Risk Shocks*

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May 13, 2012

Abstract

We augment a standard monetary DSGE model to include a Bernanke-Gertler-Gilchrist financial accelerator mechanism. We fit the model to US data, allowing the volatility of cross-sectional idiosyncratic uncertainty to fluctuate over time. We refer to this measure of volatility as 'risk'. We find that fluctuations in risk are the most important shock driving the business cycle.

JEL classification: E3; E22; E44; E51; E52; E58; C11; G1; G21; G3

Keywords: DSGE model; Financial frictions; Financial shocks; Bayesian estimation; Lending channel; Funding channel

*This paper expresses the views of the authors and not necessarily those of the European Central Bank, the Eurosystem or the National Bureau of Economic Research. We thank D. Andolfatto, K. Aoki, M. Gertler, S. Gilchrist, W. den Haan, M. Iacoviello, A. Levin, P. Moutot, L. Ohanian, P. Rabanal, S. Schmitt-Grohé, F. Schorfheide, C. Sims, M. Woodford and R. Wouters for helpful comments. We thank T. Blattner, P. Gertler and Patrick Higgins for excellent research assistance and we are grateful to H. James for editorial assistance. We are particularly grateful for advice and for extensive programming assistance from Ben Johannsen.

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1 Introduction

We introduce the type of agency problems proposed by Robert Townsend (1979) and later implemented in dynamic stochastic general equilibrium models in the seminal work of Ben Bernanke and Mark Gertler (1989) and Bernanke, Gertler and Simon Gilchrist (1999) (BGG).[1] Our estimates suggest that fluctuations in the severity of these agency problems account for a substantial fraction of business cycle fluctuations over the past two and a half decades.

Entrepreneurs play a central role in our business cycle model. They combine their own resources with loans to acquire raw, physical capital. They then convert this capital into effective capital in a process that is characterized by substantial idiosyncratic uncertainty. We refer to the degree of dispersion in this uncertainty as 'risk'. The notion that idiosyncratic uncertainty in the allocation of capital is important in practice can be motivated informally in several ways. For example, it is well known that a large proportion of firm start ups end in failure.[2] Entrepreneurs and their suppliers of funds experience these failures as a stroke of bad luck. Even entrepreneurs such as Steve Jobs and Bill Gates experienced failures as well as the successes for which their are famous.[3] Another example of the microeconomic uncertainty involved in the allocation of capital is the various 'wars' that have occured over industry standards. In these wars, entrepreneurs commit a large amount of raw capital to one or another standard. From the perspective of these entrepreneurs and their sources of finance, the ultimate result of their bet can be thought of as the outcome of a gamble.[4] We model this uncertainty experienced by entrepreneurs with the assumption that if an entrepreneur purchases K units of physical capital, that capital then turns into $K\omega$ units of effective capital. Here, $\omega \geq 0$ is a random variable drawn independently by each entrepreneur, normalized to have mean unity.[5] Entrepreneurs that draw ω larger than unity experience a success, while

[1] Other important early contributions include Carstrom and Fuerst (1997), Fisher (1999) and Williamson (1987). More recent contributions include Christiano, Motto and Rostagno (2003), Jermann and Quadrini (2011) and Arellano and Kehoe (2011).

[2] See, for example, the March 2011 review of Carmen Nobel's work in http://hbswk.hbs.edu/item/6591.html.

[3] Steve Jobs experienced tremendous success in allocating capital to the iPod, iPhone and iPad, but experienced a commercial failure when he allocated capital to the NeXT Computer (see Hammer (2011)). Similarly, Bill Gates experienced a spectacular return on the resources he invested in Microsoft. However, his previous efforts, focused on his firm, Traf-O-Data, completely failed (http://www.thedailybeast.com/newsweek/2011/04/24/my-favorite-mistake.html).

[4] For example, in the 1970s Sony allocated substantial resources to the construction of video equipment that used the Betamax video standard, while JVC and others used the VHS standard. After some time, VHS 'won' the standards war, so that the capital produced by investing in video equipment that used the VHS standard was more effective than capital produced by investing in Betamax equipment. The reasons for this outcome are still hotly debated today. However, from the ex-ante perspective of the companies involved and their suppliers of funds, the ex post outcome can be thought of as the realization of a random variable (for more discussion, see http://www.mediacollege.com/video/format/compare/betamax-vhs.html).

[5] The assumption about the mean of ω is in the nature of a normalization because we allow other random variables to capture the aggregate sources of uncertainty faced by entrepreneurs.

entrepreneurs that draw ω close to zero experience failure. The realization of ω is not known at the time the entrepreneur receives financing. However, when ω is realized its value is observed by the entrepreneur, but can be observed by the supplier of finance only by undertaking costly monitoring.[6] The cross-sectional dispersion of ω is controlled by a parameter, σ. We refer to σ as *risk*. The variable, σ, is assumed to be the realization of a stochastic process. Thus, risk is high in periods when σ is high and there is substantial dispersion in the outcomes across entrepreneurs. Risk is low otherwise.

For the reasons stressed in Robert Townsend (1979), we follow BGG in supposing that lenders interact with entrepreneurs in competitive markets in which standard debt contracts are traded. The interest rate on entrepreneurial loans includes a premium to cover the costs of default by the entrepreneurs that experience low realizations of ω. The entrepreneurs and the associated financial frictions are inserted into an otherwise standard dynamic, stochastic general equilibrium (DSGE) model.[7] According to our model, the credit spread (i.e., premium in the entrepreneur's interest rate over the risk-free interest rate) fluctuates with changes in σ. When risk is high, the credit spread is high and credit extended to entrepreneurs is low. Entrepreneurs then acquire less physical capital. Because investment is a key input in the production of capital, it follows that investment falls. With this decline in the purchase goods, output and employment fall. Consumption falls as well. For the reasons stressed in BGG, the net worth of entrepreneurs - an object that we identify with the stock market - falls too. This is because the rental income earned by entrepreneurs on their capital falls with the reduction in economic activity. In addition, the fall in the production of K results in a fall in the price of capital, which results in capital losses for entrepreneurs. Finally, the overall decline in economic activity results in a decline in the marginal cost of production and thus a decline in inflation. In this way, the σ shock in the model predicts a countercylical interest rate premium and procyclical investment, consumption, employment, inflation, the stock market and credit. These implications of the model correspond well to the analogous features of US business cycle data. [8]

[6]That the entrepreneur is in a much better position than the lender to assess the occurence of a 'failure' is illustrated by Steve Jobs' experience with the NeXT computer. Although that product was a commercial failure, it was not a complete loss. In fact, the operating system developed for the NeXT turned out to be very useful upon Jobs' return to Apple after leaving NeXT (see Hammer (2011)).

[7]Our strategy for inserting the entrepreneurs into a DSGE model follows the lead of BGG in a general way. At the level of details, our model follows Christiano, Motto and Rostagno (2003) by introducing the entrepreneurs into a version of the model proposed in Christiano, Eichenbaum and Evans (2005) and by introducing the risk shock (and an equity shock mentioned later) studied here.

[8]Our model complements recent papers that highlight other ways in which increased cross-sectional dispersion in an important shock could lead to aggregate fluctuations. For example, Nicholas Bloom (2009) and Bloom, Floetotto and Nir Jaimovich (2009) show how greater uncertainty can produce a recession by inducing businesses to adopt a 'wait and see' attitude and delay investment. For another example that resembles ours, see Cristina Arellano, Yan Bai, and Patrick Kehoe (2011).

We include other shocks in our model and then estimate it by standard Bayesian methods using 12 macroeconomic variables. In addition to the usual 8 variables used in standard macroeconomic analyses, we also make use of 4 financial variables: the value of the stock market, credit to nonfinancial firms, the credit spread and the slope of the term structure. Not surprisingly, in light of our previous observations, the results suggest that the σ shock is overwhelmingly the most important shock driving the business cycle. For example, the analysis suggests that fluctuations in σ account for 60 percent of the fluctuations in the growth rate of aggregate US output since the mid 1980s. As our presentation below makes clear, our conclusion that the risk shock is the most important shock depends crucially on including the four financial variables.

Our empirical analysis treats σ as an unobserved variable. We infer its properties from our 12 time series using the lense of our model. A natural concern is that we might have relied too heavily on 'large' values of σ to drive economic fluctuations. Motivated by this, we seek a more 'direct' measure of the risk shock by following the lead in Bloom (2009). In particular, we compute the cross-sectional standard deviation of firm-level stock returns in the Center for Research in Securities Prices (CRSP) stock-returns file. We found that those cross-sectional standard deviations have roughly the same magnitude as our estimated risk shocks.

Our model and related analyses are motivated in part by a growing body of evidence which documents that the cross-sectional dispersion of a variety of variables is countercyclical.[9] Of course, the mere fact that cross-sectional variances are countercylical does not by itself establish that risk shocks are causal, as our estimated model implies. It is in principle possible that countercyclical variation in cross-sectional dispersion is a symptom rather than a cause of business cycles.[10] We do not provide any direct test of our model's assumption about the direction of causation, and this is certainly an issue that deserves further study. In the mean time we see some support for the approach taken here in the findings of Scott R. Baker and Bloom (2011), who present empirical evidence consistent with the causal assumption in our

[9]For example, Bloom (2009) documents that various cross-sectional dispersion measures for firms in panel datasets are countercyclical. De Veirman and Levin (2011) find similar results using the Thomas Worldscope database. Matthias Kehrig (2011) documents using plant level data, that the dispersion of total factor productivity in U.S. durable manufacturing is greater in recessions than in booms. Vavra (2011) presents evidence that the cross-sectional variance of price changes at the product level is countercyclical. Also, Alexopoulos and Cohen (2009) construct an index based on the frequency of time that words like 'uncertainty' appear in the New York Times and find that this index rises in recessions. It is unclear, however, whether the evidence about uncertainty they have gathered reflects variations in cross-sectional variances or changes in the variance of time series aggregates. Our risk shock corresponds to the former.

[10]For example, Rudiger Bachmann and Giuseppi Moscarini (2011) raise the possibility that cross-sectional volatility may rise in recessions as the endogenous response of the increased fraction of firms contemplating an exit decision. D'Erasmo and Boedo (2011) and Kehrig (2011) provides two additional examples of the possible endogeneity of cross-sectional uncertainty.

model.[11]

Our work is also related to Alejandro Justiniano, Giorgio E. Primiceri and Andrea Tambalotti (2010), which stresses the role of shocks to the production of installed capital (marginal efficiency of investment shocks). These shocks resemble our risk shock in that their primary impact is on intertemporal opportunities. Our risk shock and the marginal efficiency of investment shock are hard to distinguish based on the eight standard macroecomic variables. However, the analysis strongly favors the risk shock when our four financial variables are also included in the analysis. This is because risk shocks affect the demand for capital and so imply a procyclical price of capital. We identify the value of the stock market with the net worth of the entrepreneurs and their net worth is heavily influenced by the price of capital. That is, the marginal efficiency of capital implies the value of the stock market is countercyclical. The risk shock, by contrast, operates on the demand side of capital and so implies a procyclical price of capital and, hence, stock market. This reasoning, together with the fact that we include a measure of the stock market in our data set, helps to explain why our analysis de-emphasizes the importance of marginal efficiency of investment shocks in favor of risk shocks.

We gain insight into the importance of our risk shock by comparing it to another shock, one that we call an *equity shock*. This is a disturbance that directly affects the quantity of net worth in the hands of entrepreneurs. This shock acts a little like our risk shock, by operating on the side of the demand for capital. However, unlike the risk shock, this shock has the counterfactual implication that credit is countercylical. When we include credit in the data set, the risk shock is preferred over the equity shock. We conclude that the procyclical nature of credit is an important reason for the substantial role in business cycles assigned to risk by our econometric results.

Of course, the credibility of our finding about the importance of the risk shock depends on the empirical plausibility of our model. We evaluate the model's plausibility by investigating various implications of the model that were not used in constructing or estimating it. First, we evaluate the model's out-of-sample forecasting properties. We find that these are reasonable, relative to the properties of a Bayesian vector autoregression or a simpler New Keynesian business cycle model such as the one in Christiano, Eichenbaum and Evans (2005) or Smets and Wouters (2007). We also examine the model's implications for data on bankruptcies, information that was not included in the data set used to estimate the model. Finally, we compare the model's implications for the kind of uncertainty measures proposed by Bloom.

[11] This evidence is not decisive, since the analysis performed by Baker and Bloom (2011) does not allow one to determine whether the volatility they find is causal is the sort that we emphasize (e.g., volatility of variables in the cross section) or whether it corresponds to heteroscedasticity of aggregate variables.

Although this analysis does bring out some flaws in the model, overall it performs well. We conclude that the implications of the analysis for the role in business cycles of the risk shocks deserves to be taken seriously. By this we mean that it would be useful to elaborate the mechanisms that underly the risk shock.

The plan of the paper is as follows. The next section describes the model. Estimation results and measures of fit are reported in section 3. Section 4 presents the main results. We present various quantitative measures that characterize the sense in which risk shocks are important in business cycles. We then explore the reasons why the econometric results find the risk shock is so important. The paper ends with a brief conclusion. Technical details and supporting analysis are provided in the online Appendices A-I

2 The Model

The model incorporates the microeconomics of the debt-contracting framework of BGG into an otherwise standard monetary model of the business cycle. The first subsection describes the standard part of the model and the second subsection describes the financial frictions. The time series representations of the shocks, as well as adjustment cost functions are reported in the third subsection.

2.1 Standard Part of the Model

Goods are produced according to a Dixit-Stiglitz structure. A representative, competitive final goods producer combines intermediate goods, Y_{jt}, $j \in [0,1]$, to produce a homogeneous good, Y_t, using the following technology:

$$Y_t = \left[\int_0^1 Y_{jt}^{\frac{1}{\lambda_{f,t}}} dj \right]^{\lambda_{f,t}}, \; 1 \leq \lambda_{f,t} < \infty, \tag{2.1}$$

where $\lambda_{f,t}$ is a shock. The intermediate good is produced by a monopolist using the following technology:

$$Y_{jt} = \begin{cases} \epsilon_t K_{jt}^{\alpha} \left(z_t l_{jt} \right)^{1-\alpha} - \Phi z_t^* & \text{if } \epsilon_t K_{jt}^{\alpha} \left(z_t l_{jt} \right)^{1-\alpha} > \Phi z_t^* \\ 0, & \text{otherwise} \end{cases}, \; 0 < \alpha < 1. \tag{2.2}$$

Here, ϵ_t is a covariance stationary technology shock and z_t is a shock whose growth rate is stationary. Also, K_{jt} denotes the services of capital and l_{jt} denotes the quantity of homogeneous labor, respectively, hired by the j^{th} intermediate good producer. The fixed cost in the production function, (2.2), is proportional to z_t^*. This variable is a combination of the two nonstationary stochastic processes in the model, namely z_t and an investment specific shock described below. The variable, z_t^*, has the property that Y_t/z_t^* converges to a constant in non-stochastic steady state. The monopoly supplier of Y_{jt} sets its price, P_{jt}, subject to Calvo-style frictions. Thus, in each period t a randomly-selected fraction of intermediate-goods firms, $1-\xi_p$, can reoptimize their price. The complementary fraction sets their according to:

$$P_{jt} = \tilde{\pi}_t P_{j,t-1},$$

where

$$\tilde{\pi}_t = \left(\pi_t^{target}\right)^{\iota} \left(\pi_{t-1}\right)^{1-\iota}. \tag{2.3}$$

Here, $\pi_{t-1} \equiv P_{t-1}/P_{t-2}$, P_t is the price of Y_t and π_t^{target} is the target inflation rate in the monetary authority's monetary policy rule, which is discussed below.

There exists a technology that can be used to convert homogeneous goods into consumption goods, C_t, one-for-one. Another technology converts a unit of homogenous goods into $\Upsilon^t \mu_{\Upsilon,t}$ investment goods, where $\Upsilon > 1$ and $\mu_{\Upsilon,t}$ is a shock. Because we assume these technologies are operated by competitive firms, the equilibrium prices of consumption and investment goods are P_t and $P_t/\left(\Upsilon^t \mu_{\Upsilon,t}\right)$, respectively. The trend rise in technology for producing investment goods is the second source of growth in the model, and

$$z_t^* = z_t \Upsilon^{\left(\frac{\alpha}{1-\alpha}\right)t}.$$

There is a large number of identical households, which supply capital services and labor. Households have a technology for constructing physical capital, $\bar{K}_{t+1}$, using the following technology:

$$\bar{K}_{t+1} = \bar{K}_t + \left(1 - S(\zeta_{It}\, I_t/I_{t-1})\right) I_t. \tag{2.4}$$

Here, S is a increasing and convex function described below, I_t denotes investment goods and ζ_{It} is a shock to the marginal efficiency of investment in producing capital. Capital services and physical capital are related by the utilization rate of capital, u_t, by the following expression:

$$K_t = u_t \bar{K}_t.$$

The utilization of capital is costly and requires purchasing $a\left(u_t\right)\Upsilon^{-t}$ units of final goods per unit of physical capital used (i.e., per $\bar{K}_{t+1}$). Here, a denotes an increasing and convex function described below. The trend in utilization costs is designed to help ensure a balanced growth deterministic growth path in which capital utilization is constant.

The model of the labor market is taken from Erceg, Henderson and Levin (2000), and parallels the Dixit-Stiglitz structure of goods production. A representative, competitive labor contractor aggregates the differentiated labor services, $h_{i,t}$, $i \in [0,1]$, into homogeneous labor, l_t, using the following production function:

$$l_t = \left[\int_0^1 (h_{t,i})^{\frac{1}{\lambda_w}} di \right]^{\lambda_w}, \ 1 \leq \lambda_w. \tag{2.5}$$

The labor contractor sells labor services, l_t, to intermediate good producers for nominal wage rate, W_t.

Each of the large number of identical households supplies differentiated labor, $h_{i,t}$, $i \in [0,1]$. By assuming that all varieties of labor are contained within the same household (this is the 'large family' assumption introduced by Andolfatto (1996) and Merz (1995)) we avoid confronting difficult - and potentially distracting - distributional issues. For each labor type, $i \in [0,1]$, there is a monopoly union that represents workers of that type belonging to all households. The i^{th} monopoly union sets the wage rate, W_{it}, for its members, subject to Calvo-style frictions. In particular, a randomly selected subset of $1 - \xi_w$ monopoly unions set their wage optimally, while the complementary subset sets the wage according to:

$$W_{it} = \left(\mu_{z^*,t}\right)^{\iota_\mu} \left(\mu_{z^*}\right)^{1-\iota_\mu} \tilde{\pi}_{wt} W_{i,t-1}.$$

Here, μ_{z^*} denotes the growth rate of z_t^* in non-stochastic steady state. Also,

$$\tilde{\pi}_{w,t} \equiv \left(\pi_t^{target}\right)^{\iota_w} \left(\pi_{t-1}\right)^{1-\iota_w}, \ 0 < \iota_w < 1. \tag{2.6}$$

The indexing assumptions in wage setting ensure wage-setting frictions are not distortionary along a non-stochastic, steady state growth path. The representative household's preferences are given by:

$$E_0 \sum_{t=0}^{\infty} \beta^t \zeta_{c,t} \left\{ \log(C_t - bC_{t-1}) - \psi_L \int_0^1 \frac{h_{it}^{1+\sigma_L}}{1+\sigma_L} di \right\}, \ b, \sigma_L > 0. \tag{2.7}$$

Here, $\zeta_{c,t} > 0$ is a shock. In the standard model, the representative household chooses consumption, the capital utilization rate and physical capital accumulation to maximize (2.7) subject to a budget constraint. The household takes $W_{i,t}$, $i \in [0,1]$, as given and supplies whatever quantity of $h_{i,t}$ that is demanded at that wage rate. In addition, the household has access to a nominally non-state contingent one-period bond with gross payoff R_{t+1} in period $t+1$. Loan market clearing requires that, in equilibrium, the quantity of this bond that is traded is zero.

We express the monetary authority's monetary policy rule directly in linearized form:

$$R_{t+1} - R = \rho_p (R_t - R) + \left(1 - \rho_p\right) \left[\alpha_\pi \left(\pi_{t+1} - \pi_t^*\right) + \alpha_{\Delta y} \frac{1}{4} \left(g_{y,t} - \mu_{z^*}\right)\right] + \frac{1}{400} \varepsilon_t^p, \tag{2.8}$$

where ε_t^p is a shock to monetary policy and ρ_p is a smoothing parameter in the policy rule. Here, $400\,(R_{t+1} - R)$ is the deviation of the net quarterly interest rate, R_{t+1}, from its steady state, expressed in annual, percent terms. Similarly, $400\,(\pi_{t+1} - \pi_t^*)$ is the deviation of anticipated inflation from the central bank's inflation target, also expressed in annual, percent terms. The expression, $100\,(g_{y,t} - \mu_{z^*})$ is quarterly GDP growth, in deviation from its steady state, expressed in percent terms. Finally, ε_t^p is the monetary policy shock, expressed in units of annualized percent.

2.2 Financial Frictions

In the standard model, the supply of capital services is a routine and uneventful activity. In practice, this activity more closely resembles grand opera, requiring a combination of talent and luck. In our model, the agents with the required talent are called entrepreneurs. They produce effective capital services by combining raw, physical capital with an idiosyncratic productivity shock. Inevitably, entrepreneurs are heterogeneous, because they experience different histories of shocks. We abstract from the resulting distributional consequences by adopting various linearity assumptions and by adopting the Andolfatto-Merz large household assumption, as in GK^2. In particular, each we continue to assume that all households are identical and contain all varieties of worker skill types. Now, we also asume the representative household has a large and diversified group of entrepreneurs.[12]

All the activities of entrepreneurs occur in competitive markets. An entrepreneur acquires capital by combining its own funds with loans obtained from mutual funds. The general flow of funds in financial markets is indicated in Figure 1. At the end of production in period t, households deposit funds with mutual funds and each mutual fund extends loans to a diversified group of entrepreneurs. The most straightforward interpretation of our entrepreneurs is that

[12] Although we think the GK^2 large-family metaphor helps to streamline the model presentation, the equations that characterize the equilibrium are, with one minor exception described below, the same as if we had adopted the slightly different presentation in BGG.

they are firms in the non-financial business sector. However, it is also possible to interpret them as financial firms that are risky because they hold a non-diversified porfolio of loans to risky non-financial businesses (see the 'bank→entrepreneur' entries in Figure 1).[13] We now discuss the financial frictions in detail.

At the end of period t production, each entrepreneur has a given level of net worth, N_{t+1}, which depends on the entrepreneur's history and which completely summarizes its state. At this time, each entrepreneur with a specific level of net worth, say N, obtains a loan from a mutual fund, which it combines with its own net worth to purchase raw physical capital, $\bar{K}_{t+1}^N$, in a market for capital at the price $Q_{\bar{K},t}$. As in the standard model, the business of producing physical capital and supplying it to the capital market is handled by the households.

After purchasing its capital, each entrepreneur experiences an idiosyncratic shock, ω, which converts its capital, $\bar{K}_{t+1}^N$, into efficiency units, $\omega\bar{K}_{t+1}^N$. We assume that ω has a log normal distribution that is independently drawn across time and across entrepreneurs. We adopt the normalization, $E\omega = 1$, and denote the standard deviation of $\log\omega$ by σ_t. The random variable, ω, captures the idiosyncratic risk in actual business ventures. In some cases a given amount of physical capital (i.e., metal, glass and plastic) is a great success (i.e., the Apple iPad or the Blackberry cell phone) and in other cases it is less successful (i.e, the NeXT computer or the Blackberry Playbook). The object, σ_t, characterizes the extent of cross sectional dispersion in ω, which we allow to vary stochastically over time. We refer to σ_t as 'the risk shock'.

After observing the period $t+1$ shocks, each entrepreneur determines the utilization rate, u_{t+1}^N, of its effective capital and rents out the associated capital services in competitive markets in return for $u_{t+1}^N\omega\bar{K}_{t+1}^N r_{t+1}^k$ units of currency. Here, r_{t+1}^k denotes the nominal rental rate of a unit of capital services. As in the standard model, the utilization of capital is costly and requires purchasing $a\left(u_{t+1}^N\right)\Upsilon^{-(t+1)}$ units of final goods per unit of efficiency capital used (i.e., per $\omega\bar{K}_{t+1}^N$). The function, a, is increasing and convex, and is described below.

At the end of production in period $t+1$, the entrepreneur is left with $(1-\delta)\,\omega\bar{K}_{t+1}^N$ units of physical capital, after depreciation. This capital is sold in competitive markets to households at the price, $Q_{\bar{K},t+1}$. Households use this capital, whose economy-wide supply is $(1-\delta)\,\bar{K}_{t+1}$, to build $\bar{K}_{t+2}$ using the technology in (2.4). We conclude that the entrepreneur with net worth, N, at the end of period t enjoys rate of return, ωR_{t+1}^k, at $t+1$, where

$$R_{t+1}^k \equiv \frac{\left(1-\tau^k\right)\left[u_{t+1}r_{t+1}^k - a(u_{t+1})\right]\Upsilon^{-(t+1)}P_{t+1} + (1-\delta)Q_{\bar{K},t+1} + \tau^k\delta Q_{\bar{K}',t}}{Q_{\bar{K},t}}. \tag{2.9}$$

[13]We have in mind the banks in Gertler and Kiyotaki (2011). For a detailed discussion, see section 6 in Christiano and Ikeda (2011).

Here, τ^k denotes the tax rate on capial income and we assume depreciated capital can be deducted at historical cost. In (2.9), we have deleted the superscript, N, from the capital utilization rate. We do so because the only way utilization affects the entrepreneur is through (2.9) and the choice of utilization that maximizes (2.9) is evidently independent of the entrepreneur's net worth. From here on, we suppose that u_{t+1} is set at this optimizing level, which is a function of r_{t+1}^k and $\Upsilon^{-(t+1)}P_{t+1}$, variables that are beyond the control of the entrepreneur.

Thus, each entrepreneur in effect has access to a stochastic, constant rate of return technology, $R_{t+1}^k\omega$.[14] Part of the uncertainty in this return, R_{t+1}^k, is aggregate and the other part is idiosyncratic. The entrepreneur with net worth, N, purchases assets, $Q_{\bar{K},t}\bar{K}_{t+1}^N$, using a combination of its own net worth and a loan, $B_{t+1}^N = Q_{\bar{K},t}\bar{K}_{t+1}^N - N$. In the market for loans, the entrepreneur is presented with a menu of standard debt contracts. A standard debt contract specifies a loan amount and a state $t+1$ contingent interest rate, Z_{t+1}. For a portion of entrepreneurs, it is infeasible to repay $B_{t+1}^N Z_{t+1}$ because they experienced a low ω. Such an entrepreneur declares bankruptcy. The value of ω, $\bar{\omega}_{t+1}$, that separates bankrupt and non-bankrupt entrepreneurs is defined by:

$$R_{t+1}^k \bar{\omega}_{t+1} Q_{\bar{K},t}\bar{K}_{t+1}^N = B_{t+1}^N Z_{t+1}. \tag{2.10}$$

Note that we have left off the superscript, N, on $\bar{\omega}_{t+1}$ and Z_{t+1}. This is to minimize notation, and a reflection of the well known fact (see below) that in equilibrium these objects are the same for entrepreneurs with all levels of net worth.[15] An entrepreneur with $\omega \leq \omega_{t+1}^N$ declares bankruptcy. It is then monitored by its mutual fund, which then takes all the entrepreneur's assets. Bankrupt entrepreneurs are nevertheless able to borrow in the following period, because each entrepreneur receives a (relatively small) transfer, W_{t+1}^e, financed by lump-sum taxes on the household at the beginning of period t.[16] Before completing the discussion of the entrepreneurs, we must first discuss the mutual funds.

It is convenient (though it involves no loss of generality) to imagine that mutual funds specialize in lending to entrepreneurs with specific levels of net worth, N. Each mutual fund holds a large portfolio of loans, so that it is perfectly diversified relative to the idiosyncratic

[14] In the case where the entrepreneur is interpreted as a financial firm, we follow Gertler and Kiyotaki (2010) in supposing that $R_{t+1}^k\omega$ is the return on securities purchased by the financial firm from a non-financial firm. The non-financial firm possesses a technology that generates the rate of return, $R_{t+1}^k\omega$, and it turns over the full amount to the financial firm. This interpretation requires that there be no financial frictions between the non-financial and the financial firm.

[15] The result that in equilibrium all entrepreneurs receive standard debt contracts with the same interest rate in part reflects our assumption that all entrepreneurs have the same ex ante risk, σ_t.In principle, the environment could be modified to allow for entrepreneurs with different levels of risk in the ex ante sense.

[16] To help ensure balanced growth, we assume that W_t^e grows with the rest of the economy. We achieve this by setting $W_t^e = z_t^* w^e$, where w^e is a constant.

risk experienced by entrepreneurs. To make loans, B_{t+1}^N per entrepreneur, the representative mutual funds issue B_{t+1}^N in deposits to households at the competitively determined nominal interest rate, R_{t+1}, which is not contingent upon period $t+1$ uncertainty. We assume that mutual funds do not have access in period t to period $t+1$ state-contingent markets for funds. As a result, the funds received in each period $t+1$ state of nature must be no less than the funds paid to households in that state of nature. That is, the representative mutual fund satisfies:

$$[1 - F_t(\bar{\omega}_{t+1})] Z_{t+1} B_{t+1}^N + (1-\mu) \int_0^{\bar{\omega}_{t+1}} \omega dF_t(\omega) R_{t+1}^k Q_{\bar{K}',t} \bar{K}_{t+1}^N \geq B_{t+1}^N R_{t+1}, \tag{2.11}$$

in each period $t+1$ state of nature. The object on the left of the equality in (2.11) is the average return, per entrepreneur, on revenues received by the mutual fund from entrepreneurs. The first term on the left indicates revenues received from the fraction of entrepreneurs with $\omega \geq \bar{\omega}_{t+1}$ and the second term indicates the revenues obtained from bankrupt entrepreneurs. These revenues are net of mutual funds' monitoring costs, which take the form of final goods and correspond in currency units to a proportion, μ, of the assets of bankrupt entrepreneurs. The left term in (2.11) also cannot be strictly greater than the term on the right in any period $t+1$ state of nature because otherwise mutual funds would make positive profits and this is incompatible in equilibrium with free entry and competition.[17] It follows that the weak inequality in (2.11) must be a strict equality in every state of nature. Using this fact and rearranging (2.11) after subsituting out for $Z_{t+1}B_{t+1}^N$ using (2.10), we obtain:

$$\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1}) = \frac{L_t - 1}{L_t} \frac{R_{t+1}}{R_{t+1}^k}, \tag{2.12}$$

in each period $t+1$ state of nature. In (2.12),

$$\Gamma_t(\bar{\omega}_{t+1}) \equiv [1 - F_t(\bar{\omega}_{t+1})] \bar{\omega}_{t+1} + G_t(\bar{\omega}_{t+1}), \; G_t(\bar{\omega}_{t+1}) = \int_0^{\bar{\omega}_{t+1}} \omega dF_t(\omega), \; L_t = \frac{Q_{\bar{K},t}\bar{K}_{t+1}^N}{N},$$

so that L_t represents leverage and $\Gamma_t(\bar{\omega}_{t+1})$ represents the share of average entrepreneurial earnings, $R_{t+1}^k Q_{\bar{K}',t} \bar{K}_{t+1}^N$, received by mutual funds. Note that we have left the superscript, N,

[17] In an alternative market arrangement, mutual funds in period t interact with households in period $t+1$ state contingent markets for funds. This would be in addition to the nominally non-state contingent markets for deposits already assumed. Under this market arrangement a mutual fund has a single zero profit condition in period t, which can be represented as the requirement that the period t expectation of the left minus the right side of (2.11) equals zero. With this market arrangement, we could assume, for example, that the interest rate paid by entrepreneurs, Z_{t+1}, is not contingent on the realization of period $t+1$ uncertainty. The market arrangement described in the text is the one proposed in BGG and we have not explored the alternative, complete market, arrangement described in this footnote.

off of leverage. We show below that in equilibrium all entrepreneurs choose the same level of leverage, regardless of their level of net worth.

The $(\bar{\omega}_{t+1}, L_t)$ combinations which satisfy (2.12) corresponds to the menu of state $t+1$ contingent standard debt constracts offered to entrepreneurs.[18] In period t, the representative household instructs its entrepreneurs to maximize expected period $t+1$ net worth. Given that entrepreneurs take R^k_{t+1} and their current level of net worth as given, this corresponds to maximizing $E_t \left[1 - \Gamma_t \left(\bar{\omega}_{t+1}\right)\right] R^k_{t+1} L_t$ by choice of $(\bar{\omega}_{t+1}, L_t)$ subject to (2.12) being satisfied in each period $t+1$ state of nature.[19] The fact that entrepreneurial net worth does not appear in the objective or constraints of this problem explains why the equilibrium interest on loans and the value of leverage are the same for all entrepreneurs.

After entrepreneurs have sold their undepreciated capital, collected rental receipts and settled their obligations with their mutual fund at the end of period $t+1$, a randomly selected fraction, $1 - \gamma_{t+1}$, of the entrepreneurs in the family become workers. The remaining fraction of entrepreneurs, γ_{t+1}, survives to continue another period. Enough workers convert to entrepreneurs so that the proportion of workers and entrepreneurs in the household remains constant. After entry and exit are complete, all entrepreneurs receive a net worth transfer, W^e_{t+1}, from the household. Because W^e_{t+1} is relatively small, this exit and entry process helps to ensure that entrepreneurs as a group do not accumulate so much net worth that they outgrow their dependence on loans. We refer to γ_{t+1} as an 'equity shock'. A drop in γ_{t+1} reduces the average net worth of entrepreneurs because exiting entrepreneurs typically have more net worth than W^e_{t+1}.[20] At the end of the entry and exit process in $t+1$ and the transfer of W^e_t, each entrepreneur's net worth is determined. Each now proceeds to a mutual fund to obtain a loan and the process just described continues.

Using the discussion in the previous paragraph, we derive an expression for $\bar{N}_{t+1}$, the aggregate net worth of all entrepreneurs that take out bank loans at the end of period t. This is defined as:

$$\bar{N}_{t+1} = \int_0^\infty N f_t(N)\, dN, \tag{2.13}$$

where $f_t(N)$ denotes the density of entrepreneurs with net worth, N, presenting themselves to mutual funds at the end of period t, to obtain loans. By the law of large numbers the

[18] Note that a specification of $(\bar{\omega}_{t+1}, L_t)$ is equivalent to a specification of (Z_{t+1}, L_t). To see this, note that (2.10) implies $R^k_{t+1}\bar{\omega}_{t+1}\left(N + B^N_{t+1}\right) = B^N_{t+1} Z_{t+1}$. After rearranging, we obtain $Z_{t+1} = R^k_{t+1}\bar{\omega}_{t+1} L_t / \left(L_t - 1\right)$.

[19] The number of objects chosen is a single value for L_t and one $\bar{\omega}_{t+1}$ for each period $t+1$ state of nature.

[20] One distinction between the arrangement used here and the one in BGG has to do with exiting entrepreneurs. In BGG, exiting entrepreneurs consume a fraction, Θ, of their net worth while only $1 - \Theta$ is transferred in lump-sum form to households. This distinction is quantitatively insignificant because Θ is a very small number in practice.

aggregate profits of all entrepreneurs with net worth N at the end of t, just before entry and exit occurs, is $\left[1-\Gamma_{t-1}\left(\bar{\omega}_t\right)\right] R_t^k Q_{\bar{K},t-1} \bar{K}_t^N$. The aggregate stock of capital at the beginning of period t satisfies the analog of (2.13):

$$\bar{K}_t = \int_0^\infty \bar{K}_t^N f_{t-1}\left(N\right) dN. \tag{2.14}$$

Integrating entrepreneurial profits over all N and using (2.14) we find that the aggregate financial resources of all entrepreneurs in the typical household at the end of $t+1$, prior to entry and exit, is $\left[1-\Gamma_{t-1}\left(\bar{\omega}_t\right)\right] R_t^k Q_{\bar{K},t-1} \bar{K}_t$. We conclude that

$$\bar{N}_{t+1} = \gamma_t \left[1-\Gamma_{t-1}\left(\bar{\omega}_t\right)\right] R_t^k Q_{\bar{K},t-1} \bar{K}_t + W_t^e. \tag{2.15}$$

In sum, $\bar{N}_{t+1}$, $\bar{\omega}_{t+1}$ and L_t can be determined by (2.44) and the two equations which characterize the solution to the entrepreneur's problem.[21] Notably, it is possible to solve for these aggregate variables without determining the distribution of net worth in the cross-section of entrepreneurs, $f_t\left(N\right)$, or the law of motion over time of that distribution. By the definition of leverage, L_t, these variables place a restriction on $\bar{K}_{t+1}$. This restriction replaces the intertemporal equation in the standard model, which relates the rate of return on capital, R_{t+1}^k, to the intertemporal marginal rate of substitution in consumption. The remaining two financial variables to determine are the aggregate quantity of debt extended to entrepreneurs in period t, B_{t+1}, and their state-contingent interest rate, Z_{t+1}. Note,

$$B_{t+1} = \int_0^\infty B_{t+1}^N f_t\left(N\right) dN = \int_0^\infty \left[Q_{\bar{K},t} \bar{K}_{t+1}^N - N\right] f_t\left(N\right) dN = Q_{\bar{K},t} \bar{K}_{t+1} - \bar{N}_{t+1},$$

where the last equality uses (2.13) and (2.14). Finally, Z_{t+1} can be obtained by integrating (2.10) relative to the density $f_t\left(N\right)$ and solving $Z_{t+1} = R_{t+1}^k \bar{\omega}_{t+1} L_t$.

[21] The relations that characterize the solution to the time t entrepreneur's problem are, first, one zero profit condition,

$$\left[\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right] \frac{R_{t+1}^k}{R_{t+1}} L_t - L_t + 1 = 0,$$

for each period $t+1$ state of nature; and second, the following single efficiency condition:

$$E_t \left\{ \left[1-\Gamma_t(\bar{\omega}_{t+1})\right] \frac{R_{t+1}^k}{R_{t+1}} + \frac{\Gamma_t'(\bar{\omega}_{t+1})}{\Gamma_t'(\bar{\omega}_{t+1}) - \mu G_t'(\bar{\omega}_{t+1})} \left[\frac{R_{t+1}^k}{R_{t+1}} \left(\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1})\right) - 1 \right] \right\} = 0.$$

2.3 Household Problem and Resource Constraint

The budget constraint of the representative household is as follows:

$$
\begin{aligned}
& \left(1+\tau^{c}\right) P_{t} C_{t}+B_{t+1}+B_{t+40}^{L}+\left(\frac{P_{t}}{\Upsilon^{t} \mu_{\Upsilon, t}}\right) I_{t}+Q_{\bar{K}, t}(1-\delta) \bar{K}_{t} \\
\leq \quad & \left(1-\tau^{l}\right) \int_{0}^{1} W_{t}^{i} h_{i, t} d i+R_{t} B_{t}+\left(R_{t}^{L}\right)^{40} B_{t}^{L}+\Pi_{t}+Q_{\bar{K}, t} \bar{K}_{t+1} .
\end{aligned} \tag{2.16}
$$

Here, B_{t+1} denotes mutual fund deposits acquired by the household at the end of period t and R_t denotes the gross nominal return on deposits acquired in period $t-1$, which is not contingent on the period t state of nature. Also, τ^c and τ^l denote the tax rate on consumption goods and on wage income, respectively. We also give the household access to a long term (10 year) bond, B^L_{t+40}, which pays off R^L_{t+40} in period $t+40$. The nominal return on this bond, R^L_{t+40}, is known at time t. The expression, Π_t, denotes profits net of lump sum taxes earned by the household. The remaining terms in (2.16) pertain to the household's activities in constructing capital. At the end of the production period in t, the household purchases investment goods, I_t, from final good producers and existing capital, $(1-\delta)\bar{K}_t$, from entrepreneurs and uses these to produce and sell new capital, $\bar{K}_{t+1}$ using the technology in (2.4).

The household's problem is to maximize (2.7) subject to (2.16). We complete the description of the model with a statement of the resource constraint:

$$
Y_t = D_t + G_t + C_t + \frac{I_t}{\Upsilon^t \mu_{\Upsilon,t}} + a(u_t)\Upsilon^{-t}\bar{K}_t,
$$

where the last term on the right represents the aggregate capital utilization costs of entrepreneurs, an expression that makes use of (2.14) and the fact that each entrepreneur sets the same rate of utilization on capital, u_t. Also, D_t is the aggregate resources used for monitoring by mutual funds:

$$
D_t = \mu G(\bar{\omega}_t)\left(1+R_t^k\right)\frac{Q_{\bar{K},t-1}\bar{K}_t}{P_t}.
$$

Finally, G_t denotes government consumption, which we model as

$$
G_t = z_t^* g_t, \tag{2.17}
$$

where g_t is a stationary stochastic process. We adopt the usual sequence of markets equilibrium concept.

2.4 Shocks, Information and Model Perturbations

In our analysis, we include a measurement error shock on the long term interest rate, R_t^L. In particular, we interpret

$$\left(R_t^L\right)^{40} = \left(\tilde{R}_t^L\right)^{40} \eta_{t+1} \cdots \eta_{t+40},$$

where η_t is an exogenous measurement error shock. The object, R_t^L, denotes the long-term interest rate in the model, while $\tilde{R}_t^L$ denotes the long-term interest rate in the data. If η_t accounts for only a small portion of the variance in $\tilde{R}_t^L$, then we infer that the model's implications for the long term rate are good.

The model we estimate includes 12 aggregate shocks: η_t, ϵ_t, μ_{zt}, λ_{ft}, π_t^*, $\zeta_{c,t}$, $\mu_{\Upsilon,t}$, $\zeta_{I,t}$, γ_t, σ_t, ε_t^p and g_t. We model the log-deviation of each shock from its steady state as a first order univariate autoregression. In the case of the inflation target shock, we simply fix the autoregressive parameter and innovation standard deviation to $\rho_{\pi^*} = 0.975$ and $\sigma_{\pi^*} = 0.0001$, respectively. This representation is our way of accommodating the downward inflation trend in the early part of our data set. Also, we set the first order autocorrelation parameter on each of the monetary policy and equity shocks, ε_t^p and γ_t, to zero.

We now discuss the timing assumptions that govern when agents learn about shocks. A standard assumption in estimated equilibrium models is that a shock's statistical innovation (i.e., the one-step-ahead error in forecasting the shock based on the history of its past realizations) becomes known to agents only at the time that the innovation is realized. Recent research casts doubt on this assumption. For example, Alexopoulos (2011) and Ramey (2011) use US data to document that people receive information about the date t statistical innovation in technology and government spending, respectively, before the innovation is realized. These observations motivate us to consider the following shock representation:

$$x_t = \rho_x x_{t-1} + \overbrace{\xi_{0,t} + \xi_{1,t-1} + \ldots + \xi_{p,t-p}}^{=u_t}, \tag{2.18}$$

where $p > 0$ is a parameter. In (2.18), x_t is the log deviation of the shock from its nonstochastic steady state and u_t is the *iid* statistical innovation in x_t.[22] We express the variable, u_t, as a sum of *iid*, mean zero random variables that are orthogonal to x_{t-j}, $j \geq 1$. We assume that at time t, agents observe $\xi_{j,t}$, $j = 0, 1, \ldots, p$. We refer to $\xi_{0,t}$ as the 'unanticipated component' of u_t and to $\xi_{j,t}$ as the 'anticipated components' of u_{t+j}, for $j > 0$. These bits of news are assumed

[22] This is a time series representation suggested by Josh Davis (2007) and also used in Christiano, Ilut, Motto and Rostagno (2010).

to have the following correlation structure:

$$\rho_{x,n}^{|i-j|} = \frac{E\xi_{i,t}\xi_{j,t}}{\sqrt{\left(E\xi_{i,t}^2\right)\left(E\xi_{j,t}^2\right)}},\ i,j=0,...,p, \tag{2.19}$$

where $\rho_{x,n}$ is a scalar, with $-1 \leq \rho_{x,n} \leq 1$.[23] The subscript, n, indicates 'news'. For the sake of parameter parsimony, we place the following structure on the variances of the news shocks:

$$E\xi_{0,t}^2 = \sigma_{x,0}^2,\ E\xi_{1,t}^2 = E\xi_{2,t}^2 = ...E\xi_{p,t}^2 = \sigma_{x,n}^2.$$

In sum, for a shock, x_t, with the information structure in (2.18), there are four free parameters: ρ_x, $\rho_{x,n}$, $\sigma_{x,0}$ and $\sigma_{x,n}$. For a shock with the standard information structure in which agents become aware of u_t at time t, there are two free parameters: ρ_x, σ_x.

We consider several perturbations of our model in which information structure in (2.18) is assumed for one or more of the following set of shocks: technology, monetary policy, government spending, equity and risk shocks. As we shall see below, the model that has the highest marginal likelihood is the one with signals on the risk shock, and so this is our 'baseline' model specification. We also consider a version of our model called CEE, which does not include financial frictions. Essentially, we obtain this model from our baseline model by adding an intertemporal Euler equation corresponding to household capital accumulation and dropping the three equations that characterize the financial frictions: the equation characterizing the contract selected by entrepreneur, the equation characterizing zero profits for the financial intermediaries and the law of motion of entrepreneurial net worth.

3 Inference About Parameters and Model Fit

This sectior reviews the basic results for inference on our model. We discuss the data used in the analysis, the posteriors for model parameter values, measures of model fit and our specification of news shocks.

3.1 Data

We use quarterly observations on 12 variables covering the period, 1985Q1-2010Q2. These include 8 variables that are standard in empirical analyses of aggregate data: GDP, consumption, investment, inflation, the real wage, the relative price of investment goods, hours worked

[23] We allow for correlation because in preliminary estimation runs, we found that the estimated news shocks were correlated.

and the federal funds rate. We interpret the price of investment goods as a direct observation on $\Upsilon^t \mu_{\Upsilon,t}$. The aggregate quantity variables are measured in real, per capita terms.[24]

We also use four financial variables in our analysis. For our period t measure of credit, B_{t+1}, we use data on credit to non-financial firms taken from the Flow of Funds dataset constructed by the US Federal Reserve Board.[25] Our measure of the slope of the term structure, $R_t^L - R_t$, is the difference beween 10-year constant maturity US government bond yield and the Federal Funds rate. Our period t indicator of entrepreneurial net worth, N_{t+1}, is the Dow Jones Wilshire 5000 index, deflated by the Implicit Price Deflator of GDP. Finally, we measure the credit spread, $Z_t - R_t$, by the difference between the interest rate on BAA-rated corporate bonds and the 10 year US government bond rate.[26]

3.2 Priors and Posteriors for Parameters

We partition the model parameters into two sets. The first set contains parameters that we simply fix a priori. Thus, the depreciation rate δ, capital's share, α, and the inverse of the Frisch elasticity of labor supply σ_L are fixed at 0.025, 0.4 and 1, respectively. We set the mean growth rate, μ_z, of the unit root technology shock and the quarterly rate of investment-specific technological change, Υ, to 0.41% and 0.42%, respectively. We chose these values to ensure that the model steady state is consistent with the mean growth rate of per capita GDP in our sample, as well as the average rate of decline in the price of investment goods. The steady state value of g_t in (2.17) is set to ensure that the ratio of government consumption to GDP is 0.20 in steady state. Steady state inflation is fixed at 2.4 percent on an annual basis. The household discount rate, β, is fixed at 0.9987. There are no natural units for the measurement of hours worked in the model, and so we arbitrarily set ψ_L so that hours worked is unity in steady state. Following CEE, the steady state markups in the labor market λ_w and in the product market

[24] GDP is deflated by its implicit price deflator; real household consumption is the sum of household purchases of nondurable goods and services, each deflated by their own implicit price deflator; investment is the sum of gross private domestic investment plus household purchases of durable goods, each deflated by their own price deflator. The aggregate labor input is an index of nonfarm business hours of all persons. These variables are converted to per capita terms by dividing by the population over 16. (Annual population data obtained from the Organization for Economic Cooperation and Development were linearly interpolated to obtain quarterly frequency.) The real wage, W_t/P_t, is hourly compensation of all employees in nonfarm business, divided by the GDP implicit price deflator, P_t. The short term risk-free interest rate, R_t, is the 3 month average of the daily effective Federal Funds rate. Inflation is measured as the logarithmic first difference of the GDP deflator. The relative price of investment goods, $P_t^I/P_t = 1/\left(\Upsilon^t \mu_{\Upsilon,t}\right)$, is measured as the implicit price deflator for investment goods, divided by the implicit price deflator for GDP.

[25] From the 'flow data' tables we take the 'credit market instruments' components of 'net increase in liabilities' for nonfarm, nonfinancial corporate business and nonfarm, non-corporate business.

[26] We also considered the spread measure constructed in Gilchrist and Zakrajcek (2011). They consider each loan obtained by each of a set of firms taken from the COMPUSTAT database. In each case, they compare the interest rate actually paid by the firm with what the US government would have paid on a loan with a similar maturity. When we repeated our empirical anlaysis using the Gilchrist-Zakrajcek spread data, we obtained similar results.

λ_f are fixed at 1.05 and 1.2, respectively. The steady state value of the quarterly survival rate of entrepreneurs, γ, was set to 0.985. This is fairly similar to the 0.973 value used in Bernanke, et al (1999). Our settings of the consumption, labor and capital income tax rates, τ^c, τ^l and τ^k, respectively, are discussed in Christiano, Motto and Rostagno (2010, pages 79-80).

The second set of parameters to be assigned values consists of the 36 parameters listed in Tables 1a and 1b. We study these using the Bayesian procedures surveyed in An and Schorfheide (2005). Table 1a considers the parameters that do not pertain to the exogenous shocks in the model. The price and wage stickiness parameters, ξ_p and ξ_w, were given relatively tight priors around values that imply prices and wages remain unchanged for on average one-half and one year, respectively. The posteriors for these parameters are higher. The relatively large value of the posterior mode on the parameter, σ_a, governing the capital utilization cost function implies constant utilization. In most cases, there is a reasonable amount of information in the data about the parameters, indicated by the fact that the standard deviation of the posterior distribution is often less than half of the standard deviation of the prior distribution.[27]

We choose to treat the steady state probability of default, $F(\bar{\omega})$, as a free parameter. We do this by making the variance of $\log \omega$ a function of $F(\bar{\omega})$ and the other parameters of the model. The mean of our prior distribution for $F(\bar{\omega})$, 0.007, is close to the 0.75 quarterly percent value used in Bernanke, et al (1999), or the 0.974 percent value used in Fisher (1999). The mode of the posterior distribution is not far away, 0.0056. The mean of the prior distribution for the monitoring cost, μ, is 0.275. This is within the range of $0.20 - 0.36$ that Carlstrom and Fuerst (1997) defend as empirically relevant. The mode of the posterior distribution for μ is close, 0.2149. Comparing prior and posterior standard deviations, we see that there is a fair amount of information about the monitoring cost in our data and somewhat less about $F(\bar{\omega})$. The steady state value of the risk shock, $\sigma = \sqrt{Var(\log(\omega))}$, that is implied by the mode of our model parameters is 0.26. Section 5 below discusses some independent evidence on the empirical plausibility of this result for the risk shock.

Values for the parameters of the shock processes are reported in Table 1b. The posterior mode of the standard deviation of the unanticipated component of the shock to $\log \sigma_t$, $\xi_{0,t}$, is 0.07. The corresponding number associated with the anticipated components, $\xi_{i,t}$, $i = 1, ..., 8$, is 0.0283. This implies that a substantial 57 percent of the variance in the statistical innovation in $\log \sigma_t$ is anticipated.[28] The posterior mode on the correlation among signals is 0.4. Thus,

[27] In this remark, we implicitly approximate the posterior distribution with the Laplace approximation, which is Normal.

[28] In particular,

$$0.57 = \frac{8 \times 0.0283^2}{8 \times 0.0283^2 + 0.07^2}.$$

when agents receive information, $\xi_{i,t}$, $i = 0, ..., 8$ about current and future risk, there is a substantial correlation in news about adjacent periods, while that correlation is considerably smaller for news about horizons three periods apart and more.[29]

For the most part, the posterior modes of the autocorrelations of the shocks are quite large. The exception is the autorcorrelation of the growth rate of the persistent component of technology growth, $\mu_{z,t}$. This is nearly zero, so that $\log z_t$ is nearly a random walk. There appears to be substantial information in the data about the parameters of the shock processes, as measured by the small size of the posterior standard deviation relative to the prior standard deviation. The exception is the anticipated and unanticipated components of the risk shock, where the standard deviation of the posterior is actually larger than the standard deviation of the prior.

3.3 Where is the News?

In our baseline model we include 'news shocks' on risk and not on other variables. On the other hand, much of the news literature includes these shocks on technology and government consumption. This section reports marginal likelihood statistics which suggest that the most preferred shock to put news on is the risk shock.

Consider Table 2. According to that table the (log) marginal likelihood of our baseline model is 4563.37. When we drop signals altogether, the marginal likelihood drops a tremendous amount, roughly 400 log points. We then consider adding news shocks to various other shocks (keeping the news shocks off of risk shocks). When we add news shocks only to the equity shock, γ, the marginal likelihood jumps substantially, but not as much as when we add news shocks to risk. The same is true when we add news shocks to the monetary policy shock and to all our technology shocks. When we add news shock to government consumption shocks, the marginal likelihood actually drops a little. Overall, the analysis favors the use of news shocks, but most prefers adding them to risk, as in our baseline specification.

3.4 Measures of Fit

Our model has more parameters than a standard medium-sized DSGE model like CEE. Although we have at the same time confronted our model with more data, we nevertheless want to guard against overparameterization. A symptom of overparameterization is that model

[29] For example, the correlation between $\xi_{1,t}$ and $\xi_{4,t}$ is only $0.4^3 = 0.06$.

predictions deteriorate for objects not included in the estimation sample.[30] For this reason, this section examines our model's out of sample forecasts along two dimensions. We find little evidence of overparameterization. We also display the results of an in-sample measure of fit: the model and data correlations between output and various other variables.

Figure 2 displays out-of-sample root mean square errors (RMSE's) at forecast horizons, $j = 1, 2, ..., 12$. Our first set of 12 forecasts is computed in 2001Q3 and our last set of forecasts is computed in 2008Q1. We include forecasts for each of the 12 variables in our dataset. Thus, we consider forecasts of quarterly growth rates of the variables our model predicts are not covariance-stationary and we consider forecasts of levels of the variables that our model predicts are stationary. We include two benchmark RMSE's for comparison. The first benchmark corresponds to the RMSE's implied by a Bayesian vector autoregression (BVAR), constructed using the procedure applied in SW.[31] The second benchmark corresponds to the RMSE's implied by the version of our DSGE model labeled CEE and discussed in section 2.4. Forecasts of the BVAR are based on the posterior modes of the parameters updated each quarter. In the case of the DSGE models, we update the parameters every other quarter. The grey area in the figures is centered on the RMSE's for the BVAR. It is constructed so that if the RMSE of our baseline model lies in the grey area for a particular variable and forecast horizon, then the classical null hypothesis that the two RMSE's are actually the same in population fails to be rejected at the 95 percent level at that horizon.[32]

With one exception, our baseline model's performance is the same or better than that of the CEE model and - in the case of variables not in the CEE model - the baseline model does about the same or better than the BVAR. In the case of inflation, the baseline model does noticeably better than the CEE model and even lies below the grey area about the BVAR. The exceptional case, in which the baseline model performs noticeably worse than the BVAR, corresponds to the credit spread. Our overall impression is that there is little evidence of overparameterization in our baseline model.

[30] A dramatic illustration of the dangers of overparameterization is provided by the demonstration file, census.m, provided with the program language MATLAB. Decadal observations on the US population, 1900-2000, are fitted with a sequence of higher order polynomial trends. Each polynomial provides a better in-sample fit of the data until the 10th order polynomial provides a perfect fit to the 11 observations. Low order polynomials provide reasonable forecasts for the post-2000 population, but as the order increases above 4 the forecasts become increasingly erratic and bizarre.

[31] In particular, we work with a first order vector autoregression specified in levels (or, in case of the real quantities, log levels) of all the variables. With one exception we implement the so-called Litterman priors. In particular, for the variables that our model predicts are non-startionary, we center the priors on a unit root specifiation. For the variables that our model predicts are stationary, we center the priors on the first order autoregressive representation with autoregressive coefficient 0.8. [Fill in the rest of the details about how the priors are parameterized and how ML's are not robust to priors, though RMSEs are.]

[32] The procedure we use is the one proposed in Christiano (1989). The sampling theory we use does not take into account that the test is executed for multiple horizons.

For our second out-of-sample test of the model we use the two-sided Kalman smoother to estimate the period t default rate, $F_{t-1}(\bar{\omega}_t)$, implied by our model and compare it with the deliquency rate on all loans extended by commerical banks.[33] The results are reported in Figure 3. Note that the default rate implied by our model rises and falls with each of the three recessions in our sample, just like the loan delinquency rate. However, the match between our model's default rate and the delinquency rate is not perfect since the latter lags recessions somewhat. First, the levels of the two variables are different. To some extent, this may reflect that the loan delinquency rate is only an indicator of the model's default rate. It may be that in practice, troubled firms default on other creditors first and only on commercial banks later and as a last resort. Second, our model's default rate peaks during the first and last recessions in our sample and actually leads the middle recession somewhat. We suspect that the reason our model's default rate does not lag the cycle like the delinquency rate is that the credit spread used in our analysis also does not lag the cycle.

In sum, we provide two out-of-sample tests of our model. In both cases, the model passes reasonably well.

Figure 4 displays the model's implications for the dynamic cross-correlations of year-over-year output growth with several variables.[34] The grey area is a centered 95% confidence interval about the corresponding empirical estimates, which are not displayed.[35] The line with stars are the model correlations when all shocks are fed to it. (The lines with circles are discussed later.)[36] For the most part, the model correlations conform with the corresponding sample statistics from our dataset. There are some exceptions. For example, the model understates the contemporaneous correlation between output and consumption and overstates the dynamic correlation between output and future consumption (see Panel F). Also, while the model captures the general countercyclical pattern in the credit spread, the model implies the credit spread lags output slightly while there is (modest) evidence that the spread leads output in the data. The economic reasons behind these exceptions are discussed later.

[33] The data were obtained from the St. Louis Federal Reserve Bank's online database, FRED. The FRED mnenomic is DRALACBS.

[34] Variables that are non-stationary according to the model are measured in year-over-year growth rates, while the credit spread and term structure slope are measured in levels.

[35] The confidence intervals were computed using standard Generalized Method of Moments formulas. We stacked all the parameters in the cross correlation, $corr\,(y_t, x_{t-k})$, between HP filtered and logged output, y_t, and some other variable, x_t, in a vector, say β. We then formed a vector, $u_t(\beta)$, such that $Eu_t\left(\beta^0\right) = 0$, where β^0 denotes the true value of the cross-correlations. The exactly identified estimator of β, $\hat{\beta}$, sets the sample average of $u_t(\beta)$ to zero. The object, $\hat{\beta}$, has an asymptotically Normal distribution with variance-covariance matrix that requires a consistent estimator of the spectral density at frequency zero of $u_t\left(\beta^0\right)$. Let $\Gamma_j\left(\beta^0\right) \equiv Eu_t\left(\beta^0\right) u_{t-j}\left(\beta^0\right)'$ for $|j| \geq 0$. Our estimator of the zero frequency spectral density is $\Gamma_0\left(\hat{\beta}\right)+\Gamma_1\left(\hat{\beta}\right)+\Gamma_1\left(\hat{\beta}\right)'$.

[36] Model-based calculations were executed on a single sample of artificial data of length 100,000.

4 The Risk Shock

Our main finding in this paper is that the risk shock is a key driver of the business cycle. We begin this section by describing various quantitative indicators of the importance of the shock. We then discuss what it is about our model and data that explains our finding. Finally, we show what shocks are displaced with the introduction of the risk shock.

4.1 Measuring the Importance of the Risk Shock

Consider first the results in Figure 5. The solid line in panel a displays the year over year growth rate in per capita, real US gross domestic product (GDP) for our sample. An interpretation of this line is that it is the result of simulating our model's response to all of the estimated shocks and to the initial conditions. The dotted line shows the result of this same simulation when we only feed our model the estimated risk shock, including its unanticipated and anticipated components. The notable feature of panel a is how close the dotted and solid lines are to each other. According to the results, the decline in GDP growth associated with the 2001 recession is closely associated with the risk shock. The 2007 recession is somewhat different. The initial phase of that recession seems to have been driven by factors other than the risk shock. However, according to the results the accelerated collapse in economic activity that occured in late 2008 was largely due to an increase in risk at that time. Not coincidentally, this is also the time when the credit spread increased sharply (see panel f). The remaining panels in Figure 5 indicate that the risk shock is even more closely associated with aggregate financial variables than it is with aggregate output. Thus, panel b shows that the risk shock alone accounts for a large portion of the fluctuations in the log level of per capita, real equity. Panel c shows that a very large part of the movements in the year over year growth rate in real per capita credit are accounted for by the risk shock. Panel d indicates that the risk shock accounts for a substantial component of the fluctuations in the slope of the term structure of interest rates. Panel e shows that the risk shock accounts for a very large part of the movements in the credit spread. In sum, the risk shock accounts for a large part of the movements of the key variables in our data set.

To gain additional insight into the results in panel e, panel f displays the estimated risk shock and our measure of the credit spread, copied for convenience from Figure 3.[37] Note that although the risk shock, σ_t, and the credit spread are positively related, they are by no means perfectly correlated. This is so, despite the panel e result that when we feed only the estimated

[37] The estimated risk shock was obtained by applying the Kalman smoother and our model with its parameters evaluated at their posterior mode, to the data. The risk variable reported in the figure is $(\sigma_t - \sigma)/\sigma$.

anticipated and unanticipated innovations in σ_t to the baseline model, the resulting simulated credit spread tracks the corresponding empirical measure very closely. In effect, the position taken by the model is that the credit spread is a complicated dynamic function of the signals about the risk shock, σ_t, and not just a simple function of the contemporaneous value of σ_t.

Our final indicator of the importance of risk shocks appears in Table 3. That table reports the percent of the variance in the level of several variables at business cycle frequencies, contributed by our shocks.[38] This is done for several specifications of our model. The entries in the first column of panels have a format, $x|y|z$, where x, y and z each denote the percent of business cycle variance due to various components of the innovations to risk. The variable, x pertains to both anticipated and unanticipated components, $\xi_{0,t}, ..., \xi_{8,t}$; y pertains to the unanticipated component, ξ_t^0; and z pertains to the anticipated component, $\xi_{1,t}, ..., \xi_{8,t}$. The sum, $x + y + z$, does not always add to unity because there is a small amount of correlation between the shocks (see (2.19)). In each case, the model is evaluated at the mode of its parameters, computed using the dataset indicated in the first column.

Consider the results in the first row of each panel, which correspond to our baseline model with the values of the parameters set at their posterior mode (subsequent rows are considered later). The first column of panels pertain to the risk shock. Consistent with the evidence in Panel a of Figure 5, over 60 percent of the business cycle variance in output is accounted for by the risk shock. Indeed, the risk shock is by far more important for GDP than are any of the other shocks. Again, consistent with the findings in Figure 5, the risk shock also plays a big role in the business cycle fluctuations of financial variables, namely the level of the log of the real value of each of the stock market ('Equity'), the premium ('Premium'), credit ('Credit') and the slope of the term structure ('Slope'). Interestingly, the risk shock makes the linear term structure model of interest rates look good, because our term premium shock (i.e., the 'error in the linear term structure) only accounts for 7 percent of the fluctuations in the term structure. The other rows in each panel of Table 3 provide some insight into why the risk shock is so important, and these are discussed later.

4.2 *Why* is the Risk Shock So Important?

The simple answer to the question in the title is that when fed to our model, the risk shock generates responses that resemble the business cycle. One way that we show this is by studying our model's impulse responses to disturbances in risk. In principle, model impulse responses

[38] We compute the variance of the (log) levels of the variables in the frequency domain, leaving off frequencies lower than the business cycle.

point to another way to evaluate a model, namely by comparing them to analogous objects estimated using minimally restricted vector autoregressions (VAR). However, the model developed here implies that standard methods for identifying VARs do not work.[39] These considerations motivate us to also consider a second type of evidence, one based on the implications of risk shocks for the dynamic cross-correlations of aggregate output with various macroeconomic variables. Finally, we ask which variables in our dataset account for the pre-eminence of the risk shock over other variables.

4.2.1 Impulse Response Functions

Turning to impulse response functions, Figure 6 displays the dynamic response of various variables to an unanticipated shock in risk (i.e., $\xi_{0,t}$, solid line) and to a 2 year-ahead anticipated shock (i.e., $\xi_{8,t}$, line with circles). (The thick solid line and thick line with circles will be discussed later.) Both shocks occur in period 0. To simplify the interpretation of the impulse responses, each of $\xi_{0,0}$ and $\xi_{8,0}$ are disturbed in isolation, ignoring the fact that according to our empirical analysis, these variables are correlated. In addition, we restrict both shocks to be the same magnitude, with $\xi_{0,0} = \xi_{8,0} = 0.10$.

Panel H displays the dynamic response of σ_t to the two shocks. The response of σ_t to $\xi_{8,0}$ is the same as the response to $\xi_{0,0}$, except that it is displaced by 8 periods. According to Panel A, the response of the credit spread to $\xi_{0,0}$ and $\xi_{8,0}$ differs in the same way that the response in σ_t to these shocks differs.[40] Still, the response of the credit spread is countercyclical in each case. The dynamic responses of the other variables to $\xi_{0,0}$ and to $\xi_{8,0}$ are much more similar. In particular, credit, investment, output and inflation all drop immediately and persistently in response to both $\xi_{0,0}$ and $\xi_{8,0}$. In all these cases, the eventual response to $\xi_{8,0}$ exceeds the eventual response to $\xi_{0,0}$. The slope of the term structure of interest rates, $R_t^L - R_t$, responds countercylically in response to jumps in response to both risk shocks. Notably, the peak

[39] The results in Figure 5 (e) and in Table 3 suggest that the risk shock and the credit spread are very similar. This might tempt one to pursue a standard identification strategy to obtain an empirical estimate of the impulse response function of macroeconomic variables to risk shocks. This strategy would interpret one-step-ahead forecast errors in the interest rate spread computed using a limited list of standard aggregate variables as shocks to σ_t that are unexpected by economic agents. Under this interpretation, the estimated dynamic responses in economic variables to the one-step-ahead forecast error in the interest rate spread would constitute an empirical estimate of the model's impulse response to risk shocks. But, this standard identification strategy is not justified in our framework because of our assumption that components of the one-step-ahead forecast error in risk are anticipated as much as two years in advance. Ramey (2011) in particular has emphasized how the standard identification strategy leads to distorted inference when agents receive advance news about one-step-ahead forecast errors.

[40] Note that $\xi_{0,t}$ has a smaller impact on the period t interest rate spread than on subsequent values of the spread. This is because the period t spread corresponds to loans extended in period $t-1$. Disturbances in $\xi_{0,t}$ affect σ_t, which has a direct impact on loans extended in period t and therefore on the period $t+1$ spread. The fact that $\xi_{0,t}$ has some effect on the period t spread reflects the state contingency in the interest rate paid by entrepreneurs.

response of the slope to $\xi_{8,0}$ is twice as big as the peak response of the slope to $\xi_{0,0}$.

Consider Panel F, which displays the response of consumption to a jump in risk. There is perhaps a small qualitative difference in the response of consumption to the $\xi_{0,0}$ and $\xi_{8,0}$ shocks. Consumption drops immediately in response to $\xi_{0,0}$ while it exhibits almost no response in the immediate aftermath of a disturbance in $\xi_{8,0}$. Still, in both cases consumption eventually drops sharply. We now discuss the economics of the decline in consumption in the wake of a rise in risk.

From the perspective of the representative household in our model, a rise in risk resembles an increase in the tax rate on the return to investment.[41] This is because as risk increases, a larger share of the return to investment is siphoned off by the monitoring costs associated with increased bankruptcy. Of course, there is a wealth effect that works in the other direction, dragging consumption down after a rise in risk. For example, if monitoring costs absorbed a substantial portion of output, then we would expect these wealth effects to be important. However, these wealth effects play only a minor role in our model. From this perspective, one is led to anticipate that a rise in risk induces substitution away from investment and towards the alternatives: consumption and leisure. In particular, this intuition leads one to anticipate that risk shocks counterfactually predict consumption is countercyclical and that they therefore cannot be important impulses to the business cycle. So, a key challenge for understanding why our analysis concludes risk shocks are in fact a very important source of business cycles is to explain why the consumption response to risk shocks is procyclical.

One way to understand the impact of risk shocks begins with the identity that total output equals total spending. If a component of spending is reduced for some reason (say, because of a rise in risk), then output will decline by the same amount, unless some other component of spending on goods increases. In practice, it is desirable for other components of spending to rise to at least partially offset the fall in investment because otherwise productive resources such as capital and labor are wasted. Frictionless markets avoid this inefficient outcome by engineering a fall in the price of the goods whose demand has declined, relative to the price of other goods. One such relative price in the present example is the price of current goods relative to the price of future goods, i.e., the real interest rate. For example, when there is a temporary jump in the tax on the period $t+1$ return to capital, then the real interest rate from

[41] For a formal discussion of this point, see Christiano and Davis (2006). They show that a model like the one in this paper is isomorphic to a real business cycle model with shocks to the tax rate on the rate of return on capital. Christiano and Davis (2006) build on the analysis of Chari, Kehoe and McGrattan (2007), who stress the insights one gains by mapping a given dynamic model into a real business cycle model with 'wedges'. Chari, Kehoe and McGrattan (2007) illustrate their point by displaying the isomorphism between a real business cycle model with suitably constructed wedges and the model of financial frictions proposed by Carlstom and Fuerst (1997).

t to $t+1$ drops and time t consumption rises. The market signal that encourages households to raise consumption is a drop in the real interest rate.[42]

This reasoning suggests that the dynamics of the real interest rate holds the key to understanding why risk shocks make consumption procyclical.[43] In our model the real interest rate is not entirely determined by market forces because the nominal rate of interest is controlled by the monetary authority. Of course, the fact that the monetary authority controls the nominal interest rate would be irrelevant if prices were fully flexible, because for the most part it is the real interest rate that controls allocations. But, in our model prices do not adjust flexibly to shocks, both because there are direct frictions in changing prices and because of inertia in wages. As a result, the fact that the monetary authority controls the nominal rate of interest implies that it also controls the real rate of interest. This suggests the possibility that the response of consumption to a risk shock depends on the nature of monetary policy.

To evaluate these ideas, Figure 7 displays the response of consumption and the real interest rate to a positive shock in $\xi_{0,0}$, under various model perturbations. Here, we use the long-term concept of the real interest rate.[44] In both panels of Figure 7, the solid line displays the responses in our baseline model, taken from the relevant portions of Figure 6. The lines with circles correspond to the case of flexible prices and wages, i.e., $\xi_p = \xi_w = 0$. Note that, consistent with the intuition outlined above, consumption rises in the wake of a positive shock

[42] The following calculations illustrate the logic in the text. Consider an annual real business cycle model in which the resource constraint is $C_t + I_t \leq K_t^{0.36} h_t^{0.64}$, $I_t = K_{t+1} - 0.9K_t$, and the period utility function is $\log C_t + 2.5 \log(1 - h_t)$ with discount factor, $\beta = 0.97$. The after tax rate of return on capital constructed in period t, K_{t+1}, is $(1-\tau_t)\left[0.36\left(h_{t+1}/K_{t+1}\right)^{0.64} + 0.9\right]$, where τ_t is observed in period t, and is the tax rate on the time $t+1$ realized return on capital. Perturbations in τ_t are a reduced form representation of shocks to σ_t, according to the analysis in Christiano and Davis (2006). The revenue effects of τ_t are assumed to be distributed in lump sum form back to households, thus eliminating wealth effects associated with τ_t. We suppose that $\tau_t = 0.9\tau_{t-1} + \varepsilon_t$, where ε_t is an iid shock. In steady state, $C/Y = 0.73$. We solved the model by a standard log-linearization procedure. We set $\varepsilon_0 = 0.01$ and $\varepsilon_t = 0$ for $t > 0$. The shock has a substantial negative impact on investment, which drops 16 percent in period 0. Absent a response in C_0, output would have fallen 2.7 percent. In fact, C_0 rises by 2.7 percent so that the actual fall in output is smaller (though not a lot smaller!). The market force that guides the rise in C_0 is a drop in the real rate of interest.

[43] Our discussion assumes separability between consumption and leisure in the utility function. Furlanetto and Seneca (2011) show that consumption could fall in response to a contractionary intertemporal shock such as a jump in risk if the marginal utility of consumption is increasing in labor.

[44] According to the model, the period t long term real interest rate is more closely connected to period t consumption than, for example, the one period real interest rate at period t. Our long term interest rate is the real non-state contingent interest rate on a 10 year bond purchased in period t which pays off only in period $t+40$. It is the value of r_t^L which solves:

$$u_{c,t} = \left(r_t^L \beta\right)^{40} E_t u_{c,t+40},$$

where $u_{c,t}$ denotes the derivative of date t present discounted utility with respect to C_t. To see the importance of r_t^L for current consumption, suppose marginal utility is a function of C_t alone and note that $E_t u_{c,t+40}$ does not respond to stationary shocks at time t, such as disturbances to risk. In this way the above equation represents C_t as a function of r_t^L alone. In our environment, we assume habit persistence so that $u_{c,t}$ is not just a function of C_t, but the logic based on the assumption of time separable utility is nevertheless a good guide to intuition.

to risk under flexible wages and prices. This outcome is accomplished by a greater drop in the real rate of interest in the flexible wage and price case. These results suggest that if monetary policy were to cut the interest rate more aggressively in the wake of a risk shock, consumption would respond by rising. We verified this by introducing a term, $-(\sigma_t - \sigma)$, in the monetary policy rule (recall, a variable without a subscript refers to its steady state value). In this way, the monetary authority reduces the nominal rate of interest more sharply in response to a risk shock than it does in our baseline specification. Panel A in Figure 7 confirms that in this case, consumption indeed does rise in the wake of a risk shock.

Thus, our analysis indicates that consumption is procyclical in response to risk shocks because under our (standard) representation of monetary policy, the authorities do not cut the interest rate very aggressively in response to a contractionary risk shock. This is so, despite the fact that our empirical estimate of the weight on anticipated inflation in the policy rule, 2.4, is somewhat high relative to other estimates reported in the literature (see Table 1a). Given that a positive shock to risk reduces inflation, a relatively high weight on inflation in the monetary policy rule implies that the monetary authority reduces the interest rate relatively sharply in response to such a shock.[45] Still, the high weight assigned to inflation in our estimated policy rule is not large enough to support allocations that resemble the ones that occur under flexible wages and prices. We have found that one must raise the weight on inflation to an unrealistically high level of around 30 to support those allocations.

The finding that the interest rate response to risk shocks under the standard formulation of monetary policy is too weak to support the flexible price and wage allocations has been found for other shocks as well.[46] Consistent with this intuition, the thick lines in Panel F of Figure 6 show that when the weight on inflation in the monetary policy rule, α_π, is reduced to 1.5, then the drop in consumption in the wake of a risk shock is stronger. The impact is particularly noticeable for the anticipated shock, $\xi_{8,0}$. The cut in the value of α_π does not have an interesting impact on any of the other responses in Figure 6, and so we do not display those in the figure.

4.2.2 Dynamic Cross Correlations

Figure 4 provides a second way to make precise our assertion that risk shocks generate dynamics that resembles the business cycle. For these purposes, we define the business cycle as the

[45] This is a numerical finding. A higher weight on inflation leads the monetary authority to cut the interest rate more for a given fall in inflation. However, the magnitude of the fall in inflation is itself reduced with a higher coefficient on inflation. Based on these a priori considerations, it is not clear whether the interest rate should fall more or less in the wake of a positive shock to risk, when the weight on inflation is increased.

[46] For further discussion, see Christiano, Trabandt and Walentin (2011).

dynamic cross correlations between output and the variables in Figure 6. As discussed earlier, before computing the correlations in Figure 4, our data on output, credit, investment, equity and consumption were logged and converted to year-over-year growth rates. The grey area is a centered 95 percent confidence interval about the empirical correlations, which are not themselves displayed. In the figure, 'slope' indicates the slope of the term premium, $R^L - R$, and credit spread indicates $Z - R$, the premium of the interest rate paid by (non-defaulting) entrepreneurs over the risk-free rate. The circled lines in Figure 4 display the model-implied correlations when only the risk shocks (both unanticipated and anticipated) are activated. We emphasize two results in Figure 4. First, the dynamic correlations implied by the model with only risk shocks resemble the correlations when all shocks are activated. This illustrates how risk shocks are a dominant shock in the model. Second, the dynamic correlations with only the risk shock resemble broadly the corresponding objects in the data and in this sense, they generate what looks like a business cycle.

Taken together the impulse response functions and cross correlation analysis quantify the sense in which risk shocks in the model generate dynamics that resemble the business cycle. This is the principle reason why our econometric analysis assigns such an important role in business cycles to risk shocks.

4.2.3 Which Data Account for the Importance of the Risk Shock?

Our conclusion that the risk shock is the most important shock driving the business cycle depends very much on the fact that we include financial variables in the analysis. We can see this by examining the rows beyond the first one in each panel of Table 3. Those rows report our analysis when the variable or variables in the left column are deleted from the dataset. For example, the second row in the first panel reports what happens when credit is dropped (see 'delete credit'). Generally, the number of model parameters is invarient to which row is considered, with two obvious exceptions. When equity is dropped from the data set, the measurement error variance for equity drops from the set of model parameters. Similarly, when the slope of the term structure is dropped, then the parameters governing the term structure shock drop from the set of model parameters.

The key thing to note is that when all financial variables are dropped, then the risk shock vanishes in importance and the marginal efficiency of investment shock appears to be the most important driver of the business cycle. Thus, note that the row, 'drop all fin. var' indicates that risk shocks play virtually no role in fluctuations in output, consumption and investment. In the absence of the financial variables from the dataset, the resulting model resembles, in terms of the explanatory role of the shocks, the CEE model. In particular, the major shock driving fluctuations is the marginal efficiency of invesment shock, $\xi_{I,t}$. To some extent, the degree to which the risk shock is pushed out when the financial variables are dropped is overstated in Table 3. The Laplace approximation of the log marginal likelihood of the model without financial variables is 3112.9. With the same dataset, we found another local maximum of the posterior density where the Laplace approximation of the log marginal likelihood is only 6 log points lower at 3106.1. The properties of this alternative parameterization of the model resemble those of our baseline model in that the marginal efficiency of investment plays only a modest role and the risk shock is the most important shock. For this reason, we conclude that in the absence of financial variables it is hard to distinguish a parameterization of the model in which the risk shock is important and the marginal efficiency of investment is not important, from another in which the reverse is true. When the financial data are introduced, it is no longer the case that these two parameterizations are hard to distinguish.[47]

According to the results in Table 3, all the financial variables are important for the conclusion that the risk shock is important. However, credit and the credit spread stand out as most important. When either one of those variables are dropped individually, the role of the risk shock decreases substantially, although not as much as when all financial variables are dropped. Evidently, there are interaction effects among the variables that are not apparent when variables are dropped one at a time.

4.3 Why Do Risk Shocks Drive Out Other Intertemporal Shocks?

Our model includes three shocks that affect intertemporal decisions: risk, σ_t, the marginal efficiency of investment, $\zeta_{I,t}$, and shocks to equity, γ_t. We find that the risk shock is far more important than the other two shocks. For example, according to Table 3, disturbances in σ_t account for 62 percent of the fluctuations in output while shocks to $\zeta_{I,t}$ and γ_t only account for 13 and 0 percent of the business cycle component of output, respectively. We discuss the reasons for these results below.

4.3.1 Marginal Efficiency of Investment Shock

Our finding for $\zeta_{I,t}$ differs sharply from results in the literature, which assign a very substantial role in business cycles to $\zeta_{I,t}$ (see for example, Justiniano, Primiceri and Tambalotti, (2010,

[47] Our results suggest that the posterior distribution when none of the four financial variables are included is the only case where there is a local maximum near the mode. When we included some or all the financial data, we never encountered a local maximum near the mode. Of course, we cannot definitively rule out such alternative maxima.

2011)). We reproduced the finding in the literature for $\zeta_{I,t}$ by estimating the CEE model using a version of our data set that excludes the four financial variables: credit, equity, the credit spread and the term premium. The variance decomposition of the resulting model is reported in Table 3 in square brackets. The entries corresponding to risk and equity shocks are empty, since these shocks do not appear in the CEE model. In addition, we do not include the term premium shock in the CEE model, so that the entry corresponding to this shock is also empty. Consistent with findings reported in the literature, ζ_{It} is the most important shock driving output in the CEE model and accounts for 39 percent of the business cycle fluctuations in that variable.

The key reason that our model prefers the risk shock over the marginal efficiency of investment has to do with the information contained in our data on equity, the credit spread and the flow of credit. To see this, first consider Figure 8, which displays the dynamic response of the variables in our model to several shocks. To facilitate comparison, we repeat the impulse responses to the unanticipated component in risk, $\xi_{0,0}$, from Figure 6 (solid line). The line with circles displays the dynamic responses to an innovation in ζ_{It} in our model. For ease of comparison, we have scaled this innovation so that the maximal decline in output coincides with the maximal decline in the output response to $\xi_{0,0}$. Consider Panel E, which displays the dynamic responses in equity. Note in particular that equity is countercyclical in response to the innovation in ζ_{It}. Evidently, the marginal efficiency of investment shock has the strongly counterfactual implication that the value of equity is countercyclical. This stands in sharp contrast to the risk shock which, consistent with the data, implies that the value of equity is procyclical.

Another way to see the contrasting implications of risk versus the marginal efficiency of investment for the cyclical properties of equity appears in Figure 9. The solid lines indicate historical observations on year over year output growth and on the real value of the stock market. The dotted lines indicate the results of simulating the indicated model responses to the indicated shocks. The left column of graphs reproduce the relevant portions of Figure 5. It shows what output and equity would have been according to the estimated baseline model if only the estimated risk shocks had been active in our sample. The right column of graphs shows what output and equity would have been according to the estimated CEE model if only the marginal efficiency of investment had been active.[48] Note that each shock accounts well for the dynamics of output growth. However, when equity is brought into the picture, the implications of the two perspectives on the sources of economic fluctuations differ sharply.

[48] In the CEE model, we proxy equity by the real price of capital, $Q_{\bar{K},t+1}/P_t$.

The risk shock accounts well for the fluctuations in equity. In contrast, the marginal efficiency of investment predicts stock market booms when there are busts, and busts when there are booms.

The intuition for these results is very simple. Consider a Marshallian cross representation of the market for capital with the price of capital, $Q_{\bar{K},t+1}$, on the vertical axis and the quantity of capital, $\bar{K}_{t+1}$, on the horizontal (see Figure 10). The supply curve corresponds to the marginal cost of building capital, derived from the household's technology for constructing capital discussed just after (2.16). The marginal efficiency of investment perturbs this supply curve. Entrepreneurs are the source of demand for capital. This demand curve is perturbed by the equity and risk shocks, γ_t and σ_t, that affect the terms of entrepreneurial loan contracts with banks. The price of capital is a major input determining entrepreneurs' net worth, N_{t+1}, which we identify with the value of equity in the data.[49] For purposes of intuition, we can think of the price of capital and the value of equity as being the same thing.

Now, suppose that there is a shock to the marginal efficiency of investment which shifts the supply curve to the left. The figure indicates that the equilibrium quantity of capital decreases. This in turn implies that fewer investment goods are purchased by the producers of capital goods, so that there is a decline in production and employment. This explains why the ζ_{It} shock implies that investment is procyclical. A similar logic reaches the conclusion that the σ_t and γ_t shocks also imply procyclical invesment. This intuition is consistent with the results in Figure 8, Panel C.[50] Although the demand and supply shocks have the same implications for the cyclical properties of investment, they have opposite implications for the price of capital and, hence, the value of equity. This explains the results in panel E of Figure 8, as well as the results in Figure 9.

Consider the implications of ζ_{It} for the credit spread. According to Panel A of Figure 8, the marginal efficiency of investment predicts, counterfactually, that the credit spread is procylical. In addition, according to Panel B of Figure 8, the ζ_{It} shock implies that credit rises modestly in a contraction launched by the marginal efficiency of investment shock. This, too, is counterfactual.[51]

[49] The equation that characterizes net worth is given in (2.44). The price of capital enters that expression via the rate of return on capital, (2.9).

[50] The dynamic responses to an innovation in γ_t are displayed with the curve indicated by *'s and the equity innovation has been scaled so that the maximal decline in output coincides with the maximal decline in output in response to a risk shock.

[51] Note from Panel F that consumption is countercyclical in the first two years after a ζ_{It} shock. However, this failure of the model is not robust to alternative parameterizations. For example, when we reduce the coefficient on inflation in the interest rate rule to 1.5, then consumption falls after a ζ_{It} shock, for the reasons discussed in section 4.2.1 above.

4.3.2 Equity Shock

The risk shock, σ_t, also drives out equity shocks, γ_t (recall the variance decomposition results in Table 3). According to Table 3, an important variable underlying this conclusion is credit. To gain intuition into this result, consider the dynamic response of our variables to a negative innovation in γ_t. Again, the size of the innovation is normalized so that the maximal impact on output is the same across the three shocks displayed in Figure 8. According to Panel B, equity and risk shocks have opposite implications for the cyclicality of credit. The reason why equity shocks counterfactually imply countercyclical credit is explored in detail in Appendix C of the online appendix. The idea is that a drop in γ_t, by reducing the net worth of entrepreneurs, causes a drop in the demand for capital at the end of period t (panel E of Figure 8 shows the response of net worth to a decline in γ_t). Because the price of capital is expected to return back up to steady state over time, the period t drop in the price of capital triggers a jump in the expected return to capital. This can be seen in panel H, which shows the immediate drop in the excess return to capital, $\left(1 + R_t^k\right) / \left(1 + R_t\right)$, in period t as the price of period t capital drops, followed by a persistently high excess return. The jump in the expected return on capital causes entrepreneurs to receive more credit in period t. Although credit expands, it does not expand by enough to offset the initial decline in net worth that causes the contraction in spending by entrepreneurs in the first place.

5 Risk Shocks and Uncertainty Measure in Bloom (2009)

In an influential paper, Bloom (2009) has stressed the role of what he refers to as uncertainty in business cycle fluctuations. In that and other papers, 'uncertainty' refers to both cross-sectional dispersion and aggregate volatility. In this paper, we use 'risk' exclusively as a measure of cross-sectional dispersion.

A measure of uncertainty used by Bloom (2009) is the cross-section standard deviation in firm-level stock returns in the CRSP data set. This object is very similar to our risk shock. We show that the stock return data in CRSP provide support for key assumptions in our model about the idiosyncratic shocks, ω, to entrepreneurial returns. The results reported here are motivated by the work Ferreira (2012).

According to our model the log of the realized gross return earned by the i^{th} entrepreneur at $t+1$, $r_{i,t+1}$ has the following decomposition:

$$r_{i,t+1} = \log\left(R_{t+1}^k\right) + \log \omega_{it}, \tag{5.20}$$

where R^k_{t+1} is defined in (2.9). In (5.20), (i) $\log \omega_{it}$ is independently distributed over different t's for each given i, (ii) $\log \omega_{it}$ is independent of $\log\left(R^k_{t+1}\right)$ for all i, and each t and (iii) our econometric procedure provides an estimate of the standard deviation of of $\log \omega_{it}$ for each t. The time subscript on ω_{it} refers to the date in our model when the variance of the idiosyncratic shock to entrepreneurial returns realized in $t+1$ becomes known. The risk shock in our model, σ_t, is the standard deviation of $\log \omega_{it}$.

We begin with (iii), by evaluating our model's implications for the standard deviation of $\log \omega_{it}$. Our environment rationalizes estimating this standard deviation at each date by computing the cross-sectional standard deviation of firm stock returns. This is one of the measures of uncertainty studied by Bloom (2009) and others. Although Bloom (2009) reports results using monthly stock returns, we instead compute quarterly returns to ensure comparability with our risk shock, which is estimated at a quarterly frequency.[52]

The line with circles in Figure 11 corresponds to our risk shock, computed using the Kalman smoother.[53] The line with stars is the cross-sectional standard deviation of firm-level stock returns in CRSP. In particular, if N_t is the number of firms in the CRSP data set in period t, then the period t cross-sectional standard deviation of stock returns is σ^U_t :

$$\sigma^U_t = \left(\frac{1}{N_t}\sum_{i=0}^{N_t}\left[r_{it} - \log\left(1+R^k_t\right)\right]^2\right)^{1/2},\ 1+R^k_t = \frac{1}{N_t}\sum_{i=0}^{N_t}\exp\left(r_{it}\right),$$

where the superscript, 'U' denotes 'uncertainty'. Our estimator of R^k_t makes use of our model assumption that the mean of ω is unity in each period. Given the large typical value of N_t in the dataset, we expect that the estimator of the unobserved common return, R^k_t, is fairly precise. The total number of firms in the data set is 17,757. However, the number of these firms that are in the data set in any particular quarter is smaller. For example, N_t for $t = 1985Q1$ is 4,810. The value of N_t increases to 8,500 in the middle of the data set and then comes down thereafter, to 5,678 at the end of the dataset, $t = 2010Q4$.[54] We refer to σ^U_t as the CRSP-based measure of uncertainty. To ensure comparability, the risk shock reported for period t in Figure 11 is what we call σ_{t-1} in the model.[55]

Note first that the average level and volatility of our risk shock corresponds roughly to the level and volatility of the CRSP-based measure of uncertainty. This suggests that our

[52] Bloom (2009)'s CRSP-based measure of volatility, or uncertainty, appears in row 2 of Table I.

[53] The line with circles in Figure 11 corresponds to σ_t. This differs from the risk shock reported in Figure 5, panel f, which is $(\sigma_t - \sigma)/\sigma$.

[54] Only firms for which there are at least 10 consecutive observations are included.

[55] Recall that in our model, the idiosyncratic shock, ω, to an entrepreneur's time $t+1$ ex post return is drawn from a distribution whose parameters are known at time t. The variance of this distribution is what we call the risk shock and is denoted σ_t.

econometric evidence of the importance of the risk shock in output fluctuations is not based on counterfactually large movements in the risk shock.

Now consider the pattern of time variation in Figure 11. The risk shock reaches a local peak before the 2001 recession and reaches a peak during the 2007 recession. In addition, it exhibits a modest rise during the recession in the early 1990s. These features are also shared by the CRSP-based uncertainty measure, though the volatility of the latter makes discerning a definite pattern difficult. Two differences we see between our risk shock and the measure of uncertainty are: risk is monotonically increasing after the 2001 recession, while the CRSP measure of uncertainty decreases before exhibiting a sharp rise before the 2007 recession; and the rise in CRSP uncertainty in the wake of the recession of the early 1990s is more pronounced than the rise in our measure of risk at that time. Overall, however, we were surprised at the degree of agreement between those measures, given the very different ways in which they are computed.

We now turn to an evaluation of implications (i) and (ii) above. We proceed by first removing our estimate of the aggregate stock return, $\log\left(1+R_t^k\right)$, from each individual firm's return, r_{it}. Following (5.20), we interpret the result as the logarithm of the idiosyncratic component of the firm's return, $\log\omega_{i,t-1}$. For each firm in our dataset, we computed the first order lag coefficient, ρ, and constant in a first order autoregressive representation for $\log\omega_{i,t}$. The histogram of the 17,757 firm-level estimates of ρ is reported in the top left panel of Figure 12. We also computed the correlation of $\log\omega_{i,t-1}$ with $\log\left(1+R_t^k\right)$ for each firm in the dataset. The histogram of these correlations appears in the top right panel of Figure 12. Under the hypothesis of our model, the idiosyncratic shock is independently distributed over time and so it implies $\rho=0$. Similarly, the correlation between the idiosyncratic shock and the aggregate return should be zero. Turning to the estimated ρ's, we find that they are typically small: nearly 70% of them lie in the interval, $(-0.2, 0.2)$. In the case of the correlations, they are also small in that 65% lie inside $(-0.2, 0.2)$. We now ask whether these results are what are to be expected given (i) and (ii) above, i.e., the hypothesis that the true correlations and autorcorrelations are all zero.

We constructed an environment that satisfies the null hypothesis, (i) and (ii), but is consistent with all other aspects of our panel dataset. We did this by randomly reordering the $\log(\omega_{it})$'s of each individual firm in the dataset.[56] In this way, essentially all features of our data set are preserved (e.g., the variance of each firm's idiosyncratic shocks, the details of the

[56] Let $\log(\omega_{it})$, $t=t_1,...,t_2$ denote the observations on the idiosyncratic component of the i^{th} firm's stock return. We randomly re-ordered these idiosyncratic variables by randomly drawing, with replacement, from the set, $\log(\omega_{it})$, $t=t_1,...,t_2$. We found that the histograms in the bottom row of Figure 12 remained essentially unchanged if we did additional second random re-orderings.

unbalanced panel), except that by construction the $\log(\omega_{it})$'s of each firm are independent over time and uncorrelated with the aggregate return. The computer program applied to the actual data that produced the results in the top row of Figure 12 was applied to the re-ordered data to produce the bottom panels in Figure 12. We see there that under the null hypothesis, the probability that the first order autoregressive parameter is less than 0.2 in absolute value is 74. This is somewhat greater than it is for the actual data, where the probability is 69 percent. Thus, there is some evidence that the ρ's in the data are further away from zero than is consistent with the null hypothesis. However, that evidence is quantitatively small, as the histogram in the 1,1 panel roughly resembles the histogram in the 2,1 panel. Similarly, the correlations between the idiosyncratic returns and the aggregate in the data are slightly further away than they should be under the null hypothesis, but only by a small amount (compare the histograms in the 1,2 and 2,2 panels of Figure 12).

We are also interested in whether the constant term, *const*, in the autoregression fit to each firm's time series of idiosyncratic shocks corresponds to what our model predicts. We checked this by noting that $const/(1-\rho)$ is the implied mean of $\log(\omega_{it})$. The top left panel of Figure 12 reports the average, over all 17,757 firms, of this object. This average, -0.051, is reasonably similar to the value predicted by our model. According to the model, the mean value of $\log(\omega_{it})$ is $-\sigma_t^2/2$, where σ_t denotes the standard deviation of $\log(\omega_{it})$. From Figure 11, we see that the average value of σ_t is about 0.3, which implies a mean of -0.045.

In sum, the risk shock estimated in this paper behaves similarly, in terms of absolute magnitude and cyclical movements, to the CRSP-based measure of uncertainty reported in Bloom (2009). Moreover, crucial assumptions in our model about the lack of autocorrelation in the idiosyncratice shock, ω, and its independence with the aggregate return, are supported by the CRSP stock return data. Of course, these results can only be viewed as suggestive, since many details of the mapping from our model to the stock return data in CRSP have been left unspecified.

6 Conclusion

We started with a model that combines CEE with BGG and added the assumption that the cross sectional standard deviation of an idiosyncratic productivity shock varies through time, as in Christiano, Motto and Rostagno (2003). We call this cross-sectional standard deviation a 'risk' shock. When we study US macroeconomic data over the period 1985-2010, we conclude that the risk shock accounts for a very large part of the fluctuations in GDP and other macroeconomic variables. It is the fact that we include financial variables in an otherwise standard macroeconomic data set that allows us to differentiate the risk shock from more standard macroeconomic shocks. To evaluate the credibility of our result, we study the implications of our model for variables not included our data sample. In particular, we examine the implications of the model for loan deliquency rates, for out-of-sample forecasts, and for key features of the cross-sectional dispersion of firm-level stock returns recently emphasized by Bloom (2009) and others. We find that the model does well on these out-of-sample tests, and infer that its implication that risk shocks are important deserves to be taken seriously.

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Table 1a: Model Priors and Posteriors - Economic Parameters							
parameter name	parameter	prior mean	mode	s.d.	t-statistic	prior dist	prior stdv
Calvo wage stickiness	ξ_w	0.75	0.8128	0.0188	43.1424	beta	0.1
Habit parameter	b	0.5	0.7358	0.0499	14.7389	beta	0.1
Steady state probabiliy of default	$F(\bar{\omega})$	0.007	0.0056	0.0023	2.4523	beta	0.0037
Monitoring cost	μ	0.275	0.2149	0.0727	2.957	beta	0.15
Curvature, utilization cost	σ_a	1	2.5356	0.6972	3.6365	normal	1
Curvature, investment adjust cost	S''	5	10.78	1.7051	6.3224	normal	3
Calvo price stickiness	ξ_p	0.5	0.7412	0.0346	21.4073	beta	0.1
Policy weight on inflation	α_π	1.5	2.3965	0.1633	14.6736	normal	0.25
Policy smoothing parameter	ρ_p	0.75	0.8503	0.0154	55.0754	beta	0.1
price indexing weight on inflation target	ι	0.5	0.8974	0.0489	18.3559	beta	0.15
wage indexing weight on inflation target	ι_w	0.5	0.4891	0.1149	4.2558	beta	0.15
wage indexing weight on persistent technology growth	ι_μ	0.5	0.9366	0.0293	32.0111	beta	0.15
Policy weight on output growth	$\alpha_{\Delta y}$	0.25	0.3649	0.0992	3.6776	normal	0.1

Table 1b: Model Priors and Posteriors - shocks							
parameter name	parameter	prior mean	mode	s.d.	t-statistic	prior dist	prior stdv
Correlation among signals	$\rho_{\sigma,n}$	0	0.3861	0.0952	4.0559	normal	0.5
Autocorrelation, price markup shock	ρ_{λ_f}	0.5	0.9109	0.0344	26.4618	beta	0.2
Autocorrelation, price of investment goods shock	ρ_{μ_Ψ}	0.5	0.987	0.0085	115.9056	beta	0.2
Autocorrelation, government	ρ_g	0.5	0.9427	0.0232	40.5649	beta	0.2
Autocorrelation, persistent technology growth	ρ_{μ_z}	0.5	0.1459	0.0704	2.073	beta	0.2
Autocorrelation, transitory technology	ρ_ϵ	0.5	0.8089	0.0646	12.5291	beta	0.2
Autocorrelation, risk shock	ρ_σ	0.5	0.9706	0.0093	104.0775	beta	0.2
Autocorrelation, consumption preference shock	ρ_{ζ_c}	0.5	0.8968	0.0314	28.5483	beta	0.2
Autocorrelation, marginal efficiency of investment	ρ_{ζ_I}	0.5	0.9087	0.0174	52.1844	beta	0.2
Autocorrelation, term structure shock	ρ_η	0.5	0.9744	0.0247	39.3785	beta	0.2
std, anticipated risk shock	$\sigma_{\sigma,n}$	0.001	0.0283	0.0028	10.0271	invg2	0.0012
std, unanticipated risk shock	$\sigma_{\sigma,0}$	0.002	0.07	0.0099	7.0955	invg2	0.0033
std, measurement error on net worth		0.01	0.0175	0.0009	18.8434	Weibull	5
Standard deviations, shock innovations							
price markup	σ_{λ_f}	0.002	0.011	0.0022	4.9846	invg2	0.0033
investment price	σ_{μ_Ψ}	0.002	0.004	0.0003	14.4766	invg2	0.0033
government consumption	σ_g	0.002	0.0228	0.0016	14.3544	invg2	0.0033
persistent technology growth	σ_{μ_z}	0.002	0.0071	0.0005	13.1152	invg2	0.0033
equity	σ_γ	0.002	0.0081	0.001	7.9605	invg2	0.0033
temporary technology	σ_ε	0.002	0.0046	0.0003	14.1249	invg2	0.0033
monetary policy	σ_{ε^p}	0.583	0.4893	0.0369	13.2507	invg2	0.825
consumption preference	σ_{ξ_c}	0.002	0.0233	0.003	7.8926	invg2	0.0033
marginal efficiency of investment	σ_{ξ_I}	0.002	0.055	0.0116	4.748	invg2	0.0033
term structure	σ_η	0.002	0.0016	0.0007	2.2162	invg2	0.0033

Note: invg2 – ‘inverse gamma distribution, type 2’.

Table 2. Comparison of the Marginal Likelihood of Different Version of the DSGE Model

Model Variants	Marginal Likelihood
DSGE Baseline	4563.37
DSGE Uncorrelated Signals	4559.00
DSGE without Signals	4192.16
DSGE with Signals on Equity Shock (γ) and No Signals on Risk Shock (σ)	4458.91
DSGE with Signals on Monetary Policy and No Signals on Risk Shock (σ)	4507.88
DSGE with Signals on Exogenous Spending Shock (g) and No Signals on Risk Shock (σ)	4140.21
DSGE with Signals on Technology Shocks and No Signals on Risk Shock (σ)	4502.82

Note: The marginal likelihood in DSGE models is computed using Geweke (1998) modified harmonic mean to evaluate the integral over the posterior sample.

<table>
<tr><th colspan="10">Table 3. Variance Decomposition at Business Cycle Frequency (in percent)</th></tr>
<tr><th>shock
variable</th><th>Risk
σ_t</th><th>Equity
γ_t</th><th>M.E.I.
$\zeta_{I,t}$</th><th>Technol.
ε_t, $\mu_{z,t}$,</th><th>Markup
$\lambda_{f,t}$,</th><th>M.P.
ϵ_t</th><th>Demand
$\zeta_{c,t}$</th><th>Exog.Spend.
g_t</th><th>Term</th></tr>
<tr><td>GDP</td><td>62|16|38</td><td>0</td><td>13</td><td>2</td><td>12</td><td>2</td><td>4</td><td>3</td><td>0</td></tr>
<tr><td>drop credit</td><td>{24|0|24}</td><td>{16}</td><td>{19}</td><td>{2}</td><td>{24}</td><td>{2}</td><td>{6}</td><td>{5}</td><td>{0}</td></tr>
<tr><td>drop equity</td><td>(70|16|44)</td><td>(1)</td><td>(0)</td><td>(5)</td><td>(10)</td><td>(3)</td><td>(4)</td><td>(4)</td><td>(0)</td></tr>
<tr><td>drop premium</td><td>39|0|39</td><td>2</td><td>11</td><td>10</td><td>24</td><td>5</td><td>4</td><td>5</td><td>0</td></tr>
<tr><td>drop slope</td><td>61|15|39</td><td>1</td><td>2</td><td>1</td><td>24</td><td>2</td><td>4</td><td>4</td><td>0</td></tr>
<tr><td>drop all fin. var</td><td>1|0|1</td><td>0</td><td>44</td><td>12</td><td>22</td><td>3</td><td>11</td><td>8</td><td>0</td></tr>
<tr><td>CEE</td><td>[-]</td><td>[-]</td><td>[39]</td><td>[18]</td><td>[31]</td><td>[4]</td><td>[3]</td><td>[5]</td><td>[-]</td></tr>
<tr><td>Equity</td><td>69|23|35</td><td>2</td><td>23</td><td>0</td><td>1</td><td>2</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>drop credit</td><td>{21|0|20}</td><td>{58}</td><td>{16}</td><td>{0}</td><td>{1}</td><td>{2}</td><td>{0}</td><td>{0}</td><td>{0}</td></tr>
<tr><td>drop premium</td><td>40|0|40</td><td>8</td><td>43</td><td>0</td><td>2</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>drop slope</td><td>49|16|26</td><td>(3)</td><td>(42)</td><td>(0)</td><td>(2)</td><td>(2)</td><td>(0)</td><td>(0)</td><td>(0)</td></tr>
<tr><td>Credit Spread</td><td>95|39|42</td><td>1</td><td>3</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>drop credit</td><td>{69|0|69}</td><td>{28}</td><td>{2}</td><td>{0}</td><td>{0}</td><td>{1}</td><td>{0}</td><td>{0}</td><td>{0}</td></tr>
<tr><td>drop equity</td><td>97|34|48</td><td>1</td><td>0</td><td>0</td><td>0</td><td>1</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>drop slope</td><td>(90|33|45)</td><td>(1)</td><td>(8)</td><td>(0)</td><td>(0)</td><td>(0)</td><td>(0)</td><td>(0)</td><td>(0)</td></tr>
<tr><td>Credit</td><td>64|12|46</td><td>10</td><td>17</td><td>2</td><td>4</td><td>1</td><td>1</td><td>0</td><td>0</td></tr>
<tr><td>drop equity</td><td>83|16|57</td><td>8</td><td>0</td><td>2</td><td>4</td><td>0</td><td>2</td><td>0</td><td>0</td></tr>
<tr><td>drop premium</td><td>47|0|47</td><td>20</td><td>22</td><td>3</td><td>3</td><td>3</td><td>2</td><td>1</td><td>0</td></tr>
<tr><td>drop slope</td><td>61|10|46</td><td>14</td><td>16</td><td>2</td><td>3</td><td>1</td><td>2</td><td>0</td><td>0</td></tr>
<tr><td>Consumption</td><td>16|3|12</td><td>0</td><td>11</td><td>3</td><td>19</td><td>2</td><td>46</td><td>3</td><td>0</td></tr>
<tr><td>drop credit</td><td>{2|0|2}</td><td>{1}</td><td>{3}</td><td>{1}</td><td>{28}</td><td>{1}</td><td>{63}</td><td>{1}</td><td>{0}</td></tr>
<tr><td>drop equity</td><td>7|1|6</td><td>(0)</td><td>(0)</td><td>(6)</td><td>(11)</td><td>(4)</td><td>(69)</td><td>(3)</td><td>(0)</td></tr>
<tr><td>drop premium</td><td>17|0|17</td><td>1</td><td>14</td><td>10</td><td>18</td><td>1</td><td>36</td><td>3</td><td>0</td></tr>
<tr><td>drop slope</td><td>12|2|10</td><td>0</td><td>15</td><td>0</td><td>21</td><td>1</td><td>49</td><td>1</td><td>0</td></tr>
<tr><td>drop all fin. var</td><td>0|0|0</td><td>0</td><td>2</td><td>15</td><td>26</td><td>3</td><td>51</td><td>2</td><td>0</td></tr>
<tr><td>CEE</td><td>[-]</td><td>[-]</td><td>[6]</td><td>[12]</td><td>[9]</td><td>[1]</td><td>[67]</td><td>[5]</td><td>[-]</td></tr>
<tr><td>Investment</td><td>73|18|46</td><td>0</td><td>21</td><td>0</td><td>4</td><td>1</td><td>1</td><td>0</td><td>0</td></tr>
<tr><td>drop credit</td><td>{28|0|28}</td><td>{25}</td><td>{32}</td><td>{0}</td><td>{11}</td><td>{2}</td><td>{0}</td><td>{0}</td><td>{0}</td></tr>
<tr><td>drop equity</td><td>92|20|59</td><td>(1)</td><td>(0)</td><td>(0)</td><td>(4)</td><td>(2)</td><td>(0)</td><td>(0)</td><td>(0)</td></tr>
<tr><td>drop premium</td><td>58|0|58</td><td>3</td><td>24</td><td>2</td><td>9</td><td>3</td><td>2</td><td>0</td><td>0</td></tr>
<tr><td>drop slope</td><td>78|18|51</td><td>1</td><td>8</td><td>0</td><td>10</td><td>1</td><td>2</td><td>0</td><td>0</td></tr>
<tr><td>drop all fin. var</td><td>2|0|2</td><td>0</td><td>85</td><td>2</td><td>7</td><td>2</td><td>2</td><td>0</td><td>0</td></tr>
<tr><td>CEE</td><td>[-]</td><td>[-]</td><td>[57]</td><td>[10]</td><td>[24]</td><td>[3]</td><td>[5]</td><td>[0]</td><td>[-]</td></tr>
<tr><td>Slope</td><td>56|12|38</td><td>0</td><td>17</td><td>3</td><td>8</td><td>6</td><td>2</td><td>0</td><td>7</td></tr>
<tr><td>drop credit</td><td>{13|0|13}</td><td>{15}</td><td>{27}</td><td>{3}</td><td>{10}</td><td>{13}</td><td>{4}</td><td>{1}</td><td>{14}</td></tr>
<tr><td>drop equity</td><td>55|11|38</td><td>0</td><td>0</td><td>4</td><td>14</td><td>10</td><td>4</td><td>0</td><td>12</td></tr>
<tr><td>drop premium</td><td>49|0|49</td><td>(2)</td><td>(20)</td><td>(3)</td><td>(6)</td><td>(7)</td><td>(1)</td><td>(1)</td><td>(10)</td></tr>
</table>

Notes: For each variable, figures for the baseline model are in the first row. The alternative models, if present, are in the following rows. Numbers in each row may not add up to 100 due to rounding. The table does not display shocks (such as π_t^* and $\mu_{\Upsilon,t}$) whose contribution is less than 1/2 of 1%. Data on equity is explained also by measurement error, which is estimated to contribute for 3% in the baseline model. The contribution of the risk shock, σ_t, is presented in the following way: the first entry is the contribution of the entire shock, the second entry is the contribution coming from ξ_0, and the third entry is the contribution coming from $\xi_1 - \xi_8$. The latter two contributions do not sum up to the first entry as they ignore the correlation between the ξs. Business cycle frequency is measured as periodic component with cycles of $8 - 32$ quarters, obtained using the model spectrum.

Figure 1: Flow of Funds Through Financial Markets

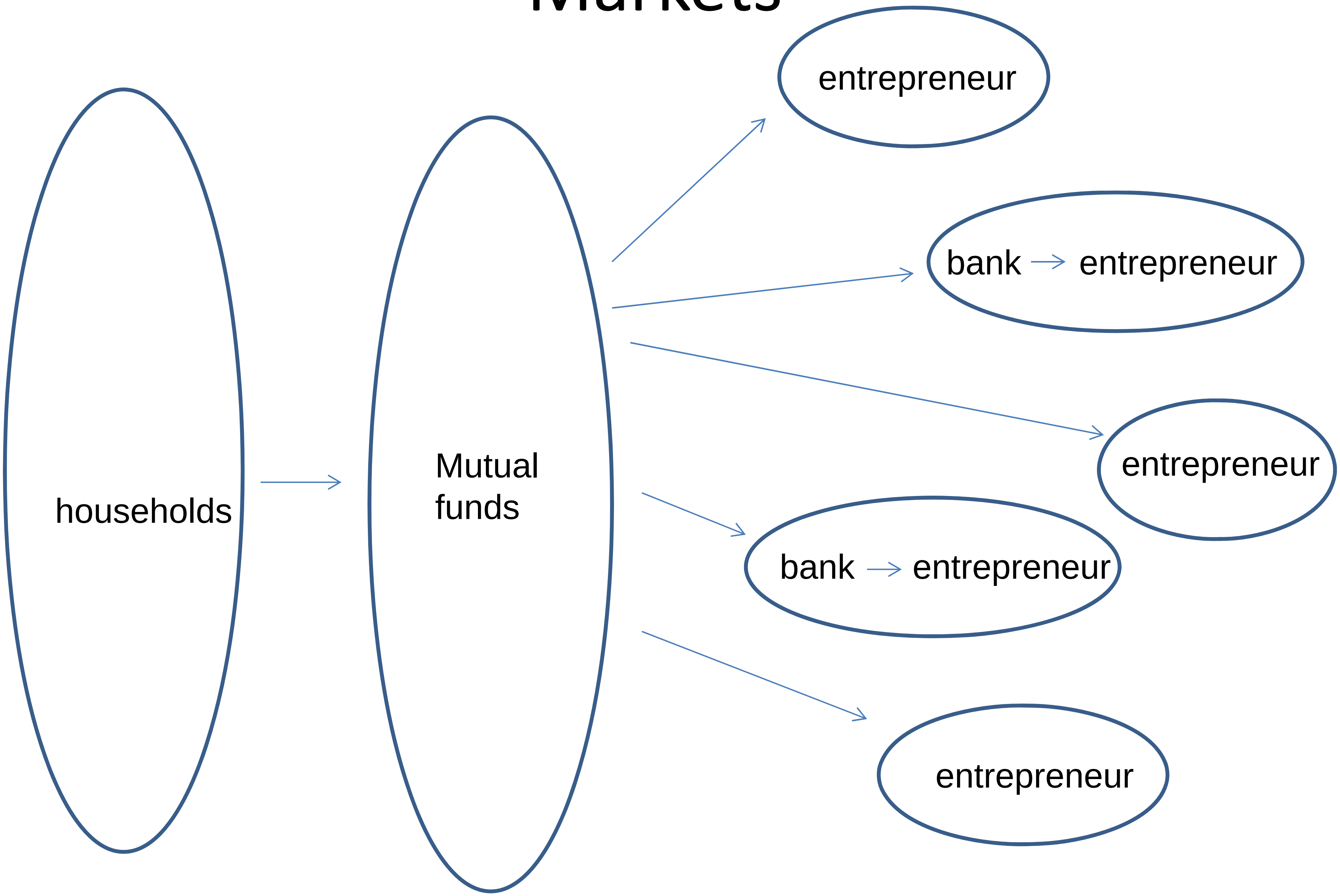


Figure 2: Out of Sample RMSE's

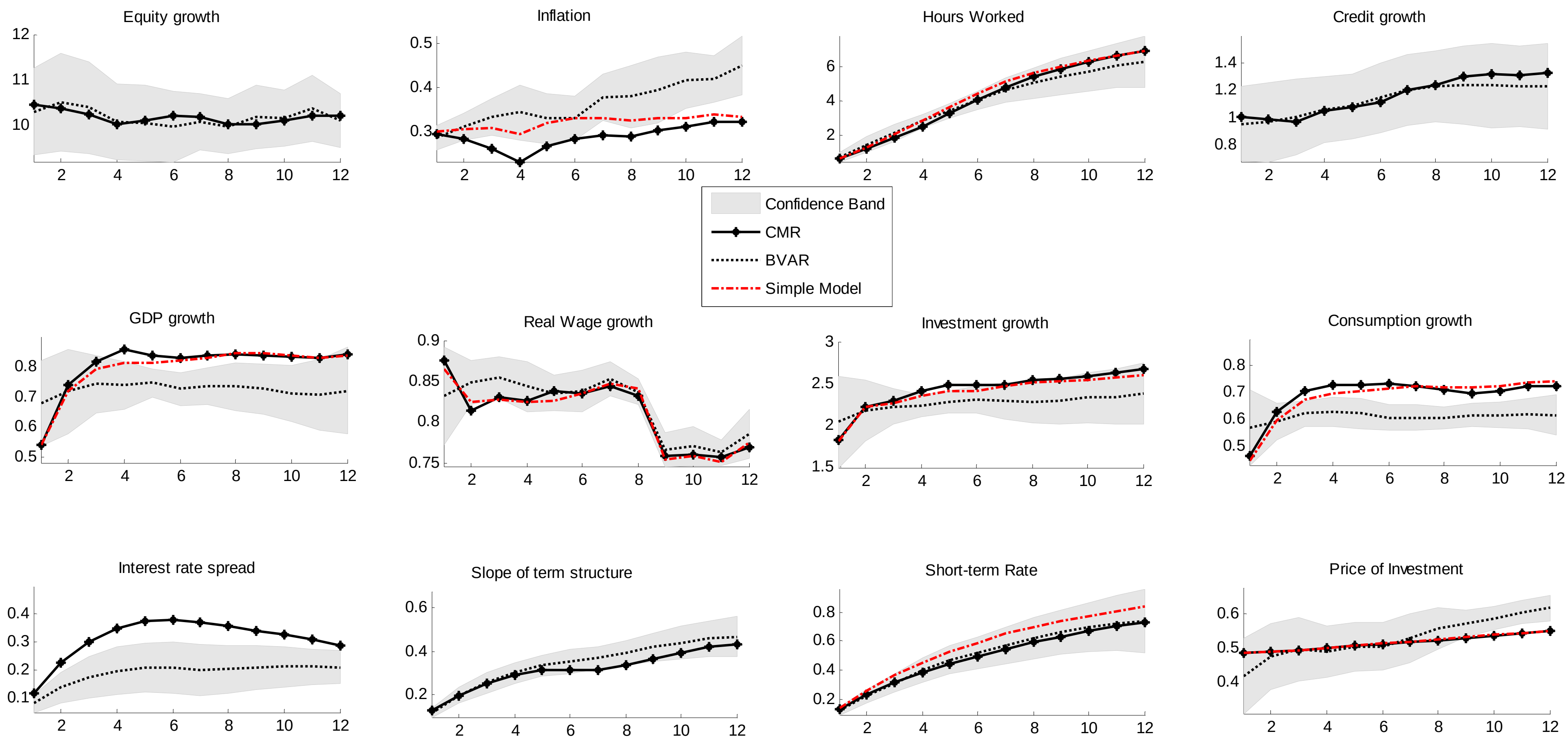


Figure 3: Model Bankruptcy Rate, Versus Loan Delinquency Rate

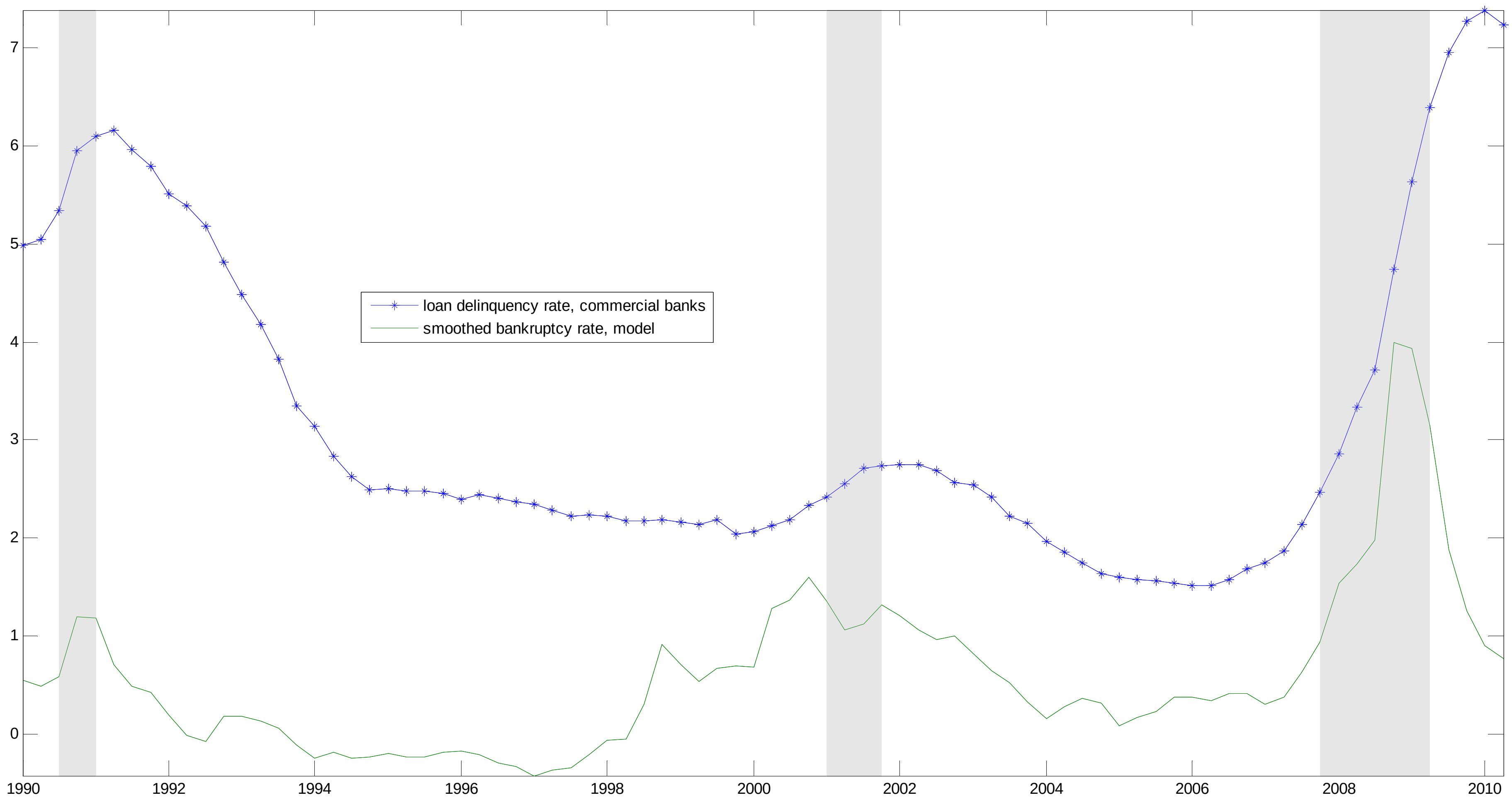


Figure 4: Selected Cross-correlations, Model and Data

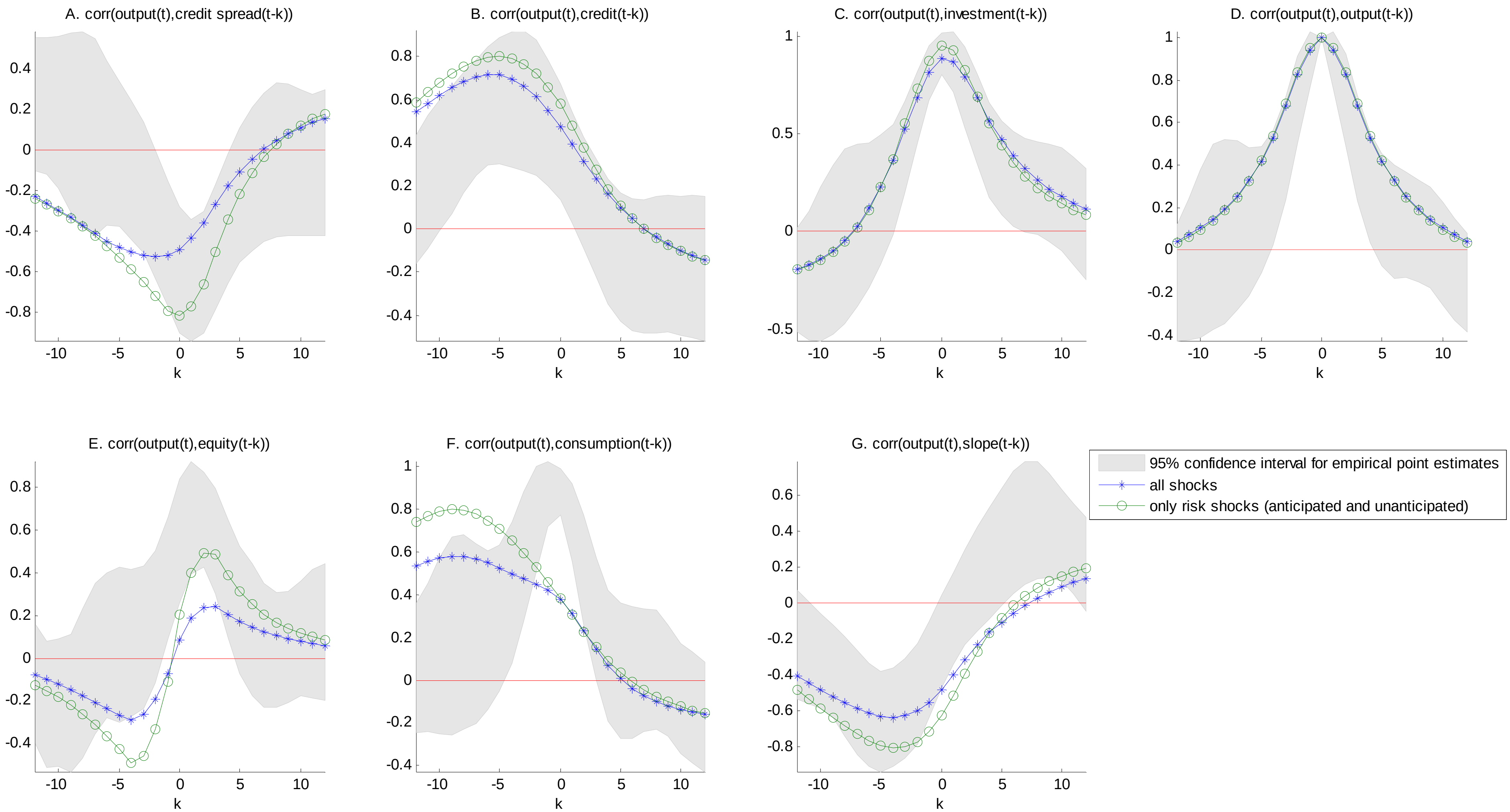
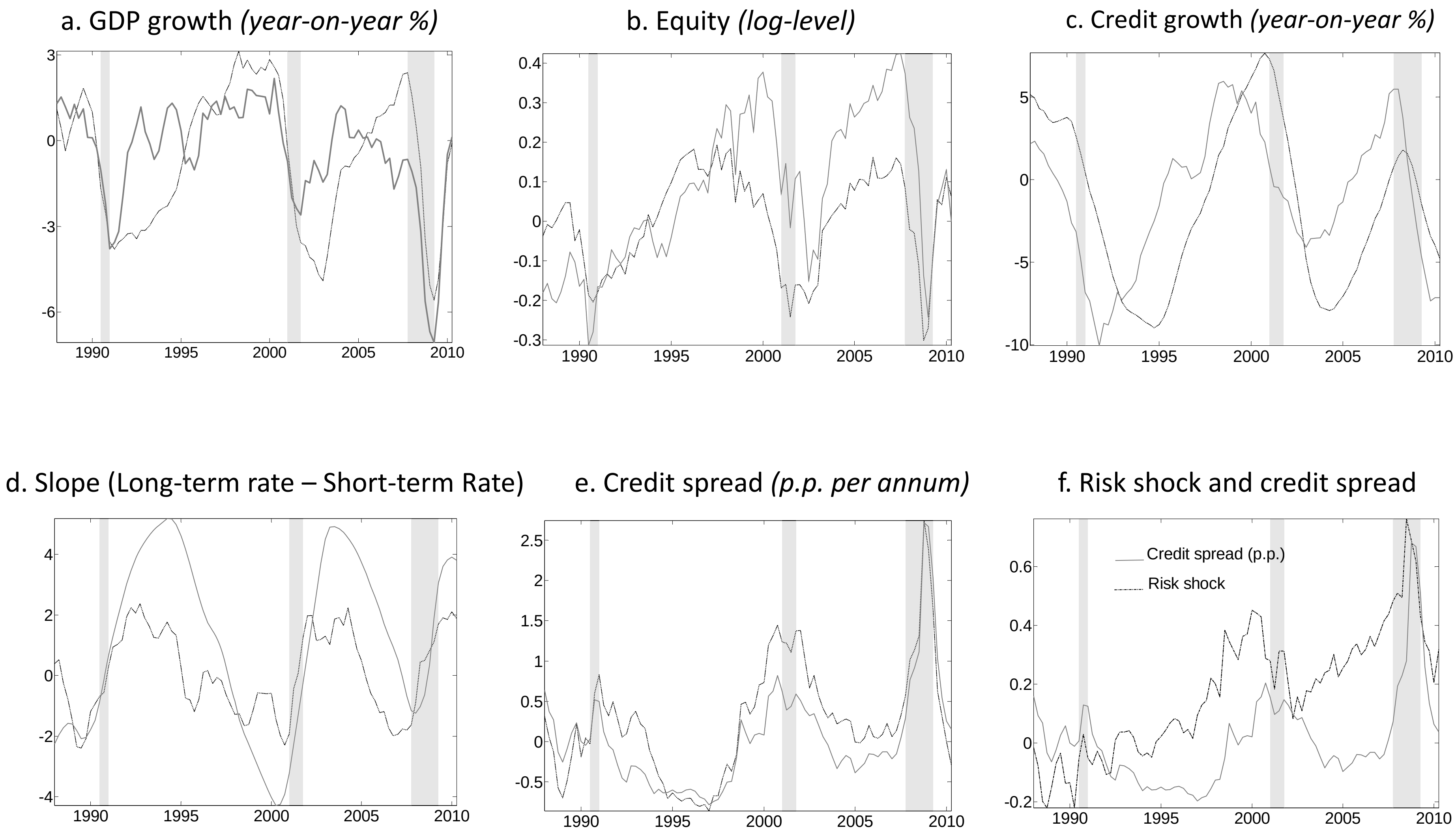


Figure 5:The Role of the Risk Shock in Selected Variables



With exception of panels b and f, the grey solid line is the data. Panel b is the smoothed equity data which differs from the actual data by a small estimated measurement error. The dashed line is the result of feeding only the estimated risk shock to the model. Panel f displays the demeaned credit spread and the risk shock (the latter expressed as a ratio to its steady state value, minus unity).

Figure 6: Dynamic Responses to Unanticipated and Anticipated Components of Risk Shock

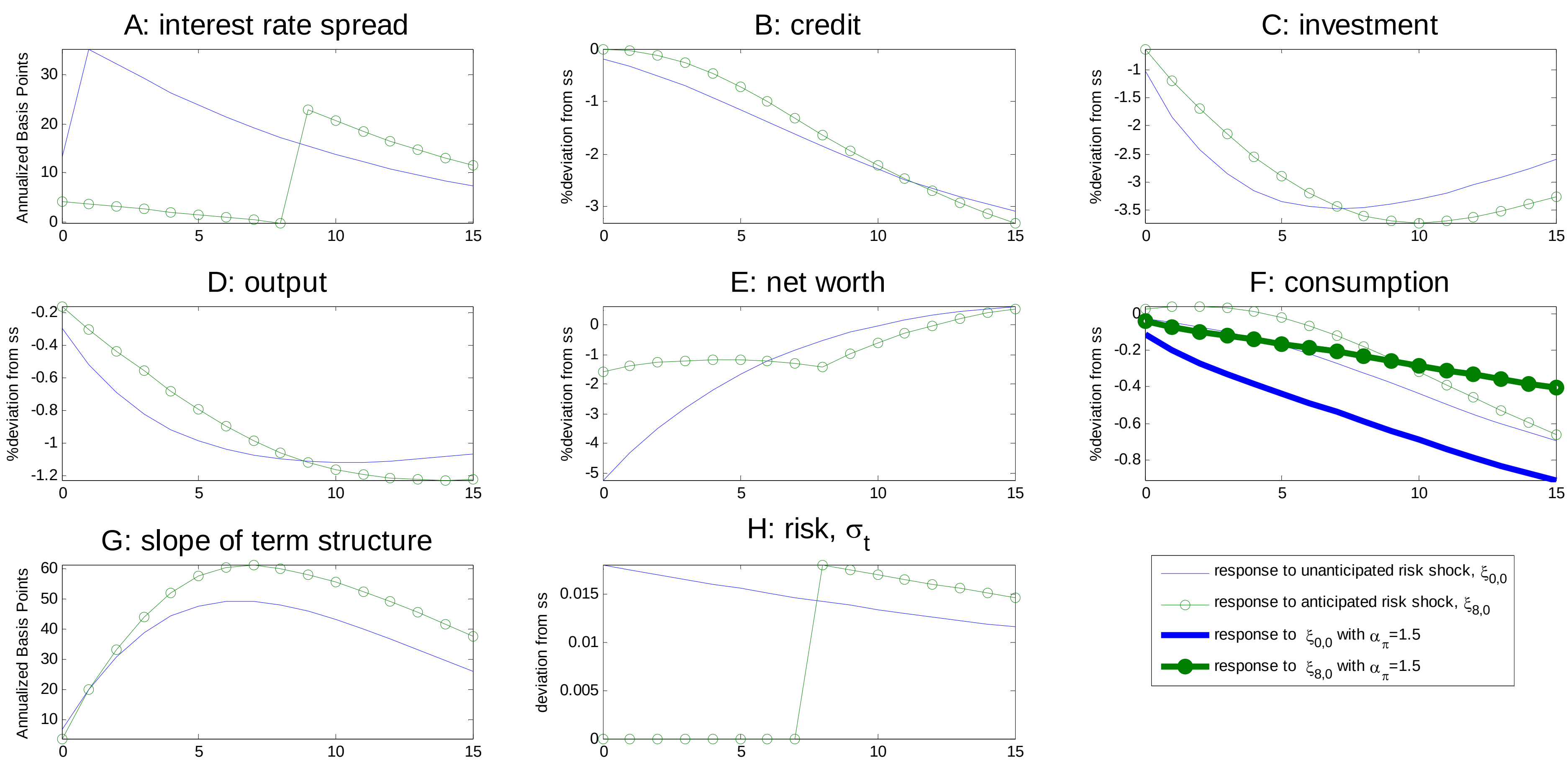


Figure 7: Responses to Unanticipated Risk Shock

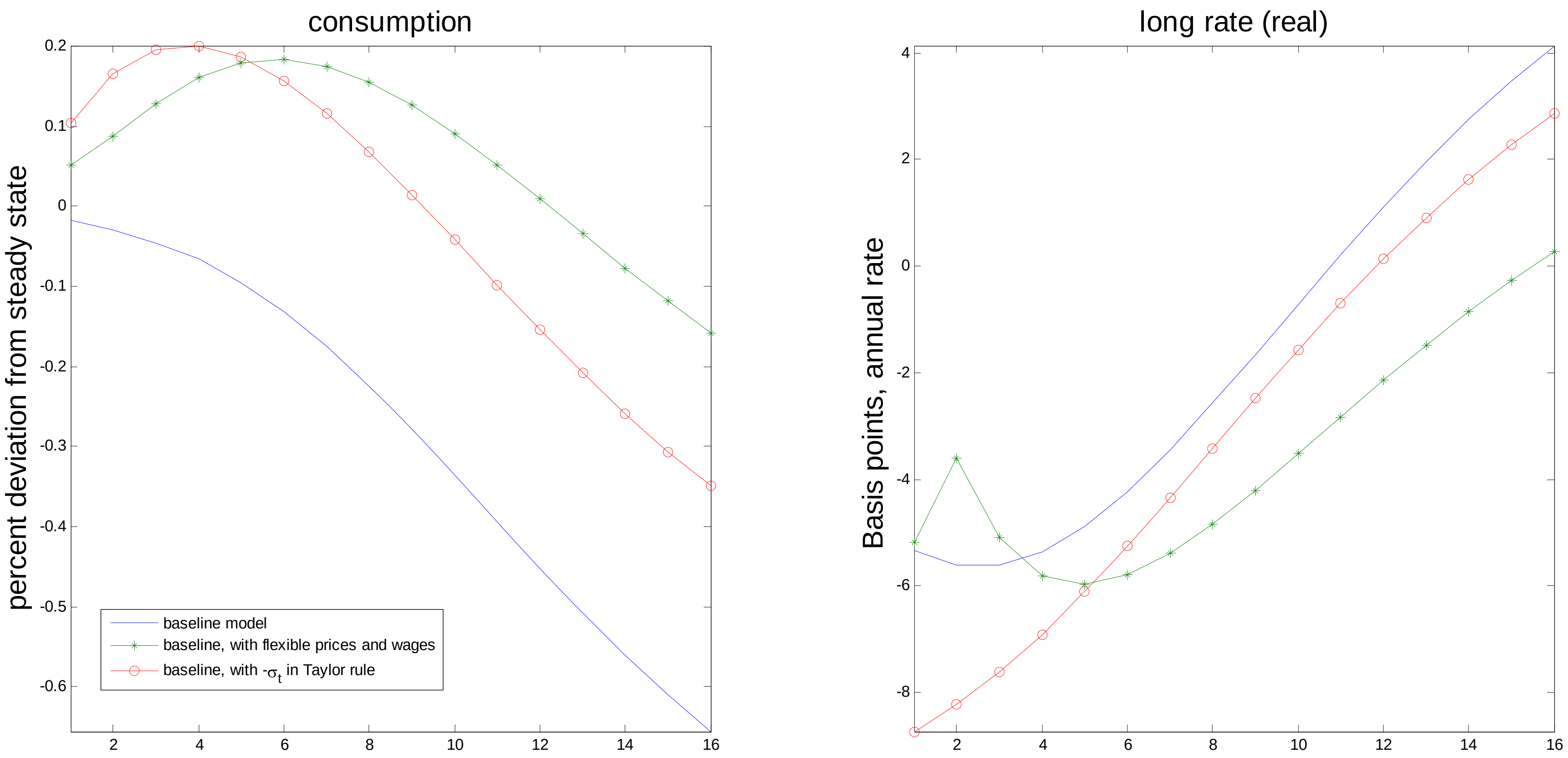


Figure 8: Dynamic Responses to Three Shocks

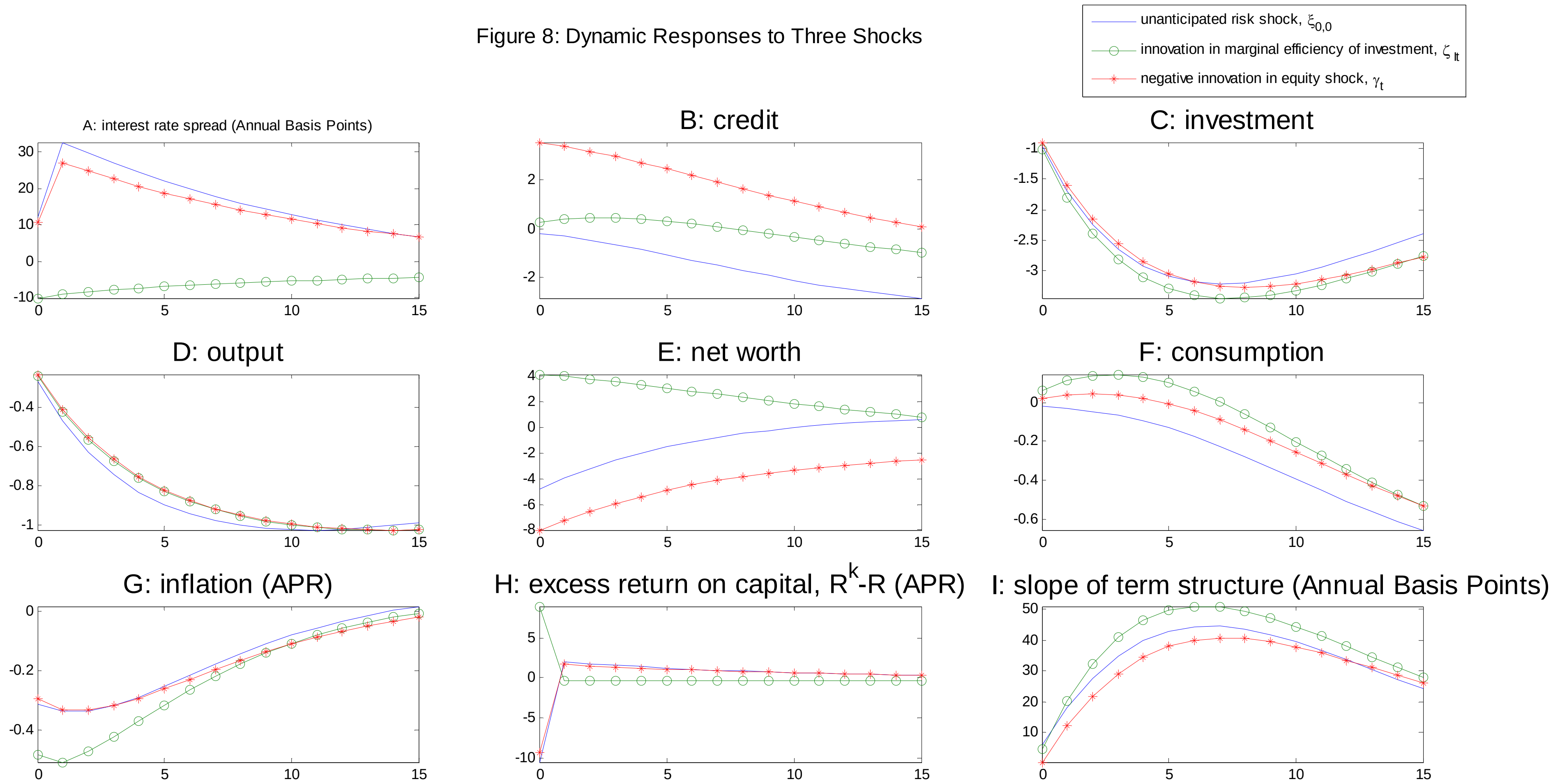
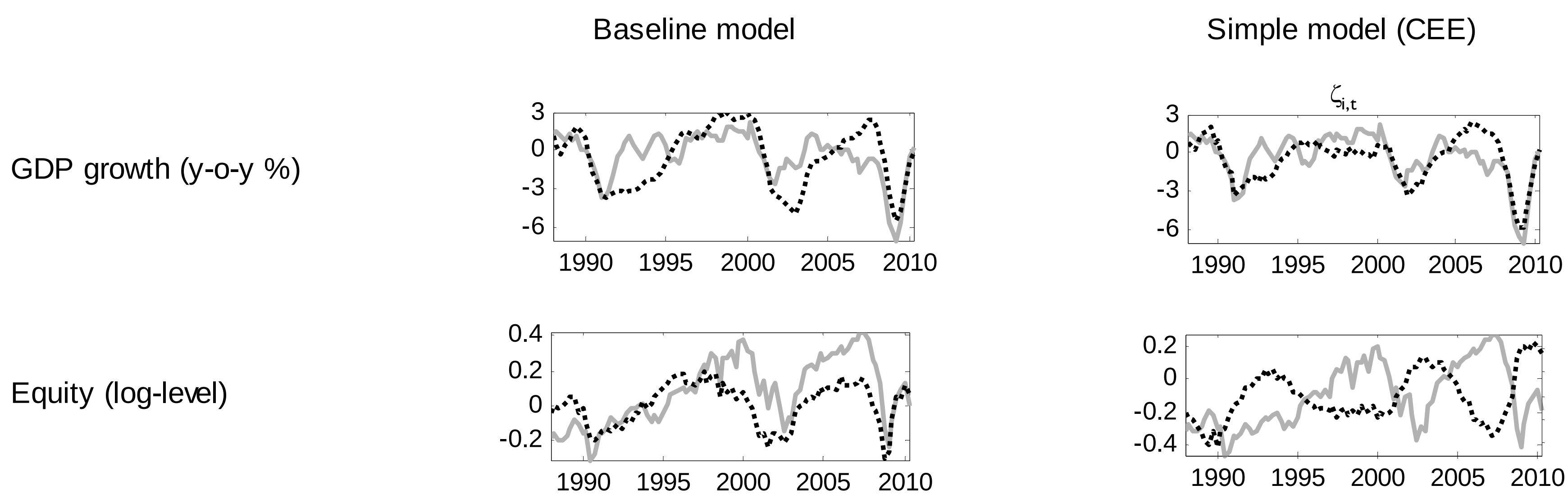


Figure 9: Historical Decompositions in Two Models



Notes: The grey solid line represents the (two-sided) fitted data. The dotted black line is the model simulations.

Figure 10: The Risk and Equity Shocks, Versus the Marginal Efficiency of Investment

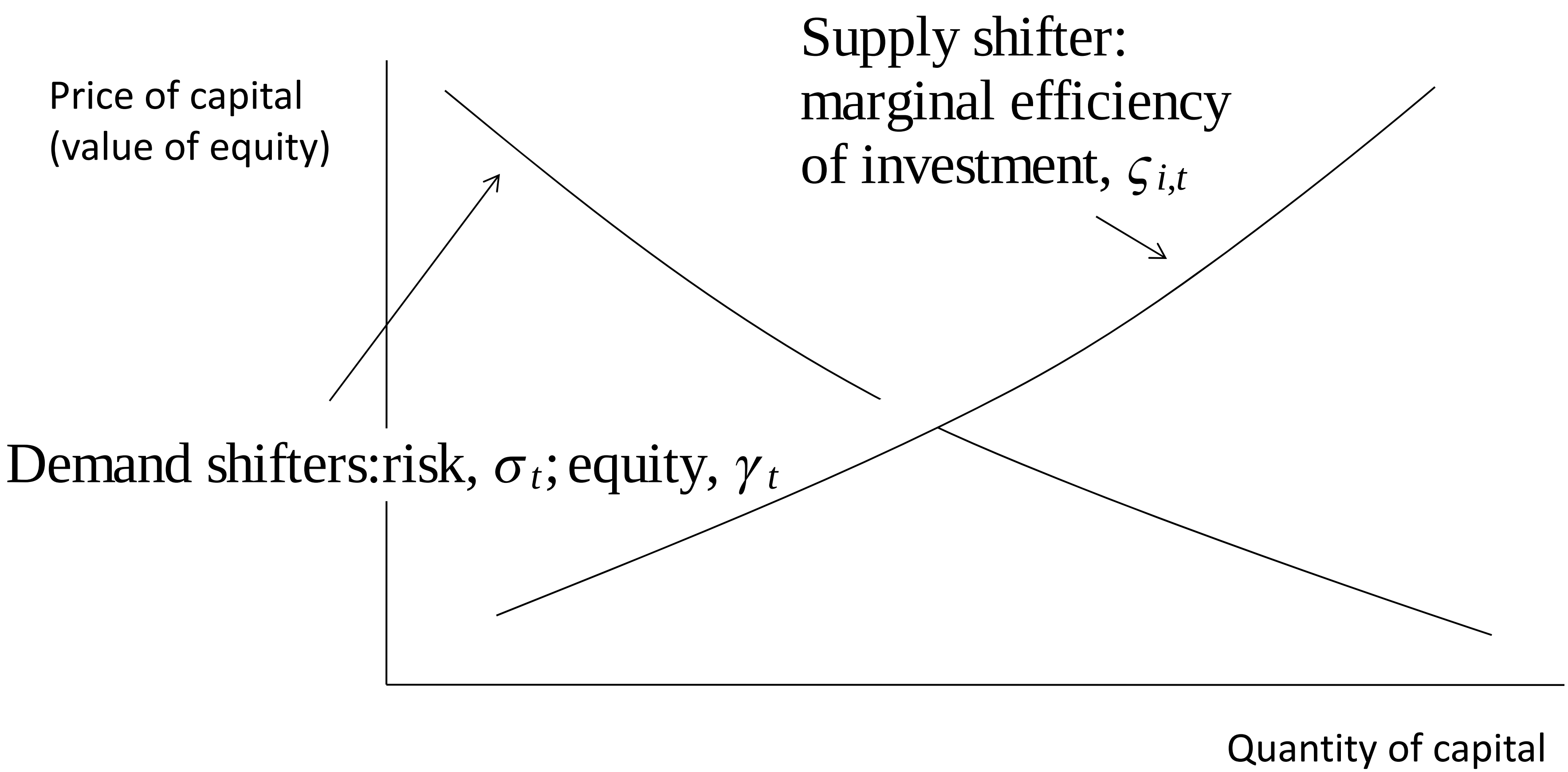
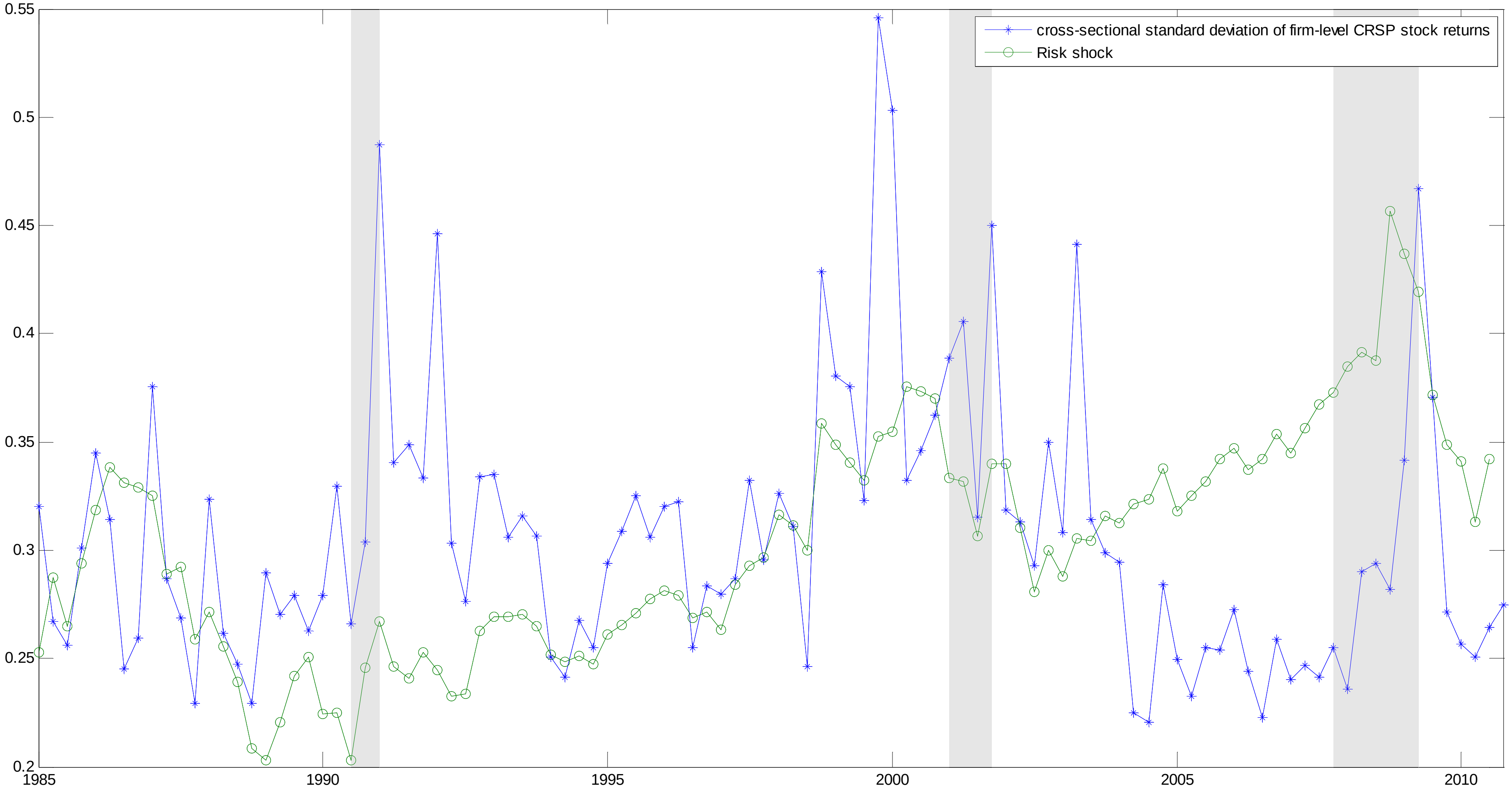


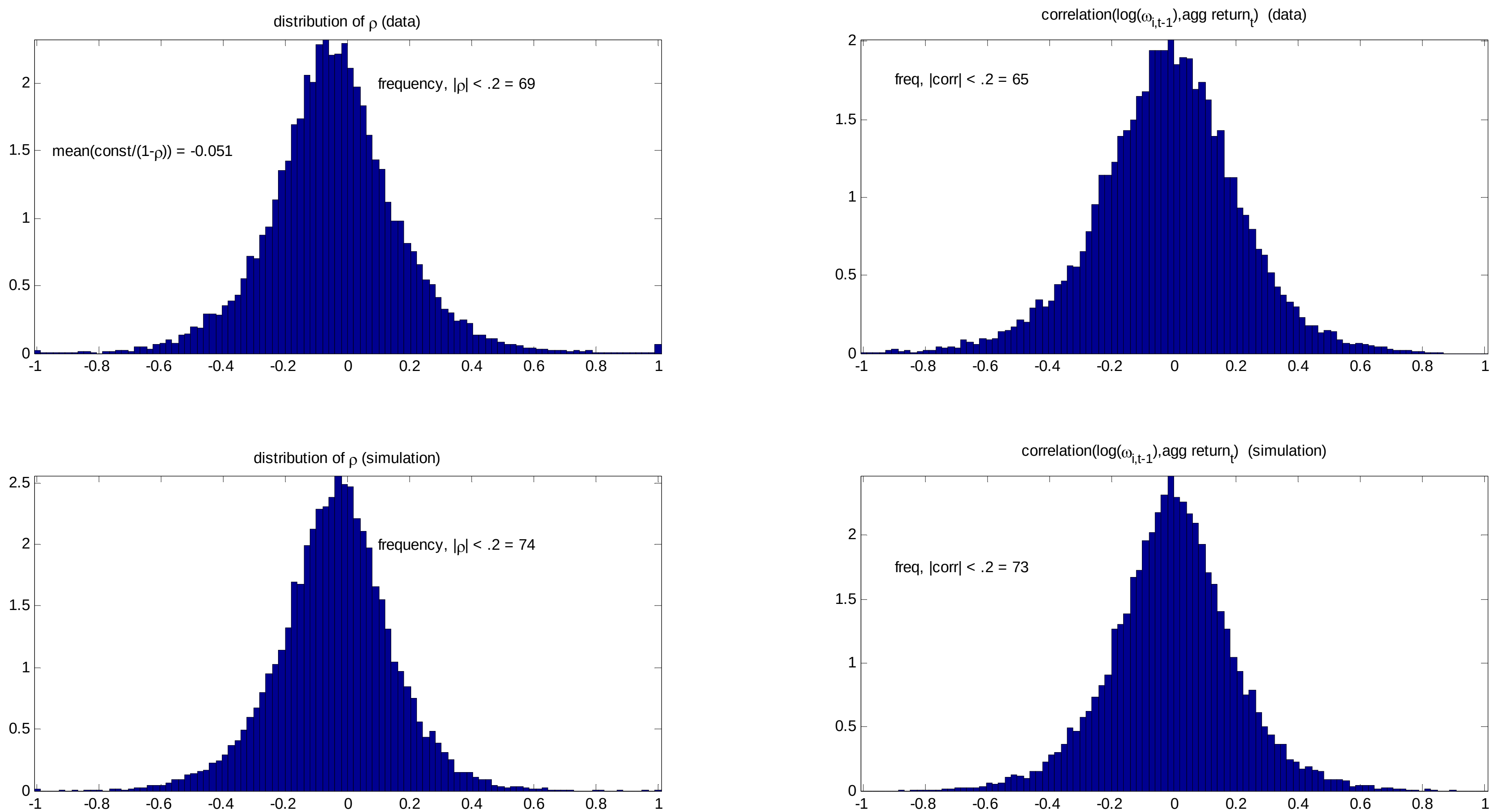
Figure 11: CRSP-based Measure of Uncertainty and Risk



Notes: stock return volatility corresponds to second row variable in Table I of Bloom (2009), as computed in Ferreira (2012). To ensure comparability, stock returns were first converted to quarterly rates. 'Risk shock' is the smoothed estimate of σ_t using the baseline model evaluated at the posterior mode of its parameters.

Figure 12: Idiosyncratic Shock, Tests

$$\log \omega_{it} = \text{const} + \rho \log \omega_{i,t-1} + \varepsilon_{it}, \ \text{corr}(\log \omega_{it}, r_t)$$



Note: top row provides distribution of indicated objects related to firm-level idiosyncratic return shocks in actual panel of CRSP firms; bottom row provides distribution of same objects when temporal order of firm-level idiosyncratic shock is randomized. The point of the Figure is that the distributions in the top and bottom rows are similar, consistent with our assumed properties of idiosyncratic shocks.