5-factor TFP (from the NBER manufacturing database). The 32.5% figure denotes the percentage increase in the spread for a year with all four quarters defined as recessionary, estimated by regressing the annual spread against an annual indicator reporting the fraction of quarters in a recession in that year. Row (5) contains the average quarterly conditional standard deviation of monthly industrial production (final products and non-industrial supplies, SA) estimated from an AR(12) regression with ARCH(2) errors. Row (6) contains the quarterly average of the CBOE's VXO index (daily implied volatility on the S&P 100) from 1987 onwards. Pre 1987 the VXO is not available so the standard deviation of daily returns on the S&P 500 is used, normalized to the same mean and variance as the VXO when they overlap (1987-2005). Rows (7) and (8) contain standard deviation/mean of the 4-quarter ahead forecasts for unemployment and nominal GDP, obtained from the Survey of Professional Forecasters, with 41 and 53 quarterly observations on average respectively. Row (9) contains the (non-zero mean) principal component factor on the quarterly indicators displayed in columns (1) to (3) and (5) to (8). From 1968:4 to 1971:4 the missing industrial output growth IQR is forecasted from the other six indicators.

# Figure 1: Industrial production growth has a higher spread during in recessions



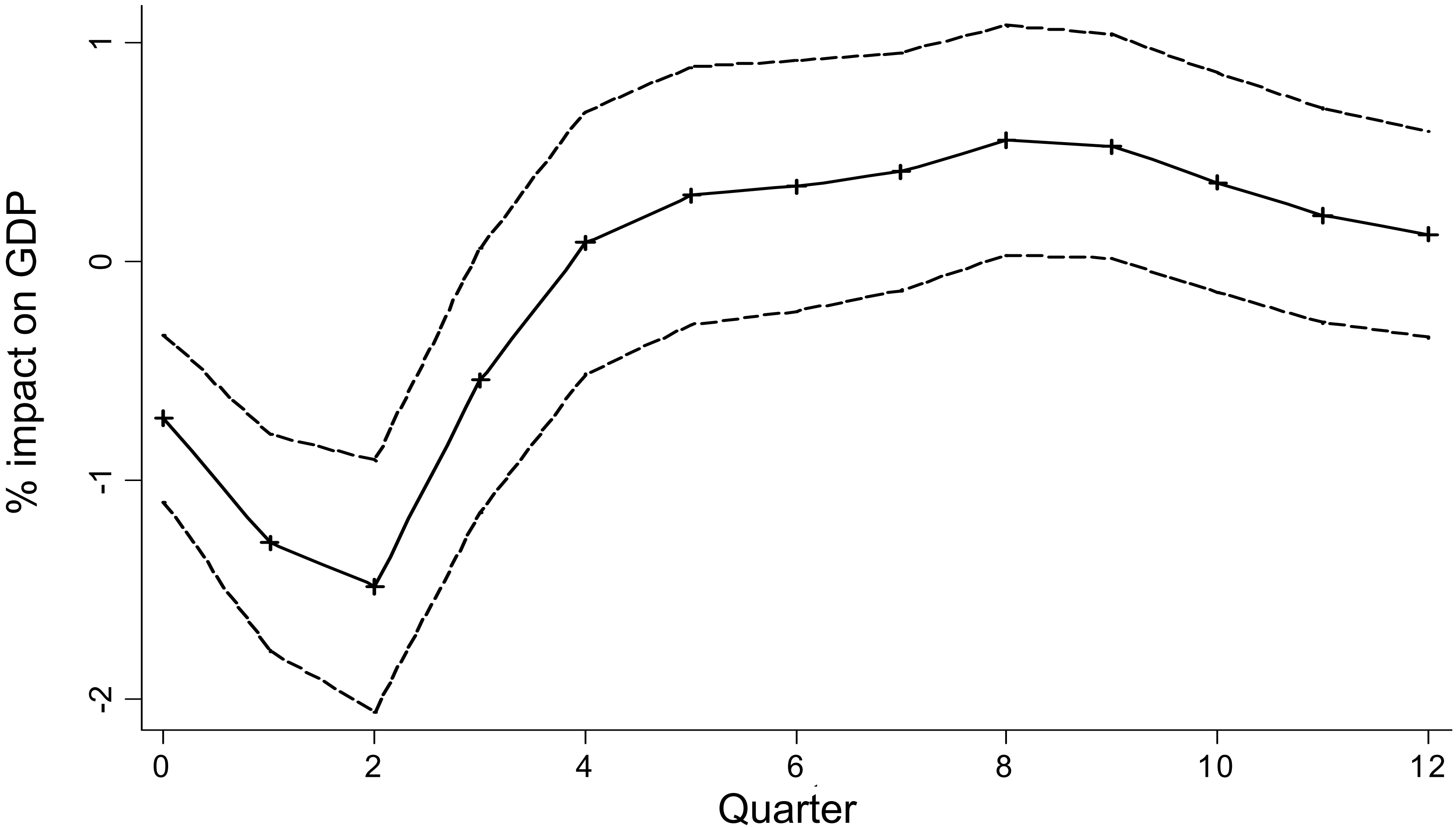

**Note: Plots the histogram of the 3-month growth rates of industrial production, 1972 to 2006. In black is the density for non-recessionary quarters, and in grey the density for recessionary quarters, defined according to the NBER Business Cycle dating Committee. Sample covers the manufacturing sector broken into 73 NAICS 3-digit sectors, representing 8,833 observations in non-recessionary quarters and 1,606 in recessionary quarters. Source: Federal Reserve Board**

# Figure 2: The uncertainty is higher in recessions



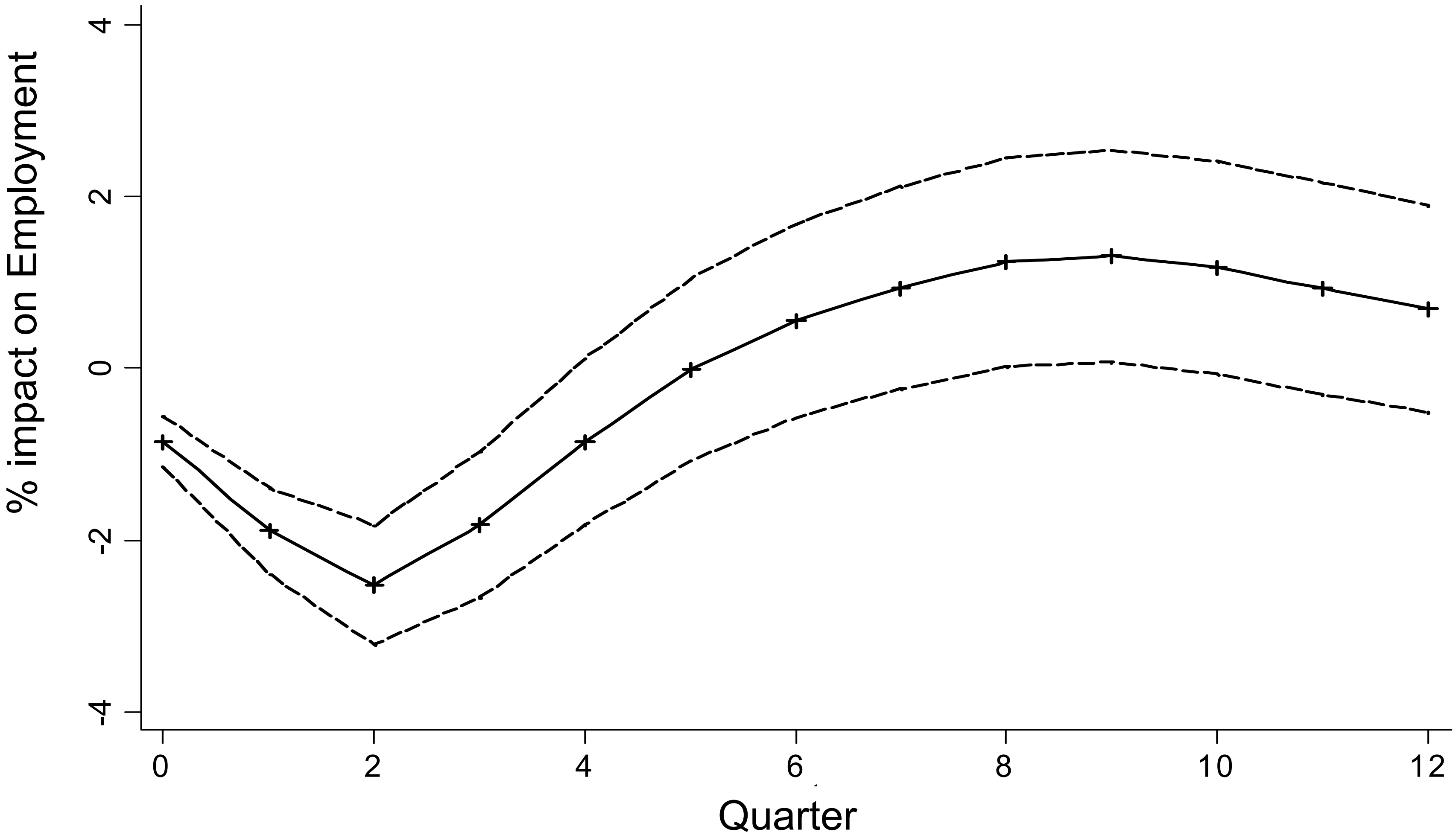

**Notes: Uncertainty proxy defined as principal component factor on the seven quarterly measures of uncertainty reported in Table 1 [weights] (quarterly inter-quartile range of firm-level sales growth and stock returns, quarterly interquartile range of industry-level output growth, the quarterly average conditional standard-deviation of aggregate monthly industrial production, the quarterly volatility of aggregate stock-returns, and the forecast-spread of unemployment and of GDP). Gray-shading denotes recessionary periods, as dated by the NBER business cycle dating committee.**

# Figure 3: VAR estimation of the impact of a recessionary increase in uncertainty on GDP



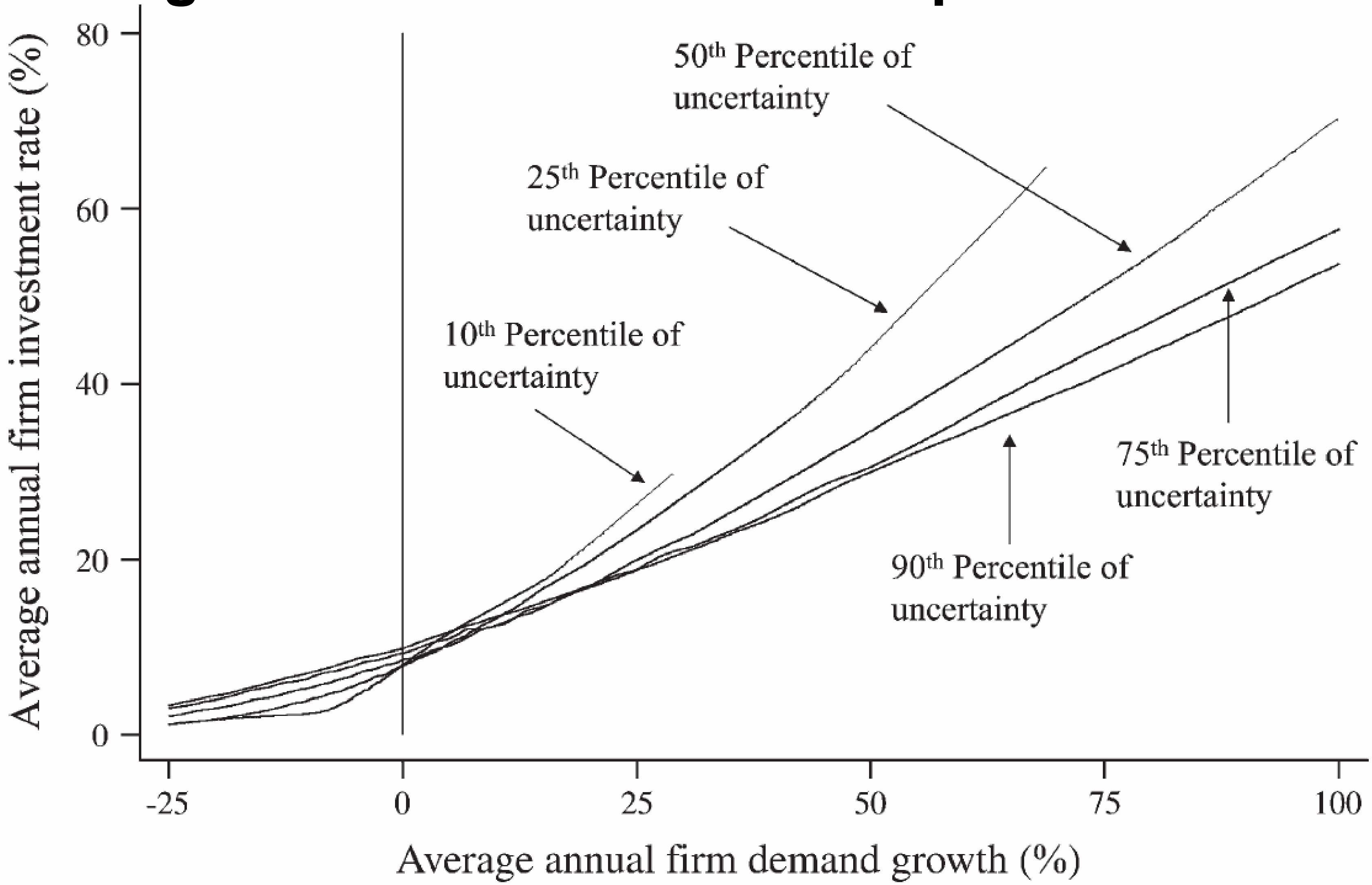

**Notes: VAR Cholesky orthogonalized impulse response to a 33% increase in the uncertainty index, calibrated to the average increase on the uncertainty index during a recession. Estimated on quarterly data from 1968:4 to 2004:3 using 4 lags. Dotted lines in top and bottom figures are the 95% confidence intervals. Variables (in order) are log real GDP, log employment, hours, log wages, log CPI, federal funds rate, the uncertainty index and log S&P500 levels. Detrending by Hodrick-Prescott filter with smoothing parameter of 1600.**

# Figure 4: VAR estimate of the impact of a recessionary increase in uncertainty on employment



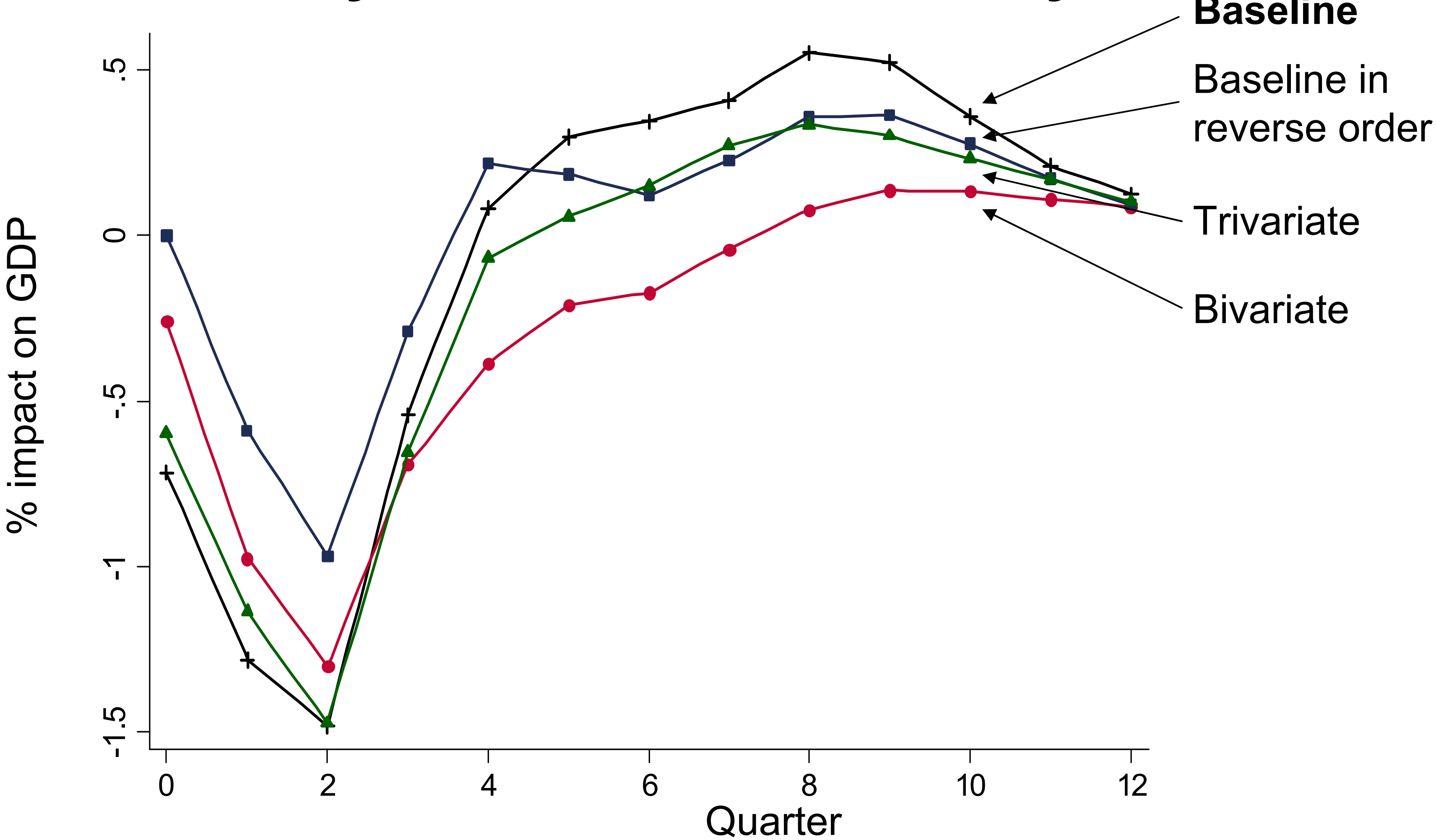

**Notes: VAR Cholesky orthogonalized impulse response to a 33% increase in the uncertainty index, calibrated to the average increase on the uncertainty index during a recession. Estimated on quarterly data from 1968:4 to 2004:3 using 4 lags. Dotted lines in top and bottom figures are the 95% confidence intervals. Variables (in order) are log real GDP, log employment, hours, log wages, log CPI, federal funds rate, the uncertainty index and log S&P500 levels. Detrending by Hodrick-Prescott filter with smoothing parameter of 1600.**

# Figure 5: The cautionary impact of uncertainty in reducing firm level investment responsiveness



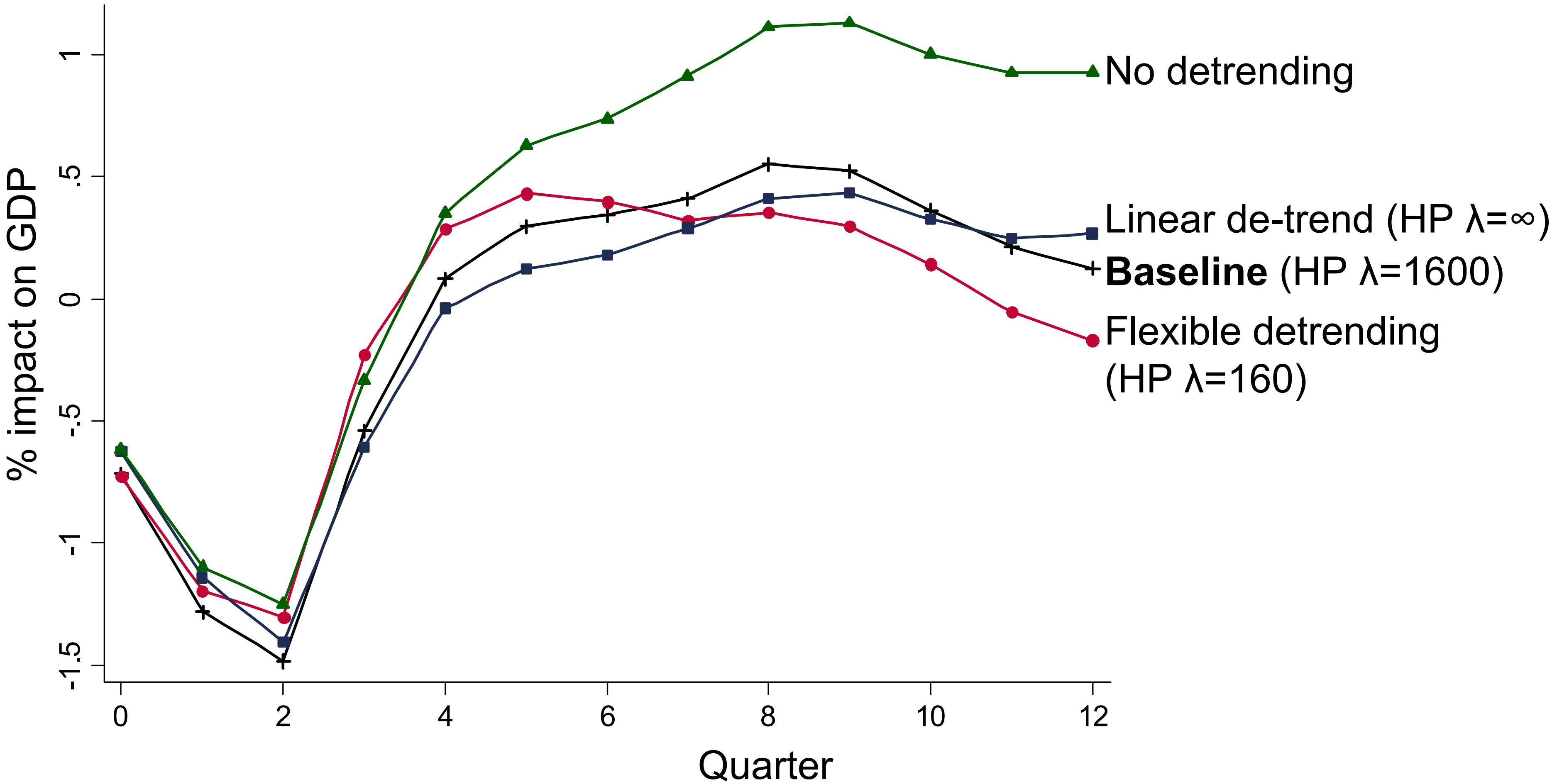

**Notes: This is Figure 1 from page 398 of Bloom, Bond and Van Reenen (2007, Review of Economic Studies, April 2007). It plots a Lowess estimate of the average firm-level investment response to demand shocks at different levels of uncertainty. The key result in the figure is that firms are much less response to demand shocks at higher levels of uncertainty due to the increase option value of waiting – that is they become more cautious.**

# Figure A1: VAR estimates of the impact of a recessionary increase in uncertainty on GDP




**Notes: VAR Cholesky orthogonalized impulse responses to a 33% increase in the uncertainty index, calibrated to the average increase on the uncertainty index during a recession. Estimated on quarterly data from 1968:4 to 2004:3 using 4 lags. Variables (in order) are: (i) "Baseline": log real GDP, log employment, hours, log wages, log CPI, federal funds rate, the uncertainty index and log S&P500 levels. Detrending by Hodrick-Prescott filter with smoothing parameter of 1600; (ii) "Baseline in reverse order" as in Baseline but order reversed; (iii) "Trivariate" log real GDP, log employment and the uncertainty index; and (iv) "Bivariate" log real GDP and the uncertainty index.**

# Figure A2: VAR estimates of the impact of a recessionary increase in uncertainty on GDP




**Notes: VAR Cholesky orthogonalized impulse responses to a 33% increase in the uncertainty index, calibrated to the average increase on the uncertainty index during a recession. Estimated on quarterly data from 1968:4 to 2004:3 using 4 lags. Variables (in order) are log real GDP, log employment, hours, log wages, log CPI, federal funds rate, the uncertainty index and log S&P500 levels. Detrending as follows: (i) "Baseline" by Hodrick-Prescott filter with a smoothing parameter λ of 1600; (ii) "HP λ=160" has an HP smoothing parameter of 160; (ii) "Linear de-trended" has an HP smoothing parameter of λ=∞, and (iv) "No detrending" has no detrending applied to any of the variables, with the VAR estimated in levels.**