Risk Shocks*

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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

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1 Introduction

We introduce agency problems associated with financial intermediation into an otherwise standard model of business cycles. Our estimates suggest that fluctuations in the severity of these agency problems account for a substantial portion of business cycle fluctuations over the past two and a half decades.

The agency problems we introduce are those associated with asymmetric information and costly monitoring proposed by Robert Townsend (1979). Our implementation most closely follows the work of Ben Bernanke and Mark Gertler (1989) and Bernanke, Gertler and Simon Gilchrist (1999) (BGG).[1] Entrepreneurs play a central role in the 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 idiosyncratic uncertainty. We refer to the magnitude of 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 that we now think of as 'sure bets', such as Steve Jobs and Bill Gates, experienced failures as well as the successes for which they are famous.[3] Another illustration of the microeconomic uncertainty associated with the allocation of capital may be found in the various 'wars' over industry standards. In these wars, entrepreneurs commit large amounts of raw capital to one or another standard. Whether that raw capital turns into highly effective capital or becomes worthless is, to a substantial degree, up to chance.[4]

We model the idiosyncratic uncertainty experienced by entrepreneurs by 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

[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, Bai 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).

each entrepreneur, normalized to have mean unity.[5] Entrepreneurs that draw ω larger than unity experience a success, while entrepreneurs that draw ω close to zero experience failure. The realization of ω is not known at the time the entrepreneur receives financing. 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. We denote the time t cross-sectional standard deviation $\log \omega$ by σ_t. We refer to σ_t as *risk*. The variable, σ_t, is assumed to be the realization of a stochastic process. Thus, risk is high in periods when σ_t is high and there is substantial dispersion in the outcomes across entrepreneurs. Risk is low otherwise.

Our econometric analysis assigns a large role to σ_t in business fluctuations because a jump in σ_t triggers responses in our model that resemble actual recessions. The underlying intuition is simple. As in BGG, we suppose that entrepreneurs receive a standard debt contract. 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.[6] 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_t. When risk is high, the credit spread is high and credit extended to entrepreneurs is low. With fewer financial resources, entrepreneurs 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 of goods, output, consumption and employment fall. For the reasons stressed in BGG, the net worth of entrepreneurs - an object that we identify with the stock market - falls too. This occurs because the rental income of entrepreneurs falls with the decline in economic activity and because they suffer capital losses as the price of capital drops. Finally, the overall decline in economic activity results in a decline in the marginal cost of production and thus a decline in inflation. So, according to the model the risk shock implies a countercyclical credit spread and procyclical investment, consumption, employment, inflation, stock market and credit. These implications of the model correspond well to the analogous features of US business cycle data.[7]

[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.

[6] 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. To our knowledge, the first paper to appeal to variations in risk as a driver of business cycles is Williamson (1987).

[7] 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,

We include other shocks in our model and then estimate the values of its parameters by standard Bayesian methods using 12 aggregate 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. As with any empirical analysis of this type, it can be interpreted as a sort of accounting exercise. We in effect decompose our 12 aggregate variables into a large number of shocks. In light of the observations in the previous paragraph, it is perhaps not surprising that one of these shocks, σ_t, emerges as the most important by far. For example, the analysis suggests that fluctuations in σ_t account for 60 percent of the fluctuations in the growth rate of aggregate US output since the mid 1980s. Our conclusion that the risk shock is the most important shock depends crucially on including the four financial variables in our dataset.

Our empirical analysis treats σ_t as an unobserved variable. We infer its properties using our model and our 12 aggregate time series. A natural concern is that we might have relied on excessively large fluctuations in σ_t to drive economic fluctuations. To guard against this, we look outside the data set used in the econometric analysis of the model for evidence on the degree of cyclical variation in σ_t. For this, we study a measure of 'uncertainty' proposed 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. According to our model, the time series of this measure of uncertainty is dominated by the risk shock. We use our model to project Bloom (2009)'s measure of uncertainty onto the 12 data series used in the econometric analysis of our model. We find that the degree of cyclical variation in the empirical and model-based measures of uncertainty are very similar. We interpret this as important support for the model

Our analysis is related to a growing body of evidence which documents that the cross-sectional dispersion of a variety of variables is countercyclical.[8] Of course, the mere fact that cross-sectional volatility is countercyclical does not by itself prove the hypothesis in our model, that risk shocks are causal. It is in principle possible that countercyclical variation in cross-

see Cristina Arellano, Yan Bai, and Patrick Kehoe (2011). For an example of how countercyclical dispersion may occur endogenously, see Christiano and Ikeda (2012).

[8] 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) uses plant level data to document 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. Christiano and Ikeda (2012) present evidence on the countercyclicality of the cross-sectional dispersion of equity returns among financial firms. 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 their evidence about uncertainty concerns variations in cross-sectional dispersion or changes in the variance of time series aggregates. Our risk shock corresponds to the former.

sectional dispersion is a symptom rather than a cause of business cycles.[9] Some support for the assumption about causal ordering in our model is provided by the work of Scott R. Baker and Bloom (2011).

Our work is also related to Alejandro Justiniano, Giorgio E. Primiceri and Andrea Tambalotti (2010), which stresses the role of technology shocks in the production of installed capital (marginal efficiency of investment shocks). These shocks resemble our risk shock in that they primarily affect intertemporal opportunities. Our risk shock and the marginal efficiency of investment shock are hard to distinguish when we only include the eight standard macroeconomic variables in our analysis. However, the analysis strongly favors the risk shock when our four financial variables are included in the dataset. In part this is because, consistent with the data, the risk shock implies the value of the stock market is procyclical while the marginal efficiency of investment shock implies it is countercyclical. The intuition for this follows from two observations: (i) the fact that the marginal efficiency of investment shock perturbs the supply of capital while the risk shock (by the affecting amount of credit extended to entrepreneurs) affects the demand for capital; and (ii) movements in the price of capital are an important determinant of entrepreneurial net worth.

To gain intuition into our model and promote comparability with the literature, we also include a shock that we refer to as an *equity shock.* Several analyses of the recent financial crisis assign an important causal role to the equity shock (see, e.g., Saki Bigio (2012), Gertler and Peter Karadi (2011) and Gertler and Nobuhiro Kiyotaki (2011)). This is a disturbance that directly affects the quantity of net worth in the hands of entrepreneurs.[10] The equity shock acts a little like our risk shock, by operating on the demand side of the market for capital. However, unlike the risk shock the equity shock has the counterfactual implication that credit is countercyclical. Thus, the procyclical nature of credit is also an important reason that our econometric analysis assigns a pre-eminent status to risk shocks in business cycles.

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

[9]For example, Rudiger Bachmann and Giuseppe Moscarini (2011) explore the idea that the cross-sectional volatility of price changes 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 volatility. Another example of endogeneity in cross-sectional volatility is provided by Christiano and Ikeda (2012).

[10]In the literature, the equity shock perturbs the net worth of banks. As explained below, our entrepreneurs can be interpreted as banks.

model such as the one in Christiano, Eichenbaum and Evans (2005) (CEE) or Frank Smets and Rafael 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, as discussed above we compare the model's implications for the kind of uncertainty measures proposed by Bloom. Although the match is far from perfect, overall it performs well.

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 Appendix, Christiano, Motto and Rostagno (2012).

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. Although these parts of the model can be found in many sources, we include it nevertheless so that the presentation is self contained. In addition, the presentation fixes notation and allows us to be precise about the shocks in the model. The second subsection describes the role of the entrepreneurs in the model and the agency problems that occur in supplying them with credit. 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

2.1.1 Goods Production

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 Dixit-Stiglitz 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 effective 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^*. The fixed cost 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 its price as follows:

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

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

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

2.1.2 Labor Market

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

$$l_t = \left[\int_0^1 (h_{t,i})^{\frac{1}{\lambda_w}} di \right]^{\lambda_w}, \ 1 \leq \lambda_w. \tag{2.4}$$

The labor contractor sells labor services, l_t, to intermediate good producers for nominal wage rate, W_t. The labor contractor's first order condition for $h_{i,t}$ represents its demand curve for that labor type. There are several ways of conceptualizing the supply of each labor type, each of which leads to the same equilibrium conditions. We find it convenient to adopt the following framework. For each labor type, i, there is a monopoly union which represents all workers of that type in the economy. The union sets the wage rate, $W_{i,t}$, for that labor type, 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,

$$\tilde{\pi}_{w,t} \equiv \left(\pi_t^{target}\right)^{\iota_w} \left(\pi_{t-1}\right)^{1-\iota_w}, \ 0 < \iota_w < 1. \tag{2.5}$$

The indexing assumptions in wage setting ensure wage-setting frictions are not distortionary along a non-stochastic, steady state growth path.

2.1.3 Households

There is a large number of identical and competitive households. Each household contains every type of differentiate 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 David Andolfatto (1996) and Monika Merz (1995)) we avoid confronting difficult - and potentially distracting - distributional issues. Similarly, each household also has a large number of entrepreneurs, but we defer our discussion of these agents to the next subsection. Finally, households are the agents who build the physical stock of capital in the economy.

After goods production in period t, the representative household constructs end-of-period t physical capital, $\bar{K}_{t+1}$, using the following technology:

$$\bar{K}_{t+1} = (1 - \delta) \bar{K}_t + \left(1 - S(\zeta_{I,t} \, I_t / I_{t-1})\right) I_t. \tag{2.6}$$

To produce new capital, the household must purchase existing capital and investment goods, I_t. The quantity of existing capital available at the end of period t production is $(1-\delta)\bar{K}_t$, where $0<\delta<1$ denotes the rate of depreciation on capital. In (2.6), S is an increasing and convex function described below and $\zeta_{I,t}$ is a shock to the marginal efficiency of investment in producing capital. The household buys I_t at the price described in the previous subsection.[11]

In addition, the household purchases the existing physical stock of capital for the price, $Q_{\bar{K},t}$. It sells new capital for the same price. The household is competitive, so that it takes the price of capital and investment goods as given.

The preferences of the representative household are as follows:

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

Here, $\zeta_{c,t}>0$ is a preference shock and C_t denotes the per capita consumption of the members of the household. The budget constraint of the representative household is:

$$\begin{aligned} & (1+\tau^c) P_t C_t + B_{t+1} + B_{t+40}^L + \left(\frac{P_t}{\Upsilon^t \mu_{\Upsilon,t}}\right) I_t + Q_{\bar{K},t}(1-\delta)\bar{K}_t \\ \leq \ & \left(1-\tau^l\right) \int_0^1 W_t^i h_{i,t} di + R_t B_t + \left(R_t^L\right)^{40} B_t^L + Q_{\bar{K},t}\bar{K}_{t+1} + \Pi_t. \end{aligned} \tag{2.8}$$

According to the left side of the budget constraint, the household allocates funds to consumption, two types of bonds, investment and existing capital. The household's sources of funds are the earnings from differentiated labor and bonds, as well as the revenues from selling physical capital. Finally, Π_t represents various lump sum payments. These include profits from intermediate goods, transfers from entrepreneurs (discussed in the next subsection) and lump sum transfers from the government, net of lump sum transfers. Wages of differentiated labor, $W_{i,t}$, are set by the monopoly unions as discussed in the previous section. In addition, the household agrees to supply whatever labor of each type that is demanded at the union-set wage rate. So, the household treats labor income as exogenous.

In (2.8), the tax rates on consumption and wage income, τ^c and τ^l, are exogenous and constant. The revenues from these taxes are refunded to households in the form of lump sum taxes via Π_t. The object, B_{t+1} denotes one-period bonds that pay a gross nominal return, R_t,

[11]The specification of the production function for new capital in (2.6) is often used in DSGE models in part because it improves their fit to aggregate data (see, e.g., CEE). Microeconomic evidence that also supports a specification like (2.6) includes Janice Eberly and Sergio Rebelo (2012), Kiminori Matsuyama (1984), and Robert Topel and Sherwin Rosen (1988). Papers that provide interesting theoretical foundations which rationalize (2.6) as a reduced form specification include Lucca (2006) and Matsuyama (1984).

which is not contingent on the realized period $t+1$ state of nature. In addition, we give the household access to a long term (10 year) bond, B^L_{t+40}. These pay gross return, R^L_t, in period $t+40$, at a quarterly rate. The nominal return on the long term bond purchased in period t, R^L_t, is known at time t. As discussed in the next section, the one period bond is the source of funding for entrepreneurs and plays a critical role in the economics of the model. The long term bond plays no direct role in resource allocation and the market for this bond clears at $B^L_{t+40} = 0$. We include this bond because it allows us to diagnose the model's implications for the slope of the term structure of interest rates.

The representative household's problem in period t is to choose C_t, $\bar{K}_{t+1}$, $\bar{K}_t$, I_t, B_{t+1}, B^L_{t+40}. It makes this choice for each date with the objective of maximizing (2.7) subject to (2.8).

2.2 Financial Frictions

Each of the identical households in the economy has a large number of entrepreneurs.[12] After production in period t entrepreneurs receive loans from mutual funds. At this time, the state of an entrepreneur is summarized by his net worth, $N \geq 0$. The density of entrepreneurs with net worth, N, is denoted $f_t(N)$ and we denote the total net worth in the hands of all entrepreneurs at this point by

$$N_{t+1} = \int_0^\infty N f_t(N)\, dN. \tag{2.9}$$

We refer to an entrepreneur with net worth N as an $N-$type entrepreneur. Each $N-$type entrepreneur purchases physical capital using his own net worth and a loan and converts physical capital into effective capital services. In period $t+1$ each $N-$type entrepreneur earns income by supplying capital services and from capital gains; he then repays his loan and transfers funds between himself and his household. At this point, each entrepreneur's net worth in period $t+1$ is determined. Each entrepreneur then acquires a new loan and the cycle continues. All markets visited by entrepreneurs are competitive.

The general flow of funds in financial markets is indicated in Figure 1. Households are the source of funds to entrepreneurs. The most straightforward interpretation of our entrepreneurs is that they are firms in the non-financial business sector. However, it is also possible to interpret entrepreneurs as financial firms that are risky because they hold a non-diversified portfolio of loans to risky non-financial businesses (see the 'bank→entrepreneur' entries in Figure 1).[13]

[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.

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

The following subsection describes the details of one period in the life of an $N-$type entrepreneur. The subsection after that discusses the implications for the aggregates of all entrepreneurs.

2.2.1 One Period in the Life of an Entrepreneur

Each $N-$type entrepreneur obtains a loan, B_{t+1}^N, from a mutual fund, which the entrepreneur combines with N to purchase raw physical capital, $\bar{K}_{t+1}^N$, in an anonymous and competitive market at a price of $Q_{\bar{K},t}$. That is,

$$Q_{\bar{K},t}\bar{K}_{t+1}^N = N + B_{t+1}^N.$$

As explained in section 2.1.3, entrepreneurs purchase capital from households. Entrepreneurs do not acquire capital from their own household.

After purchasing capital, each $N-$type entrepreneur experiences an idiosyncratic shock, ω, which converts its capital, $\bar{K}_{t+1}^N$, into efficiency units, $\omega\bar{K}_{t+1}^N$. Following BGG, we assume that ω has a unit-mean log normal distribution that is independently drawn across time and across entrepreneurs. Denote the period t standard deviation of $\log\omega$ by σ_t. The random variable, ω, captures the idiosyncratic risk in actual business ventures. For example, in the hands of some entrepreneurs 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 risk shock, σ_t, characterizes the extent of cross sectional dispersion in ω. We allow σ_t to vary stochastically over time and we discuss its law of motion below.

After observing the period $t+1$ aggregate rates of return and prices, each $N-$type entrepreneur determines the utilization rate, u_{t+1}^N, of its effective capital and supplies an amount of capital services, $u_{t+1}^N\omega\bar{K}_{t+1}^N$, for a competitive market rental rate denoted by r_{t+1}^k.

At the end of period $t+1$ production, the $N-$type entrepreneur that experienced shock, ω, 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, $Q_{\bar{K},t+1}$. In this way, an $N-$type entrepreneur who draws a shock, ω, at the end of period t enjoys rate of return, ωR_{t+1}^k, at $t+1$, where

$$R_{t+1}^k \equiv \frac{(1-\tau^k)\left[u_{t+1}r_{t+1}^k - a(u_{t+1})\right]\Upsilon^{-(t+1)}P_{t+1} + (1-\delta)Q_{\bar{K},t+1} + \tau^k\delta Q_{\bar{K}',t}}{Q_{\bar{K},t}}. \tag{2.10}$$

Christiano and Ikeda (2012). To interpret our entrepreneurs as financial firms, it is necessary that there be no agency problem between the entrepreneur and the bank, as in GK[2].

Here, the increasing and convex function, a, captures the idea that capital utilization is costly (we describe this function below). We have deleted the superscript, N, from the capital utilization rate. We do so because the only way utilization affects the entrepreneur is through (2.10) and the choice of utilization that maximizes (2.10) is evidently independent of the entrepreneur's net worth. From here on, we suppose that u_{t+1} is set to its optimizing level, which is a function of r_{t+1}^k and $\Upsilon^{-(t+1)}P_{t+1}$. Finally, τ^k in (2.10) denotes the tax rate on capital income and we assume depreciated capital can be deducted at historical cost.

Thus, each entrepreneur in period t, regardless of his net worth, has access to a stochastic, constant rate to scale technology, $R_{t+1}^k\omega$.[14] The loan obtained by an $N-$type entrepreneur in period t takes the form of a standard debt contract, (Z_{t+1}, L_t). Here, $L_t \equiv (N + B_{t+1}^N)/N$ denotes leverage and Z_{t+1} is the gross nominal rate of interest on debt. Let $\bar{\omega}_{t+1}$ denote the value of ω that divides entrepreneurs who cannot repay the interest and principal from those that can repay. In particular,

$$R_{t+1}^k \bar{\omega}_{t+1} Q_{\bar{K},t} \bar{K}_{t+1}^N = B_{t+1}^N Z_{t+1}. \tag{2.11}$$

Entrepreneurs with $\omega \leq \omega_{t+1}^N$ declare bankruptcy. Such an entrepreneur is monitored by his mutual fund, which then takes all the entrepreneur's assets. We have left off the superscript, N, on L_t, $\bar{\omega}_{t+1}$ and Z_{t+1}. This is to minimize notation, and a reflection of the fact (see below) that the equilibrium value of these objects is independent of N. Note that given (2.11), a standard debt contract can equivalently be represented as (Z_{t+1}, L_t) or $(\bar{\omega}_{t+1}, L_t)$. We assume that $N-$type entrepreneurs value a particular debt contract according to the expected net worth in period $t+1$:

$$E_t \left\{ \int_{\bar{\omega}_{t+1}}^{\infty} \left[R_{t+1}^k \omega Q_{\bar{K},t} \bar{K}_{t+1}^N - B_{t+1}^N Z_{t+1} \right] dF(\omega, \sigma_t) \right\} = E_t \left[1 - \Gamma_t(\bar{\omega}_{t+1}) \right] R_{t+1}^k L_t N. \tag{2.12}$$

Here,

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

so that $1 - \Gamma_t(\bar{\omega}_{t+1})$ represents the share of average entrepreneurial earnings, $R_{t+1}^k Q_{\bar{K}',t} \bar{K}_{t+1}^N$,

[14] In the case where the entrepreneur is interpreted as a financial firm, we can 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, $R_{t+1}^k\omega$, which it turns over in full to the financial firm. This interpretation requires that there be no agency costs in the financial/non-financial fiirm relationship.

received by entrepreneurs.[15] In (2.12) we have made use of (2.11) to express Z_{t+1} in terms of $\bar{\omega}_{t+1}$.

Before describing equilibrium in the market for loans, we 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 of the identical $N-$type mutual funds holds a large portfolio of loans that is perfectly diversified across $N-$type entrepreneurs. To extend loans, B_{t+1}^{N} per entrepreneur, the representative $N-$type mutual fund issues B_{t+1}^{N} in deposits to households at the competitively determined nominal interest rate, R_t. As discussed in section 2.1.3, this rate is assumed not to be contingent on the realization of date $t+1$ uncertainty. We assume that mutual funds do not have access in period t to period $t+1$ state-contingent markets for funds, outside of their debt contracts with entrepreneurs. 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 following cash constraint

$$[1-F_t(\bar{\omega}_{t+1})]\, Z_{t+1}B_{t+1}^{N} + (1-\mu)\int_0^{\bar{\omega}_{t+1}} \omega dF_t(\omega)\, R_{t+1}^{k} Q_{\bar{K}',t} \bar{K}_{t+1}^{N} \geq B_{t+1}^{N} R_t, \qquad (2.13)$$

must be satisfied in each period $t+1$ state of nature. The object on the left of the equality in (2.13) is the return, per entrepreneur, on revenues received by the mutual fund from its 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 corresponds to revenues obtained from bankrupt entrepreneurs. The latter revenues are net of mutual funds' monitoring costs, which take the form of final goods and correspond to the proportion, μ, of the assets of bankrupt entrepreneurs. The left term in (2.13) also cannot be strictly greater than the term on the right in any period $t+1$ state of nature because in that case mutual funds would make positive profits and this is incompatible in equilibrium with free entry.[16] Thus, free entry and the cash constraint in (2.13) jointly imply that (2.13) must hold as a strict equality in every state of nature. Using this fact and rearranging (2.13) after substituting out for $Z_{t+1}B_{t+1}^{N}$ using (2.11), we obtain:

$$\Gamma_t(\bar{\omega}_{t+1}) - \mu G_t(\bar{\omega}_{t+1}) = \frac{L_t - 1}{L_t}\frac{R_t}{R_{t+1}^{k}}, \qquad (2.14)$$

[15] BGG show that $\Gamma_t(\bar{\omega})$ is strictly increasing and concave, $0 \leq \Gamma_t(\bar{\omega}) \leq 1$, $\lim_{\bar{\omega}\to\infty}\Gamma_t(\bar{\omega}) = 1$, and $\Gamma_t(0) = 0$.

[16] In an alternative market arrangement, mutual funds in period t interact with households via two types of financial instrument. One corresponds to the non state contingent deposits discussed in the text. Another is a financial instrument in which payments are contingent on the period $t+1$ state of nature. Under this complete market arrangement a mutual fund has a single zero profit condition in period t. Using equilibrium state-contingent prices, that zero profit condition corresponds to the requirement that the period t expectation of the left side of (2.13) equals the right side of (2.13). The market arrangement described in the text is the one implemented in BGG and we have not explored the complete markets arrangement described in this footnote.

in each period $t+1$ state of nature.

The $(\bar{\omega}_{t+1}, L_t)$ combinations which satisfy (2.14) define a menu of state $t+1$ contingent standard debt contracts offered to entrepreneurs. Entrepreneurs select the contract that maximizes their objective, (2.12). Since N does not appear in the constraint and only as a constant of proportionality in the objective, it follows that all entrepreneurs select the same $(\bar{\omega}_{t+1}, L_t)$ regardless of their net worth.

After entrepreneurs have sold their undepreciated capital, collected capital rental receipts and settled their obligations to their mutual fund at the end of period $t+1$, a random fraction, $1-\gamma_{t+1}$, of each entrepreneur's assets is transferred to their household. The complementary fraction, γ_{t+1}, remains in the hands of the entrepreneurs. In addition, each entrepreneur receives a lump sum transfer, W_{t+1}^e, from the household. The objects, γ_{t+1} and W_{t+1}^e, are exogenous.

A more elaborate model would clarify why the transfer of funds back and forth between households and their entrepreneurs is exogenous and not responsive to economic conditions. In any case it is clear that, given our assumptions, the larger is the net worth of a household's entrepreneurs, the greater are the resources available to the household. This is why it is in the interests of the representative household to instruct each of its entrepreneurs to maximize expected net worth. By the law of large numbers, this is how the household maximizes the aggregate net worth of all its entrepreneurs. Entrepreneurs comply with their household's request in exchange for perfect consumption insurance.[17]

2.2.2 Implications for Aggregates

The quantity of physical capital purchased by entrepreneurs in period t must equal the quantity produced, $\bar{K}_{t+1}$, by households:

$$\bar{K}_{t+1} = \int_0^\infty \bar{K}_{t+1}^N f_t(N)\, dN. \tag{2.15}$$

The aggregate supply of capital services by entrepreneurs is:

$$K_t = \int_0^\infty \int_0^\infty u_t^N \omega \bar{K}_t^N f_{t-1}(N)\, dF(\omega)\, dN = u_t \bar{K}_{t+1}, \tag{2.16}$$

[17] A variety of decentralizations of the entrepreneur side of the model is possible. An alternative is the one used in BGG, in which entrepreneurs are distinct households who maximize expected net worth as a way of maximizing utility from consumption. In this arrangement, a fraction of entrepreneurs die in each period and the complementary fraction are born. Dying entrepreneurs consume a fraction, Θ, of their net worth with the rest being transferred in lump-sum form to households. Entrepreneurs' motive for maximizing expected net worth is to maximize expected end-of-life consumption. The mathematical distinction between the BGG decentralization and the one pursued here is that BGG include entrepreneurial consumption in the resource constraint. Since Θ is a very small number in practice, this distinction is very small.

where the last equality uses (2.15), the fact that utilization is the same for all N and that the mean of ω is unity. Market clearing in capital services requires that the supply of capital services, K_t, equal the corresponding demand, $\int_0^1 K_{j,t}dj$, by the intermediate good producers in section 2.1.1.

By the law of large numbers the aggregate profits of all $N-$type entrepreneurs at the end of period t is $[1-\Gamma_{t-1}(\bar{\omega}_t)]\, R_t^k Q_{\bar{K},t-1}\bar{K}_t^N$. Integrating this last expression over all N and using (2.15) evaluated at $t-1$, we obtain $[1-\Gamma_{t-1}(\bar{\omega}_t)]\, R_t^k Q_{\bar{K},t-1}\bar{K}_t$. Thus, after transfer payments, aggregate entrepreneurial net worth at the end of period t is:

$$N_{t+1} = \gamma_t\left[1-\Gamma_{t-1}(\bar{\omega}_t)\right] R_t^k Q_{\bar{K},t-1}\bar{K}_t + W_t^e. \tag{2.17}$$

In sum, $\bar{N}_{t+1}$, $\bar{\omega}_{t+1}$ and L_t can be determined by (2.14), (2.45) and an expression that characterizes the solution to the entrepreneur's optimization problem.[18] Notably, it is possible to solve for these aggregate variables without determining the distribution of net worth in the cross-section of entrepreneurs, $f_t(N)$, 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,

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

where the last equality uses (2.9) and (2.15). Finally, Z_{t+1} can be obtained by integrating (2.11) relative to the density $f_t(N)$ and solving $Z_{t+1} = R_{t+1}^k\bar{\omega}_{t+1}L_t$.

2.3 Monetary Policy and Resource Constraint

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

$$R_t - R = \rho_p\left(R_{t-1}-R\right) + \left(1-\rho_p\right)\left[\alpha_\pi\left(\pi_{t+1}-\pi_t^*\right) + \alpha_{\Delta y}\frac{1}{4}\left(g_{y,t}-\mu_{z^*}\right)\right] + \frac{1}{400}\varepsilon_t^p, \tag{2.18}$$

[18] The first order condition associated with the entrepreneur's optimization problem is:

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

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

We complete the description of the model with a statement of the resource constraint:

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

where the last term on the right represents the aggregate capital utilization costs of entrepreneurs, an expression that makes use of (2.15) 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

$$G_t = z_t^* g_t, \tag{2.19}$$

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

2.4 Adjustment Costs, Shocks, Information and Model Perturbations

Our specification of the adjustment cost function for investment is as follows:

$$S(x_t) = \frac{1}{2}\left\{\exp\left[\sqrt{S''}\left(x_t - x\right)\right] + \exp\left[-\sqrt{S''}\left(x_t - x\right)\right] - 2\right\},$$

where $x_t \equiv \zeta_{I,t} I_t / I_{t-1}$ and x denotes the steady state value of x_t. Note that $S\left(x\right) = S'\left(x\right) = 0$ and $S''\left(x\right) = S''$, where S'' denotes a parameter to be estimated. The value of the parameter, S'', has no impact on the model steady state, but it does affect dynamics. Also, the utilization adjustment cost function is:

$$a\left(u\right) = r^k\left[\exp\left(\sigma_a(u-1)\right) - 1\right]\frac{1}{\sigma_a},$$

where $\sigma_a > 0$ and r^k is the steady state rental rate of capital in the model. This function is designed so that utilization is unity in steady state, independent of the value of the parameter, σ_a.

We now turn to the shocks in the model. 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 in the empirical analysis we find that 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 Valerie 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:

$$x_t = \rho_x x_{t-1} + \overbrace{\xi_{0,t} + \xi_{1,t-1} + ... + \xi_{p,t-p}}^{=u_t}, \tag{2.20}$$

where $p > 0$ is a parameter. In (2.20), 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.[19] 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

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

time t, agents observe $\xi_{j,t}$, $j = 0, 1, ..., p$. 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 to have the following correlation structure:

$$\rho_{x,n}^{|i-j|} = \frac{E\xi_{i,t}\xi_{j,t}}{\sqrt{\left(E\xi_{i,t}^2\right)\left(E\xi_{j,t}^2\right)}}, \ i, j = 0, ..., p, \tag{2.21}$$

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

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

In sum, for a shock, x_t, with the information structure in (2.20), 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 (2.20) 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 that we call 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 section 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 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.[20]

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.[21] Our measure of the slope of the term structure, $R_t^L - R_t$, is the difference between the 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.[22]

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 (2.19) 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.

[20] 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.

[21] 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.

[22] 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.

Following CEE, the steady state markups in the labor market λ_w and in the product market λ_f are fixed at 1.05 and 1.2, respectively. The steady state value of the parameter controlling the rate at which the household transfers equity from entrepreneurs to itself, $1-\gamma$, was set to 1-0.985. This is fairly close to the 1-0.973 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). These parameter values are reported in Table 1.

The second set of parameters to be assigned values consists of the 36 parameters listed in Tables 2a and 2b. We study these using the Bayesian procedures surveyed in Sungbae An and Frank Schorfheide (2005). Table 2a 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 utilization fluctuates relatively little. 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.[23]

We 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 0.0075 value used in Bernanke, et al (1999), or the 0.0097 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 5.1 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 2b. 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, $\xi_{i,t}$, $i=1,...,8$,

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

is 0.0283. This implies that a substantial 57 percent of the variance in the statistical innovation in $\log \sigma_t$ is anticipated.[24] The posterior mode on the correlation among signals is 0.4. Thus, 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.[25]

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 roughly a random walk. For the most part, there is 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 larger than the standard deviation of the prior.

Table 3 reports the steady state properties of the model, as well as the analog objects in the data. Overall, the model and data match well. An exception is the capital output ratio, which is a little low. In part, the relatively low stock of capital that reflects the effects of the financial frictions in the model.

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 4. 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,

[24] In particular,

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

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

but most prefers adding them to risk, as in our baseline specification.

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 2. 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 occurred 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 2 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.[26] Note that although the risk shock, σ_t, and

[26] The estimated risk shock was obtained by applying the Kalman smoother and our model with its parameters

the credit spread are positively related, they are by no means perfectly correlated. This is so, despite the result in panel e which shows that when we feed only the estimated 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 σ_t itself.

Our final indicator of the importance of risk shocks appears in Table 5. That table reports the percent of the variance in the level of several variables at business cycle frequencies, contributed by our shocks.[27] 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 (2.21)). 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 pertains to the risk shock. Consistent with the evidence in Panel a of Figure 2, 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 2, 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 5 provide some insight into why the risk shock is so important, and these are discussed later.

evaluated at their posterior mode, to the data. The risk variable reported in the figure is $(\sigma_t - \sigma)/\sigma$.

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

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 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.[28] 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

As stressed in the introduction, the economic intuition underlying the response of the model to a jump in the risk shock is simple. With a rise in risk, the probability of a low ω increases and banks raise the interest rate charged on loans to entrepreneurs to cover the resulting costs. Entrepreneurs respond by borrowing less, so that credit drops. With fewer financial resources, entrepreneurs purchase less capital, which has the consequence that investment is lower. The drop in investment leads to a fall in output and consumption. The reasons for the drop in consumption may not be obvious at first, so we discuss this in detail below. The fall in investment produces a fall in the price of capital, which reduces the net worth of entrepreneurs and this magnifies the impact of the jump in risk through standard accelerator effects. The decline in economic output leads to a fall in costs and thus inflation is reduced. The decline in credit is smaller in percent terms than the decline in net worth, because in these dynamic responses there is a partially offsetting effect on credit. In particular, when the price of capital drops there is an expectation that it will return to steady state. Other things the same, the resulting higher prospective return on capital raises credit. The net impact of all these effects

[28]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. See also Olivier Blanchard, Jean-Paul L'Huillier and Guido Lorenzoni (2012).

on credit is negative. However, this reasoning explains why credit falls less than net worth, in percent terms. For a more detailed discussion of these observations, see the technical appendix, section C.

Figure 3 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.[29] 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, $R_t^L - R_t$, is countercyclical in response to each shock to risk. Notably, the peak 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.[30] This is because as risk increases, a

[29] 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.

[30] 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

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 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.[31]

This reasoning suggests that the dynamics of the real interest rate holds the key to understanding why risk shocks make consumption procyclical.[32] In our model the real interest rate

(1997).

[31]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. The market force that guides the rise in C_0 is a drop in the real rate of interest.

[32]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.

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 4 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.[33] In both panels of Figure 4, the solid line displays the responses in our baseline model, taken from the relevant portions of Figure 3. 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 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. The left panel in Figure 4 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 2a).

[33] 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.

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. 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.[34] Consistent with this intuition, the thick lines in Panel F of Figure 3 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 3, and so we do not display those in the figure.

4.2.2 Dynamic Cross Correlations

Here, we define the business cycle as the dynamic cross correlations between output and the variables in Figure 5. Before computing the correlations in Figure 5, 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 5 display the model-implied correlations when only the risk shocks (both unanticipated and anticipated) are activated. We emphasize two results in Figure 5. 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.

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

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 5. 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 invariant 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 investment 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 5. 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.[35]

According to the results in Table 5, all the financial variables are important for the conclusion that the risk shock is important. However, credit and the credit spread stand out as

[35] 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.

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 5, 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, 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 5 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 6, 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 3 (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 7. 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 2. 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.[36] 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. 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 8). The supply curve corresponds to the marginal cost of building capital, derived from the household's technology for constructing capital discussed just after (2.8). 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.[37] 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}

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

[37] The equation that characterizes net worth is given in (2.45). The price of capital enters that expression via the rate of return on capital, (2.10).

shock implies that investment is procyclical. A similar logic reaches the conclusion that the σ_t and γ_t shocks also imply procyclical investment. This intuition is consistent with the results in Figure 6, Panel C.[38] 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 6, as well as the results in Figure 8.

Consider the implications of ζ_{It} for the credit spread. According to Panel A of Figure 6, the marginal efficiency of investment predicts, counterfactually, that the credit spread is procylical. In addition, according to Panel B of Figure 6, the ζ_{It} shock implies that credit rises modestly in a contraction launched by the marginal efficiency of investment shock. This, too, is counterfactual.[39]

4.3.2 Equity Shock

The risk shock, σ_t, also drives out equity shocks, γ_t (recall the variance decomposition results in Table 5). According to Table 5, 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 6. 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 6 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, $\left(1+R_t^k\right)/\left(1+R_{t-1}\right)$, 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.

[38]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.

[39]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.

5 Various Measures of Model Out-of-Sample Performance

The key finding of this paper is that variations in risk are the most important impulse to business cycles. Whether this finding should be taken seriously depends on how seriously we take the underlying model. In this section we offer a defense of the model based on various measures of out-of-sample fit.

We begin by examining two variables not used in our formal econometric analysis. The first of these is a measure of uncertainty recently proposed by Bloom (2009). The second is an indicator of bankruptcy rates. We use our model to project these two variables onto the sample data used in model estimation. If our analysis overstates the importance of risk shocks in the business cycle, then we expect the model to overstate the degree of cyclical variation in Bloom's measure of uncertainty and in the bankruptcy rate. We show that, in fact, the predicted and actual degrees of cyclical variation in these two variables are very similar.

We then turn to the Federal Reserve's survey of senior loan officers to test another aspect of our analysis. Our model stresses that the origins of business cycle fluctuations lie in cyclical variations in the cross section dispersion of a technology shock experienced by agents in the non-financial business sector. In addition, in the empirical analysis of the model we make the assumption that the agency problems which propagate the cyclical variation in risk also lie with non-financial firms.[40] Although it is the standard debt contract offered by the financial system that is crucial in propagating the risk shock, that role is smaller than the role assigned to financial firms in several recent studies of the 2008 financial crisis.[41] We display evidence in the survey of senior loan officers that lends support to the approach taken in this paper.

Finally, we examine more conventional measures of model fit and find that the model performs well on these too.

5.1 Implications for Uncertainty

In an influential paper, Bloom (2009) pointed to cyclical variation in the cross-sectional standard deviation of firm-level stock returns as evidence of the importance in business cycles of what he called uncertainty. These data, for non-financial business firms, is displayed in Figure 9a.[42] In order to focus on the cyclical component of this measure of uncertainty, we also show

[40] In section 2.2 we indicate that in principle some of our entrepreneurs could be interpreted as financial firms. However, our measure of credit in the data corresponds to borrowing by non-financial firms. So, in the empirical analysis we in effect assume that our entrepreneurs are non-financial firms.

[41] See Christiano and Ikeda (2012) as well as the studies that they cite.

[42] There are two differences between the data studied by Bloom (2009) (see row 2 of his Table I) and our data. First, the time period in our model is quarterly while the Center for Research in Securities Prices (CRSP) data used by Bloom (2009) are monthly. To ensure comparability, we use the data constructed in Ferreira (2012)

its Hodrick-Prescott trend. The trend rises in the earlier portion of the data set and then generally falls until 2007. As Bloom (2009) emphasized, this measure of uncertainty is relatively high during recessions. In the 1990 and 2007 recessions it is highest near to the business cycle trough, while in the 2001 recession it rose sharply somewhat before the recession started (vertical grey bars indicate NBER recession periods).

We computed the analog of Bloom's measure of uncertainty in our model. Conditional on the period t aggregate shocks, an entrepreneur with idiosyncratic shock ω earns the following, as a ratio to his net worth:

$$R_t^e(\omega) \equiv \max\{0, [\omega - \bar{\omega}_t]\} \times R_t^k L_{t-1}.$$

Here, L_{t-1} denotes leverage and R_t^k is the cross-sectional average return on capital. According to the model, $R_t^e(\omega)$ is not a function of the entrepreneur's level of net worth, N. The standard deviation, std, of the entrepreneurial return on equity in a cross section which only includes non-bankrupt entrepreneurs (i.e., those with $\omega > \bar{\omega}$) is:

$$std\left(R_t^e(\omega)\,|\omega > \bar{\omega}_t\right) = R_t^k L_{t-1}\sqrt{Var\left(\omega - \bar{\omega}_t|\omega > \bar{\omega}_t\right)}.$$

Here, $Var(x|D)$ denotes the variance of x conditional on the event, D.[43] We computed the projection of std onto the dataset used in the formal econometric analysis of our model. The results are displayed in Figure 9b. Although the levels and trends of the variables in panels a and b are different, the cyclical and higher frequency movements appear more similar. The cyclical components of the two series are compared in panel c. Note that in both the data and the model, uncertainty is high towards the end of the 1990 and 2007 recessions. In the case of the 2001 recession the model implies that uncertainty is high before the onset of the recession, as in the data. We conclude that our model is reasonably consistent with a key measure of uncertainty proposed in Bloom (2009).

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which aggregates the monthly CRSP returns to quarterly returns. Second, we work specifically with data on non-financial firms rather than all firms, as in Bloom (2009). This choice of data is more consistent with our analysis, given the way we map from entrepreneurial credit and interest rate spreads into the data in our econometric analysis. However, there would have been virtually no change to Figure 4 if we had instead reported results based on CRSP data for non-financial and financial firms.

[43] Ferreira (2012) shows that

$$Var\left(R_t^e(\omega)\,|\omega \geq \bar{\omega}_t\right) = \frac{1}{1-F(\bar{\omega}_t)}e^{\sigma^2}\left[1-\Phi\left(\frac{\log\bar{\omega}_t}{\sigma}-\frac{3}{2}\sigma\right)\right]-\left(\frac{1-G(\bar{\omega}_t)}{1-F(\bar{\omega}_t)}\right)^2.$$

For completeness, Ferreira's derivation is reproduced in the technical appendix to this paper, Christiano, Motto and Rostagno (2012).

5.2 Implications for Bankruptcy Rates

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 commercial banks.[44] The results are reported in Figure 10. 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. Still, the two variables are reasonably similar, bearing in mind that empirical measures of default played no role in model estimation.

5.3 Senior Loan Officer Opinion Survey

Each quarter, the Federal Reserve surveys the opinions of senior loan officers at commercial banks. We focus on a key question in this survey: "If you have tightened or eased over the last three months, what are the reasons?" Loan officers are referred to the following seven considerations for tightening or easing bank credit: (1) Bank capital position; (2) Liquidity conditions in secondary markets for loans; (3) Current and expected liquidity position; (4) Less favorable or more uncertain macroeconomic outlook; (5) Tolerance to risk; (6) Industry specific developments; (7) Banks competition. For each of these 7 considerations, the respondent is asked to report whether it was 'Very important', 'Somewhat important', or 'Not Important' in the decision to tighten or ease bank credit. We collected the reasons into three categories: factors having to do with banks' own balance sheets (considerations 1, 2, 3), factors associated with macroeconomic conditions not related to banks' balance sheets (considerations 4, 5, 6), factors related to microeconomic conditions (consideration 7).

We summarize respondents' answers in Figure 11, which covers the period from the first quarter of 2008 to the second quarter of 2011.[45] There are potentially four bars associated with each quarter in Figure 11. The length of the bars above the zero line indicate how many banks reported that they were tightening credit. The length of the two bars extending below the zero line indicate how many banks reported that they were easing credit. Evidently, in late 2008 and early 2009 no bank was easing credit. In each quarter, the left bars summarize the importance assigned to factors having to do with the banks' balance sheets and the right bar summarizes the importance assigned to macro factors originating outside the banks. Each

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

[45] The survey of loan officers begins before 2008. However, the Fed did not publish how many banks responded to each question prior to 2008.

bar has a black part, a grey part and a white part. The length of the black part indicates the average number of 'very important' responses across the three considerations in the associated category. Similarly, the length of the grey part indicates the average number of 'somewhat important' responses and the length of the white part indicates the number of 'not important responses'. The sum of the average responses is equal to the number of banks tightening or easing. This is why the length of the bars on the right and the left is always equal.

The key result is that the black and grey areas extend further for the bars on the right than for the bars on the left. That is, changing conditions outside banks' balance sheets are relatively more important that changes in banks' own balance sheets in determining whether banks tighten or ease credit conditions.

We view the evidence in Figure 11 as providing some support for our choice to leave out considerations strictly related to banks' balance sheets from the model. It is important, however, to stress the limitations of the evidence in Figure 11. First, the evidence applies to a relatively short subperiod of our dataset. At the same time, this evidence is perhaps notable because it covers a period when many think problems in banks' balance sheets were a principle reason for the business cycle contraction.[46] Second, the loan officer survey only covers a portion of the financial system, namely the commercial banks. What is true about the commercial banks need not necessarily be true for financial firms as a whole. Still, we regard the evidence in Figure 11 as supportive of our model.

5.4 Conventional Out-of-Sample Measures of Fit

Figure 12 displays out-of-sample root mean square errors (RMSE's) at forecast horizons, $j = 1, 2, ..., 12$ for various variables. 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. We consider forecasts of quarterly growth rates for the variables which our model predicts are not covariance-stationary and of levels for the variables which 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 Smets and Wouters.[47] The second benchmark corresponds to the RMSE's implied by the version of our DSGE model labeled CEE and discussed in section

[46] For this view, see Christiano and Ikeda (2012) and the references they cite.

[47] 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.

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.[48]

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, with the exception of the credit spread. In the case of inflation, the baseline model does noticeably better than the CEE and BVAR models. Overall, the model does reasonably well in terms of RMSE's.

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 over 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 large share 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 the database used to estimate the model. In particular, we examine the implications of the model for loan deliquency rates, for out-of-sample forecasts, and for features of the cross-sectional dispersion of firm-level stock returns recently stressed by Bloom (2009) and others. We infer that the risk shock deserves to be taken seriously because the model does well on these out-of-sample tests.

Our analysis suggests that understanding the countercyclicality of the credit spread holds the key for understanding business cycles. What moves the credit spread in the model is variations in risk, σ_t. While these variations are exogenous in our model, endogenous fluctuations in σ_t would presumably also move the spread and other aggregate variables in a similar way. To think about this further requires contemplating the possible interpretations of our finding about the importance of variations in σ_t. One possibility is that changes in σ_t reflect changes

[48]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.

in the type of investment projects favored by entrepreneurs. For example, we might expect σ_t to be determined by the proportion of investment projects that involve technologies in which only one standard can ultimately survive (e.g., Betamax versus VHS). This proportion is presumably endogenous and fluctuates over time. Another possibility is that our finding reflects the effects of variations in uncertainty about the level of the net worth of potential borrowers. Though this kind of uncertainty is not literally present in our model, its economic effects can be expected to resemble those of variations in σ_t. This is because increased uncertainty about the level of net worth has the effect of increasing the likelihood of adverse outcomes from the perspective of lenders, just like an increase in σ_t does. In the recent financial crisis uncertainty about the net worth of borrowers shot up as potential lenders became less certain about the market value of potential borrowers' mortgage backed securities. This increase in uncertainty is clearly an endogenous response to the collapse in housing prices. Still, its effects may be the same as those of an increase in σ_t. Understanding the mechanisms by which σ_t varies over time is an important task for research.[49]

[49] For two examples, see Bachmann and Moscarini (2011) and Christiano and Ikeda (2012).

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Table 1: Calibrated Parameters (Time unit of Model: quarterly)

β	Discount rate	0.9987
σ_L	Curvature on disutility of labor	1.00
ψ_L	Disutility weight on labor	0.7705
λ_w	Steady state markup, suppliers of labor	1.05
μ_z	Growth rate of the economy	0.41
Υ	Trend rate of investment-specific technological change	0.42
δ	Depreciation rate on capital	0.025
α	Power on capital in production function	0.40
λ_f	Steady state markup, intermediate good firms	1.20
$1-\gamma$	Fraction of entrepreneurial net worth transferred to households	$1-98.50$
W^e	Transfer received by new entrepreneurs	0.005
η_g	Steady state government spending-GDP ratio	0.20
π^{target}	Steady state inflation rate (APR)	2.43
τ^c	Tax rate on consumption	0.05
τ^k	Tax rate on capital income	0.32
τ^l	Tax rate on labor income	0.24

Table 2a : 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 2b: 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 Table 2a	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 3: Steady State Properties, Model versus Data

Variable	Model	Sample averages
$\frac{i}{y}$	0.26	0.24[1]
$\frac{c}{y}$	0.54	0.59[2]
$\frac{g}{y}$	0.20	0.16
$\frac{k}{y}$	7.79	10.7[3]
$\frac{N}{K-N}$ (Equity to Debt ratio)	1.44	1.3-4.7[4]
Transfer received by new entrepreneurs as % of GDP	0.17	not known
Banks monitoring costs as % of GDP	0.50	not known
Credit velocity	1.25	1.67[5]
Inflation (APR)	2.43	2.47[6]
Short-term risk free rate (APR)	4.67	4.80[7]

Notes: All sample averages are computed over the period 1985:1-2008:2, except inflation and the short-term interest rate, which are computed over 1987:1-2008:2. Model objects are computed on the basis of the estimated parameters at the posterior mode. [1]Investment includes residential, non-residential, equipment, plants, business durables, change in inventories and durable consumption. Source: BEA. [2]Personal Consumption Expenditure includes non-durables and services. Source: BEA. [3]Capital stock includes private non-residential fixed assets, private residential, stock of consumer durables and stock of private inventories. Source: BEA. [4]Masulis (1988) reports an equity to debt ratio for U.S. corporations in the range of 1.3-2 over the period 1937-1984. McGrattan and Prescott (2004) estimate an equity to debt ratio of 4.7 for the corporate sector over the period 1960-1995. [5]Credit velocity is computed as annual GDP over credit, where credit is defined as credit market instruments liabilities of nonfarm nonfinancial corporate business plus credit market instruments liabilities of nonfarm noncorporate business. Source: Flow of Funds Accounts of the Federal Reserve Board. [6]Computed on the basis of the GDP Price Index. Source: BEA. [7]3-month average of the daily effective Federal Funds rate. Source: Federal Reserve Board.

Table 4. 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 5: Variance Decomposition at Business Cycle Frequency (in percent)

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

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

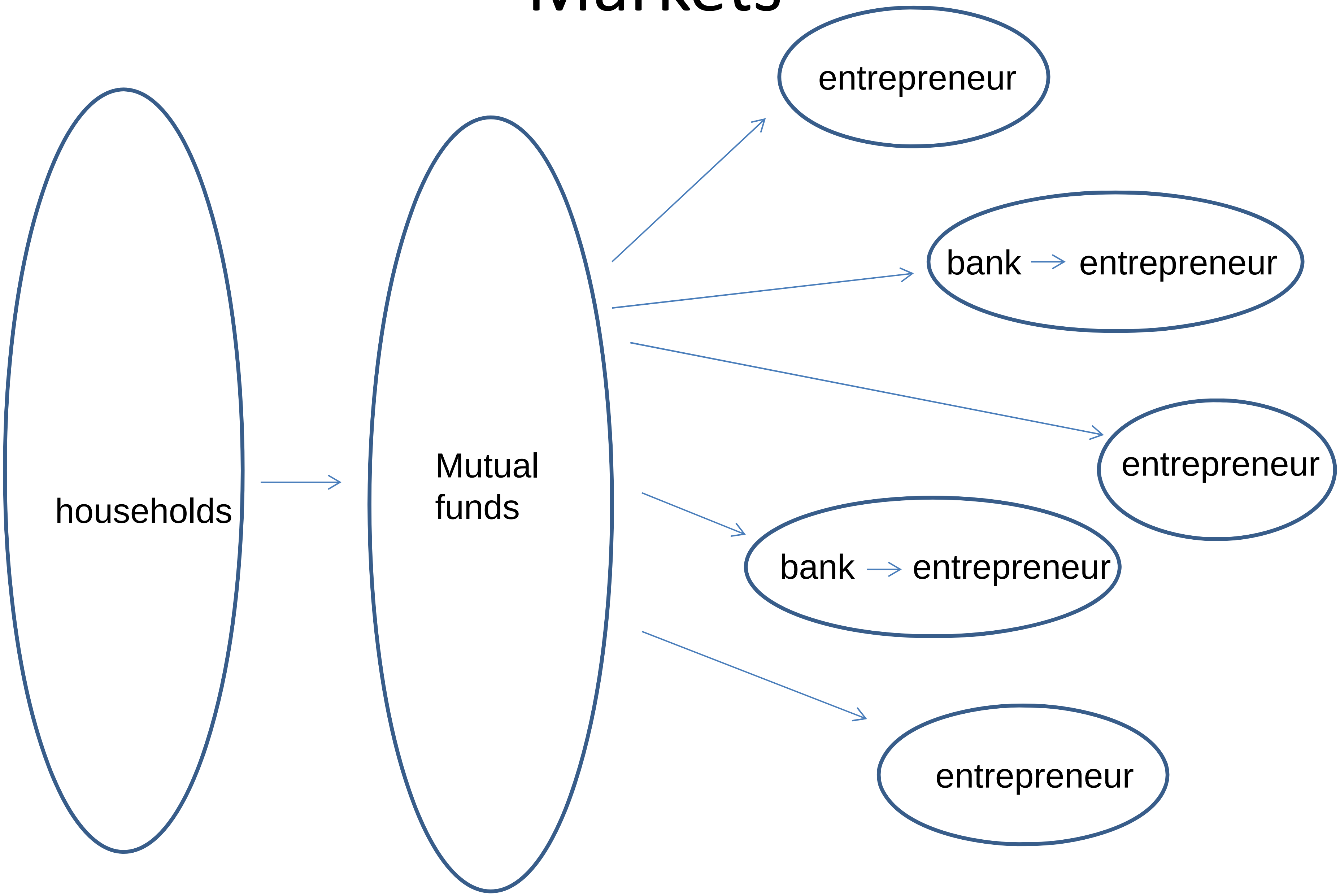
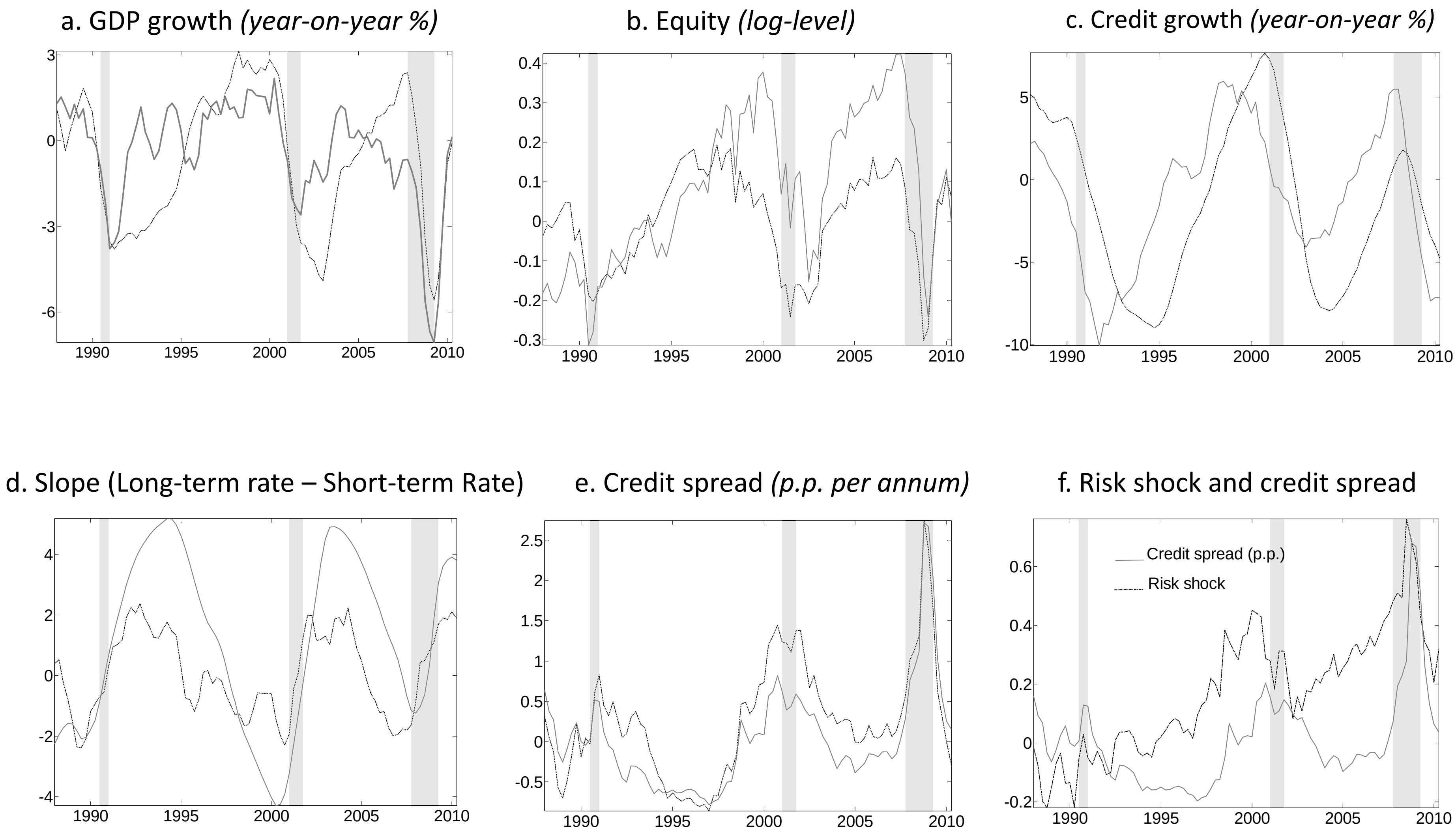


Figure 2:The Role of the Risk Shock in Selected Variables



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 3: : Dynamic Responses to Unanticipated and Anticipated Components of Risk Shock

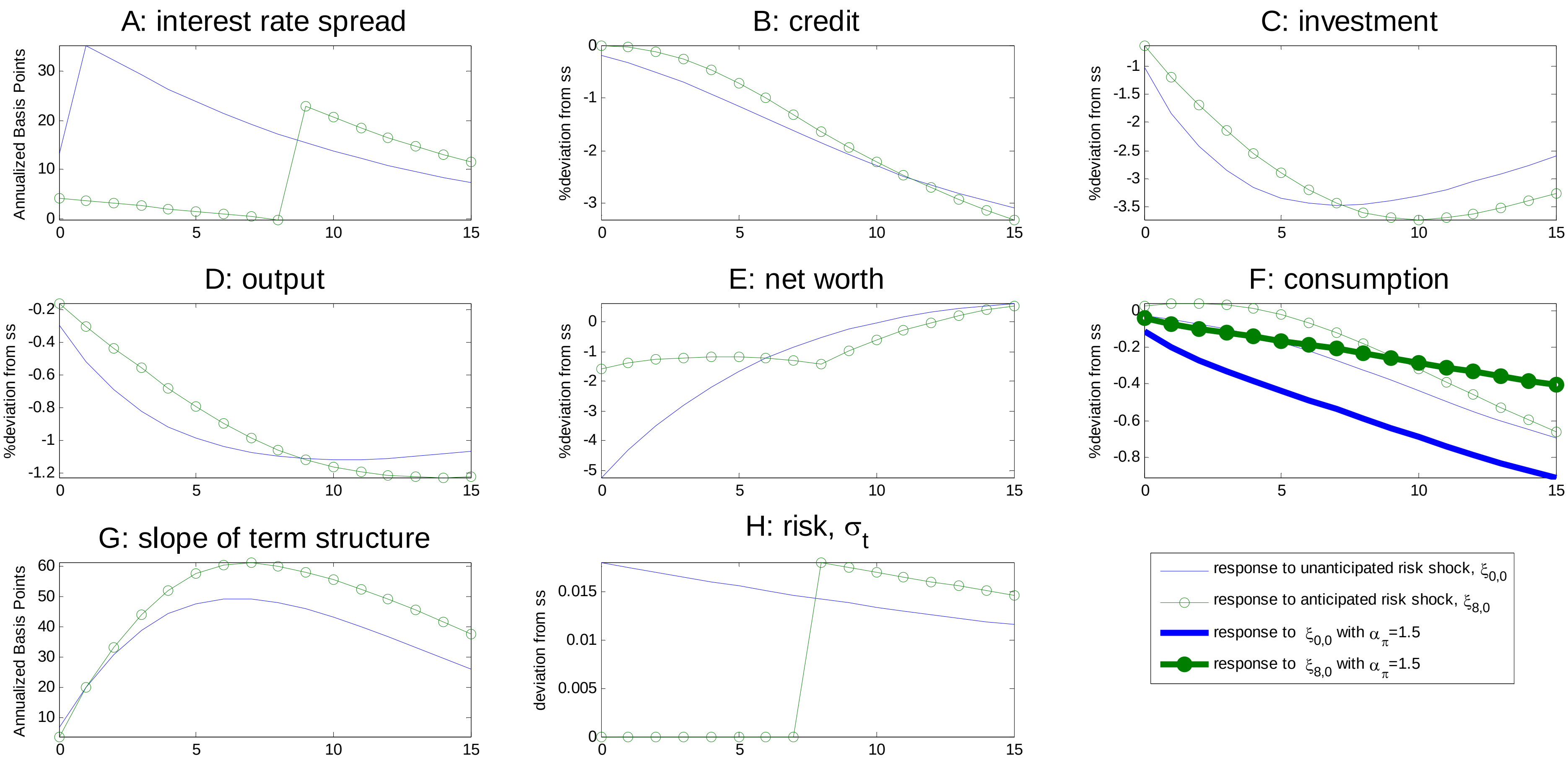


Figure 4: ': Responses to Unanticipated Risk Shock

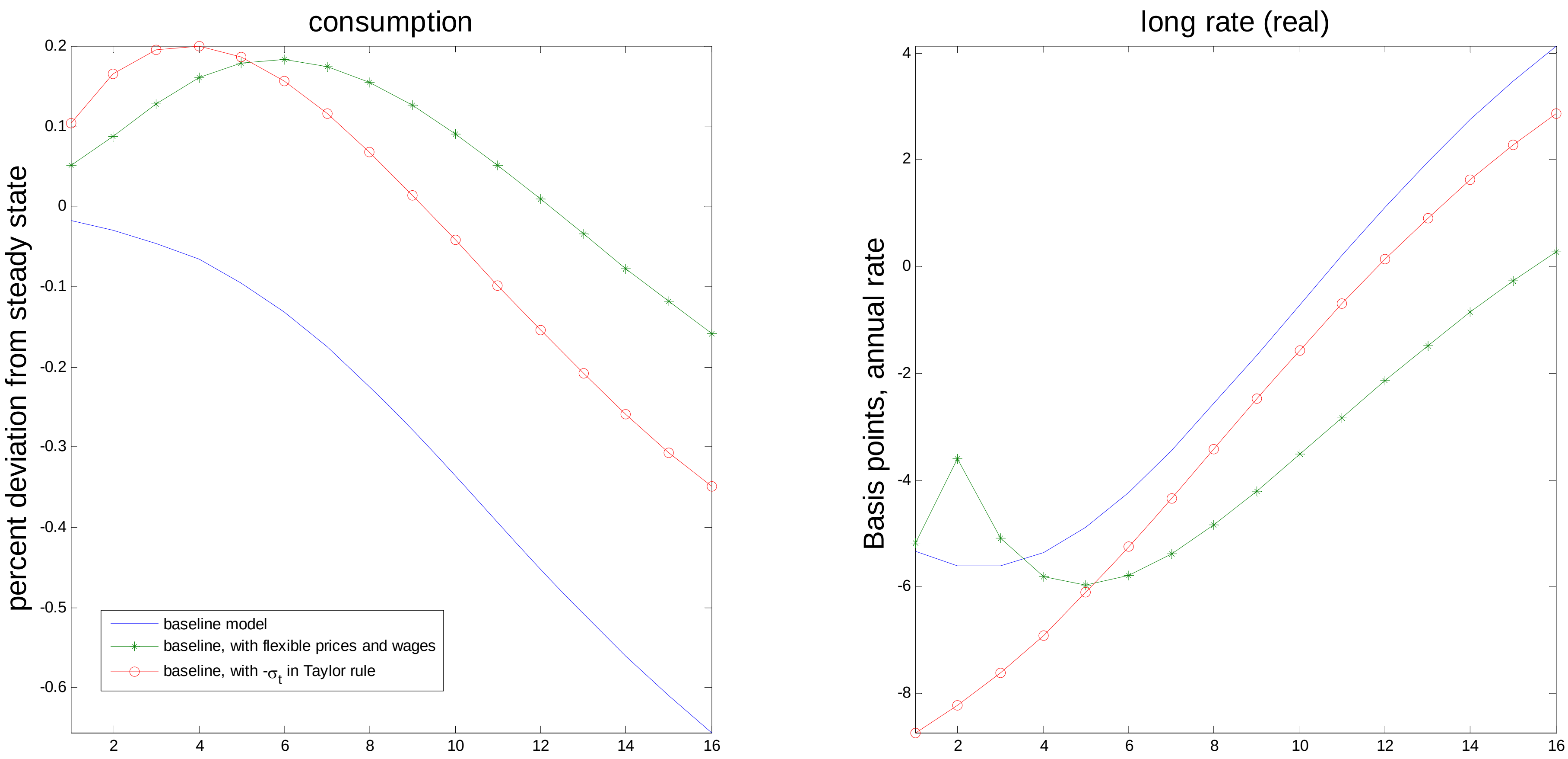


Figure 5: Selected Cross-correlations, Model and Data

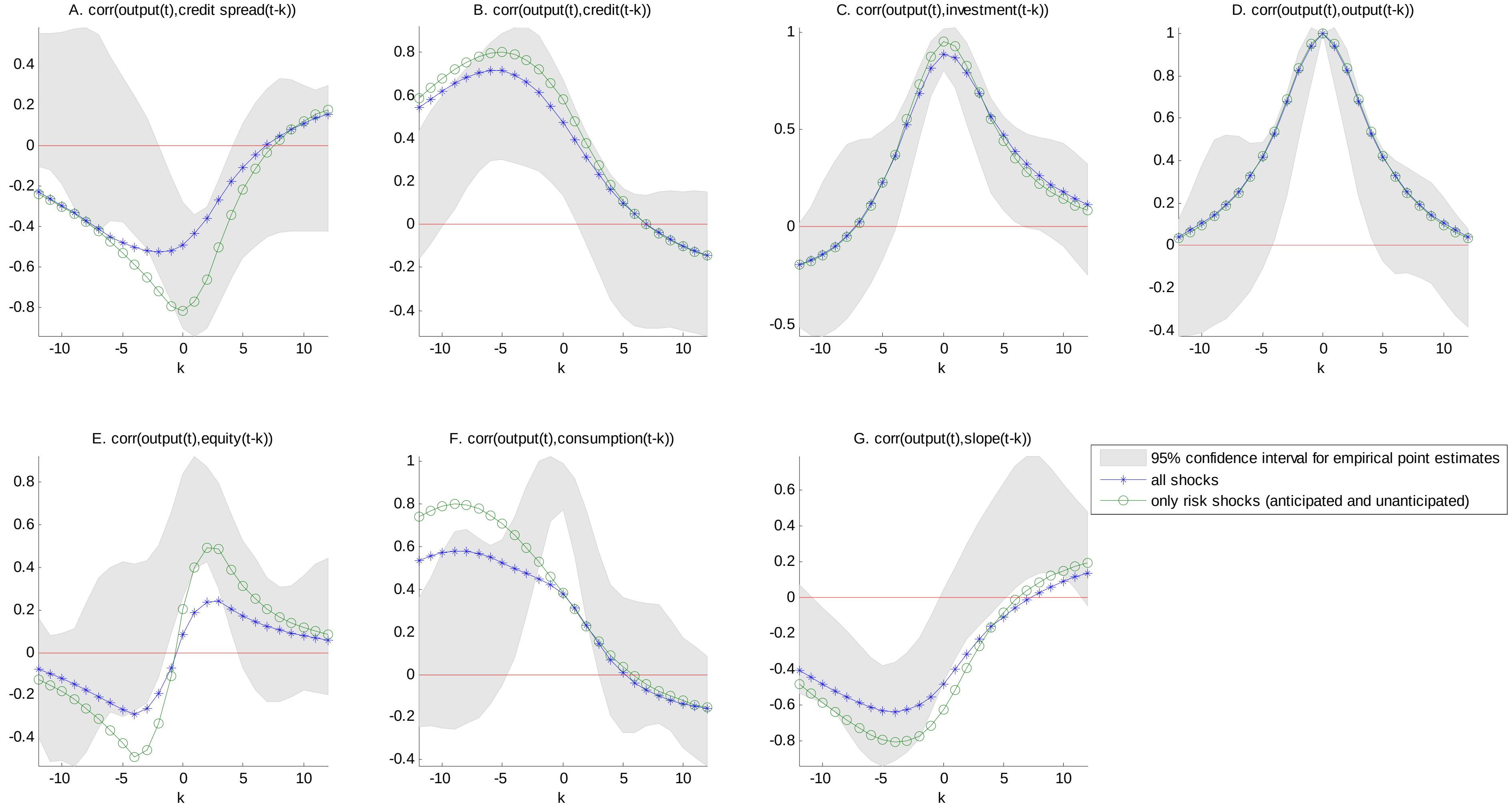


Figure 6:: Dynamic Responses to Three Shocks

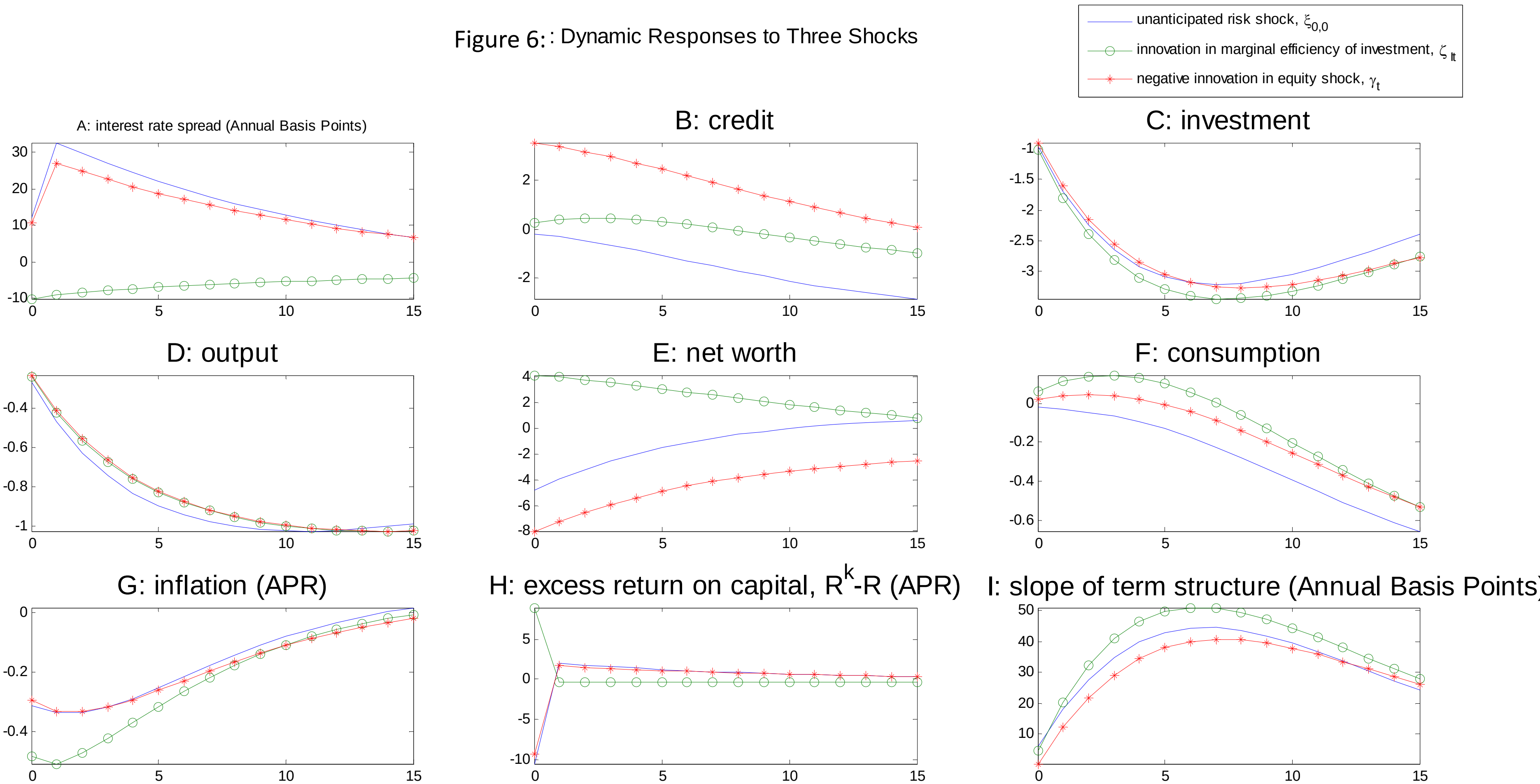


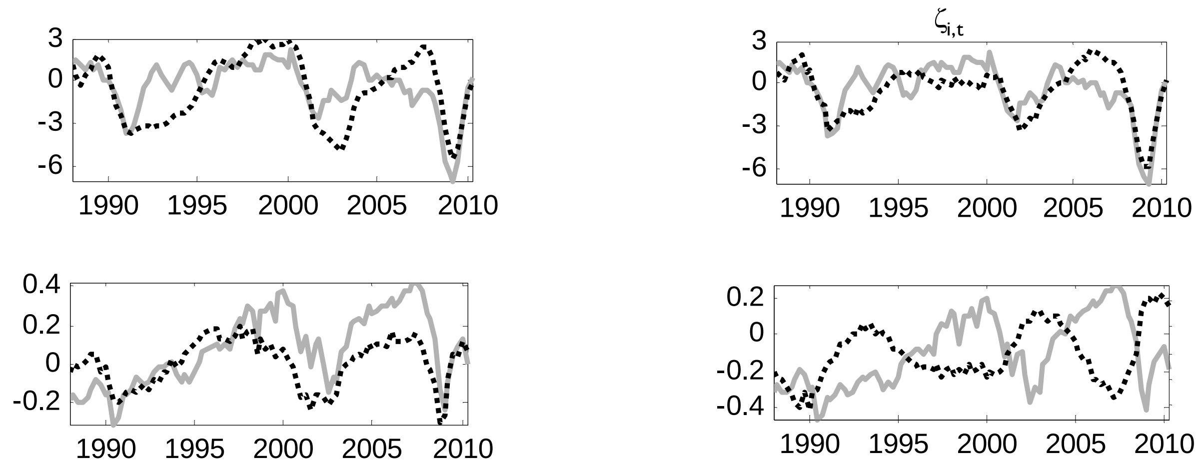
Figure 7: Historical Decompositions in Two Models

Baseline model

Simple model (CEE)

GDP growth (y-o-y %)

Equity (log-level)



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

Figure 8: The Risk and Equity Shocks, Versus the Marginal Efficiency of Investment

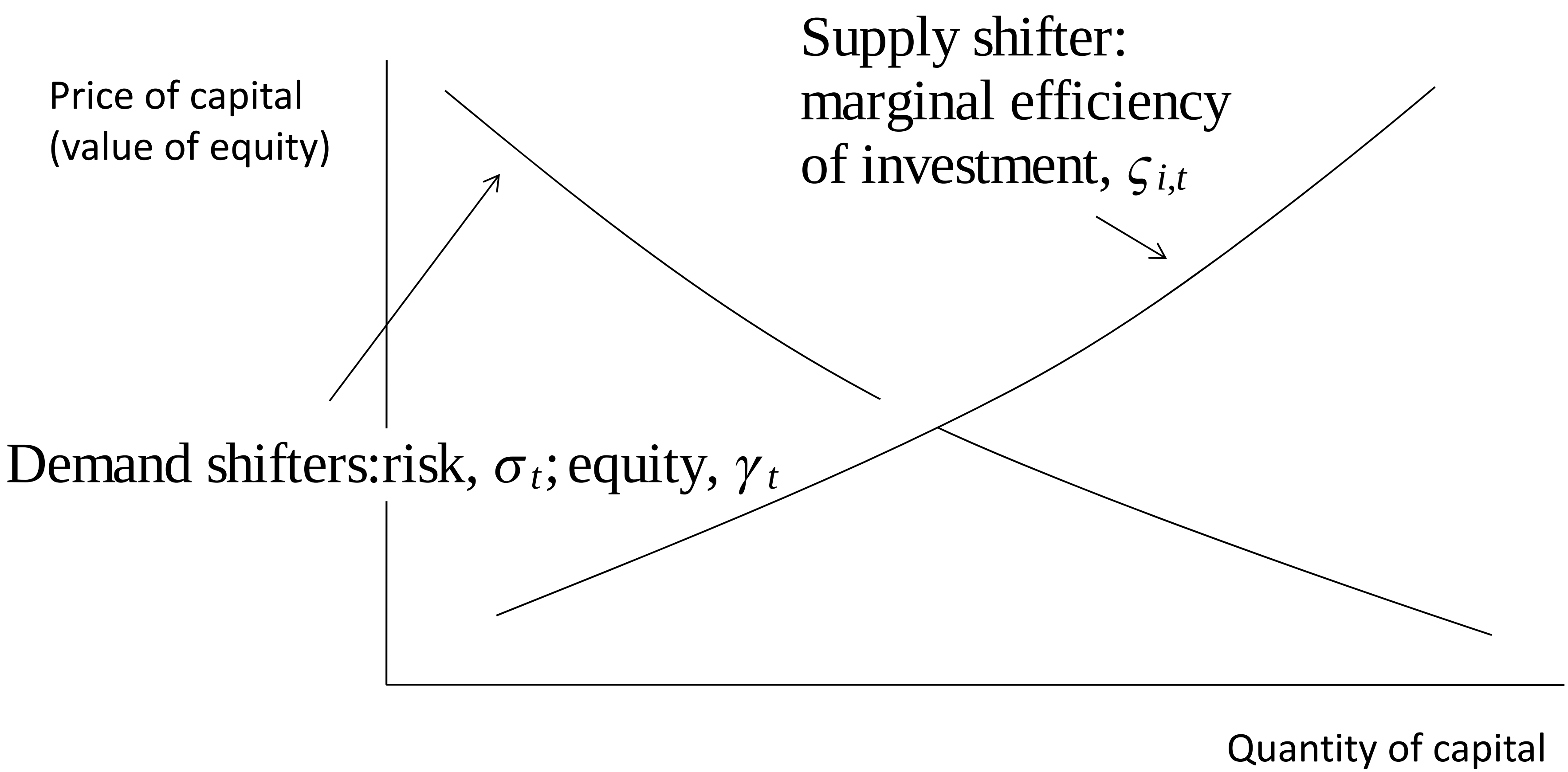


Figure 9a: Uncertainty, non-financial firms, H-P trend

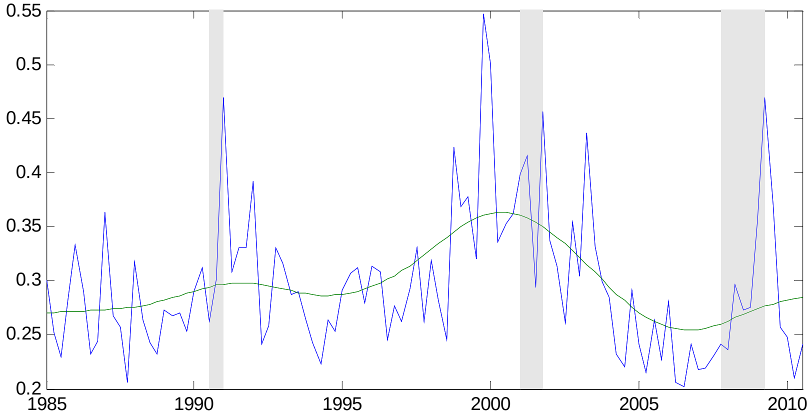


Figure 9b: Model implication for uncertainty, H-P trend

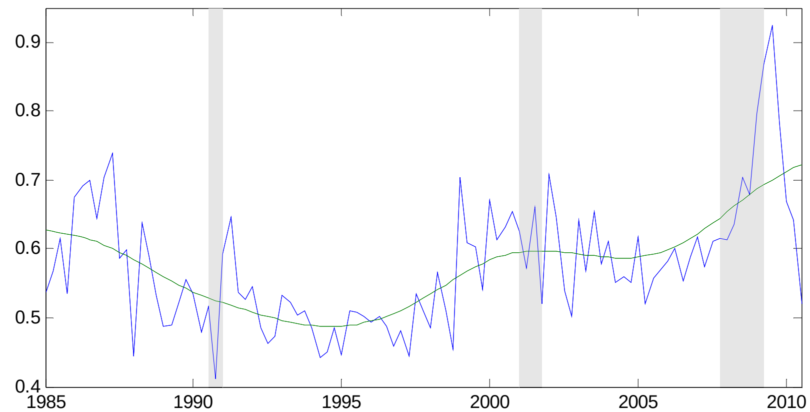


Figure 9c: Detrended data

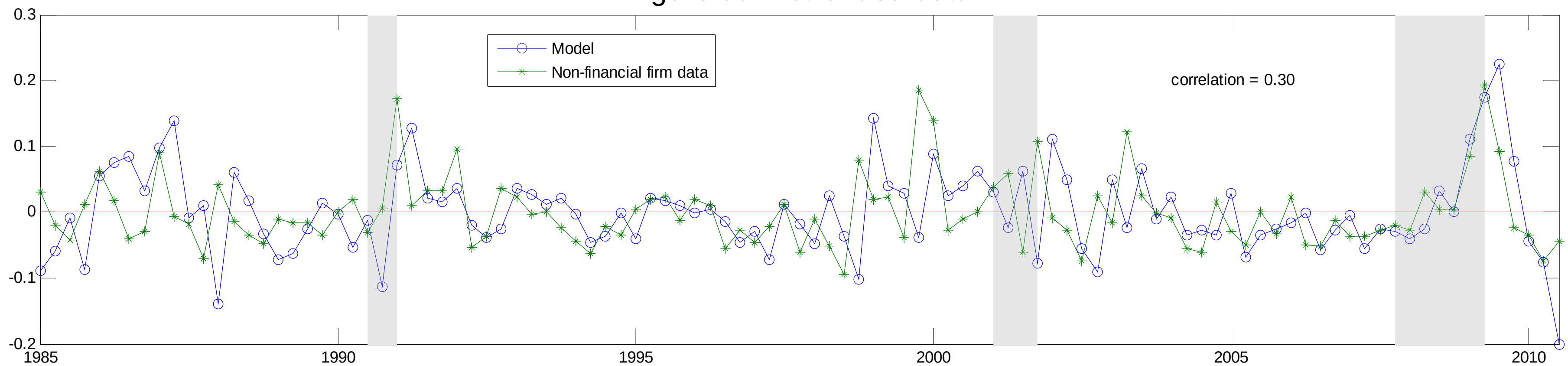


Figure 10: Model Bankruptcy Rate, Versus Loan Delinquency Rate

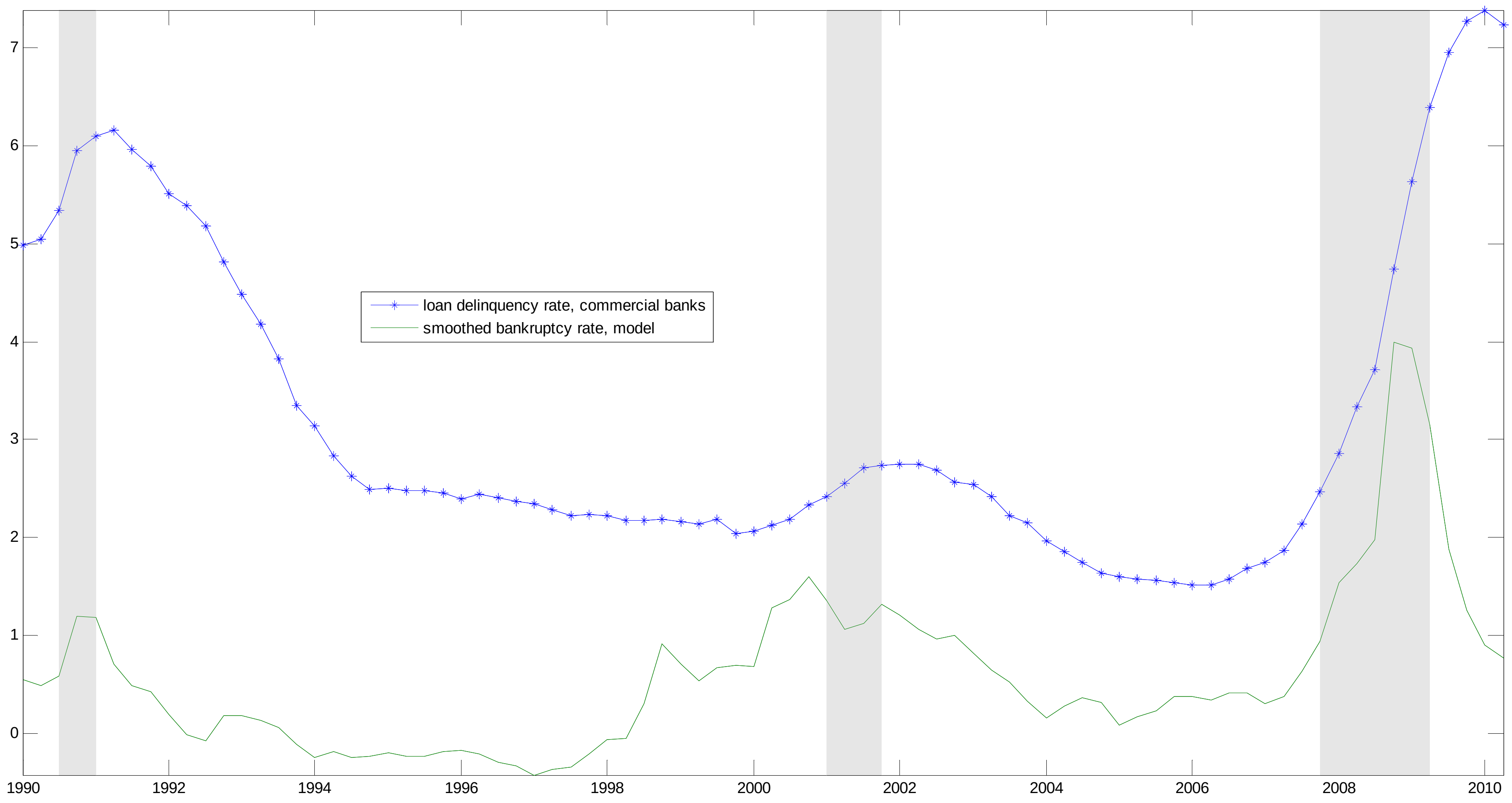
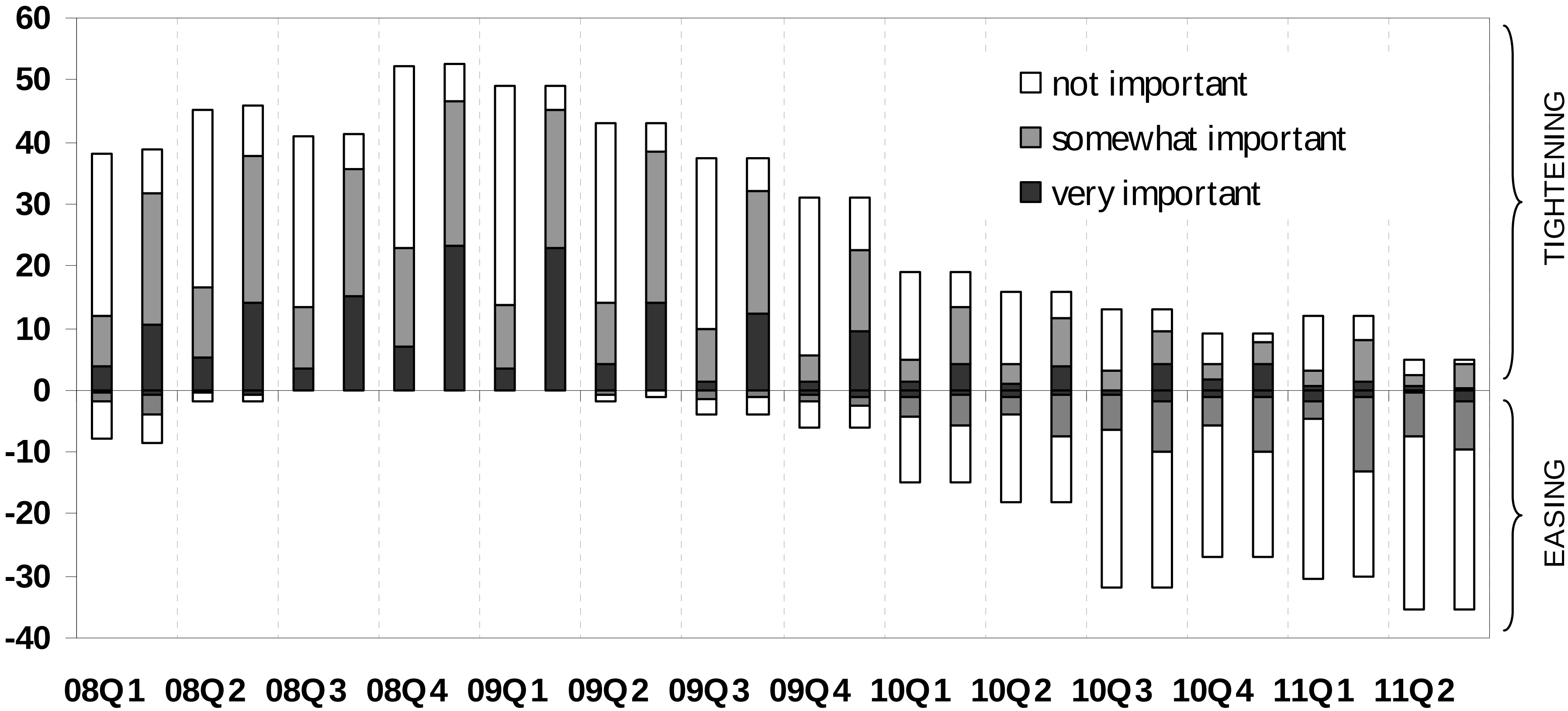


Figure 11

Contribution of bank balance sheet factors and non-financial firms factors to tightening/easing
(number of banks responding)



Notes: For each quarter, the first bar refers to the contribution of bank balance sheet factors, and the second bar refers to the contribution of non-financial firm factors.

Figure 12: Out of Sample RMSE's