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by Lawrence Christiano, Roberto Motto and Massimo Rostagno

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CONTENTS

Abstract

We augment a standard monetary DSGE model to include a banking sector and financial markets. We fit the model to Euro Area and US data. We find that agency problems in financial contracts, liquidity constraints facing banks and shocks that alter the perception of market risk and hit financial intermediation – 'financial factors' in short – are prime determinants of economic fluctuations. They have been critical triggers and propagators in the recent financial crisis. Financial intermediation turns an otherwise diversifiable source of idiosyncratic economic uncertainty, the 'risk shock', into a systemic force.

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

NON-TECHNICAL SUMMARY

The global financial has drawn attention to at least five distinct phenomena at the intersection of macroeconomics and finance. They are: (1) asymmetric information and agency problems in financial contracts; (2) the possibility of sudden and dramatic re-appreciations of market risk; (3) adjustments in credit supply as a critical channel by which market risk becomes systemic; (4) bank funding conditions – the creation of inside money – as major determinants of bank lending decisions; (5) central bank liquidity as a substitute for market liquidity when private credit vanishes

In this paper we present and evaluate a model that helps study these phenomena. We find that, indeed, the monetary and financial sector is the powerhouse of the economy. Factors that pertain to this sector – the frictions that motivate and shape finance and the shocks that hit the banking function – are prime determinants of economic fluctuations. They have been critical triggers and propagators in the recent financial crisis.

Our model is a variant of Christiano, Motto and Rostagno (2003, 2007). It combines a standard Christiano-Eichenbaum-Evans (CEE), or Smets-Wouters (SW) core with a detailed representation of the financial sector which we borrow from Bernanke, Gertler and Gilchrist (BGG, 1999) and Chari, Christiano and Eichenbaum (1995). In the model, the financial intermediaries – 'banks' – extend loans to finance firms' working capital requirements and entrepreneurs' longer-term investment projects. They fund these loans by issuing transferable deposits, which pay holders a contractual nominal rate of interest that is determined at the time the deposit is originated and is not contingent on the shocks that intervene until maturity. Entrepreneurial loans are risky for banks because the returns on the underlying investments are subject to idiosyncratic shocks. A sufficiently unfavourable shock can lead to the borrower's insolvency. The idiosyncratic shock is observed by the entrepreneur, but not by the bank, and the variance of the shock is the realisation of a time-varying process. Banks hedge against credit risk and imperfect information by charging a premium over and above the risk-free rate at which they can borrow from savers. As in BGG, this premium varies inversely with entrepreneurs' equity – the net worth that borrowers can pledge to secure the loan – and positively with the underlying investment risk.

We estimate our model on Euro Area and US observations, augmenting the data series that are used in standard estimations of CEE/SW-type models with a stock market index (a proxy for the price of capital), a measure of the external finance premium, the stock of credit, two measures of money, and the spread between the short-term interest rate and the 10-year bond rate. We document the good empirical properties of the model with conventional measures of fit.

In the estimation, we feed the model with a variety of economic shocks hitting preferences, technologies and policies. We place emphasis on four shocks in particular that potentially control the real-financial nexus in the economy. Two of these four shocks hit the supply-side of capital formation: the 'price of investment shock' perturbs the technical transformation of consumption goods into investment goods, and thus, indirectly, the relative price of investment; the 'marginal efficiency of investment shock' changes installation costs, and thus the transformation of investment goods into capital ready for production. The two other shocks, the 'financial shocks', hit the demand for capital. The 'financial wealth shock' changes the value of total equity in the economy – investors' purchasing power. The 'risk shock' is the process that governs the dispersion of returns on investment: it measures the current and anticipated state of the investment risk in the economy, and thus it influences investors' propensity to invest and banks' propensity to lend.

We find that the financial shocks are responsible for a substantial portion of economic fluctuations. The risk shock is the dominant force. Over the business cycle, this shock explains more than a third of the volatility of investment in the EA and 60 percent of that volatility in the US. The contribution of the risk shock increases at lower frequencies, when the co-integration of financial variables and the real economy is strongest. At those frequencies, the share in the variance of investment is 42 percent for the EA and 64 percent for the US. For GDP, it is 35 percent in the EA and 47 percent in the US. In the same spectral region, the risk shock explains a preponderant share of the stock market and gives a significant contribution to the long term interest rate spread as well.

Most of the economic effects of the financial shocks occur as agents respond to advance information, 'news', about the future realization of these processes. These are predominantly revisions of beliefs in the credit market about future investment risk conditions. Unlike in Beaudry and Portier (2000, 2003, 2004), Christiano, Ilut, Motto and Rostagno (2008), Schmitt-Grohé (2008) and Jaimovich and Rebelo (2009), news on the future technology for producing goods are unimportant.

We show that the inclusion of the financial variables in our empirical analysis profoundly modifies inferences. Without the financial contract and neglecting information on the stock market, the marginal efficiency of investment shock is a prime force of macroeconomic motion. However, the counter-cyclical implications of this shock for the price of capital mean that, once the model is forced to use information on equity, much of its explanatory power is lost. Neglecting information on credit, instead, tips the balance of evidence in favour of an important role for the financial wealth shock – unexpected and largely unexplained innovations to the value of aggregate equity. However, a model that assigns importance to stochastic shocks to equity cannot explain the credit market and the observed cyclical co-movements of investment, consumption and hours. The reason the risk shock is so important is that it behaves as a prototypical business cycle force. A risk shock innovation drives investment, consumption, hours worked, inflation, the stock market and credit in the same direction, while it moves the credit risk premium and the spread between long term interest rates and short rates in the opposite direction.

The asymmetric information associated with the asset part of the financial sector's balance sheet introduces two propagation mechanisms relative to the standard environment with no financial frictions. Both mechanisms operate through changes in entrepreneurs' equity. The classic 'financial accelerator effect' channel alters equity by changes in the flow of entrepreneurial earnings and by capital gains and losses on entrepreneurial assets. This is the channel highlighted in BGG and it tends to magnify the economic effects of a shock that raises economic activity. But our specification of the financial contract introduces a second, less conventional propagation mechanism, a 'Fisher deflation effect' channel. This operates through the movements in entrepreneurial equity that occur when an unexpected change in the price level alters the real value of entrepreneurial debt. The Fisher and accelerator effect mechanisms reinforce each other in the case of shocks that move the price level and output in the same direction, and they tend to cancel each other in the wake of shocks which move the price level and output in opposite directions. We show that the Fisher deflation effect is as an additional, empirically critical source of nominal rigidity in the economy.

Our analysis suggests that banks' decisions over the size of their balance sheets – how much credit they create – are *always* critical for the behaviour of the economy. We find that banks' decisions over their funding sources, the 'bank funding channel,' are also important, even in normal times. On rare occasions, changes in banks' liquidity preferences can become a major cause of disruption for the broad economy. We show how growth since the second half of 2008 can partly be interpreted in terms of the macroeconomic fallout of a gigantic shift in banks' preferences for liquidity. We also quantify the support that central banks have provided by engaging in unconventional liquidity policies.

1 Introduction

The global financial crisis that flared up in August 2007 has advertised the need for researchers to concentrate on at least five distinct phenomena at the intersection of macroeconomics and finance. They are: (1) asymmetric information and agency problems in financial contracts; (2) the possibility of sudden and dramatic re-appreciations of market risk; (3) adjustments in credit supply as a critical channel by which market risk becomes systemic; (4) bank funding conditions – the creation of inside money – as major determinants of bank lending decisions; (5) central bank liquidity as a substitute for market liquidity when private credit vanishes.[1]

In this paper we present and evaluate a model that helps study these phenomena. We find that the agency problems shaping financial contracts, the liquidity constraints facing banks and shocks that alter the perception of market risk and hit financial intermediation – 'financial factors' in short – are prime determinants of economic fluctuations. They have been critical triggers and propagators in the recent financial crisis. The liquidity policies enacted by central banks have greately attenuated the impact of the financial panic.

Our model is a variant of Christiano, Motto and Rostagno (2003, 2007). Borrowing from Bernanke, Gertler and Gilchrist (1999), (BGG, henceforth) and Chari, Christiano and Eichenbaum (1995), (CCE, henceforth), we integrate financial intermediation and a monetary sector into an otherwise canonical dynamic equilibrium model, of the type studied by Christiano, Eichenbaum and Evans (2005) (CEE, henceforth), and Smets and Wouters (2003, 2007). The real economy is made of households, firms, capital producers and entrepreneurs. Households consume, supply differentiated work in a monopolisitic labour market, and allocate saving across assets with varying degrees of liqudity. Firms producing intermediate goods are monopolists and subject to a standard Calvo mechanism for price setting. They need to pay for working capital in advance of production. Capital producers combine undepreciated physical capital with new investment. The technology for converting investment into productive capital is subject to a 'marginal efficiency of investment shock.' Entrepreneurs have a special ability to operate capital. They acquire plant capacity from capital producers, extract production services from it – which they rent out to firms – re-sell the stock of undepreciated capital at the end of the production cycle, and accumulate net worth in the process. Net worth – their 'equity' – is subject to 'financial wealth shocks' and is used to pay for capital in the next production round. But, in order to run their activity on an efficient scale, entrepreneurs need to borrow a fraction of the value of capital which they are not able to self-finance. The financial system provides the credit necessary to cover

[1] On the lessons which researchers and policymakers can draw from the recent events, see, among others, Brunnermeier (2009) and Brunnermeier, Crockett, Goodhart, Persaud and Shin (2009). On central bank credit as a substitute for private credit, see Bernanke (2009) and Trichet (2010).

this funding gap.

The financial sector has one representative intermediary, the 'bank'. This combines features of a genuine commercial bank, which engages in the production of inside money, and features that are more typical of an arms-length (shadow-banking) financial system of the sort described by Gorton (2009), Brunnermeier (2009), Adrian and Shin (2010) and others. As part of its commercial banking activities, the bank makes loans to finance firms' working capital requirements, and issues demand deposits and very liquid securities redeemable on sight. We postulate that the bank holds an inventory of cash as a fractional reserve against the production of sight liabilities. The bank obtains these cash balances from households' deposits of base money, and from central bank liquidity injections. Bank efficiency in transforming cash into deposits and liquid securities – and the bank's preferences for liquid balances – vary stochastically through time.

As part of its shadow-banking intermediation activity, the bank finances entrepreneurs' investment projects. As in BGG, we assume that entrepreneurial loans are risky: returns on the underlying investments are subject to idiosyncratic shocks. A sufficiently unfavourable shock can lead to the borrower's bankrupctcy. The idiosyncratic shock is observed by the entrepreneur, but not by the bank which, as in Townsend (1979), must pay a fixed monitoring cost in order to observe the entrepreneur's realised return. To mitigate problems stemming from this source of asymmetric information, entrepreneurs and the bank sign a standard debt contract. Under this contract, the entrepreneur commits to paying back the loan principal and a non-default interest rate, uless it declares default. In case of default, the bank conducts a costly verification of the residual value of the entrepreneur's assets and seizes the assets as a partial compensation.

We assume that the variance of the idiosyncratic shock that hits the entrepreneur's return is the realisation of a time-varying process. This stochastic process – the 'risk shock' – changes the cross-sectional dispersion of returns on entrepreneurial projects. By making the cross-sectional distribution of returns vary through time, this process produces time variation in bankruptcies, and thereby in credit risk. The risk shock has a realised and an anticipated, 'signal' component. Each time, economic agents observe the present realisation of risk and receive signals that update their perceptions of the future evolution of risk. The signals received at each time are correlated because, in forming expectations of future risk conditions, agents rely on a single source of information available at present. That single source reflects the 'mood of the day' and sets the general tone of current perceptions about the future.

The bank hedges against credit risk by charging a premium over and above the risk-free rate at which it can borrow from households. The risk-free rate that the bank views as its opportunity cost to lending is a contractual nominal interest rate that is determined at the time the bank liability to households is issued. Unlike in BGG, this rate is not contingent on the shocks that intervene before the entrepreneurial loan matures.

The cost of borrowing fluctuates endogenously with the cycle. This reflects two general equilibrium mechanisms. The first one is a genuine BGG-type 'financial accelerator' effect, which makes the contractual loan rate depend on entrepreneurs' equity – the net worth that borrowers can pledge to secure the loan. The contractual interest rate is countercyclical because equity varies positively with the state of the cycle: the flow of entrepreneurial earnings depend on aggregate demand, boost equity and increases the protection of the loan. The second mechanism is absent in BGG. It is due to the assumption that in our economy banks' obligations to households are expressed in nominal terms, while loans to entrepreneurs are state-contingent. As a consequence, surprises to the price level can alter *ex post* the real burden of entrepreneurial debt because the bank is immunised from any risk related to macroeconomic uncertainty. We refer to this mechanism as the 'Fisher deflation effect'. It is an important source of nominal rigidity in our economy, and a prime financial factor shaping the model's dynamics. The 'Fisher' and 'accelerator' effect mechanisms reinforce each other in the case of shocks that move the price level and output in the same direction, and they tend to cancel each other in the wake of shocks which move the price level and output in opposite directions.

The central bank steers the short-term interest rate in response to inflation, output growth, credit growth and money market liquidity conditions. The two latter components of the monetary policy feed-back rule are unconventional. Reaction to credit introduces some 'leaning against the wind' elements in monetary policy. Reaction to interbank liquidity conditions allows for some degree of quantity-setting and price-taking behaviour in liquidity providing operations on the side of the central bank.

We estimate our model by standard Bayesian methods, using data spanning the 1985-2008 period for the Euro Area (EA) and for the United States (US). In the baseline estimation we treat 16 variables as observables. These include monetary and financial variables such as the stock market (a proxy for the price of capital), a measure of the external finance premium, real credit growth, two definitions of money, bank reserves and the spread between the 10-year bond rate and the short-term interest rate. We also estimate two reduced-scale variants of our baseline model, which we use to assess the extent to which the financial frictions that we study alter inference about the impulses and propagation mechanisms driving aggregate fluctuations. What we refer to as the *Simple Model* preserves the minimal structure of CEE, but does not incorporate financial frictions. The *Financial Accelerator Model* adds the entrepreneurial contract to the *Simple Model*, but does not consider the mechanisms by which the bank finances its assets – the 'bank funding channel'.

We organise our findings in eight points.

1. Data Coherence

First, our model is a plausible framework for understanding the interactions of key asset returns, financial stocks, money and the macro-economy. The unconditional cross-correlations of real and financial variables that are generated by the model by and large reproduce the correlations that are measurable in the data. And the model is very competitive in terms of out-of-sample predictive performance.

2. Financial Frictions

Second, each financial friction contributes importantly to the model's empirical fit. We show that the *Simple Model,* with no financial factors, has countercyclical – and thus counterfactual – implications for the price of capital. In that model, investment is explained by shocks to the marginal efficiency of investment. But these shocks – investment technology shocks – move the supply of capital, and thus shift investment and the price of capital in opposite directions. So, in the *Simple Model*, the stock market has a 'negative beta', an implication which clearly contradicts the evidence. The *Financial Accelerator Model* yields the correct procyclical behaviour of the price of capital and the observed countercyclical pattern of the premium. But, in this model the stock market and investment are explained by shocks to the aggregate value of equity. Since these shocks change equity more than they shift the demand for capital, they produce a negative correlation between credit and investment, which is counter-factual. By conventional Bayesian evaluation methods, we find that the data prefers our baseline model specification over alternative perturbations, whether these imply removing certain financial channels from the model or modelling financial channels differently. A test comparing marginal data densities unambiguously favors the baseline specification with the 'Fisher deflation' channel, over an alternative with a financial contract defined in real terms. The same test finds that the 'bank funding channel' – inside money creation – also makes a substantial contribution to the fit of the model.

3. The Credit Market

Third, information on the credit market is critical to inference. Inclusion of the premium *and* the stock of credit in the estimation feeds the econometrics with the information necessary to identify the risk shock as the main factor behind economic fluctuations. Our risk shock is a mean-preserving shift in the cross-sectional dispersion of entrepreneurial returns. Being idiosyncratic, it is diversifiable. Indeed, the bank can immunise itself from this risk. But, the economy as a whole can not. This happens because the risk shock interacts with the standard credit contract and becomes a tax on aggregate investment. After a positive risk shock, the bank – other things equal – bears the cost of more bankruptcies, as a fatter left tail of entrepreneurial returns falls below the solvency threshold, but does not participate in the higher returns of those borrowers who find themselves on the (fatter) right tail. Therefore, break-even dictates that the bank react to the shock by raising the contractual interest rate on the loan. This is the way the bank can shed this risk. However, a higher borrowing cost is a tax on everyone's investment. Thus, a seemingly diversifiable source of risk becomes systemic. Information on the premium – the 'price side' of the credit market – is not enough to identify the transmission. The premium is counter-cyclical in the data, increasing when the volume of credit and investment are weak and falling when they are booming. If the estimation is not constrained by information on the stock of credit – the 'quantity side' – which is procyclical, the model interprets an increase in the premium as a shift in the demand for financing and for capital. This is counterfactual – as the demand for capital and credit in fact declines when the premium increases – and plays against assigning the risk shock a high explanatory power for investment and for the economy more broadly. Including credit in the estimation, instead, places some of the burden of adjustment on shifts in the supply of credit. In this way, the model can reconcile an increase in the premium with a falling aggregate demand. And the risk shock becomes the prototype of an aggregate shock.

4. The risk shock

Fourth, the risk shock explains virtually all of the credit market. Its share in the variance of the external finance premium is 85 and 96 percent, in the EA and US respectively, at business cycle frequencies. It is 60 percent and 73 percent, in the two economies, for real credit. From the credit market, the risk shock propagates to the rest of the economy through the investment margin. Over the business cycle, the risk shock explains more than a third of the volatility of investment in the EA and 60 percent of that volatility in the US. The contribution of the risk shock increases at lower frequencies, when the cointegration of financial variables and the real economy is strongest. For periodic components with cycles of 9-to-15 years, the share in the variance of investment is 42 percent for the EA and 64 percent for the US. For GDP, it is 35 percent in the EA and 47 percent in the US at the same frequencies. In that spectral region, it explains a preponderant share of the stock market and gives a significant contribution to the long term interest rate spread as well. Shocks to the marginal efficiency of investment lose much of the macroeconomic explanatory power which they possess in the *Simple Model*. The financial wealth shock – which was important in the *Financial Accelerator Model* – becomes nearly irrelevant. A structural decomposition of the time path of the model-consistent expected equity premium shows that the rise in *expected* stock market returns after the most severe episodes of market collapse in the current crisis are largely explained by an increase in the demand for risk compensation.

5. Signals

Fifth, virtually the entire explanatory power of the risk shock is due to its signals. It is the steady process of revision of past perceptions about future market risk that shifts the economy. Signals help the model match the dynamic correlations between credit, the price of capital, hours worked and real activity, because they can introduce persistence in the expected return on capital. Without signals, a negative shock to the price of capital in the current period – even a severe crash in the stock market – produces a sharp, but temporary, drop in the returns on capital. Without signals, the return on capital has a tendency to revert quickly to normal levels in expectation. Because it is costly to change investment plans in the model, capital formation, at least in the anticipations of the economy, remains sticky. This has two implications. First, there is no incentive for entrepreneurs to deleverage in response to a fall in equity. In fact – as we wrote above – without signals, the *Financial Accelerator Model* predicts that credit and leverage *increase* after a negative equity shock. Second, because capital is sticky, the marginal product of labour does not change much after a negative equity shock. But, if the wealth effect of the drop in equity is sufficiently powerful, workers will be encouraged to supply more hours. So, with labour demand relatively sticky and labour supply shifting to the right, hours will tend to move in the 'wrong' direction relative to the cycle. With signals, instead, a major share of the original wealth destruction is caused by bad news about future risk conditions. This produces a protracted decline in the returns on capital, a sequence of expected capital losses and thus an incentive to respond to the present shock by disinvesting and deleveraging. Deleveraging generates the 'correct' cyclical response of credit. The contraction in investment makes the marginal product of labour and the demand for labour decline sharply. So, in the baseline model the expected component of the risk shock sets off a generalised cyclical downturn. Indeed, the model associates the recent financial crisis with a confluence of adverse signals about future risk – bad news – at all horizons. Signals on the future state of the goods or capital production technologies – as in Christiano, Ilut, Motto and Rostagno (2008) or Schmitt-Grohé and Uribe (2008) – are not a plausible substitute for signals on risk. They have a conter-cyclical impact on the stock market. This explains why the marginal data density of a version of the model with signals on technology deteriorates substantially relative to the data density of our baseline specification.

6. Liquidity shocks

Sixth, liquidity shocks have been a relatively mild source of uncertainty for much of the period we consider in this paper. However, the outbreak of the crisis coincides in the model with an unprecedented spike in banks' desire for precautionary liquidity balances, a bank liquidity shock. In the model, banks make room for more liquidity by shedding loans. The money multiplier, which converts bank liquidity reserves into inside money, also contracts as a result. The joint drop in loans and money tighten firms' production costs and weighs down on consumption. The implications for aggregate real activity are severe. The model estimates that, between the summer of 2008 and the second quarter of 2009, bank funding problems may have detracted between 0.5 and 1 percent in the EA, and between 1/3 and 1.5 percentage points in the US off GDP growth.

7. Monetary policy

Seventh, monetary policy has been consistently expansionary over the period 2008-2009. The model interprets an abnormal expansion in banks' demand for refinancing and excess reserves, in conjunction with a sharp decline in the short-term interest rate, as indicative of an extraordinary degree of liquidity accommodation. The sequence of expansionary policy shocks that result from this mechanism have helped compensate the drain that the bank liquidity shocks would otherwise have exerted on the economy.

8. A money-base rule counterfactual

Eighth, an early shift to a money-base rule to stabilise broad money growth in the US would have sustained credit to the broad economy – as opposed to the actual policy of guaranteeing a steady access to credit for targeted sectors in the economy. We show that this alternative policy – which is in line with the switching strategy studied in Christiano and Rostagno (2001) – would have attenuated the severity of the recession.

Our paper is at the cross-roads of many research streams. First, with the new generation dynamic general equilibrium empirical literature that starts with Leeper and Sims (1994) and Schorfheide (2000) and reaches a high level of sophistication with CEE, Smets and Wouters (2003, 2007), Altig, Christiano, Eichenbaum and Lindé (2005), Levin, Onatski, Williams and Williams (2006), Del Negro, Schorfheide, Smets and Wouters (2007), and Adolfson, Laséen, Lindé and Villani (2008), among many others, we share the effort of estimating a relatively large-scale optimising model meant to be empirically relevant. As in much of this literature, we employ the Bayesian estimation and evaluation methods described in Smets and Wouters (2003) and An and Schorfheide (2007). Second, we learn from papers – such as Levin, Natalucci and Zakrajšek (2004), Covas and den Haan (2007) and Gilchrist, Yankov and Zakrajšek (2009) – which have documented the empirical interaction of financial quantities and real variables and we try to replicate those interactions using an optimising model of the business cycle with financial frictions. The modelling of financial frictions mainly follows BGG and CCE, but we share some modelling choices with Carlstrom and Fuerst (1997), Kiyotaki and Moore (1997), Cooley, Marimon, and Quadrini (2004), De Fiore and Uhlig (2005), Iacoviello (2005), Gertler, Gilchrist and Natalucci (2007), Hopenhayn and Werning (2008), Cúrdia and Woodford (2009), Gilchrist, Ortiz and Zakrajšek (2009) and Jermann and Quadrini (2009). Third, as Kiyotaki and Moore (2008), Gertler and Kiyotaki (2009) and Adrian and Shin (2010), we embed financial frictions in a model of banking intermediation where banks finance assets by creating inside money and other forms of liquidity. Fourth, our risk shock resembles the volatility shock of Bloom (2009) and Bloom, Floetotto and Jaimovich (2009), to the extent that it is a time-varying source of dispersion of economic returns. Fifth, we contribute to the literature on 'news' shocks, which has been revived by Beaudry and Portier (2004) and first applied to a monetary model of the business cycle similar to the one presented here by Christiano, Ilut, Motto and Rostagno (2008) and to a real business cycle model by Schmitt-Grohé and Uribe (2008) and Jaimovich and Rebelo (2009). Finally, as Gertler and Karadi (2009) and Gertler and Kiyotaki (2010), we use the model to simulate unconventional monetary policy interventions of the type that has been tested during the recent financial crisis.

The plan of the paper is as follows. The next section describes the model. The empirical properties are documented in section 3. Section 4 illustrates how inference changes by adding financial channels, one at a time, and why financial frictions shift emphasis from real shocks to financial shocks. Section 5 discusses the main empirical finding of the model: the key role of the risk shock in generating fluctuations and the economic channels by which it does so. We present some extra-model validation and robustness analysis in section 6. Section 7 measures the contribution of the 'Fisher deflation effect' and the 'bank funding channel' to the model's fit. Section 8 uses the model to interpret the financial crisis, the role played by monetary policies in dampening its macroeconomic fallout, and shows how a money-base rule can mitigate the recession. The paper ends with a brief conclusion. Technical details are in the Appendices.

2 The Model

This section provides a brief overview of the model. Details about the equilibrium conditions associated with the different sectors of the economy are derived in Appendix A. The model is composed of households, firms, capital producers, entrepreneurs and the bank. At the beginning of the period, households supply labor and entrepreneurs supply capital to homogeneous factor markets. In addition, households divide their high-powered money into currency and bank deposits. Currency pays no interest, and is held for the transactions services it generates. Bank deposits pay interest and generate liquidity services. The bank uses household deposits to loan firms the funds they need to pay their wage bills and capital rental costs in advance of production and to fund the provision of external finance to entrepreneurs. Firms and banks use labor and capital to produce output and liquidity services, respectively.

The output produced by firms is converted into consumption goods, investment goods, goods used up in capital utilization and in bank monitoring. Capital producers combine investment goods with used capital purchased from entrepreneurs to produce new capital. This new capital is then purchased by entrepreneurs. Entrepreneurs make these purchases using their own resources – net worth, or equity, which they accrue by compounding the net proceeds of their activity from one time to the next – as well as bank loans.

2.1 Goods Production

Final output, Y_t, is produced by a perfectly competitive, representative firm using the technology

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

where Y_{jt} denotes the time-t input of intermediate good j and $\lambda_{f,t}$ is a shock, $j \in (0,1)$. The time series representations of $\lambda_{f,t}$ and all other stochastic processes in the model will be discussed below. Let P_t and P_{jt} denote the time-t price of Y_t and $Y_{j,t}$ respectively. The firm chooses Y_{jt} and Y_t to maximize profits, taking prices as given.

We assume that ongoing technological advances in the production of investment goods makes the cost of producing one unit of equipment, measured in terms of consumption units, decline at the rate $\left(\Upsilon^t \mu_{\Upsilon,t}\right)$, where $\Upsilon > 1$ is the trend rate of investment-specific technical change, and $\mu_{\Upsilon,t}$ is a stationary stochastic process, which we refer to as the relative price of investment shock. Because firms that produce consumption and investment goods using final output are assumed to be perfectly competitive, the date t equilibrium price of consumption and investment goods are P_t and $P_t / \left(\mu_{\Upsilon,t}\Upsilon^t\right)$, respectively.

The j^{th} intermediate output used in (1) is produced by a monopolist using the following production function:

$$Y_{jt} = \begin{cases} \epsilon_t K_{jt}^{\alpha} \left(z_t l_{jt}\right)^{1-\alpha} - \Phi z_t^* & \text{if } \epsilon_t K_{jt}^{\alpha} \left(z_t l_{jt}\right)^{1-\alpha} > \Phi z_t^* \\ 0, & \text{otherwise} \end{cases}, \ 0 < \alpha < 1, \tag{2}$$

where K_{jt} and l_{jt} denote the services of capital and homogeneous labor, the non-negative scalar, Φ, parameterizes fixed costs of production, ϵ_t is a stationary shock to technology and z_t represents the persistent component of technology, with the following time series representation:

$$z_t = \mu_{z,t} z_{t-1} \tag{3}$$

In (3), $\mu_{z,t}$ is a stationary stochastic process. Due to capital embodied technological progress, the growth rate of output is determined by the following condition:

$$z_t^* = z_t \Upsilon^{\left(\frac{\alpha}{1-\alpha}t\right)},\ \Upsilon > 1, \tag{4}$$

which also motivates our choice concerning the structure of the firm's fixed costs in (3), Φz_t^*, and ensures that the non-stochastic steady state of the economy exhibits balanced growth path.

Firms are competitive in factor markets, where they confront a nominal rental rate, $P\tilde{r}_t^k$, on capital services and a nominal wage rate, W_t, on labor services. Each firm must finance a constant fraction, ψ_k, of its rental cost of capital, $P_t\tilde{r}_t^k K_t$, and a constant fraction, ψ_l, of its wage bill, $W_t l_{jt}$, in advance of production at a gross interest rate, R_t. As a result, the real marginal cost of producing one unit of output Y_{jt} is:

$$s_t = \left(\frac{1}{1-\alpha}\right)^{1-\alpha}\left(\frac{1}{\alpha}\right)^{\alpha}\frac{\left(\tilde{r}_t^k\left[1+\psi_k R_t\right]\right)^{\alpha}\left(\frac{W_t}{P_t}\left[1+\psi_l R_t\right]\right)^{1-\alpha}}{\epsilon_t z_t^{1-\alpha}} \tag{5}$$

As, in equilibrium, real marginal costs must be equal to the cost of renting one unit of capital divided by the marginal productivity of capital, the rental rate satisfies the following condition:

$$\tilde{r}_t^k = \frac{\alpha}{1-\alpha}\left(\frac{l_{jt}}{K_{jt}}\right)\frac{\left(\frac{W_t}{P_t}\left[1+\psi_l R_t\right]\right)}{\left[1+\psi_k R_t\right]} \tag{6}$$

The homogeneous labor employed by firms in (2) and the differentiated labor supplied by individual households are related as follows:

$$l_t = \left[\int_0^1 \left(h_{t,j}\right)^{\frac{1}{\lambda_w}} dj\right]^{\lambda_w},\ 1 \leq \lambda_w. \tag{7}$$

Below, we discuss how $h_{t,j}$ is determined.

We adopt a variant of Calvo sticky prices. In each period, t, a fraction of intermediate-goods firms, $1-\xi_p$, can reoptimize their price. If the i^{th} firm in period t cannot reoptimize, then it sets price according to:

$$P_{it} = \tilde{\pi}_t P_{i,t-1},$$

where

$$\tilde{\pi}_t = \left(\pi_t^{target}\right)^{\iota}\left(\pi_{t-1}\right)^{1-\iota}. \tag{8}$$

Here, $\pi_{t-1} = P_{t-1}/P_{t-2}$ and π_t^{target} is the inflation objective in the monetary authority's monetary policy rule, which is discussed below. The i^{th} firm that can optimize its price at time t chooses $P_{i,t} = \tilde{P}_t$ to maximize discounted profits over future histories in which it cannot reoptimize.

2.2 Capital Producers

We suppose there is a single, representative, competitive capital producer. At the end of period t, the capital producer purchases newly produced equipment – at a currency unit price of $P_t\left(\Upsilon^t \mu_{\Upsilon,t}\right)^{-1}$– and the undepreciated fraction of physical capital, x, which has been used during the period t production cycle. Old capital and investment goods are combined to produce new installed capital, x', using the following technology:

$$x' = x + \digamma(I_t, I_{t-1}, \zeta_{i,t}) = x + \left(1 - S(\zeta_{i,t}\ I_t/I_{t-1})\right) I_t. \tag{9}$$

The technology to transform new investment into capital input ready for production, $\digamma(\bullet)$, involves installation costs, $S(\zeta_{i,t}\ I_t/I_{t-1})$, which increase in the rate of investment growth. We allow for exogenous stochastic variation to the investment cost function: a positive $\zeta_{i,t}$ is a negative disturbance to the marginal efficiency of investment, in that it raises installation costs. Following Christiano, Eichenbaum and Evans (2005), we restrict the function, S, to satisfy the following properties: $S = S' = 0$, and $S'' > 0$. Given our linearization-based estimation strategy, which we discuss in section 3, the only feature of S about which we can draw inference from data is S''.

Since the marginal rate of transformation from previously installed capital (after it has depreciated) to new capital is unity, the price of new and used capital are the same, and we denote it by $Q_{\bar{K}',t}$. The firm's time-t profits are:

$$\Pi_t^k = Q_{\bar{K}',t}\left[x + \left(1 - S(\zeta_{i,t}\ I_t/I_{t-1})\right) I_t\right] - Q_{\bar{K}',t}x - \frac{P_t}{\Upsilon^t \mu_{\Upsilon,t}} I_t. \tag{10}$$

The capital producer solves:

$$\max_{\{I_{t+j}, x_{t+j}\}} E_t \left\{ \sum_{j=0}^{\infty} \beta^j \lambda_{t+j} \Pi_{t+j}^k \right\}, \tag{11}$$

where E_t is the expectation conditional on the time-t information set, which includes all time-t shocks. Also, λ_t is the multiplier on the household's budget constraint. Let $\bar{K}_{t+j}$ denote the beginning-of-period $t+j$ physical stock of capital in the economy, and let δ be the depreciation rate. From the capital producer's problem it is evident that any value of x is profit maximizing. Thus, setting $x = (1-\delta)\bar{K}_{t+j}$ is consistent with profit maximization and market clearing.

Making the latter substitution in (10) and solving the capital producer's dynamic decision problem in (11) leads to the following optimality condition linking the price of installed capital, $Q_{\bar{K}',t}$, to the price of investment goods, $\frac{P_t}{\Upsilon^t \mu_{\Upsilon,t}}$:

$$E_t \left[\lambda_t Q_{\bar{K},t} \digamma_{1,t} - \lambda_t \frac{P_t}{\Upsilon^t \mu_{\Upsilon,t}} + \beta \lambda_{t+1} Q_{\bar{K},t+1} \digamma_{2,t+1} \right] = 0. \tag{12}$$

In (12), $\digamma_{i,t}$ denotes the derivative of the transformation technology, $\digamma(I_t, I_{t-1}, \zeta_{i,t})$, with respect to its argument, i. The aggregate stock of physical capital evolves as follows

$$\bar{K}_{t+1} = (1-\delta)\bar{K}_t + \digamma(I_t, I_{t-1}, \zeta_{i,t}) = (1-\delta)\bar{K}_t + \left(1 - S(\zeta_{i,t}\ I_t/I_{t-1})\right) I_t. \tag{13}$$

2.3 Entrepreneurs

There is a large number of entrepreneurs. An entrepreneur's state at the end of period t is its level of net worth, N_{t+1}. At the end of the time-t goods market, the entrepreneur combines its net worth with a bank loan to purchase new, installed physical capital, $\bar{K}_{t+1}$, from the capital producer. The entrepreneur then experiences an idiosyncratic shock, ω. The purchased capital, $\bar{K}_{t+1}$, is transformed into $\bar{K}_{t+1}\omega$, where ω is a lognormally distributed random variable across all entrepreneurs with a cumulative distribution function denoted by $F_t(\omega)$. The assumption about ω implies that entrepreneurial investments in capital are risky. The mean and standard deviation of $\log \omega$ are μ_{ϖ} and σ_t, respectively. The parameter, μ_{ϖ}, is set so that $E\omega = 1$ when σ_t takes on its steady state value. The standard deviation, σ_t, is the realisation of a stochastic process, which we refer to below as the 'risk shock'. This shock captures the notion that the riskiness of entrepreneurs varies over time. The random variable, ω, is observed by the entrepreneur, but can only be observed by the bank if it pays a monitoring cost.

After observing the period $t+1$ shocks, the entrepreneur determines the utilization rate of capital, u_{t+1}, and then rents out capital services in competitive markets. The rental rate of a unit of capital services, in currency units, is denoted by $\tilde{r}^k_{t+1}P_{t+1}$. In choosing the capital utilization rate, each entrepreneur takes into account the 'user cost' function:

$$P_{t+1}\Upsilon^{-(t+1)}\tau^{oil}_{t+1}a(u_{t+1})\omega\bar{K}_{t+1}. \tag{14}$$

In our specification, more energy is consumed as capital is used more intensely. Accordingly, in our empirical analysis we treat τ^{oil}_{t+1} as an exogenous process, which we identify with the real price of oil. We assume that: $u = 1$, $a(1) = 0$, $a'(u) = r^k$, and $a''(u) = \sigma_a r^k$, where r^k is the steady state value of the rental rate of capital. Then, $a''(u)/a'(u) = \sigma_a \geq 0$ is a parameter that controls the degree of convexity of costs.

After determining the utilization rate of capital and earning rent (net of utilization costs), the entrepreneur sells the undepreciated fraction, $1-\delta$, of its capital at price $Q_{\bar{K},t+1}$ to the capital producer. The total pay-off in period $t+1$ received by an entrepreneur with idiosyncratic productivity, ω, expressed in currency units is:

$$\left\{\left[u_{t+1}\tilde{r}^k_{t+1} - \Upsilon^{-(t+1)}\tau^{oil}_{t+1}a(u_{t+1})\right]P_{t+1} + (1-\delta)Q_{\bar{K},t+1}\right\}\omega\bar{K}_{t+1}.$$

We find it convenient to express the latter as follows:

$$\left(1+R^k_{t+1}\right)Q_{\bar{K},t}\omega\bar{K}_{t+1},$$

where $1+R^k_{t+1}$ is the average gross nominal rate of return on capital across entrepreneurs in $t+1$:

$$1+R^k_{t+1} \equiv \frac{\left[u_{t+1}\tilde{r}^k_{t+1} - \Upsilon^{-(t+1)}\tau^{oil}_{t+1}a(u_{t+1})\right]P_{t+1} + (1-\delta)Q_{\bar{K},t+1}}{Q_{\bar{K},t}} + \tau^k\delta, \tag{15}$$

where τ^k is the con constant tax rate on capital. As in BGG, entrepreneurs can self-finance only a fraction of the capital stock. They need external finance to complement their net worth as a source of funding. Entrepreneurs obtain external finance from the bank in the form of bank loans. The standard debt contract that they enter foresees that entrepreneurs with ω above an endogenously determined cutoff value, $\bar{\omega}_{t+1}$, pay gross interest, Z_{t+1}, on their bank loan. The cutoff is defined by the following expression:

$$\bar{\omega}_{t+1}\left(1+R^k_{t+1}\right)Q_{\bar{K}',t}\bar{K}_{t+1} = Z_{t+1}B_{t+1}, \tag{16}$$

where $B_{t+1} = Q_{\bar{K}',t}\bar{K}_{t+1} - N_{t+1}$ is the loan received from the bank. Entrepreneurs with $\omega < \bar{\omega}_{t+1}$ cannot fully repay their bank loan. Bankrupt entrepreneurs must turn over their assets, $\left(1+R^k_{t+1}\right)\omega Q_{\bar{K}',t}\bar{K}_{t+1} < Z_{t+1}B_{t+1}$, to the bank. In this case, the bank must monitor the enterpreneur, at cost $\mu\left(1+R^{k}_{t+1}\right)\omega Q_{\bar{K}',t}\bar{K}_{t+1}$ and retain the liquidation value of the entrepreneur's assets, $(1-\mu)\left(1+R^{k}_{t+1}\right)\omega Q_{\bar{K}',t}\bar{K}_{t+1}$. The monitoring costs are proportional to gross entrepreneurial revenues. The interest rate, Z_{t+1}, and the loan amount are determined as in a standard debt contract. We provide details on financial intermediation in the following section.

After entrepreneurs have settled their debt to the bank in period $t+1$, and capital has been re-sold to capital producers, entrepreneurs' period $t+1$ net worth is determined. At this point, entrepreneurs exit the economy with probability $1-\gamma_{t+1}$, and survive to continue another period of activity with probability γ_{t+1}. A fraction Θ of the total net worth owned by those entrepreneurs who close business is consumed upon exit, and the remaining fraction of their net worth is transferred as a lump-sum payment to households. The probability, γ_{t+1}, is the realization of a stochastic process. Each period new entrepreneurs enter in sufficient numbers so that the population of entrepreneurs remains constant. New entrepreneurs entering in period $t+1$ receive a 'start-up' transfer of net worth, W^e. Because W^e is relatively small, this exit and entry process helps to ensure that entrepreneurs do not accumulate enough net worth to escape the financial frictions.

The law of motion for net worth averaged across entrepreneurs, $\bar{N}_{t+1}$, is as follows:

$$\begin{aligned}\bar{N}_{t+1} = \gamma_t\Big\{\left(1+R^k_t\right)Q_{\bar{K}',t-1}\bar{K}_t - &\left[1+R^e_t \;+\mu\frac{\int_0^{\bar{\omega}_t}\omega dF_t(\omega)\left(1+R^k_t\right)Q_{\bar{K}',t-1}\bar{K}_t}{Q_{\bar{K}',t-1}\bar{K}_t-\bar{N}_t}\right] \\ &\times\left(Q_{\bar{K}',t-1}\bar{K}_t-\bar{N}_t\right)\Big\}+W^e,\end{aligned} \tag{17}$$

where $Q_{\bar{K}',t-1}\bar{K}_t - \bar{N}_t = B_t$. The object in braces in (17) represents total receipts by entrepreneurs active in period t minus their total payments to banks. The object in square brackets represents the average payments by entrepreneurs to banks, per unit of currency borrowed. Note that, as $F_t(\omega)$ is time variant and subject to risk shocks, so is the premium, which is defined below:

$$P^e_t = \mu\frac{\int_0^{\bar{\omega}_t}\omega dF_t(\omega)\left(1+R^k_t\right)Q_{\bar{K}',t-1}\bar{K}_t}{Q_{\bar{K}',t-1}\bar{K}_t-\bar{N}_t} \tag{18}$$

Note also that the value of entrepreneurs' net worth at the end of period t in (17) is perturbed by two shocks with a different time structure. Shock γ_t, the 'financial wealth shock', is realized at time t and has a contemporaneous impact on net worth, $\bar{N}_{t+1}$. The risk shock that has an impact on the external finance premium paid at time t, and which detracts from entrepreneurial profits and end-of-period-t net worth, $\bar{N}_{t+1}$, is realized at the end of the previous period, σ_{t-1}. At the end of period $t+1$, after entry and exit has occurred, all active entrepreneurs have a specific level of net worth. The process then continues for another period.

2.4 Banks

We assume that there is a representative, competitive bank. A snapshot of the bank's consolidated balance sheet at the end of time t, a minute before the end of the time-t

production period is structured as follows:

Infra-Period Assets	**Infra-Period Liabilities**
- *Reserves,* A_t	- *Household deposits,* $D_t^h = A_t$
- *Working Capital loans,* S_t^w	- *Firm deposits,* $D_t^f = S_t^w$
Inter-temporal Assets	**Inter-temporal Liabilities**
Entrepreneurial loans, B_t	- *Short-term marketable securities,* D_t^m
	- *Other financial securities,* T_{t-1}

(19)

Our 'bank' combines features of a genuine commercial bank, which engages in the production of means of payment, and features that are more characteristic of an arms-length financial system, where intermediation is channeled through securities markets rather than traditional relationship-based banking. The functions more closely associated with commercial banking are concentrated on the upper side of the balance sheet. The lower portion of the balance sheet records claims and obligations which can arise with or without the intervention of a bank. The bank's assets consist of cash reserves and loans, to firms and entrepreneurs. The bank's liabilities include bank deposits owned by households and firms, short-term marketable securities and other financial securities held by households. We concentrate first on loans and defer the analysis of the bank's funding options to the second sub-section below.

2.4.1 Lending

The T-account shows that the bank issues two classes of loans. First, it grants working capital loans to firms, S_t^w. These loans are extended at the beginning of the period and retired at the end of the period, so their timing corresponds to the production cycle. Working capital loans coming due at the end of the period pay R_t in interest:[2]

$$(1+R_t)S_t^w = (1+R_t)\left(\psi_l W_t l_t + \psi_k P_t \tilde{r}_t^k K_t\right). \tag{20}$$

Second, the bank finances the entrepreneural sector by issuing entrepreneurial loans. These loans are created at the end of the period and retired at the end of the following period. In this case, the timing of the loan corresponds to the time when the loan matures and the payoff originated by that capital stock occurs. We imagine that a specialised entrepreneurial-loan branch within the bank is responsible for making loans to entrepreneurs. In period t the branch receives B_{t+1} from its parent bank. The internal rules commit the entrepreneurial-loan managers to paying the bank a non-state contingent nominal interest rate, R_{t+1}^e, at time $t+1$. Consequently, the amount of credit supplied to entrepreneurs at the end of time t, B_{t+1}, the interest rate, R_{t+1}^e, and the gross interest rate applied on entrepreneurial loans, Z_{t+1}, need to maximize the entrepreneur's expected state (i.e., their net worth) at the end of the loan contract, subject to a zero profit condition for the bank branch:

$$\left[1-F_t\left(\bar{\omega}_{t+1}\right)\right] Z_{t+1}B_{t+1} + (1-\mu)\int_0^{\bar{\omega}_{t+1}} \omega dF_t\left(\omega\right)\left(1+R_{t+1}^k\right) Q_{\bar{K}',t}\bar{K}_{t+1} = \left(1+R_{t+1}^e\right) B_{t+1}.$$

The object on the right of the equality is the quantity of funds the branch must pay to the parent institution at the end of period $t+1$. This is a known quantity at the end of period t. As explained more extensively below, we assume that R_{t+1}^e is not contingent on

[2]Recall that ψ_l and ψ_k are the fraction of the wage and capital rental bills, respectively, that must be financed in advance.

$t+1$ shocks. The first term in the expression on the left of the equality is the number of non-bankrupt entrepreneurs, $1-F_t(\bar{\omega}_{t+1})$, times the interest and principal payments paid by each one. The second term corresponds to the funds received by the entrepreneurial-loan subsidiary from bankrupt entrepreneurs, net of monitoring costs. Multiplying this expression by $\left(1+R^e_{t+1}\right)/N_{t+1}$ and taking into account the definition of $\bar{\omega}_{t+1}$, we obtain:

$$[\Gamma_t(\bar{\omega}_{t+1})-\mu G_t(\bar{\omega}_{t+1})]\frac{1+R^k_{t+1}}{1+R^e_{t+1}}(B_{t+1}+N_{t+1})=B_{t+1}, \tag{21}$$

where

$$\begin{aligned}\Gamma_t(\bar{\omega}_{t+1}) &\equiv \bar{\omega}_{t+1}[1-F_t(\bar{\omega}_{t+1})]+G_t(\bar{\omega}_{t+1})\\ G_t(\bar{\omega}_{t+1}) &\equiv \int_0^{\bar{\omega}_{t+1}}\omega dF_t(\omega).\end{aligned}$$

Here, $\Gamma_t(\bar{\omega}_{t+1})$ is the share of entrepreneurial earnings, $\left(1+R^k_{t+1}\right)Q_{\bar{K}',t}\bar{K}_{t+1}$, received by the bank subsidiary before monitoring costs. The object, $\Gamma_t(\bar{\omega}_{t+1})-\mu G_t(\bar{\omega}_{t+1})$, is this share net of monitoring costs. Also, $1-\Gamma_t(\bar{\omega}_{t+1})$ denotes the share of gross entrepreneurial earnings retained by entrepreneurs. The standard debt contract has two parameters, the loan amount, B_{t+1}, and a no-default interest rate, Z_{t+1} (or, equivalently, $\bar{\omega}_{t+1}$). The two parameters are chosen to maximize the end-of-contract level of net worth for the entrepreneur subject to the bank subsidiary's zero profit condition:

$$\begin{aligned}\max_{B_{t+1},\{\bar{\omega}_{t+1}\}} & E_t\{[1-\Gamma_t(\bar{\omega}_{t+1})]\frac{1+R^k_{t+1}}{1+R^e_{t+1}}(B_{t+1}+N_{t+1}) \\ &+\eta_{t+1}\left([\Gamma_t(\bar{\omega}_{t+1})-\mu G_t(\bar{\omega}_{t+1})]\frac{1+R^k_{t+1}}{1+R^e_{t+1}}(B_{t+1}+N_{t+1})-B_{t+1}\right)\}.\end{aligned} \tag{22}$$

where η_{t+1} represents the Lagrange multiplier, which is a function of the period $t+1$ state of nature. The first order conditions of the problem are the zero profit condition, (21), and the first order necessary conditions associated with the optimization problem. Appendix E provides details about the optimization problem.

Total credit outstanding at the end of period t, B^{Tot}_t, is defined as the sum of working capital loans – a minute before they are retired – and the newly-created entrepreneurial loans:

$$B^{Tot}_t=\psi_l W_t l_t+\psi_k P_t\tilde{r}^k_t K_t+B_{t+1}. \tag{23}$$

We adopt the convention that working capital loans are not used until the end of the period.

2.4.2 Funding

In intermediating financial resources between households and the productive sector – firms and entrepreneurs – the bank creates three classes of liabilities: bank deposits, short-term marketable securities and other financial securities. Bank deposits and short-term marketable securities are bundled with liquidity services. This means that the bank has to expend resources in financing its loan activity with these two classes of liabilities. The other financial securities do not offer liquidity services and can be produced at zero cost.

As in Chari, Christiano and Eichenbaum (1995) and Lucas (1990), we assume that the bank uses a technology for converting homogeneous labor, l_t^b, capital services, K_t^b, and excess reserves, E_t^r, into the liquidity services associated with its most liquid liabilities:

$$\frac{D_t^h + D_t^f + \varsigma D_t^m}{P_t} = x_t^b \left(\left(K_t^b\right)^\alpha \left(z_t l_t^b\right)^{1-\alpha} \right)^{\xi_t} \left(\frac{E_t^r}{P_t} \right)^{1-\xi_t} \tag{24}$$

Here D_t^h and D_t^f denote bank deposits issued to households and firms, respectively, D_t^m indicates short-term marketable securities held by households, ς is a positive scalar and $0 < \alpha < 1$. In (24), x_t^b and $\xi_t \in (0,1)$ are stochastic processes that reflect, respectively, a funding technology shock and a shock that governs the bank's demand for free reserves, E_t^r, which are defined below. We include free reserves as an input to the production of liquidity services as a reduced form way to capture the precautionary motive of a bank concerned about the possibility of unexpected withdrawals.

Household deposits are issued at the beginning of each period t, just prior to production, when households place an amount A_t of high-powered money into the bank in exchange for a bank account:

$$D_t^h = A_t. \tag{25}$$

A_t constitutes the total cash reserves of the banking sector. Contemporaneously, the bank extends working capital loans to intermediate goods-producing firms and makes them available to firms in the form of deposit accounts, D_t^f. Note that, while D_t^h is fully backed by cash reserves, $D_t^f = S_t^w$ is backed by the book value of the working capital loans. This is the sense in which our bank can be thought of as operating a fractional reserve system of liquidity creation.

The bank is required to hold minimum reserves against deposits, with a required reserve ratio, τ. Therefore, out of its total cash reserves A_t, only a fraction E_t^r can be used as an input of production of liquidity services:

$$E_t^r = A_t - \tau \left(D_t^h + D_t^f \right). \tag{26}$$

Deposits pay interest, R_t^a. We suppose that the interest on bank deposits that are created as a vehicle for granting working capital loans are paid to the recipient of the loans. Firms hold these deposits until the wage bill and the rental cost of capital are paid in the settlement period that occurs after the goods market closes. We denote the interest rate that firms pay on working capital loans by $R_t + R_t^a$. Since firms receive interest, R_t^a, on deposits, net interest on working capital loans is R_t. Deposits held by households or firms are redeemed at the settlement stage that occurs after each period's goods market.

Short-term marketable securities, D_{t+1}^m, and other financial securities, T_t are issued at the end of the production period to finance the bank's loans to entrepreneurs:

$$D_{t+1}^m + T_t = B_{t+1}. \tag{27}$$

Short-term marketable securities and the other financial securities are entirely backed by entrepreneurial loans and are not subject to minimum reserve requirements. Their maturity structure coincides with that of the underlying entrepreneurial debt contract. They are created at the end of a given period's goods market, when newly constructed capital is sold by capital producers to entrepreneurs, and they pay off at the end of next period's goods market, when the entrepreneurs sell their undepreciated capital to capital producers.

Short-term marketable securities and the other financial securities differ in that the former can be cashed in before maturity at no cost. So, unlike T_t, D^m_{t+1} provide liquidity services, which explains why this type of liability figures as an output of the bank's liquidity production technology (24). This difference between these two sources of funding is reflected in the returns that they pay to households upon maturity: R^m_{t+1} and R^T_{t+1}, respectively. We assume that both $R^m_{t+1}$and R^e_{t+1} are contingent on all shocks realized in period t, but are *not* contingent on the $t+1$ aggregate shocks.[3] Because there are no costs to the bank for producing T_t, we can impose the condition, $R^e_{t+1} = R^T_{t+1}$ in all dates and states of nature. From this equality it follows that R^T_{t+1} also shares the property of not being contingent on $t+1$ aggregate shocks.

At the end of the goods market, the bank settles claims for transactions that occurred in the time-t goods market and that arose from its activities in the previous period's markets for entrepreneurial loans, for short-term marketable securities and other financial securities. The bank's sources of funds at this point in time are: interest and principal on working capital loans, $(1+R_t+R^a_t)S^w_t$, interest and principal on entrepreneurial loans extended in the previous period, $(1+R^e_t)B_t$, the reserves the bank has received from households at the start of the period, A_t, and newly created short-term marketable securities and other financial securities, $D^m_{t+1}+T_t$. The bank's uses of funds include new loans, B_{t+1}, extended to entrepreneurs, principal and interest payments on deposits, $(1+R^a_t)D_t$, interest and principal on short-term marketable securities, $(1+R^m_t)D^m_t$, principal and interest on other financial securities, $\left(1+R^T_t\right)T_{t-1}$, and gross expenses on labor and capital services. Thus, the bank's net source of funds at the end of the period, Π^b_t, is:

$$\begin{aligned}\Pi^b_t &= (1+R_t+R^a_t)S^w_t + (1+R^e_t)\,B_t + A_t + T_t + D^m_{t+1} - B_{t+1} - (1+R^a_t)\left(D^h_t + D^f_t\right)\\ &\quad - (1+R^m_t)D^m_t - \left(1+R^T_t\right)T_{t-1} - \left[(1+\psi_k R_t)\,P_t\tilde{r}^k_t K^b_t\right] - \left[(1+\psi_l R_t)\,W_t l^b_t\right].\end{aligned}$$

In solving its problem, the bank takes rates of return and factor prices as given. In addition, B_{t+1} is determined by the considerations spelled out in the previous sub-section, and so here $\{B_{t+1}\}$ is also taken as given. At date t, the bank takes D^m_t, T_{t-1} as given, and chooses $S^w_t = D^f_t$, D^m_{t+1}, T_t, A_t, K^b_t, l^b_t, E^r_t. The constraints are (27), (20), (25), (24) and (26).

2.4.3 Two Transmission Channels

We pause to draw attention on two important channels of propagation in our model. We shall refer to them as the 'financial accelerator channel' and the 'bank funding channel', respectively.

We start discussiong the former. The '*financial accelerator channel*' is associated with the decisions that the bank and the entrepreneurs have to make to optimise – from their respective view points – the terms of their financial contract, as stated in (22). The financial contract itself is an istrument to overcome the asymmetric information between lenders and borrowers in the market for entrepreneurial credit. It does so by making the terms of the loan dependent on the borrowers' net worth. So, this channel operates through changes in the net worth of entrepreneurs. Changes in net worth are propagated through

[3] In our specification, banks do not participate in state-contingent markets. In separate calculations, we show that if banks had access to state-contingent markets, so that they have a single zero-profit condition, rather one that applies to each period $t+1$ state of nature separately, the results would be largely unaffected.

two avenues which are economically distinct. There is a genuine 'accelerator' avenue which alters net worth by changes in the flow of entrepreneurial earnings and by capital gains and losses on entrepreneurial assets. This is the channel highlighted in BGG, and it tends to magnify the economic effects of any shock that has a pro-cyclical impact on economic activity. However, there is a second, complementary avenue by which changes in net worth are propagated. Following Irving Fisher (1933), we sub-categorise this second mechanism as the 'Fisher deflation channel'. The 'Fisher deflation channel' presupposes that debt contracts are formulated in nominal terms. If this is true – at least on a large scale – then (negative) surprises to the price level can alter *ex post* the real burden of the debt that the borrower will have to bear when the contract will eventually mature. Indeed, unlike in BGG, in our model the entrepreneurial contract embodies an important nominal rigidity: the opportunity cost perceived by the bank when lending to the entrepreneurs at time t – R^e_{t+1}, R^T_{t+1} and R^m_{t+1} – is not contingent on the time-$t+1$ shocks, which however will modify the profitability of the contract from the point of view of the borrower before maturity.[4] As we will show later, the 'Fisher deflation' and the pure 'accelerator' mechanisms reinforce each other in the case of shocks that move the price level and output in the same direction, but tend to cancel each other in the wake of shocks which move the price level and output in opposite directions.[5]

The second channel of propagation is what we refer to as the '*bank funding channel*'. Combine the expressions in (27), (26), (24) and (23) with households' demand for liquidity services, which we present below in (28). These conditions jointly establish an economic link, within the bank's accounts, between both forms of lending – to firms and to entrepreneurs – and the conditions that prevail in the market for bank funding. Obviously, the presence of the 'financial accelerator channel' described above means that our model violates the Modigliani-Miller irrelevance theorem for the financing of non-bank enterprises. It is interesting to understand whether the non-irrelevance result extends to the funding of banks.

One goal of this paper is to test whether the 'financial accelerator channel' and the 'bank funding channel' are important for explaining the data. It is also interesting to discriminate between what in the fit of the model is due to a genuine 'accelerator' mechanism and what comes from the 'Fisher deflation channel'. We comment on the results of these tests in section 7.

2.5 Households

There is a continuum of households, indexed by $j \in (0, 1)$. Households consume, save, take portfolio decisions and supply a differentiated labor input. They set their wages using the variant of the Calvo (1983) frictions proposed by Erceg, Henderson and Levin (2000).

The preferences of the j^{th} household are given by:

$$E_t^j \sum_{l=0}^{\infty} \beta^l \zeta_{c,t+l} \{ u(C_{t+l} - bC_{t+l-1}) - \psi_L \frac{h_{j,t+l}^{1+\sigma_L}}{1+\sigma_L} - H\left(\frac{\frac{M_{t+l}}{P_{t+l}}}{\frac{M_{t+l-1}}{P_{t+l-1}}}\right) \tag{28}$$
$$- \upsilon \frac{\left[\left(\frac{(1+\tau^c)P_{t+l}C_{t+l}}{M_{t+l}} \right)^{(1-\chi_{t+l})\theta} \left(\frac{(1+\tau^c)P_{t+l}C_{t+l}}{D^h_{t+l}} \right)^{(1-\chi_{t+l})(1-\theta)} \left(\frac{(1+\tau^c)P_{t+l}C_{t+l}}{D^m_{t+l}b} \right)^{\chi_{t+l}} \right]^{1-\sigma_q}}{1-\sigma_q} \},$$

[4] Our model does not incorporate a rationale for this nominal rigidity. For such a discussion, see Meh, Quadrini, and Terajima (2008).

[5] This point was stressed in Christiano, Motto and Rostagno (2003). See also Iacoviello (2005).

where E_t^j is the expectation operator, conditional on aggregate and household j idiosyncratic information up to, and including, time t; C_t denotes time t consumption; h_{jt} is time-t hours worked; τ^c is a tax on consumption; $\zeta_{c,t}$ is an exogenous shock to time-t preferences. The term in square brackets captures the notion that currency, M_t, short-term marketable securities, D_t^m, and household bank deposits, D_t^h, contribute to utility by providing liquidity services. The value of those services are an increasing function of the level of consumption expenditures (inclusive of the consumption tax, τ^c). The function, H, represents a cost of adjusting (real) currency holdings. The function H is convex, and achieves its global minimum when real currency growth is at its steady state value. Note that liquidity preferences are calibrated by two constant parameters, υ and θ, and are perturbed by χ_t, a shock to the demand for short-term marketable securities relative to the other forms of liquid holdings. To ensure balanced growth, we specify u to be the natural logarithm. When $b > 0$, (28) allows for internal habit formation in consumption preferences.

We now discuss the household's period-t uses and sources of funds. The household begins the period holding high-powered money balances, M_t^b. It divides this between currency, M_t, and deposits at the bank, A_t subject to:

$$M_t^b - (M_t + A_t) \geq 0. \tag{29}$$

In exchange for A_t, the household receives a deposit liability, D_t^h, from the bank.

The period-t money injection is X_t. This is transferred to the household, so that by the end of the period the household is in possession of M_t+X_t units of currency. We assume that the household's period-t currency transactions services are a function of M_t only, because X_t arrives 'too late' to be useful in current period transactions. We make a similar assumption about bank deposits. At the end of the period, the household receives wage payments from firms and interest on its D_t^h balances, which however cannot be spent in the current-period goods market.

Time-t sources of funds include after-tax wage payments, $\left(1-\tau^l\right) W_{j,t}h_{j,t}$, where $W_{j,t}$ is the household's wage rate; currency holdings, $M_t +\ X_t$ (including the late money injection) and bank deposits, $(1+R_t^a)\, D_t^h$ including interest earned during the current period; principal and interest related to short-term marketable securities, $(1+R_t^m)\, D_t^m$, and other financial securities, $\left(1+R_t^T\right) T_{t-1}$, acquired at the end of period $t-1$ and maturing at the end of the current period; profits, Π_t, from producers of capital, the bank and intermediate-goods firms; and $A_{j,t}$. The latter is the net payoff on the state contingent securities that the household purchases to insulate itself from uncertainty associated with being able to reoptimize its wage rate. In addition, households receive lump-sum transfers, $Lump_t$ and $(1-\Theta)(1-\gamma_t)\, V_t$, where $V_t = \frac{\bar{N}_{t+1}-W^e}{\gamma_t}$ is the net worth held by each individual entrepreneur who exits the economy at the end of the current period.

Uses of funds include payments for consumption goods, $(1+\tau^c)\, P_tC_t$ and acquisitions of high powered money, M_{t+1}^b, short-term marketable securities, D_{t+1}^m, and other financial securities, T_t. In addition, households pay a lump sum tax, W^e, earmarked to finance the transfer payments made to the γ_t entrepreneurs that survive and to the $1-\gamma_t$ newly born entrepreneurs.

These observations are summarized in the following asset accumulation equation:

$$\begin{aligned}
&(1+R_t^a)\left(M_t^b - M_t\right) + X_t - T_t - D_{t+1}^m \\
&- (1+\tau^c)\, P_tC_t + (1-\Theta)(1-\gamma_t)\, V_t - W^e + Lump_t \\
&\quad -B_{t+40}^L + \eta_t^L(1+R_t^L)B_t^L + \left(1+R_t^T\right) T_{t-1} + (1+R_t^m)\, D_t^m \\
&\quad + \left(1-\tau^l\right) W_{j,t}h_{j,t} + M_t + \Pi_t + A_{j,t} \geq M_{t+1}^b > 0.
\end{aligned} \tag{30}$$

Equation (30) also allows the household to purchase a 10-year bond, B_{t+40}^L, which pays R_t^L at maturity. Because households are identical in terms of their portfolios and preferences, equilibrium requires that B_t^L are in zero net supply. We nevertheless find it useful to introduce B_t^L as a way to diagnose model fit. The mean value of η_t^L is fixed at unity. If the estimation strategy finds that the variance of η_t^L is zero, we infer that the model has no difficulty in accounting for the term spread. Formally, we treat η_t^L as a tax on the return to B_t^L, whose proceeds are returned to the household in $Lump_t$. The household knows the value of R_t^L at date, $t-40$, when B_t^L is purchased. The household becomes aware of η_t^L at the date when the bond matures.

The j^{th} household faces the following demand for its labor:

$$h_{j,t} = \left(\frac{W_{j,t}}{W_t}\right)^{\frac{\lambda_w}{1-\lambda_w}} l_t, \; 1 \leq \lambda_w, \tag{31}$$

where l_t is the quantity of homogeneous labor employed by goods-producing intermediate good firms and banks, W_t is the wage rate of homogeneous labor, and $W_{j,t}$ is the j^{th} household's wage. Homogeneous labor is thought of as being provided by competitive labor contractors who use the production function, (7). The j^{th} household is the monopoly supplier of differentiated labor of type $h_{j,t}$. In a given period the j^{th} household can optimize its wage rate, $W_{j,t}$, with probability, $1-\xi_w$. With probability ξ_w it cannot reoptimize, in which case it sets its wage rate as follows:

$$W_{j,t} = \tilde{\pi}_{w,t} \left(\mu_{z^*}\right)^{1-\vartheta} \left(\mu_{z^*,t}\right)^{\vartheta} W_{j,t-1},$$

where $0 \leq \vartheta \leq 1$ and

$$\tilde{\pi}_{w,t} \equiv \left(\pi_t^{target}\right)^{\iota_w} \left(\pi_{t-1}\right)^{1-\iota_w}, \; 0 < \iota_w < 1. \tag{32}$$

Here, π_t^{target} is the target inflation rate of the monetary authority.

The household's problem is to maximize (28) subject to the various non-negativity constraints, the demand for labor, the Calvo wage-setting frictions, and (30).

2.6 Resource Constraint

We now develop the aggregate resource constraint for this economy. Clearing in the market for final goods implies:

$$\mu \int_0^{\bar{\omega}_t} \omega dF(\omega) \left(1+R_t^k\right) \frac{Q_{\bar{K}',t-1}\bar{K}_t}{P_t} + \frac{\tau_t^{oil} a(u_t)}{\Upsilon^t} \bar{K}_t + \frac{\Theta(1-\gamma_t)V_t}{P_t} + G_t + C_t + \left(\frac{1}{\Upsilon^t \mu_{\Upsilon,t}}\right) I_t \leq Y_t. \tag{33}$$

The first object in (33) represents final output used up in bank monitoring. The second term captures capital utilization costs.[6] The third term corresponds to the consumption of the $1-\gamma_t$ entrepreneurs who exit the economy in period t. We model government consumption, G_t, as:

$$G_t = z_t^* g_t,$$

[6] Here, we use the fact that an entrepreneur's rate of utilization, u_t, is independent of the draw of ω. In addition, we use the fact that the integral of ω across entrepreneurs is unity.

where g_t is a stationary stochastic process. This way of modeling G_t helps to ensure that the model has a balanced growth path. The last term on the left of the equality in the goods clearing condition is the amount of final goods used up in producing I_t investment goods. In addition, we follow the strategy of Yun (1996), in deriving the relationship between Y_t and aggregate capital and aggregate labor supply by households.

We measure real gross domestic product (GDP) in the model as follows:

$$GDP_t = G_t + C_t + \frac{1}{\Upsilon^t \mu_{\Upsilon,t}} I_t.$$

Note, once more, that the stationary investment-specific technology shock, $\mu_{\Upsilon,t}$, influences the transformation of consumption goods into investment goods and thus enters the expression for the relative price of investment, $\frac{1}{\Upsilon^t \mu_{\Upsilon,t}}$.

2.7 Monetary Policy

In the baseline estimation and model evaluation exercise that is presented below we use a generalized version of the Taylor rule. Under this rule, the monetary policy operating target is R^e_{t+1} is adjusted according to the reaction function below:

$$\begin{aligned}\hat{R}^e_{t+1} &= \rho_i \hat{R}^e_t + (1-\rho_i)\alpha_\pi \frac{\pi}{R^e}\left(E_t\left(\hat{\pi}_{t+1}\right) - \hat{\pi}^{target}_t\right) + (1-\rho_i)\frac{\alpha_{\Delta y}}{4R^e}\log\left(\frac{GDP_t}{\mu_{z^*} GDP_{t-1}}\right) \qquad (34)\\ &+ (1-\rho_i)\left[\alpha_{\Delta\pi}\frac{\pi}{R^e}\left(\hat{\pi}_t - \hat{\pi}_{t-1}\right) + \frac{\alpha_{\Delta c}}{R^e}\log\left(\frac{B^{Tot}_t}{\mu_{z^*} B^{Tot}_{t-1}}\right) + \frac{\alpha_\xi}{400R^e}\hat{\xi}_t\right] + \frac{1}{400R^e}\varepsilon_t,\end{aligned}$$

where variables with a '$\hat{\ }$' are percent deviations from their steady state values[7] and the inflation objective, π^{target}_t, has the time series representation described in sub-section (2.9). Relative to conventional formulations, the generalised Taylor rule in (34) postulates that the policy instrument is adjusted also in response to a number of variables which we collect in squared brackets. These terms include the change in inflation rate (following Smets and Wouters (2003)), total credit growth and exogenous shifts in the bank's preferences for reserves, $\hat{\xi}_t$. The presence of $\hat{\xi}_t$ in (34), in particular, is motivated by the need to keep the specification of the central bank's operating procedures flexible to the possibility of shifting targets. For example, a policy in which the central bank fully accommodates shocks to the demand for reserves – and thus resembles more closely a Taylor-based interest-rate targeting formulation – would be consistent with a coefficient $\alpha_\xi = 0$. Alternatively, a strategy in which the central bank makes policy settings also conditional on the liquidity conditions prevailing in the interbank market would be approximated by a non-zero α_ξ coefficient.[8]

[7] If we have a variable, x_t, whose steady state is x, then $\hat{x}_t \equiv \frac{x_t - x}{x} \simeq \log\frac{x_t}{x}$ denotes the percent deviation of x_t from its steady state value. It follows that $x\hat{x}_t$ is the actual deviation from steady state. When x_t is a variable such as the rate of interest, then $400x\hat{x}_t$ expresses x_t as a deviation from steady state, in annualized, percent terms.

[8] Imagine that the central bank offers liquidity through a series of competitive auctions of central bank money (the ECB) or through discrete-time outright purchases or sales of securities (the Federal Reserve). Ahead of each liquidity-supplying operation the central bank announces a pre-set volume of reserves to be auctioned off, or sold, to banks. Imagine that the central bank determines the volume in such a way as to have the *ex post* equilibrium money market interest rate settle around values consistent with the prescriptions of a conventional Taylor rule. In these conditions, any shift in banks' demand for reserves

In our empirical exercise, we set $\alpha_{\Delta c} = 0$ in the US model. Finally, ε_t in (34) denotes an unforecastable monetary policy shock.

In the last part of the paper we simulate the model under the assumption that the central bank uses a money-base rule corrected for deviations of inflation from a constant objective and output growth, in the spirit of McCallum (1988). This latter exercise is motivated by the observation that starting in late autumn 2008, the Federal Open Market Committee of the US Federal Reserve has reacted to the exacerbation of the financial crisis by placing stronger emphasis on quantitative measures of the monetary policy stance. With the target for the federal funds rate reduced to a narrow range between 0% and 0.25% in December 2008, and an ambitious menu of credit and asset purchase programs in place, a quantitative rule might be a better approximation to measuring the actual stance of the central bank than the baseline generalized Taylor rule which we use for estimation and model evaluation purposes. The quantitative rule that we use in the simulation exercise at the end of the paper is of the following form:

$$\hat{x}_t = \rho_m \hat{x}_{t-1} - (1-\rho_m)[\alpha_{m\pi}(E_t(\hat{\pi}_{t+1}) - \hat{\pi}_t^{target}) + \alpha_{m\Delta y} \log\left(\frac{GDP_t}{\mu_{z^*} GDP_{t-1}}\right) \\ + \alpha_{m\Delta\pi}(\hat{\pi}_t - \hat{\pi}_{t-1}) - \alpha_{m\xi}\xi_t] + \varepsilon_t, \tag{35}$$

where $\hat{x}_t$ is the injection of base money, defined in the identity $M_{t+1}^b = M_t^b(1+x_t)$, in deviation from steady state base money growth. The inertia and reaction coefficients, ρ_m, $\alpha_{m\pi}$, $\alpha_{m\Delta y}$, $\alpha_{m\Delta\pi}$ and $\alpha_{m\xi}$, are symmetric to those used in the generalised Taylor-type feed-back rule. The last terms, ε_t, stands for the unsystematic deviations of the observed monetary injections from the rule.

2.8 Model Solution

Our economy evolves along a stochastic growth path. The short-term nominal interest rates, the long-term interest rate, the premium paid by entrepreneurs over and above the risk-free rate, inflation and hours worked are stationary. Consumption, real wages, output, real net worth, real monetary aggregates and real credit grow at the rate determined by z_t^*. Capital and investment grow faster, due to increasing efficiency in the investment producing sector, at a rate determined by $z_t^*\Upsilon^t$, with $\Upsilon > 1$. Therefore, the solution involves the following steps. First, we rewrite the model in terms of stationary variables by detrending each variable using its specific trend growth rate, z_t^* or $z_t^*\Upsilon^t$. Note that, due to the declining relative costs of production in the investment producing sector, detrending for the relative price of capital, $\frac{Q_{\bar{K}',t}}{P_t}$, and for the real rate of return on a unit of capital services, $\tilde{r}_t^k$, involves the following transformations: $q_t = \frac{Q_{\bar{K},t}}{\Upsilon^{-t}P_t}$ and $r_t^k = \Upsilon^t \tilde{r}_t^k$, respectively. Second, we find the non-stochastic steady state for the detrended system following the procedure described in Christiano, Motto and Rostagno (2003) and construct a log-linear approximation around it. Finally, we solve

between successive open market interventions would translate in a money market interest rate higher or lower than the Taylor-based target interest rate. The coefficient α_ξ measures the degree to which the equilibrium short-term interest rate $\hat{R}_{t+1}^e$ – a three-month average of overnight money market rates – is influenced by such shifts in money market conditions, given the mechanisms by which monetary policy is implemented. While factors related to banks' demand for reserves have traditionally been a negligible source of variation for money market interest rates, in August 2007 they suddenly became a primary cause of disruption for the monetary policy transmission mechanism. See Section 8 for a discussion.

the resulting linear system of rational expectations equations using the approach proposed by Christiano (2002).

2.9 Fundamental Shocks

The model we estimate includes the following 16 shocks:

$$\left(\hat{x}_t^b \quad \hat{\mu}_{\Upsilon,t} \quad \hat{\chi}_t \quad \hat{g}_t \quad \hat{\mu}_{z^*,t} \quad \hat{\gamma}_t \quad \hat{\epsilon}_t \quad \varepsilon_t \quad \hat{\sigma}_t \quad \hat{\zeta}_{c,t} \quad \hat{\zeta}_{i,t} \quad \hat{\tau}_t^{oil} \quad \hat{\lambda}_{f,t} \quad \hat{\eta}_t^L \quad \hat{\xi}_t \quad \hat{\pi}_t^{target} \right), \tag{36}$$

Note the absence of a shock to households' labour-leisure preferences or to the wage mark-up. In preliminary experiments, we included stochastic variation for ψ_L, the parameter that calibrates households' disutility of labour. We found that the portion of the forecast error variance decomposition for any observable variable that was explained by shocks to such parameter was negligible. We therefore excluded such shocks from our baseline estimation. As demonstrated below, this omission does not detract from the empirical fit of our baseline model. We view this finding as remarkable, given that monetary business cycle models have been criticised for over-relying on labour supply shocks to match the data at business cycle frequencies.[9] Note also that, due to capital-embodied technical progress, shocks to the growth rate of output, $\mu_{z^*,t}$, are linked to shocks to the persistent component of technology, $\mu_{z,t}$, through the following expression:

$$\mu_{z^*,t} \equiv \mu_{z,t} + \frac{\alpha}{1-\alpha}.$$

The target shock, $\hat{\pi}_t^{target}$, is assumed to have the following time series representation:

$$\hat{\pi}_t^{target} = \rho_\pi \hat{\pi}_{t-1}^{target} + \varepsilon_t^{target}, \quad E\left(\varepsilon_t^{target}\right)^2 = \sigma_\pi.$$

We calibrate the autoregressive parameter, ρ_π, and the standard deviation of the shock, σ_π, at 0.965 and 0.00035 respectively, in order to accommodate the downward inflation trend in the early 1980s in the EA and the US.[10]

With one exception, the monetary policy shock, ε_t, which we assume to be *iid*, each of the shocks in our analysis has a conventional univariate first order autoregressive representation with two parameters. The autoregressive process of the risk shock, $\hat{\sigma}_t$, differs from that of the other shocks in that it has a more complex structure. Specifically, we suppose $\hat{\sigma}_t$ to evolve as follows:

$$\begin{aligned} \hat{\sigma}_t &= \rho_\sigma \hat{\sigma}_{t-1} + \nu_t^\sigma, \quad \nu_t^\sigma \,\tilde{}\, iid \\ \nu_t^\sigma &= \xi_{\sigma,t}^0 + \xi_{\sigma,t-1}^1 + \xi_{\sigma,t-2}^2 + ... + \xi_{\sigma,t-p}^p. \end{aligned} \tag{37}$$

Note that the time-t innovation to the risk shock process, ν_t^σ, is generalised to a sum of innovations including a contemporaneous unexpected component, $\xi_{\sigma,t}^0$, and p anticipated

[9] See, for example, Chari, Kehoe and McGrattan (2008). While the irrelevance of labour supply shocks in our baseline model is very intersting in its own right, we do not study it further in this paper.

[10] In charts not reported in this paper, we show that the calibration of the autoregressive process for the inflation objective indicated in the text help account for the drawn-out disinflation episode that took place in both the EA and US over the earlier part of our sample period. The simulated time series for the inflation objective in the two economies captures well the pronounced downward trend in realized inflation until the second half of the 1990s, and its flattening out in the following period.

components, $\xi^j_{\sigma,t-j}$, $j = 1, ...p$. We refer to each $\xi^j_{\sigma,t-j}$ as the period $t - j$ 'news' or 'signal' about the current realisation of ν^σ_t. Note that, even though each individual signal, $\xi^j_{\sigma,t-j}$, does not change the value of the risk shock until time t comes, it nonetheless influences the expectations of ν^σ_t already at time $t - j$ when it is received. Another way to describe the mechanics of signals is to say that, at time t, agents gain foresight about, say, the value of ν^σ_{t+1} by looking at the sum of the signals about ν^σ_{t+1} that have been received up to – and including – time t: $E_t\nu^\sigma_{t+1} = \xi^1_{\sigma,t} + \xi^2_{\sigma,t-1} + ... + \xi^p_{\sigma,t-p-1}$. Defining:

$$\sigma^2_{\sigma,i} = Var\left(\xi^i_{t-i}\right),\ i = 0, ...,\ p, \tag{38}$$

we assume $\sigma^2_{\sigma,1} = \sigma^2_{\sigma,2} = ... = \sigma^2_{\sigma,p} = \sigma^2_\sigma$. We also restrict the covariances so that signals about shocks j periods apart in time, have correlation, ρ^j_σ. In our empirical exercise we assume $p = 8$, and we assess the sensitivity of our results to this assumption (see Table A.3 in the Appendix). We experimented with the adoption of the signal structure also for technological and other financial shocks, and the results are presented in Table 7. Appendix B provides details on how we implement the signal representation of the shock.

The reason for generalising the autoregressive law of motion of the risk shock is twofold. First, and close in spirit to Del Negro and Schorfheide (2009), a generalised shock estimator helps tackle deep-seated misspecification problems in DSGE models and optimise their empirical fit. Indeed, we document below the presence of misspecification in our model, residing specifically in its endogenous financial channels. That source of misspecification becomes tangible when we add the stock market, credit and the external finance premium to the set of observable variables which the model is forced to fit in estimation. When the three variables are considered observable, the signal representation of the risk shock enhances the empirical mapping between the data and the corresponding model objects on those three dimensions. Second, introducing signals about future innovations to the risk process has a straightforward economic interpretation. In general, we are convinced that the acquisition of advance information about the future is a more appealing way to describe the mechanism by which exogenous shocks enter agents' information sets and move the economy than the traditional purely unexpected shocks. We view the acquisition of signals on future risk, in particular, as a parsimonious way to formalise agents' revisions of their own risk perceptions. In this sense signals are not a mere source of "free parameters" in our empirical exercise but are well motivated by micro facts. This interpretation receives some support in our analysis of the ongoing financial crisis which is presented below.

2.10 Model Variants

For model validation purposes we also consider two reduced-scale variants of our baseline model. They are derived from the baseline specification by deactivating the two propagation mechanisms that we described in (2.4.3): the 'financial accelerator channel' and the 'bank funding channel'.

2.10.1 The Financial Accelerator model

The first variant we consider preserves the 'financial accelerator channel', but removes the 'bank funding channel', namely the bank's supply of liquidity and households' demand for money. We refer to this specification as the *Financial Accelerator Model*. It is extracted from the baseline specification by: (1) eliminating the conditions that pertain to the bank's issuance of liabilities (sub-section 2.4.2); (2) setting the weight attached to liquidity services in households' utility (28), υ, the function for adjusting households' real currency holdings, H, all monetary variables, M_j^b, M_j, A_j, D_j^m, $j = t-1, t, t+1, ...$, in the household's budget constraint and the monetary policy reaction coefficient attached to the bank's preference for reserves in (34), α_ξ, equal to zero; (3) setting the fraction of capital services and labor services that firms need to finance in advance by working capital loans, $\psi_k = \psi_l = 0$; (4) setting the variance of the signal innovations in (38), $\sigma_{\sigma,i}^2 = 0$, at all horizons $i = 1, ..., 8$;[11] (5) setting $B_{t+j}^L = \eta_{t+s}^L = 0$, for all j and s.

2.10.2 The Simple Model

The second reduced-scale version of our model that we consider is what we refer to as the *Simple Model*. It is a variant of the model proposed by Christiano, Eichenbaum and Evans (2005) in its money-less version analyzed by Smets and Wouters (2003, 2007). This model variant is what we obtain, when we strip our baseline model of the two financial channels mentioned above, the 'financial accelerator channel' and the 'bank funding channel'. Technically, it is derived by starting from the *Financial Accelerator Model* and: (1) dropping the entrepreneurial sector (all the conditions in section 2.3 and sub-section 2.4.1); (2) setting the monetary policy reaction coefficient attached to credit growth and the bank's preference for reserves in (34), α_C and α_ξ respectively, equal to zero; (3) introducing a capital stock accumulation decision in the household's intertemporal optimization problem. The last modification implies that the nominal return on capital defined in (15) in the simple model satisfies the standard equality condition:

$$1 + R_{t+1}^e = E_t\left(1 + R_{t+1}^k\right) = \frac{r^k(\bar{K}_{,t+1}, \tau_{t+1}^{oil}) + (1-\delta)E_t Q_{\bar{K},t+1}}{Q_{\bar{K},t}} + \tau^k \delta. \tag{39}$$

where $r^k(\bar{K}_{,t+1}, \tau_{t+1}^{oil})$ stands for the the nominal rental rate of a unit of capital services net of utilization costs.

3 Estimation and Fit

As in Christiano, Motto and Rostagno (2007), we apply a Bayesian version of the maximum likelihood strategy that we used in Christiano *et al.* (2003). The strategy is designed to accommodate the fact that the computation of the model's steady state is time intensive. We partition the model parameters into two sets. The first set contains the parameters that control the steady state. The values of some of these parameters, such as the capital income share, α, and the capital depreciation rate, δ, are simply borrowed from the literature. The values of the other parameters that control the steady state are set so that the model reproduces key sample averages in the data. We report the numerical values of the steady state parameters in Table 1. We document the degree to which the steady state implications of our model match the corresponding sample averages for selected *great ratios*, for equity to debt ratios, inflation, money and credit velocities and various rates of return in Tables 2 and 3. We discuss the calibration and the fit of the steady state in detail in Appendix C.

The second set of parameters is estimated using the Bayesian procedures discussed in An and Schorfheide (2005) and Smets and Wouters (2003). The parameters estimated here

[11] For purposes of model comparison and validation, we also consider an empirical version of the financial accelerator model in which signals have a positive variance.

include the ones that characterize monetary policy, wage and price frictions, capital utilization, σ_a, investment adjustment costs, currency adjustment costs and the shock processes. We now turn to the estimation procedure.

3.1 Data

We adopt a standard state observer set-up in assuming that measured data correspond to a subset of the endogenous variables defined in the model plus a measurement error. We treat the following 16 quarterly time series as observed processes (see Appendix D for details): GDP, Consumption, Investment, GDP deflator, real wages, hours worked, the relative price of investment, the relative price of oil, the short-term interest rate, the stock market, a measure of the external finance premium, real credit, two measures of liquidity, bank reserves and the spread between the long-term interest rate and the short-term rate.

The short-term interest rate, R_{t+1}^e, is the 3-month interbank interest rate for the EA and the 3-month average of the daily federal funds rate for the US; the spread, $R_t^{long} - R_{t+1}^e$, is the difference between the 10-year government bond rate and R_{t+1}^e; the relativge price of investment, P_{It}, is the investment deflator divided by the GDP deflator. We match P_{It} with $1/\left(\Upsilon^t \mu_{\Upsilon,t}\right)$ in the model. In the EA the external finance premium is measured using an average of spreads between bank lending rates and corporate bond yields, and the yields of government securities of corresponding maturities.[12] In the US, for the external finance premium we use the difference between the BAA rate and the federal funds rate. Our measure of bank reserves for the US is total reserves held at the Federal Reserve System. For the EA, we use the total outstanding refinancing by the Eurosystem since 1999 and we back-date the series using an appropriately rescaled aggregate of central bank liabilities vis-à-vis banks for Germany, France, Spain, the Netherlands, Finland and Portugal. We have two measures of liquidity, a 'narrow' and a 'broad' measure. For the EA, we match the model's 'narrow liquidity' aggregate, defined by the sum of currency and overnight deposits, $M_t + D_t^h + D_t^f = M_t^b + D_t^f$, with data for $M1$. The model object 'short-term marketable securities', D_{t+1}^m, is matched with data for $M3 - M1$. This aggregate includes deposits with a short-term residual maturity and very liquid marketable securities issues by the EA monetary sector. For the US, we match the 'narrow liquidity' aggregate with $M2$ data, while for D_{t+1}^m we use an aggregate including financial commercial papers and repurchase agreements issued by US financial institutions. The main purpose of using $M2$ and this latter aggregate in the estimation of the US model is to have a measure which approximates a reasonably stable source of retail funding for banks ($M2$), along with a wholesale funding source (commercial papers and repos) that can easily evaporate along with market liquidity in times of crisis. Adrian and Shin (2010) study the funding patterns of banks over the 2007-2009 crisis looking at the same two aggregates.

The sample period used in the estimation is 1985Q1-2008Q2.[13] We restrict our empirical analysis to this rather short sample because of data limitations in the EA and because we want to preserve comparability between the US and the EA results. In addition, by excluding much of the so-called Volcker stabilisation period in the US, we minimize the impact of various structural breaks that are said to have occurred in the early 1980s, including shifts in the monetary policy regime.[14] Figure 1.a and Figure 1.b show the time series of our data

[12] We use the outstanding stocks as the weights to aggregate lending rates.

[13] Our data sample begins in 1981Q1. We use the first 16 quarters as a 'training sample', so that the likelihood is evaluated using data drawn from the period 1985Q1-2008Q2.

[14] That is, a possible break in monetary policy and the 'Great Moderation', the apparent

observations and the in-sample model fit. Note that, while the data used for estimation exclude the post-Lehman observations, all the charts – including Figure 1.a and Figure 1.b – that we show in the paper use a longer span of data, including the quarters from 2008Q3 to 2009Q2.[15] All data are quarterly and, except for the short-term interest rate (R^e_{t+1}), inflation, hours worked, the external finance premium and the term spread, they are logged and first-differenced. Prior to estimation, data are demeaned by removing their sample mean, with the exception of inflation and the short-term interest rate (R^e_{t+1}), which are demeaned by subtracting their steady-state values, as reported in Table 2 and Table 3. We set the steady state of variables included in the observer equation to zero. In this way, inference about the parameters governing model dynamics is not distorted by difficulties the model may have in matching the different sample averages of some of the observable variables.

In Figures 1.a and 1.b, the dark line denotes the data and the red-dotted line is the data simulated by the model in response to the estimated (by two-sided Kalman smoothing) economic shocks, computed at the mode of the posterior distribution of the parameters. With the exception of three variables – the stock market, credit and the external finance premium – data and smoothed estimates exactly coincide. For the stock market, credit and the external finance premium, we assume that data are subject to measurement errors, which we estimate in our empirical exercise. In fact, for these three variables, inspection of Figures 1.a and 1.b reveals a positive, small vertical difference between the line of the data and the line of the simulated data. We interpret 'measurement errors' mainly as stand-ins for model-specification errors. We think that specification error mostly reside in those channels of the model that are responsible for the definition of equity, credit and the external finance premium. It is evident from the figures, however, that the "measurement errors" play a very minor role in the estimation, with the possible exception of the stock market in the US model.

3.1.1 Data for Model Variants

When estimating the *Financial Accelerator Model* we use 11 observable variables: all the time series used to estimate the baseline model, except the two measures of liquidity, bank reserves, $R^{long}_t - R^e_{t+1}$ and credit growth. Note that we include the external finance premium but we exclude credit growth from estimation of the *Financial Accelerator Model*. This is done to underline the inability of the financial accelerator mechanism in itself - as it is usually implemented - to explain both prices and quantities in the credit market. We discuss this inability below, in section 4.2. The *Financial Accelerator Model* activates a smaller set of economic shocks than the baseline model: we drop $\hat{x}^b_t$, $\hat{\chi}_t$, $\hat{\eta}^L_t$ and $\hat{\xi}_t$ from the list reported in (36) and, as mentioned already, we do not consider signals for the risk shock. Estimation of the *Simple Model* is done with 9 time series only. From the *Financial Accelerator Model's* vector of observables we drop the stock market index and the external finance premium. The economic shocks are those considered when estimating the *Financial Accelerator Model*, except $\hat{\gamma}_t$ and $\hat{\sigma}_t$.

decline in macroeconomic volatility.

[15] In the last section of the paper we comment on the impact of the financial crisis on key estimated parameters and on inferences. In that section we briefly report on the changes in the estimates of selected parameters which arise from re-estimating our baseline model on the extended sample, including the 4 quarters between 2008Q3 and 2009Q2.

3.2 Estimates

The number of parameters that we estimate is 48 and 46 for the EA and US versions of the baseline model, respectively. There are two more parameters in the EA version of the baseline model because we estimate the monetary policy response to credit – which is absent in the US specification – and the curvature parameter, H'', governing real currency adjustment costs. The latter parameter turned out to be close to zero in earlier estimations of the US model and was thus excluded from the baseline version presented in this paper.[16]

Of the parameters that we estimate, eight relate to structural features of the private sector, and six pertain to the monetary policy rule. Among the former, ξ_p and ξ_w are the Calvo price and wage setting probabilities, ϑ is the weight on the permanent technology shock in the wage equation, ι and ι_w are the weights on steady state inflation in the price and wage setting equations. S'', σ_a and $H''$are the parameters calibrating investment adjustment costs, capital utilisation costs, and the costs of adjusting real currency holdings, respectively. The six policy parameters in (34) calibrate the monetary policy persistence (ρ_i) and the monetary policy response to: inflation (α_π), the change in output ($\alpha_{\Delta y}$), the change in inflation ($\alpha_{\Delta \pi}$), credit growth ($\alpha_{\Delta c}$) and shocks to the demand for reserves (α_ξ).

Prior and posterior distributions of the parameters that do not control steady state are displayed in Figures 2.a, 2.b and 2.c. Prior and posteriors modes are also reported in Table 4, along with the 5% and 95% bounds.[17] We also estimate the two variants of our baseline model that are briefly described in section 2.10. The estimation of the two reduced-scale model variants is conducted assuming the same prior distributions as for the baseline estimation. Estimates for the two models are reported in the Appendix (Tables A.1 and A.2) and we do not disucss them further here.

In the case of the Calvo parameters, ξ_p, ξ_w, our priors (Table 4) imply that prices and wages are reoptimized on average once a year in the Euro Area, and every 1.6 quarters in the US. Our priors for the frequency of price adjustments are relatively tight, reflecting the extensive empirical analysis of the behavior of prices in recent years, including firm-level evidence.[18] Despite our informative priors, posteriors on ξ_p and ξ_w are shifted substantially to the right, for the US, and to the left, for the EA (Figure 2.a). The posterior modes imply an average frequency of price and wage adjustment in the EA of 3.5 quarters and 3.4 quarters, respectively. In the case of the US, our posteriors imply that both prices and wages are reoptimized every 3.3 quarters. Our estimate of the degree of price stickiness for the US is almost identical to the baseline estimate of Smets and Wouters (2007) who, however, adopt a different price aggregator, which increases the demand elasticity of the

[16] The 48 free parameters that control the dynamics of the EA model break down as follows: there are 31 shock parameters (2 times 13 for the shocks, 4 for the risk shock with the signal representation and 1 for the monetary policy shock), 14 parameters that control the dynamics of the model, and 3 measurement error parameters.

[17] Posterior probability intervals are computed using the Laplace approximation. Smets and Wouters (2007) report that results based on the Laplace approximation are very similar to those based on the MCMC algorithm. The priors on the measurement errors have a Weibull distribution with standard deviation equal to 10 percent of the standard deviation of the underlying variable, based on the past 10 years' observations. The Weibull distribution has a second parameter, whose value is indicated Table 4.

[18] For a survey of EA evidence, see Altissimo, Ehrmann and Smets (2006). Our US priors were taken from Levin, Onatski, Williams and Williams (2006), who in turn centre their price rigidity priors to obtain a frequency of adjustment roughly in line with Bils and Klenow (2004) and Golosov and Lucas (2007). Regarding the latter, when Golosov and Lucas (2007, Table 1) calibrate their model to the micro data, they select parameters to ensure that firms re-optimize prices on average once every 1.5 quarters.

differentiated goods at the firm level. Price stickiness in our estimation is considerably less than the one reported by Levin, Onatski, Williams and Williams (2006), who find that price contracts have a duration of about 5 quarters.

The distribution of the priors for the three indexation parameters – beta, with a mean of 0.5 and a standard deviation of 0.15 – is fairly diffuse and encompasses a wide range of empirical findings in the literature. Our posterior results point to a very low level of indexation to past inflation in the EA, notably for prices. By contrast, in the US, backward indexation seems to be preponderant, relative to steady state inflation indexation, in price setting. For both economies, we find nearly full indexation of wages to the contemporaneous realisation of the persistent technology shock.

Regarding investment adjustment costs, our priors on the elasticity parameter, S'', are in line with CEE. However, the posterior distribution is shifted sharply to the right, and is larger than the posterior modes reported in Smets and Wouters (2003, 2007). The sharp increase in the posterior mode for S'' is particularly evident when we compare the results of our baseline model and the *Financial Accelerator Model* on the one hand, with those we obtain from the *Simple Model,* on the other. The latter produces a posterior estimate for the cost adjustment elasticity that is well within the bounds identified in the literature. We take this discrepancy as an indication that the inclusion of the stock market among the data that are treated as observable is not neutral with respect to inferences about S''.[19] Our estimates imply a high cost of varying capital utilization, σ_a. In this respect, our results are consistent with the findings in Altig, Christiano, Eichenbaum and Lindé (2005) and Levin *et al.* (2006), who report a similar result based on US data. Our estimate is somewhat larger than the one in Smets and Wouters (2007), who report a 90% posterior probability interval for σ_a of 0.6 to 2.6.

We now turn to the parameters of the monetary policy rule, (34). Our estimates suggest that the EA and US policy rules exhibit a high degree of inertia (the parameter, ρ_i), and a relatively strong long-run response to one-quarter-ahead anticipated inflation (α_π). In addition – although generally less precisely estimated than other parameters, notably for the US – the estimated reaction function exhibits modest sensitivity to the growth rate of output ($\alpha_{\Delta y}$) and to the recent change in inflation ($\alpha_{\Delta\pi}$). The estimated policy rules in Levin *et al.* (2006) and Smets and Wouters (2003, 2007) are consistent with our results, in that they also imply strong response of monetary policy to inflation and a high degree of inertia. Two reaction parameters, $\alpha_{\Delta c}$ and α_ξ, deserve more attention. For $\alpha_{\Delta c}$ – estimated for the EA only – we adopt a normal distribution with mean 0.05 and standard deviation 0.025. The mode of the posterior distribution is slightly shifted to the right, thus identifying a significant degree of "leaning against credit exuberance" in the EA monetary policy framework. The priors for the response coefficient α_ξ are distributed according to a very diffuse normal distribution centred at 0 and with a standard deviation of 10. The mode of the posterior distributions for both the EA and the US estimations are sharply negative and almost identical. We interpret this finding as pointing to evidence that money market conditions influence the settings of the interest rate target by the central bank over and above monetary policy considerations related to inflation and growth.

As it is difficult to quantify prior beliefs for the shock processes, we selected our priors for the autocorrelation and standard deviation of the exogenous shocks with the following criteria in mind (see Table 4 and Figures 2.b and 2.c). First, all standard deviations of the

[19] Notice that the posterior mode for S'' is virtually the same in the baseline estimation (Table 4) and in the estimation of our *Financial Accelerator* model (Table A2), which also includes the stock market in the estimation.

innovations to the shock processes are assumed to follow an inverse-gamma distribution with five degrees of freedom. As a general rule, these prior distributions have a mode of 0.001 – translating into a 0.1 percent variation per quarter. For autocorrelation parameters, we adopt beta distributions which, as a general rule and following Smets and Wouters (2007), have a mean equal to 0.5 and a standard deviation of 0.2. These priors allow for a quite disperse range of values. Second, we departed from our first criterion whenever we found evidence that a different prior mode or a looser prior on the serial correlation of a certain shock process would generate second moments for key endogenous variables that grossly violate the evidence in our sample period. Our desire to replicate more precisely the measured volatility of inflation led us to a lower prior mode for the standard deviation of the $\lambda_{f,t}$ shock and to tighter priors for the autocorrelation coefficients of four shocks: γ_t and $\zeta_{i,t}$ (for both economies), and $\lambda_{f,t}$ and σ_t (for the US model). The prior mode for the standard deviation of $\mu_{\Upsilon,t}$ was set to match the observed variability of the relative price of investment goods in the sample. The prior mode for the common standard deviations of the signals on the risk shock – recall (38) – is equal to that of the contemporaneous unexpected component of the shock, 0.01, scaled by the square root of the number of signals, $\sqrt[2]{8}$. As in Schmitt-Grohé and Uribe (2008), the latter prior calibration guarantees that at the mode of the prior distribution the variance of the unexpected risk innovation, $\xi^0_{\sigma,t}$, equals 8 times the common variance of the signals. The priors on the parameter that calibrates the correlation between the signals, ρ_σ, are normally distributed around zero and quite diffuse (Figure 2a). Finally, large measured variances of the data on monetary aggregates, of the term spread and of the oil price relative to that of the rest of the economy, led to high prior modes for the standard deviations of the innovations to x^b_t, χ_t, ξ_t, η^L_t and τ^{oil}_t.

As we mentioned already, we allow for white noise measurement errors in the observation of three variables: the stock market index, real credit growth and the external finance premium. Again, we do this as a way to capture the degree of model misspecification along those dimensions – financial frictions – that are still unconventional in equilibrium modelling. To improve the in-sample fit of the model and avoid large estimated errors, we restrict the prior distribution of the standard deviations of the measurement errors to be tight Weibull distributions with a mode equal to around 10 percent of the standard deviation of the corresponding variable, evaluated over the last 10 years of data (Table 4).

In general, Figure 2.b and Figure 2.c show that the data appear to be very informative about the stochastic properties of the exogenous shocks. The estimated degree of serial correlation is in general fairly high. Shocks related to the demand for and bank supply of liquidity are particularly persistent and highly volatile. A notable exception is the bank reserve demand shock, ξ_t, in the EA, which is nearly a white noise process. The estimated volatility of the monetary policy shocks is sizeable, with a standard deviation of 45 and 52 basis points at an annual rate, respectively, in the EA and the US. The estimated measurement errors are generally very modest with the exception of the measurement error for the stock market index. For this parameter the mode of the posterior distribution is larger than the prior mode, notably for the US estimation.

The estimated persistence and the standard deviation of the risk shock – both the contemporaneous unexpected innovations and the signal components – are elevated. Both data sets favour a marked rightward shift in the posterior distributions of the autoregressive coefficients, notably for the EA where the priors are less informative (Figure 2.b). The range of the estimated standard deviations also exceed the range of the priors. The lower tail of the posterior distributions of the unexpected component is 1 and 2 standard deviations above the respective prior mode, in the EA and the US, while the same tail for the posterior distribution of the signals exceeds the prior mode by a factor of almost 6. While the estimated range of standard deviations are rather similar in the two economies, the posterior distributions for the correlation parameter across signals, ρ_σ, are notably apart. This finding might suggest that the degree to which revisions in the perceptions about future risk – from the vantage point of any time t in the sample – reflects current waves of optimism or pessimism is relatively greater in the US than in the EA.

3.3 Model Fit

We perform two tests to evaluate our model's fit. We first inspect the complete correlation structure as implied by the model and we compare it with the correlation structure that is observable in the data. We then run forecasts and we measure the model's out of sample performance. Del Negro, Schorfheide, Smets and Wouters (2007) implement measures of model fit built on Bayesian foundations. They show that these measures work very much like RMSE tests, and so we restrict ourselves to the latter.[20]

Figure 3.a and Figure 3.b report the autocorrelations and cross-correlations at up to a 12-quarter lead and lag for a subset of observable variables. The two dotted lines mark the ± 2 std confidence interval around the auto and cross-correlations measured in the data. The black solid line in each panel shows our baseline model prediction.[21] The pictures inspires three observations. The first observation is that the baseline model, with one exception, captures quite well the decaying autocorrelation structure of the variables reported (see the panels along the diagonals). The exception is inflation in the EA, whose empirical autocorrelation structure differs markedly from that of the US, where the model comforms better with the data. The second observation is that the model's implied cross-correlations are largely consistent with those measured in the data, with detectable deviations concentrated in the premium-hours (Pe-H), credit-hours (L-H) and credit-inflation (Pe-P) quadrant in the EA, and the two inflation-hour (P-H) panels in the US. The third observation is that, overall, our baseline model performs better on US data.

RMSE results are reported in Figure 4. Our first forecast is computed in 2001Q3, when we run $1, 2, ..., 12$ steps-ahead unconditional forecasts. We demean the data recursively. We compute forecasts using our baseline model and its *Financial Accelerator* and *Simple Model* variants, re-estimating their parameters every other quarter. We benchmark the models' performance against the fit of a Bayesian Vector Autoregression (BVAR) estimated – with Minnesota priors – on the basis of the same 16 time series and over the same sample period used for the baseline estimation. We start projecting the BVAR out-of-sample in 2001Q3, re-estimating every quarter.[22] To ensure comparability of results, all data are treated symmetrically to the baseline model. First, all data, except the short-term interest rate, inflation, hours worked, the external finance premium and the term spread, are first-differenced. Second, variables are demeaned by computing their mean recursively with the

[20] For further discussion, see Christiano (2007).

[21] The model-based cross correlations are those derived from a VAR(2) representation of the model. Results do not change visibly when adding more lags to the VAR. As for the auto and cross-correlations measured in the data (the two dotted lines), results are very similar to those that we obtain when fitting a VAR(2) on the data.

[22] The original Minnesota prior was designed for variables in levels, with the aim to shrink the model to univariate random walks. We modify the prior in the following way. The prior mean on the first own lag is set to zero for all variables in growth rates, to 0.9 for highly persistent variables such as the short-term interest rate and hours worked, and to 0.5 for spreads (credit spread and term spread).

exception of inflation and the short-term interest rate. As mentioned in section (3.1), we subtract the steady-state values from the latter two variables. Finally, we bechmark our results against forecasts constructed on a random walk.

An advantage of the RMSE calculations that we report is that we can use standard sampling theory to infer the statistical significance of discrepancies in RMSE results across models. We apply the procedure suggested in Christiano (1989) for evaluating these differences. Appendix F provides details. The grey area in Figure 4 represent a ± 2 standard deviation band around the BVAR-generated RMSEs.

Consider the EA first. The baseline model performance is always statistically close to that of the BVAR, except for credit where the model's RMSEs exceed the upper bound of the tight statistical interval at horizons between 4 and 7 quarters. The three model variants that we consider yield similar RMSEs. Now consider the results for the US. The baseline model's performance is consistently in line with or better than that of the BVAR for all variables, except for the risk premium at projection intervals between 3 and 5 quarters, where the BVAR marginally outperforms the baseline model, and credit, where the baseline model outperforms the BVAR at horizons of 4 quarters or more. The RMSEs generated by the baseline model are always indistinguishable from those generated by our financial accelerator model variant, except for inflation, where they are notably smaller.

4 Data and Model Selection

To understand the motivation and economic implications of our baseline model, look at Figure 5. The two dotted lines in the panels plot confidence bands – computed asymptotically – for selected cross-correlations in the data. These correlations represent dynamic interactions that are of particular interest to us, because they articulate the intersection between the real and the financial sides of the economy which is the focus of this paper. To help visualise how the selected variables co-move over the cycle, we use HP-filtered observations.[23] Comparing the first and the second panels of Figure 5 (EA data are on the upper row, US data on the lower row) we note that the value of installed capital – measured by the stock market index, N_t – rises and falls in tight synchronization with the rate of investment (see second column). In other words, the stock market is strongly pro-cyclical. The next two panels concentrate on credit market co-movements. Here, we note that the response of credit (L_t) to the cycle is clearly positive, essentially coincidental in the EA and slightly delayed in the US. The external finance premium, P^e, however, tends to move in the opposite direction. While the volume of credit is pro-cyclical, the price of credit is counter-cyclical. Next, compare – across the second, the fourth and the last two panels – the joint cyclical patterns of the stock market, the premium, credit and the wholesale funding sources of credit institutions. Concentrating mostly on the US figure – for which data are more pertinent to the phenomena that we want to measure – we are confronted with a striking regularity. The price of credit tends to be low when the volume of credit is high, and the price of capital falls precisely when funding conditions for credit institutions tighten. This inspires the following consideration which motivates our modelling exercise and the application of our model to studying the 2007-2009 financial crisis. If market liquidity – the possibility for banks to refinance

[23]The smoothing factor is 1600. The two confidence bands correspond to ± 2 standard deviations. Lars Hansen's formulas for exactly identified GMM are used in the computation. As for the construction of Figure 3a and 3b, the results were almost unchanged when correlations were computed on the basis of a VAR(2), and applying the HP filter on its frequency domain representation.

in the market – dries up when funding liquidity – banks' ability to borrow in the market for wholesale funds – becomes scarce, then the financial system may contain destabilizing mechanisms that magnify booms and exacerbate busts.

In this section we partition the correlations of Figure 5 in groups, and we assign models to groups. For example, the *Simple Model* considered in this paper has sufficient structure to account for the rate of investment and the price of capital. We ask: how does the *Simple Model* score in terms of reproducing the cross-correlations that are shown in the two first panels? The *Financial Accelerator Model* nests the *Simple Model*. In addition, it defines credit and the external finance premium. So, we ask a second, more ambitious question: how close does the *Financial Accelerator Model* come to generating the facts displayed in the first two panels plus the positive response of credit to the cycle and the negative response of the premium to credit? Finally, our baseline model defines all the variables displayed in Figure 5. Once more, we address the same question to our baseline model, now including the cyclical behaviour of the liquidity measures.

To anticipate our main conclusion, the richer structure of our baseline model is better able to account for the interactions of asset returns, asset volumes and the business cycle. The *Simple Model,* with minimal structure, has counter-cyclical – and counterfactual – implications for the price of capital. The *Financial Accelerator Model* yields the correct pro-cyclical behaviour of equity and the correct counter-cyclical pattern of the premium. But it delivers counter-cyclical – and, again, counterfactual – implications for credit. The baseline model, which we have articulated in section 2, with its multiplicity of transmission channels, does well across the board.

In the remainder of this section we present an informal diagnosis of the empirical predictions of the *Simple Model* and the *Financial Accelerator Model* for the price of capital and the volume of credit, respectively. We refine and qualify these results in relation to our baseline model in the following section 5.

4.1 The Simple Model and the Market for Capital

In this sub-section, we diagnose the asset pricing implications of the *Simple Model*. To this end, we first need to recover the analytical condition which, in that model – and in all the model variants that we consider – defines the supply of capital. We derive that condition from the capital producers' optimality problem, as stated in (12). After scaling (12), and making use of the definition $\lambda_{z,t} = \lambda_t P_t z_t^*$, we obtain:

$$q_t = \frac{\frac{1}{\mu_{\Upsilon,t}} - \frac{\beta}{\Upsilon}\frac{\lambda_{z,t+1}}{\lambda_{z,t}} \mathcal{F}_2(\bar{k}_{t+2}, \bar{k}_{t+1}, \zeta_{i,t+1}) E_t q_{t+1}}{\mathcal{F}_1(\bar{k}_{t+1}, \bar{k}_t, \zeta_{i,t})}, \tag{40}$$

where a lower case denotes a scaled variable. In (40) q_t represents the consumption good value of one unit of installed capital to be used in production at the beginning of time $t+1$. We refer to q_t as the date-t price of a share of equity. We rely on a scaled version of (13) to replace investment at time t with capital at time $t+1$ as an argument of the transformation technology, $\mathcal{F}(I_t, I_{t-1}, \zeta_{i,t})$. Because this technology incorporates installation costs, $S(\zeta_{i,t}\, I_t/I_{t-1})$, and these costs increase in the rate of investment and are convex, (40) defines a positive schedule in a static q_t– $\bar{k}_{t+1}$ space. Figure 6.a represents this static space – where we treat expectations of future variables as exogenous shifters – for the *Simple Model*. The positive schedule denotes the supply of capital. The same condition applies in the baseline model and in the *Financial Accelerator Model*. The negative schedule is a demand for capital. The demand for capital in the *Simple Model* – unlike in the baseline model and in the *Financial Accelerator Model* (see below) – is derived from (39). After scaling, rearranging and ignoring taxation, (39) becomes:

$$q_t = \frac{r^k(\bar{k}_{t+1}) + (1-\delta)E_t q_{t+1}}{\Upsilon\left(1 + R^e_{t+1}\right)}\left(1 + \pi_{t+1}\right). \tag{41}$$

where $r^k(\bar{k}_{t+1})$, a decreasing function linking the (scaled) real rental rate on capital, r^k_{t+1}, to the (scaled) capital stock, is obtained from (6), ignoring variable utilization.

Notice two elements of Figure 6.a. First, two investment-specific shocks shift the supply schedule, (40): $\mu_{\Upsilon,t}$, the shock that changes the price at which capital producers acquire, say, new machinery from intermediate goods producers; and $\zeta_{i,t}$, which alters the productivity of that piece of machinery in terms of the capital input already on line. The presence of two shocks in (40) poses an obvious identification challenge. We address this challenge by including the investment deflator index relative to the GDP deflator in our datasets. We use the mapping between the relative price of investment and $\frac{P_t}{\Upsilon^t \mu_{\Upsilon,t}}$ to identify the separate contribution of $\mu_{\Upsilon,t}$ to the supply of capital in all of our three model variants.[24] The second noteworthy element of the chart in Figure 6a is that no investment-specific shock moves the demand schedule, (41), in the space of the chart. The absence of investment shocks in (41) poses a more fundamental problem of fit for the *Simple Model*, which is our focus in the remainder of this sub-section.

We frame the discussion of this problem around Figure 8.a and Figure 8.b. As reported earlier, the *Simple Model* is estimated using only 9 variables as observables. Following convention, these variables do not include the stock market. Figures 8.a and 8.b offer an in-sample perspective over the results of this estimation for the EA and US, respectively. The layout of the Figures has the *Simple Model* occupying the first two columns on the left, the *Financial Accelerator Model* represented on the three columns in the middle, and the baseline model on the last two columns on the right. The panels on the first row represent the estimated two-sided smoothed time processes of selected shocks. The panels on the remaining rows plot selected data (grey solid line) together with the model projections for these variables, conditional on the estimated sequence of one shock only (dotted line): the shock that appears in the column header, estimated on the basis of the corresponding model.

Concentrate on the first two columns (the *Simple Model*). Here, the two shocks that are most relevant are the price of investment shock, $\mu_{\Upsilon,t}$, and the marginal investment efficiency shock, $\zeta_{i,t}$. Note that, because of our identification choice, $\mu_{\Upsilon,t}$ matches exactly the inverse of the investment deflator relative to the price of GDP. So, the line in the left-most panel on the first row represents the time profile of the shock and the inverse of the corresponding observable variable as well.

Three results stand out. First, $\mu_{\Upsilon,t}$ propagates to a very limited extent in both economies. As evident from the second and third panel on the first column (from top to bottom), the contribution of $\mu_{\Upsilon,t}$ to investment and GDP growth is almost negligible in the *Simple Model.* Although we do not document it in the Figures, this result extends to the two remaining models. Greenwood, Hercowitz and Krusell (2000) and Fisher (2006) have argued

[24] We use a national accounts measure for the private investment deflator. As pointed out by Gordon (1990) and Cummins and Violante (2002), the methodology employed by statistical offices to account for quality adjustments might underestimate the rate of technological progress in areas such as equipment and software. We use the official measures as they are available for both economies, EA and US, over the entire sample which we use in our empirical exercise.

for an important role of investment-specific technical progress, which makes investment goods progressively cheaper, as a primary force behind the cycle. Our estimation is clearly at odds with that conclusion.

Second, $\zeta_{i,t}$ plays a preponderant role in explaining investment and output in the *Simple Model*. Note how the simulated paths for investment and GDP growth conditional on the estimated process of $\zeta_{i,t}$ alone are almost exactly overlaid with actual investment and output data (second and third panels, from top to bottom, on the second column). This result conforms well with an important literature, starting with Greenwood, Hercowitz and Huffman (1988), which has rehabilitated shocks to the marginal efficiency of investment as plausible candidate impulses for the economic cycle. For example, using a monetary model with a lot in common with our *Simple Model*, Justiniano, Primiceri and Tambalotti (2007) have recently found that this shock is the prime driver of economic fluctuations. We obtain intuition for this finding by going back to Figure 6.a. In the *Simple Model*, an *autonomous,* i.e. non-policy induced, increase in investment of the sort that can often be observed during the boom phase of the cycle can be simulated only as a positive increase in the marginal efficiency of investment. An increase in investment efficiency is equivalent to a negative innovation to $\zeta_{i,t}$. A negative innovation to $\zeta_{i,t}$ pushes marginal installation costs down, which shifts the supply curve to the right and boosts investment.

The third result has to do with the implications of the latter mechanism for the price of capital in the *Simple Model*. These implications are reported in the bottom panel on the second column of Figure 8.a and Figure 8.b. Recall that the price of capital is treated as an unobservable state variable in the estimation of the *Simple Model.* So, the dotted line reported in that panel represents the *Simple Model*'s predictions for the (latent) process of Tobin's q in-sample. The panel in each of the two Figures shows, for the EA and the US, that the simulated price of capital in the *Simple Model* is counter-cyclical relative to $\zeta_{i,t}$. Because stock market observations impose no restrictions on the estimation procedure, the unconstrained $\zeta_{i,t}$ process becomes of overwhelming importance as a driver of investment fluctuations in the *Simple Model*. However, this almost perfect fit of $\zeta_{i,t}$ relative to investment is gained at the price of generating a path for the relative price of capital in the model that almost invariably contradicts the evidence.[25] When the data shows a generalized boom in the stock market *and* in the broader economy, the *Simple Model* predicts an investment boom and a stock market bust. The reverse is also true.

The unconditional predictions of the *Simple Model* confirm its in-sample implications. In the first and second panels from left of Figure 5 (EA and US row, respectively) the dashed-dotted lines represent the *Simple Model*'s implied co-variances between investment and output (first panel), and investment and the price of capital (Tobin's q, second panel) computed in population.[26] As expected, the model does very well accounting for the procyclicality of investment. But it does poorly on the latter dimension. The H-P filtered cross-correlations in the second panel are negative and outside the statistical interval marked by the two dotted lines, at leads and lags lower than 4 quarters, reaching a minimum at the zero lag. In fact, the zero lag is when the positive correlation between the stock market and investment is strongest in the data.

To sum up: in the *Simple Model*, because the $\zeta_{i,t}$ shock is so important, the stock market

[25] Our results for the Simple Model do not change when looking at the average q rather than the marginal q. See Jaimovich and Rebelo (2009) for the distinction.

[26] The model-based correlations are computed on the basis of the VAR(2) representation of the model and applying the HP filter on its frequency domain representation. We checked whether a VAR(2) representation was sufficient to reproduce the dynamics and found that the differences in moving to a VAR(3) or higher order are minimal.

has a 'negative beta', an implication which clearly contradicts the evidence. Any extension to the model which can repair this feature is bound to detract from the explanatory power of the $\zeta_{i,t}$ shock. This latter result is indeed what we document in the remainder of this section.

4.2 The Financial Accelerator and the Market for Capital

Here we focus on the entrepreneurial contract and we test the asset pricing implication of the *Financial Accelerator Model*. It turns out that augmenting the *Simple Model* with an entrepreneurial sector and a financial contract adds (much-needed) shifters to the demand for capital. This improves the asset pricing performance of the model.

The financial channel embedded in the *Financial Accelerator Model* – and in our baseline model – can be aggregated into a demand for capital schedule of a form that differs from (41). The new demand for capital can be extracted from the solution to the standard debt contract maximisation problem, as stated in (22). To facilitate insights into the implications of the financial contract for the properties of equilibrium dynamics, we frame the discussion in terms of linear approximations to the exact conditions that describe optimal choices in the markets for capital and credit. Appendix E provides the details about the solution to the contract problem, and derives the log-linearisations on which the following discussion is based.

We start with the market for capital. The following linear condition describes the demand for capital as a function of its unit price in a neighborhood of the steady state:

$$\hat{q}_t = -\widehat{\bar{k}}_{t+1} + \hat{n}_{t+1} + \left(\frac{\bar{k}-n}{n}\right) E_t\left[A\left(\frac{R^k \hat{R}^k_{t+1}}{1+R^k} - \frac{R^e \hat{R}^e_{t+1}}{1+R^e}\right) - B\sigma\hat{\sigma}_t\right]. \tag{42}$$

As documented in Appendix E, $A > 0$ and $B > 0$ are convolutions of primitive coefficients, which in the model govern the sensitivity of the terms of the financial contract to entrepreneurial risk. E_t is the expectations operator. Compare the expression in (42) with its analog in the *Simple Model*, (41). In the *Simple Model* the demand for capital is derived by equating the definition of the expected return on capital, (15), and the short-term risk-free interest rate, R^e_{t+1}. This condition does not hold in either the *Financial Accelerator Model* or in the baseline model. Here, financial frictions introduce a wedge between the internal cost of financing, the risk-free rate R^e_{t+1}, and the cost of external finance, which entrepreneurs have to pay in order to fund their projects. This wedge is the external finance premium, as defined in (18), which is a function of entrepreneurs' leverage. Indeed, (42) incorporates a term, $-\widehat{\bar{k}}_{t+1} + \hat{n}_{t+1}$, which makes the dependence of the new demand for capital on leverage explicit.

We go back to the drawing board of Figure 6.b to represent the new demand for capital, (42), in combination with a linear approximation to the supply of capital. The following expression is a linearised version of the supply of capital in (40):

$$\hat{q}_t = C\widehat{\bar{k}}_{t+1} - \beta D E_t \widehat{\bar{k}}_{t+2} + D\frac{i}{\bar{k}} E_t\left(\hat{\zeta}_{i,t} - \beta\hat{\zeta}_{i,t+1}\right), \tag{43}$$

where the dynamic coefficients, $C > 0$ and $D > 0$, are positive functions of the elasticity of the investment installation costs to the change in the rate of investment, S''. Note, incidentally, that a positive innovation to the marginal efficiency of capital (a negative $\hat{\zeta}_{i,t}$) determines an investment boom and a stock market bust, as it shifts (43) down and to the right. This confirms our earlier analysis.

But, in the new financial contract environment – in which (41) is replaced by (42) – the counter-cyclical properties of $\hat{\zeta}_{i,t}$ relative to stock prices is not necessarily a source of empirical failure for the model. Now, as we noted before, an autonomous increase in investment can be due to a shift in the demand for capital. Condition (42) helps identify the shifters and Figure 6.b visualises the way in which they can reproduce the 'correct' correlation between investment and stock prices which can be found in the data.

There are two new shifters in (42). The first is an exogenous shock to the current realised value of entrepreneurial equity, $\hat{n}_{t+1}$. To a first approximation, we can think of this shock as reflecting innovations to γ_t , the survival probability of entrepreneurs (see (17)).[27] A positive innovation to γ_t helps equity-rich entrepreneurs – already active in the previous period – to remain in business. As a consequence, the aggregate purchasing power that entrepreneurs *as a group* can exercise in the capital market increases, relative to a situation in which a larger share of aggregate equity is owned by start-ups (a lower γ_t). Higher equity value in the aggregate means stronger demand for capital and upward pressures on its price. In Figure 6.b this mechanism is reflected in a rightward shift in demand, from $D1$ to $D2\left(\hat{\gamma}_t, \hat{\sigma}_t, \hat{R}^k_{t+1}\right)$.

The second shifter is the term in the squared brackets, a function of the anticipated excess return on capital. This latter variable is critical in our empirical study and we shall return to it in section 8. The measure of the anticipated excess return which is reported in (42) is the present-time expectation of future innovations to the *gross* returns on capital, $\hat{R}^k_{t+1}$, in deviation from changes in the cost of borrowing incurred by entrepreneurs to finance the acquisition of capital. The latter measure of the cost of borrowing changes because of innovations to the risk-free rate, $\hat{R}^e_{t+1}$ (the internal cost of funding for the bank), and because of innovations to the external finance premium, which in the expression is captured by a function of the risk shock, $\hat{\sigma}_t$.

It is interesting to 'look inside' the term in the squared brackets in (42). From (15), we know that the gross return on capital, $\hat{R}^k_{t+1}$, is a function of the rental rate on capital, and the difference between $\hat{q}_{t+1}$ and $\hat{q}_t$, the expected capital gains from the re-sale of capital at the end of the investment cycle (see also Appendix E, for a linearised version of (15)). It turns out that, empirically, the capital gains component, $\hat{q}_{t+1} - \hat{q}_t$, dominate the rental rate in explaining the time series variation of the gross return on capital. The cost of borrowing factor depends on shifts in the risk-free rate, $\hat{R}^e_{t+1}$, possibly due to policy decisions, and on changes in the premium – or, indirectly, shifts to the risk shock, $\hat{\sigma}_t$. The risk shock influences excess retuns because a lower probability of entrepreneurial default today (a negative $\hat{\sigma}_t$) translates into a lower cost of borrowing tomorrow, when the premium charged on current loans will be determined. Recall that the contractual (no-default) rate of interest on time-t loans, Z_{t+1}, is contingent on the time $t+1$ shocks, and that the default probability the bank will use to price the premium with maturity $t+1$ is the default probability function realised at the end of time t, after observing $\hat{\sigma}_t$ (see, again, the timing of (17) and (18)). So, lower risk today has two dynamic implications. First, less entrepreneurs will declare bankruptcy tomorrow. Second, non-bankrupt entrepreneurs will be able to retain a larger share of their business profits. Both effects work toward boosting equity and purchases of plant capacity

[27] Note the difference between q_t and n_{t+1}. The former, q_t, corresponds to a claim on a *unit* of the underlying capital. The latter, n_{t+1}, is the aggregate value of entrepreneurial equity built into installed capital. In practice, q_t and n_{t+1} move closely together in the model. The difference between the two quantities are due to changes in leverage and the composition of the pool of entrepreneurs, due to shifts in their survival probabilty, γ_t, and in the probability of default, $G_t(\bar{\omega}_t, \sigma_t) \equiv \int_0^{\bar{\omega}_t} \omega dF_t(\omega)$. In our quantitative analysis we match the stock market to n_{t+1}.

in the present time. A stronger demand for capital, in turn, pushes up the stock price, q_t.

Before closing this sub-section, we emphasize two things. First, unlike in the *Simple Model*, at least two non-policy induced factors can now shift the demand for capital: unexpected realised changes in the endowment of equity, $\hat{n}_{t+1}$, and anticipated changes in the terms of borrowing which are not related to monetary conditions, $\hat{R}^e_{t+1}$, but to risk considerations, $\hat{\sigma}_t$. Second, adding structure – and, notably, the two new shifters – to the demand for capital has important implications for inferences. Compare the first two columns of Figure 8.a and Figure 8.b with the following five columns. The *Simple Model* interprets investment variation over the boom-bust phase that started in the mid 1990s as reflecting swings in the supply of capital (second row, second column). However, these were times in which investment and the stock market moved sharply together (compare the panels on the third and fourth rows). Therefore, when more structure is added to the modelling of the capital market and the econometrics are fed with stock market information – the two model exercises on the last five columns – the weight of the evidence tips in favour of large shifts in the demand for capital. Not surprisingly, moving from left to right, shocks that have a large impact on the value equity, γ_t and σ_t, become the leading forces of motion for investment and output. They usurp the in-sample explanatory power of $\zeta_{i,t}$, whose identified contribution to the cycle even switches signs (compare the second and the third panels on the second and third rows). Shocks to the marginal efficiency of investment turn from being powerful pro-cyclical sources of fluctuations (*Simple Model*) into counter-cyclical smoothers. By making installation more costly, $\zeta_{i,t}$ partially helps match the stock market boom. But, at the same time, it discourages investment and partly offsets the economic fallout of the rightward shift in the demand for capital.

4.3 The Financial Accelerator and the Market for Credit

In the previous sub-section we showed that the structural interpretation of the last 15 years of data: (i) is not invariant to whether the stock market is included – or not – in the analysis; (ii) is not invariant to using a model which allows – or a model that does not allow – for contemporaneous non-policy related shifts in the demand for capital. In fact, when we use a model with a financial contract and we combine it with stock market information, financial shocks become dominant.

But this leaves us with a dual financial shock hypothesis. What is the ultimate economic source of these shocks? Is it mainly surprises to the valuation of investors' net worth, an interpretation that we propose for innovations to γ_t ? Or is it rather changes in assessments of the financial risk that is fundamentally inherent in investors' projects, an interpretation that is more pertinent for σ_t and its signals? In this sub-section we show that information on credit is essential for discriminating between these two hypotheses. More generally, we argue that looking at the credit market implications of a model with financial frictions is an indispensable test for evaluating the model's ability to study financial phenomena and, notably, financial crises.

We start with the model-based interpretation of recent history that is documented in Figure 8.a and Figure 8.b. Compare the inferences that we extract from the *Financial Accelerator Model* and the baseline model. Recall that our empirical implementation of the *Financial Accelerator Model* does not use information about the stock of credit, whereas our baseline model does. The former model (third to fifth columns) identifies in financial wealth shocks, γ_t , the prime forces behind investment, output and asset price swings and comovements. The role of the risk shock, σ_t, is very modest and mainly confined to helping the model match the premium. The baseline model, fitting credit in estimation, paints the opposite picture, however. Here (last two columns), surprises to the value of equity, γ_t , are unimportant. Instead, innovations to financial risk, σ_t – both realised and anticipated – become the prototypical source of aggregate shocks that deliver the correct comovements and the relative volatilities that we observe in the data. Again, we seek intuition for these results in the conditions that characterise equilibrium in the credit market, and we use stylised graphical analysis to study those conditions. At the end of this sub-section we return to Figure 8.a, Figure 8.b and Figure 5 to confirm our intuition.

We start with the equilibrium conditions in the credit market. We report below linear approximations to two optimising conditions which in the *Financial Accelerator Model* can be interpreted as entrepreneurs' demand for credit and banks' supply of entrepreneurial credit. Identical conditions apply in the baseline model. Appendix E provides details on the derivation.

$$\hat{P}^{e,D}_{t+1} = -\frac{n}{\bar{k}}\hat{b}_{t+1} + \frac{n}{\bar{k}}\hat{n}_{t+1} + E_t\left[H\left(\frac{R^k\hat{R}^k_{t+1}}{1+R^k}\right) - (H-1)\frac{R^e\hat{R}^e_{t+1}}{1+R^e} + J\sigma\hat{\sigma}\right], \tag{44}$$

with $H > 1$ and $J < 0$, and $\frac{n}{\bar{k}}$ denoting the equity-to-capital ratio in steady state. The condition above establishes a negative dynamic relation between deviations of the expected time-$t+1$ external finance premium, P^e_{t+1} – as defined in (18) – and deviations of time-t (scaled) credit to entrepreneurs, $\hat{b}_{t+1}$, from their respective steady state values. To understand why the time-t expectation of the $t+1$ premium appears in (44), recall that the measure of the premium which is relevant for pricing the loan that the entrepreneur is about to take on at the end of time t, b_{t+1}, is the *expected* external finance premium that the bank will apply – after observing the time $t+1$ shocks – at the end of the contract. The condition itself is derived from the entrepreneurs' first order optimality condition for loan demand (the first term in (22)), taking into account the impact that – for a given value of net worth – a larger loan is going to exert on the price of credit, the external finance premium, which banks will charge upon maturity. Note that the demand for credit – not unlike the demand for capital in (42) – shifts positively after positive surpise changes to entrepreneurs' net worth, $\hat{n}_{t+1}$, and anticipated changes in the excess return on capital. The expected excess return on capital is a function of the last term in squared brackets.

Next, consider what we interpret as the bank's supply of entrepreneurial credit:

$$\hat{P}^{e,S}_{t+1} = S\frac{n}{\bar{k}}\hat{b}_{t+1} - S\frac{n}{\bar{k}}\hat{n}_{t+1} - E_t\left[S\left(\frac{R^k\hat{R}^k_{t+1}}{1+R^k}\right) + (1+S)\frac{R^e\hat{R}^e_{t+1}}{1+R^e} - T\sigma\hat{\sigma}_t\right], \tag{45}$$

where $S, T > 0$. The positive relation in (45), linking the expected premium and the quantity of entrepreneurial credit, descends directly from the bank's zero-profit condition (21). This latter conditions needs to be met for the bank to have an incentive to participate in the financial contract. Note, once more, the connection between the last squared-bracketed term in (45) and the anticipated excess return on capital in (42).

The two linear conditions, (44) and (45), are represented in the static space of Figure 7.a, lower panel, where we describe the equilibrium in the market for credit. The upper panel in Figure 7.a reproduces the capital market equilibrium of Figure 6.b. To understand the role that the financial wealth shock plays in Figure 8.a and Figure 8.b, we illustrate the transmission of an innovation to γ_t in the stylised environment of Figure 7.a. An innovation to the financial wealth shock at time t, $\hat{\gamma}_t$, impacts directly on the value of equity which entrepreneurs can commit for capital formation in the time-t market, $\hat{n}_{t+1}$ (see (17)). This wealth effect tends to displace the demand curve in the upper panel to the right, from $D1$ to $D2(\hat{\gamma}_t,)$. As we discussed earlier, unlike in the *Simple Model*, in the *Financial Accelerator Model* – and in the baseline model as well – this shift in demand suffices to generate the joint procyclical properties that we observe in the data for stock market prices and investment.

In the credit market (lower panel), after the shock, demand and supply move as well (see the lower panel). The demand for credit tends to shift horizontally to the right, from $D1$ to $D2(\hat{\gamma}_t,)$. This reflects a fundamental feature of our financial contract set-up: holding other things unchanged, each individual entrepreneur has always an incentive to leverage up any surprise increase in equity, $\hat{n}_{t+1}$. To understand why, observe the first component within the brackets of the optimisation problem in (22). This first component corresponds to expected entrepreneurial profits. Holding the terms of the contract fixed – unchanged $\bar{\omega}_{t+1}$– this term increases unboundedly in the amount of capital that the entrepreneur is able to purchase by taking on more debt.[28] There is also action on the supply side of the credit market. After an equity shock, and (again) leaving other things the same, the bank becomes more willing to lend, because the borrower's stakes in the project which secures the loan increase ($\hat{n}_{t+1}$ is a shifter in (45)). So, the supply of credit moves down on impact, from $S1$ to $S2\left(\hat{\gamma}_t\right)$.

But the propagation of a financial wealth shock, $\hat{\gamma}_t$, doesn't stop there. The shock also propagates dynamically. An unexpected change in the current value of entrepreneurial equity, $\hat{n}_{t+1}$, boosts the current value of capital *relative to its future value*. This effect is stronger the more difficult it is for capital producers to expand plant capacity on the margin in response to an increase in investment demand (see (43)), i.e. the larger is the value of S''. Installation costs exacerbate the anticipated difference between q_t and q_{t+1} after a shock to n_{t+1}, through two avenues. A larger curvature value, S'', makes the supply of capital steeper, and thus amplifies the price effect of a shift in demand in the current period (the C coefficient in (43) rises with S''). Moreover, by incurring higher costs in the present, capital producers frontload production costs. This makes future capital cheeper to produce and thus future capital goods less expensive.

As discussed above, in the model there is a summary statistic for the expected *gross* capital gains or losses associated with the holding of the capital stock: R^k_{t+1}. An unexpected $\hat{\gamma}_t$ shock, producing a rise in equity at time t and anticipations of a capital loss in $t+1$, is reflected in negative autocorrelation in the time profile of the (gross) payoff on capital, $\hat{R}^k_t$. In fact, under our estimated coefficients, in the aftermath of an unexpected $\hat{\gamma}_t$ shock, $\hat{R}^k_t$, is sharply positive and an order of magnitude larger than the response of the risk-free interest rate, $\hat{R}^e_{t+1}$. By contrast, $\hat{R}^k_{t+1}$ is negative and large in absolute terms.

A negative $\hat{R}^k_{t+1}$ has important implications. It shifts the demand for capital back to the left at time t, from $D2(\hat{\gamma}_t,)$ to $D3(\hat{\gamma}_t, \hat{R}^k_{t+1})$ in the upper panel of Figure 7.a. Quantitatively, this partly offsets the impact effect of the equity shock, but it does not cancel it. So, the procyclical association between investment and stock market prices (between $\hat{\bar{k}}_{t+1}$ and $\hat{q}_t$ in the picture) is preserved. At the same time, however, it causes sharp and seemingly perverse retroactions in the credit market (lower panel of Figure 7.a). Both supply and demand shift back to the left at time t. The movement in demand quantitatively dominates the change in supply. What happens is that both the lender and the borrowers appreciate the degree of strategic interaction that exists in the market for capital. As individual borrowers rush to leverage up the surprise gain in their net worth, capital is made more expensive and the prospective payoff on capital turns negative for everybody. Borrowing becomes less

[28] In other words, in expectation, the net return on an entrepreneurial investment project is always positive.

attractive and the end result is twofold. First, the price of credit, the premium, falls as credit demand retracts. Second, the decline in demand also means that the present-time windfall gains, $\hat{n}_{t+1}$, are *only partly* used to finance an expansion of plant capacity. A fraction of $\hat{n}_{t+1}$ is used to pay down debt and reduce leverage. So, equilibrium borrowing falls as well, along with the premium. In sum, the model dynamics comforms nicely with the inverted cyclical properties of the premium that we documentd in Figure 5. But, it fails on the other dimension: the pro-cyclicality of credit.

Figure 8.a and Figure 8.b make the latter problem very clear. Unconstrained by information on credit, our empirical implementation of *Financial Accelerator Model* assigns a prime cyclical role to the financial wealth shock, γ_t. Note how this shock explains virtually the entire in-sample variation in the stock market. As it transmits further to the investment margin of the model, the shock helps generate the investment and the premium cycles, at least qualitatively. Quantitatively, due to the strict association between γ_t and a volatile stock market, the model overstates the variance of investment and, to a stark degree, that of the premium – notably over the stock market bust of the early 2000s. But the latent path for credit that the shock generates endogenously is nowhere close to the actual data (last panel on the fourth column). The sequence of contemporaneous shocks to γ_t, which the model uses to reproduce the cycle, triggers systematic counter-cyclical innovations to the expected returns on capital as evaluated from the vantage point of each time in the sample. Consistent with the analysis above, this expectations channel encourages a pattern of credit extintion in booms and credit creation in busts, which is clearly at odds with the facts.

Figure 5 reinforces and generalises these findings. The grey curves in the panels correspond to the *Financial Accelerator Model*. Clearly, the model's performance is very satistactory at replicating, unconditionally, the cyclical behaviours of investment, the stock market index and – although less precisely – the premium. As anticipated by the analysis above, however, it fails on the cross-correlations that involve the stock of credit. In particular, the key association between prices and quantities in the credit market (second last panel from left) is missed by a wide margin.

5 The Risk Shock in the baseline model

In the preceding section we showed that: (i) the *Financial Accelerator Model* assigns a dominant role to surprise changes to the value of entrepreneurs' equity in explaining the business cycle; (ii) this dominant role, however, is inconsistent with basic credit market facts, such as the positive correlation between credit and the cycle, and the negative correlation between credit prices and credit quantities. Our baseline model incorporates mechanisms designed to repair these empirical inconsistencies. The mechanisms are essentially two: the news representation of the risk shock which is illustrated in (37), and what we have defined 'the bank funding channel', namely the accounting and economic connections that the baseline model establish between the lending and the financing decisions of the bank. We shall comment on the bank funding channel in section 7.

In this section we describe the mechanics and behaviour of the risk shock and its news representation. As usual, we analyse the risk shock, first informally, interpreting Figure 8.a and Figure 8.b with the support of stylised comparative statics analysis. But we also broaden the range of variables for which the risk shock provides interpretation and we resort to impulse response functions to refine intuition about its propagation in relation to other shocks. Using the model to diagnose the sources of business cycle uncertainty, we identify the risk shock as a potent source of aggregate uncertainty. It is so powerful that it can generate a typical post-war cycle in the real economy, and, coincidentally, a boom-bust cycle in asset and credit markets that closely resembles those that have become recurrent in more recent times.

We start again from Figure 8.a and Figure 8.b. As noted already, the interpretation of history changes markedly moving from the middle of the Figures (occupied by the *Financial Accelerator Model*) to the two last columns (baseline model). We note three aspects of this comparison. First, the fraction of in-sample variation of the stock market that is explained by the risk shock when using the baseline model is smaller than the fraction explained by γ_t according to the *Financial Accelerator Model.* The key to understanding this difference is in (17), the evolution equation for net worth. Shocks to γ_t exert a one-to-one, contemporaneous impact on the value of net worth, the model object that we match to stock market data in estimation. Instead, shocks to σ_t have a more round-about influence, working through the premium with a lag. Our second observation derives from the first. A milder correlation between the risk shock and the stock market dampens the intensity with which this financial factor spreads from the financial side to the real side of the economy. As a consequence, the degree to which the σ_t-simulated path for investment in the baseline model overstates the variation of investment (and output and the premium itself) in the data is a lot more contained than it is when the *Financial Accelerator Model* is used to project observable variables on the basis of γ_t alone.

Third, and most importantly, the observability of credit is obviously responsible for the change in inferences between the two models. The panel on the two bottom rows and rightmost column is very suggestive. Observing the pricing side of the credit market (the premium), but disregarding the quantity side has (mis)led the model to favour unexpected – and largely unexplained – shocks to wealth as the main engine of fluctuations. For the *Financial Accelerator Model*, risk considerations are a minor factor that helps explain the premium, but almost recursively.

Including credit in the estimation of the baseline model allows the econometrics to identify σ_t and moves the interpretation of history back to fundamentals. Essentially, the risk shock is the shock that explains the credit market: prices and quantities. From the credit market, revisions to the risk properties of the underlying investment projects diffuse to the rest of the economy through the investment margin. In the baseline model, risk shocks become the single source of uncertainty which can trigger aggregate cycles and reconcile all the main facts that we report in the two Figures.

Figure 9, which we discuss in the following sub-section, broadens and shapens the focus on the diffusion process of σ_t, concentrating on the role of signals.

5.1 The Signals on Risk

The first and the fourth columns in Figure 9 plot the contribution of the risk shock process to a broad set of observable variables. This set includes variables familiar from the analysis of Figure 8.a and Figure 8.b, as well as new variables such as the spread between the long-term interest rate and the short term rate, and marketable securities (the D_t^m object in the model), for the EA and the US, respectively.[29] The second-third and fifth-sixth couples of columns disaggregate that contribution into groups of signals referring to the nearer or the more distant future. For example, along the second column, the dotted lines represent the value that the corresponding variable would have taken on at any time t if, at that

[29] For GDP growth, the stock market index, credit growth and the premium, these plots are identical to those of Figure 8a and Figure 8b.

time, only the signals already received at t and concerning the value of the risk shock at $t+1, ..t+4$, had been active and all other shocks in the economy had been set to zero. The third column gives the contribution of the signals already in time-t information sets, and referring to time $t+5$ to $t+8$. The first column adds to the sum of the contributions coming from all the signals the impact of the contemporaneous unexpected innovation, $\xi^0_{\sigma,t}$ (see the state space representation of the process in Appendix B). To appreciate the content of this pictures, recall that at time t only the cumulative impact of the signals *received in the past* plus the unexpected revision to risk which takes place at present, $\xi^0_{\sigma,t}$, can influence the current realisation of the shock: $\hat{\sigma}_t = \rho_\sigma \hat{\sigma}_{t-1} + \xi^0_{\sigma,t} + \xi^1_{\sigma,t-1} + ... + \xi^8_{\sigma,t-8}$. But this dynamic structure in the evolution of the shock is a basis for agents to run a number of forecasts of future $\hat{\sigma}_{t+j}$ – looking out from the vantage point of any t – one pertaining to each horizon j within agents' foresight reach. We assume the maximum foresight horizon to be 8 quarters. So, at time t, the expected value of the innovation to the time-$t+1$ risk process is $E_t \nu^\sigma_{t+1} = \xi^1_{\sigma,t} + \xi^2_{\sigma,t-1} + ... + \xi^8_{\sigma,t-7}$. At the same time t, the forecast of the time-$t+2$ innovation is $E_t \nu^\sigma_{t+2} = \xi^2_{\sigma,t} + \xi^3_{\sigma,t-1} + ... + \xi^8_{\sigma,t-6}$, and so forth. Two things are noteworthy. First, these forecasts are recursive and constructed on information sets that are thinner, the farther out agents look into their future. At the foresight-limit horizon, $t+8$, the forecast will use only one signal, the first ever received on the value of risk at calendar time $t+8$, $\xi^8_{\sigma,t}$. Second, the string of the 8 signals received at time t update 8 different forecasts, but – hitting all at the same time – they are correlated across each other. Recall that we restrict the covariances so that signals about shocks j periods apart in time, have correlation, ρ^j_σ. We interpret this cross-correlation as follows. In forming expectations about future risk conditions at different horizons, agents rely on the single source of information – TV news, newspapers, or internet wire services – which is available today. That single source reflects the mood of the day and sets the general tone of today's perceptions about the future.

Figure 9 brings interesting insights into the the way signals propagate both across variables – all dated at t – and across time. We start with the infra-temporal dimension of transmission. What is notable is the degree to which the risk shock spills over from the credit market to the two financial variables reported in the bottom portion of Figure 9: the term spread and the marketable securities (see the two bottom rows). Interestingly, after monetary policy innovations – whose contribution to movements in those two variables is rather large – the risk shock emerges as the second most important explanatory force behind the in-sample swings in the term spread, particularly in the US. The reason is that the risk shock acts as the quintessential aggregate demand shock in the baseline model. As monetary policy systematically and actively offsets demand shocks in the model by moving the short-term interest rate, the slope of the yield curve – the term spread – changes in locksteps with the risk shock. The contribution to wholesale funding is more ambiguous. It is good in the US, where the dramatic fall-off in the outstanding stock of commercial papers and repurchase agreements issued by credit institutions over the recent crisis masks the good fit of the risk shock in the previous period. It is less precise in the EA, except over the crisis. In this respect, we repeat what we noted already. The US measure of marketable securities is closer to the phenomenon that we want to measure – the wholesale funding available to banks in different phases of the cycle – than the EA measure (M3-M1).

The inter-temporal dimension of transmission is also remarkable. The signals about risk realisations at a more distant horizon – at $t+5$ and beyond – are those which move the economy more. Notice that the variance of the dotted lines reported on the third and sixth columns almost invariably exceeds the variance of the actual data and the variance of the dotted lines in the panels along the second and fifth columns. This can be rationalised on two fronts. First, mechanically, the impact of the time-t update, say $\xi^j_{\sigma,t}$, to the forecast of ν^σ_{t+j} on the overall information set on which that forecast is constructed is higher the farther out is j. As we saw before, longer-distant forecasts are based on fewer signal terms, so any update receives a larger weight. Second, a shock expected to materialise at a longer horizon has more time to interact – when actualised to the present through expectations – with the dynamic propagation mechanisms that are embedded in our model. It turns out that investment adjustment costs are key propagators of news about longer-term risk conditions.

Why? And what is the impact of signals? We strive to answer these questions jointly, with the help of the simple fictional example of Figure 7.b. The thought experiment is similar to that conducted earlier and described in Figure 7.a. But now, the exercise involves a risk shock. Imagine that at time t agents observe an unexpected decline in entrepreneurial risk and receive news about a further decline, say at time $t+1$. In the notation of (37), this is equivalent to a negative contemporaneous innovation to the risk shock, $\xi^0_{\sigma,t}$, accompanied by a negative signal on the value of the risk shock one period from now, $\xi^1_{\sigma,t}$. Unlike the surprise innovation to γ_t which was represented in Figure 7.a – or a surprise to any other shock – both the contemporaneous unexpected innovation to current risk conditions, $\xi^0_{\sigma,t}$, and the news on future risk, $\xi^1_{\sigma,t}$, propagate almost exclusively through anticipations of the one-period-ahead value of the premium. This introduces a fundamental difference between the exercises depicted in Figure 7.a and Figure 7.b. A $\hat{\gamma}_t$ surprise (Figure 7.a) unexpectedly boosts $\hat{R}^k_t$ relative to $\hat{R}^k_{t+1}$, which in fact sharply switches signs relative to $\hat{R}^k_t$. As we noted in our discussion above, negative autocorrelation in the anticipated profile of the *gross* returns on capital induces credit extinction after a $\hat{\gamma}_t$ surprise. Unexpected and anticipated innovations to risk, instead, induce persistence in the time profile of the *excess* returns, i.e. the return on capital after accounting for the anticipated costs of borrowing. This happens via two effects. The first effect is associated with the unexpected component of the risk shock, $\xi^0_{\sigma,t}$, and works through the premium. The anticipated value of the premium is a critical determinant of the excess returns on capital. But, given the structure of the contract, the premium that will be applied in $t+1$ is backwardly indexed to the value of risk realised today, at t.[30] The risk realisation today is influenced by $\xi^0_{\sigma,t}$. So, a negative risk surprise today has a protracted impact on the cost of borrowing tomorrow, and thus on the expected net return on capital. The second effect works through the way the signal, $\xi^1_{\sigma,t}$, impacts on the expected *gross* return on capital, $\hat{R}^k_{t+1}$. The current news that risk will continue to fall in the future tends to sustain, in expectation, the price of capital at $t+1$, $\hat{q}_{t+1}$, relative to the price of capital today, $\hat{q}_t$. This induces persistence in $\hat{R}^k_{t+1}$ relative to $\hat{R}^k_t$, and anticipations of a persistent $\hat{R}^k_{t+1}$ boost the demand for capital in the future and the demand for credit in the present. We represent the two effects jointly with rightward shifts in the capital demand curve (from $D1$ to $D2\left(\hat{\sigma}_t, \hat{R}^k_{t+1}\left(\xi^1_{\sigma,t}\right)\right)$, upper panel of 7b), and in the demand and supply curves in the market for credit (from $D1$ to $D2\left(\hat{\sigma}_t, \hat{R}^k_{t+1}\left(\xi^1_{\sigma,t}\right)\right)$ and from $S1$ to $S2\left(\hat{\sigma}_t, \hat{R}^k_{t+1}\left(\xi^1_{\sigma,t}\right)\right)$, lower panel).

Note that now, unlike in the previous example, investment adjustment costs *amplify* – rather than dampen – the demand for credit. Anticipations of future *further* shifts in the demand for capital encourages entrepreneurs to start investing now, so that adjustment costs are frontloaded and thus minimised intertemporally. This raises the desired capital stock

[30] The reason its transmission is not entirely through the expectations channel is that an unexpected $\xi^0_{\sigma,t}$ innovation observed at time t triggers an immediate impact on a range of 'jump variables', including q_t.

today relative to available equity, and widens entrepreneurs' financing gap. Credit, as a consequence, moves with investment and becomes pro-cyclical.

5.2 The Risk Shock in Population

We seek confirmation of the in-sample evidence of Figures 8.a, 8.b and 9 in the unconditional statistics of Figure 5 and of Tables 5 and 6.

In a sense, the thick solid line in Figure 5 completes our journey across models, where we have been evaluating our three model variants against their ability to reproduce groups of facts for which they can generate predictions. Our baseline specification turns out to be the best-performing on this test.[31] First, consider the six variables on which the *Financial Accelerator Model* and the baseline model can be compared. The baseline model does equally well or better reproducing the observed regularities. While the *Financial Accelerator Model* fails on the credit market test, the baseline model generates the observed co-movements involving credit and the premium in qualitative (EA) and even quantitative (US) terms. Second, consider the last panel, reporting how the stock of marketable securities co-moves with stock prices. Along this dimension, the baseline model has no competitor, as the other two models do not feature liquidity. Here, the evidence is less straightforward. For the EA, the sign of the model-based correlation seems counterfactual, although the line corresponding to the baseline model remains within the confidence interval except for leads and lags of 2 quarters or less. For the US, where data describe more closely the phenomenon that we want to capture, the sign is correct, although the baseline model is outside the confidence interval at most leads and lags. It is fair to conclude that, even on this dimension on which the model does worse relative to the data, it remains sufficiently close to the phenomenon that we want to interpret.

Tables 5.a-5.b, and 6.a-6.b help understand why the baseline model outperforms the two competitors, where a 'race' between models can be established. The reason is that, according to the baseline model, the risk shock accounts for a larger fraction of the predicted unconditional variance of a wide range of variables. Table 5.a and Table 5.b display the forecast error variance decomposition of the observable variables for the three models at business cycle frequencies: the EA model is shown in the former Table, the US model in the latter. As is standard, we define the business cycle component of a variable as the periodic components with cycles of 8-to-32 quarters, obtained using the model spectrum.[32] Table 6.a and Table 6.b report – again, for the EA and the US, respectively – the variance decomposition for periodic components with cycles of 9-to-15 years. The statistics are derived using the mode of the posterior distributions of the shocks reported in Table 4. Each cell in the Tables contains three statistics, from top to bottom: the contributions of the corresponding shock to the baseline model, the *Financial Accelerator Model* and the *Simple Model*.

Before putting the risk shock under the spotlight, we review three findings that we have discussed already. The first is the irrelevance of the price of investment shock, $\mu_{\Upsilon,t}$, which explains a negligible fraction of macroeconomic uncertainty – outside the price of investment itself – in the three model specifications, in both economies and at all frequencies. The second finding is that the marginal efficiency of investment shock, $\zeta_{i,t}$, is by far the most important source of short-term and, even more starkly, long-term fluctuations in output and investment

[31]See the last footnote in the sub-section (4.1) for details about the construction of Figure 5.

[32]Variables are in log-levels with the exception of interest rates and spreads, which are not logged.

in the *Simple Model*. This, again, confirms the provocative results of Justiniano *et al* (2007). However, the contribution of $\zeta_{i,t}$ halves in the analysis based on the *Financial Accelerator Model*, and drops even further according to the baseline model. The bulk of the drop in the explanatory power of $\zeta_{i,t}$ occurs when moving from the *Simple Model* to the *Financial Accelerator Model*, which indicates that responsibility for this change in inferences lies with the stock market. It is the absence of stock market information from the econometrics that makes shocks to the marginal efficiency of investment so powerful in the *Simple Model*. It is the presence of the stock market in the estimation that turns that result around. In fact, the drop is most severe in the US data and at low frequencies, where $\zeta_{i,t}$ explains no more than 11 percent of the variance of output in the baseline model, down from 41 percent in the *Simple Model*. Not surprisingly, that is the economy and those are the frequencies at which the cointegration properties of the stock market and the macro-economy are most evident. As anticipated before, this result should come as no surprise. A dominating role of $\zeta_{i,t}$ induces – counterfactually – 'negative beta' properties for the stock market in the *Simple Model* (recall Figure 5). When the econometrics are allowed to enforce the 'positive beta' which links the stock market and the economy, the dominating role of $\zeta_{i,t}$ is lost.

The third result is that the two financial shocks, γ_t and σ_t, absorb a large fraction of the share of the forecast variance of output and investment which is 'freed' by $\zeta_{i,t}$. However, the way the *Financial Accelerator Model* and the baseline model allocate this fraction is quite different. In line with the in-sample decompositions of Figure 8.a and Figure 8.b, the *Financial Accelerator Model* assigns virtually the entire share that is lost by $\zeta_{i,t}$ to γ_t , and relegates the risk shock to the role of explaining the premium. At the low frequencies γ_t explains more than 80 percent of the stock market index in the EA and even 90 percent in the US. As a consequence, this shock obtains the lion's share of the variance of output (26 percent in the EA and 43 percent in the US) and investment (52 percent in the EA and 75 percent in the US). Correspondingly, the contribution of the risk shock to the stock market is very moderate and the contribution to the overall economic fluctuations is negligible.

The baseline model overturns these results. The reason is that now the real stock of credit is used to inform the estimation. The share of the risk shock in the variance of real credit is 60 percent and 73 percent in the two economies at business cycle frequencies. As a consequence, the contribution of σ_t to output jumps from almost nil (in the *Financial Accelerator Model*) to 23 percent in the EA and 30 percent in the US at higher frequencies, and to 36 percent and 60 percent, respectively, for investment. At low frequencies the risk shock explains 77 percent and 88 percent of real credit variation, respectively in the EA and the US. In parallel, its share in the variance of investment increases to 42 percent and 64 percent in the two respective economies, while the share in output variance becomes 35 percent and 47 percent. Beyond its overwhelming contribution to credit, at all frequencies, σ_t is the most significant source of fluctuations for the stock market, GDP and the external finance premium. It also gives a significant contribution to the long term interest rate spread, notably at low frequencies. Here, with 22 percent, the risk shock is the second-most important shock after the term premium shock (which, strikingly, explains only 24 percent of the term structure variance) in the EA, and it is the most important shock for the term structure in the US (26 percent versus 17 percent of the idiosyncratic term premium shock). As we noted already, this result lends qualified support to the 'expectations hypothesis' of the term structure.[33]

[33] Recall that we capture the deviation of the data from the term structure hypothesis with the shock, η_t^L, included in the household's budget constraint, (30). According to Tables 5 and 6, this shock accounts for no more than a fourth of term structure variation

The explanatory power of the financial wealth shock deteriorates dramatically if compared with the results based on the *Financial Accelerator Model.* In the baseline model innovations to γ_t become a minor source of aggregate uncertainty.

5.3 Impulse Responses

We use impulse responses to support our claim that the risk shock is so important in our empirical analysis because it is the prototypical aggregate shock which can trigger a generalised cycle and – at the same time – respect the observed covariances.

Figure 10 confirms our claim. Each panel plots the impulse responses of a risk shock. Concentrate on two lines in each panel: the thin-starred line corresponds to the *Financial Accelerator Model*; the black solid line corresponds to the baseline model.[34] Recall that in the former model the economy does *not* receive advance information about shocks – including the risk shock – and thus the thin-starred lines represent impulse responses to one *unexpected* innovation to the risk process, which materialises at time zero. In the baseline model (solid lines), the economy does receive signals about future risk, and therefore the risk process that we report in the charts has an *anticipated* component as well as an *unanticipated* component. This process unfolds as follows. At time zero the economy receives a signal, $\xi^8_{\sigma,0}$, that, at time 8, the dispersion of the idiosyncratic returns to the entrepreneurial projects will increase by the estimated standard deviation of a typical signal, σ^2_σ. At time 1, the economy updates its anticipations about risk at time 8, as a new, equally sized signal is received, $\xi^8_{\sigma,1}$. The news process continues with sequential updates about the risk shock at time 8, until time 8 arrives. At that point, the actual realisation of the innovation to σ_8 is the sum of the whole string of signals received since time zero, plus an unanticipated contemporaneous innovation, $\xi^8_{\sigma,8}$. This latter update finally resolves the uncertainty about entrepreneurial risk at time 8. The unanticipated innovation has a magnitude equal to the standard deviation of the typical unexpected innovation to a risk shock, as estimated in our exercise. The left-hand side of Figure 10 uses estimates from the EA models, the right-hand side estimates from the US models. In comparing impulse responses across models we use the estimated version of each model variant, but we always normalise the standard deviations of the simulated shock to be equal to the estimated standard deviation of the shock in the baseline model.

The risk shock in both models is bad news. In the *Financial Accelerator Model*, the bad news is realised immediately at time zero, and it dissipates thereafter, as the economy slowly recovers. In the baseline model, the bad news first affects expectations, then it is realised when time 8 arrives. In both models, the stock market (net worth panel), total loans and the premium react as expected, the first and the second procyclically, and the third countercyclically. But the impact of the shock on the rest of the economy is remarkably different in the two models. In the *Financial Accelerator Model*, the unexpected risk shock produces a sharp, but temporary drop in the rate of gross return on capital in period zero (see the R^k_t panel). Since the anticipated gross returns are positive, capital formation recovers relatively

in the EA and less than a fifth in the US. That is, particularly in the US the fluctuations in the slope of the term structure are accounted for primarily by the estimated economic shocks in the system operating through the expectations hypothesis. This finding, that the term structure hypothesis accounts reasonably well for the slope of the term structure, is consistent with the findings reported in Davis (2008).

[34] The grey lines corresponds to the *Simple Model*, which does not define a risk shock, and therefore are all flat. The dotted lines represent a version of our baseline model in which the return to households, R^e_{t+1}, is state-non contingent in real terms. We shall discuss this version in the following section.

swiftly after the shock. In fact, because it is costly to change investment plans, capital formation never suffers from a deep contraction. With the capital endowment relatively sticky, the marginal product of labour does not change much, unless labour supply adjusts. But labour supply is bound to move in the opposite direction than consumption. If the wealth effect of the current and anticipated drop in income is sufficiently powerful to make current consumption decline, this is bound also to encourage workers to supply *more* work. So, investment, consumption and output display the 'correct' cyclical co-movement. But hours move in the 'wrong' direction. This 'comovement problem', caused by shocks hitting the investment margin, is a well-studied phenomenon in equilibrium growth models, at least since Barro and King (1984). Note that the 'wrong' sign of the conditional correlation between consumption and hours in the *Financial Accelerator Model* could be reversed if the utilisation of capital fell sufficiently in response to the decline in the return on capital, a point first emphasised by Greenwood *et al* (1988).[35] But in our estimation, capital utilisation is unresponsive, because the estimated σ_a is large (Table 4). So, this potential channel, which could induce a decline in the demand for labour after a contemporaneous risk shock – and thus produce pro-cyclicality in work effort – is de-activated. Note also the counter-cyclical response in inflation.

In the baseline model, the bad news about future risk conditions keep affecting the expectations of agents for a while. This produces a protracted decline in the *gross* return on capital (see the solid line in the R_t^k panel). Unlike in the *Financial Accelerator Model*, here a long sequence of expected capital losses produces a deep and elongated contraction in investment. Adjustment costs now encourage quick disinvestment, as waiting longer before downsizing production capacity would only make future costs heavier. Investment drops proportionally to output, but the fall is stronger by a factor of four. The marginal product of labour declines in tandem with the stock of capital, and the demand for labour falls as a consequence. So – unlike in the *Financial Accelerator Model* where signals are absent – in the baseline model the expected component of the risk shock can set off a process whereby a decline in consumption is not inconsistent with a decline in hours worked. Now equilibrium hours are dominated by adjustments in the demand for labour, not the supply of labour. This fall in the demand for labour is precisely what the model needs to be able to simulate a generalised cyclical downturn. Again, this mechanism does not hinge on endogenous changes in capital utilisation. It also does not rely on adjustment costs to labour supply, as in Jaimovich and Rebelo (2009). Finally, note what happens when time 8 arrives. In the absence of further news about the future looking out beyond time 8, the risk shock assumes the same dynamic properties that it possesses in the *Financial Accelerator Model*, where the anticipated component is absent.

Figure 11 and Figure 12 report the impulse responses to a marginal efficiency of investment shock, $\zeta_{i,t}$, and to a financial wealth shock, γ_t , respectively. The pictures confirm our graphical analysis of Figure 6.a and Figure 7.a. The marginal efficiency of investment shock produces a counter-cyclical stock market. This has an interesting implication that appears when comparing the black-solid line and the thin-starred line, on the one hand, with the grey line which corresponds to the *Simple Model,* on the other. A $\zeta_{i,t}$ shock converts financial frictions from 'accelerator' mechanisms into cyclical smoothers, because endogenous counter-cyclical adjustments in the purchasing power of entrepreneurs operate as buffers

[35] Greenwood *et al.* (1988) studied the role of variable capital utilisation in delivering the right response in labour. Justiniano *et al.* (2007) use many more nominal and real frictions in a monetary business framework similar to our Simple Model. However, their models still generate the "wrong" reaction of consumption to an investment-specific shock.

against swings in aggregate demand. Both shocks, $\zeta_{i,t}$ and γ_t , generate negative autocorrelation in the *gross* return on capital (R_t^k panels). So, they also yield a counter-cyclical credit, and the 'perverse' co-movement between consumption and hours which we discussed above. In exercises that we do not document, it turns out that the counter-cyclical properties of the responses of credit and hours to the shock depends critically on investment adjustment costs. They disappear if these costs are minimised.

Figure 13 shows impulse responses to a transitory technology shock, ϵ_t. These responses have several interesting features. We defer a discussion of one of them to the next section and concentrate here on two more specific aspects of the pictures. The first feature worthy of note is the negative reaction of work effort after an ϵ_t shock, which confirms the influential analysis in Galí (1999). The second aspect that we note is that, interestingly, the pattern of response to such a shock in the *Financial Accelerator Model* and in the baseline model alike resembles closely that of an unanticipated risk shock (compare Figures 12 and 10). This latter result suggests to us that the presence of signals on future risk induces a 'mutation' in the nature of the risk shock. Signals change the dynamic properties of σ_t which otherwise – with no foresight – would be close to those of a technology innovation.

6 Validation and Robustness

The preceding discussion has left some questions concerning the empirical fit unanswered. First, do latent variables defining the evolution of risk in the model come anywhere close to resembling measurable risk? Second, what is the value added of the signals in terms of fit? And, could signals on other shocks be plausible contenders of signals about future risk in explaining economic uncertainty? Third, what is the impact of the two main financial channels of transmission that we have described in section 2 on the model fit? Here, we strive to answer the first two questions in the order in which they are posed. We keep the third question in stock for the following section.

6.1 Measures of Risk

Figure 15 plots the time series of entrepreneurs' expected default probability, $E_t \int_0^{\bar{\omega}_{t+1}} \omega dF_t(\omega)$, generated by the model in-sample (black-dotted line) against its empirical analog, the EDP measure of Moody's KMV for the non-financial corporate sector (red-circled line). The left panel refers to the EA model and data, and the right panel to the US model and data. Note that the risk shock is defined as the standard deviation of entrepreneurs' idiosyncratic productivity factor, ω. So, the model-implied expected default probability that we plot and the risk shock are tightly associated in the model. The US empirical model has relatively harder time capturing the spike in default risk which the data identifies over the start of the 1990s corresponding to the 'financial headwinds' recession. It also misses the blip in the EDP around the Asian crisis in late 1998, and is slow in recognizing the drop in perceived risk in 2003-2004. However, as is apparent from the two panels, the widely-used extra-model measure of business risk that we report and the related object in the model are highly correlated. We interpret this evidence as supportive of the measure of economic risk that we generate in our estimation.

6.2 Other Signals

Table 7.a and Table 7.b help answer the second and third questions that we posed at the beginning of this section, for the EA and US models respectively. In those Tables we document a number of perturbation exercises in which our baseline model is modified to isolate the impact of one feature at a time. The metric we use to evaluate the relative fit of the various model perturbations is the marginal data density. We use the Laplace approximation to the 'true' data density, which we derive in Appendix G. In this subsection we focus on the role of signals in helping the fit of the model. The role of the transmission channels will be the subject of the last two sub-sections.

The critical importance of signals – and, specifically, signals on future risk – is apparent from various entries of the two Tables. First, compare the two values on the first two rows of the left-most columns (in Table 7.a and Table 7.b, respecitvely). These are the marginal data densities for the baseline model (top row) and for the baseline model estimated without signals (second row). For both economies the data strongly favours the baseline specification with signals over one in which all shocks are unexpected. In results not shown we see that, when estimated without signals, the model's good fit to credit growth is preserved, but the fit to the stock market deteriorates dramatically. The model without signals clearly cannot reconcile the information coming from the markets for capital and for credit.

Next, proceed from left to right in the two Tables. The entries on the second and third columns report marginal data densities of model variants estimated on data sets which are smaller than the one used for the baseline model exercise (first column). The second column corresponds to a data set that includes the 11 variables used to estimate the *Financial Accelerator Model* plus credit. Along the third column the data set coincides with the one used for the estimation of the *Financial Accelerator Model* (with no credit). The first row reports the marginal data densities of the baseline model specification; the second row from top corresponds to the baseline model specification estimated without signals; the third row refers to the *Financial Accelerator Model* which we commented above, estimated without signals; and, finally, the fourth row has a variant of the *Financial Accelerator Model*, now estimated with signals on the risk shock. Comparing entries that correspond to the same model, estimated with or without signals, it is apparent that having a signal representation for the risk shock is always preferred by the data, no matter whether the set of observations includes or excludes measures of liquidity or credit. The improvement over the alternative without signals is small if the data set excludes credit (compare entries along the third column of the two Tables). But the fit improves enormously if credit is considered in the estimation. This result lends further credence to our earlier conclusion that considering information on credit: (i) poses a critical empirical constraint on the estimation; (ii) promotes the risk shock in its characteristic signal representation to the prime driver of fluctuations.

Could a signal process for other shocks be a satisfactory substitute for signals on risk? To answer this question, we consider two further perturbations to our baseline model. The first is one in which the baseline model is re-estimated with risk shocks that are always unexpected, while signals are received on the financial wealth shock, γ_t , instead (second-last row on the left column). This perturbation is justified by the following conjecture: what the model really needs in order to be able to match the comovements across financial and real variables are signals to *any* shock hitting the financial contract, not necessarily the risk shock. Indeed, having signals on γ_t rather than on σ_t improves the fit with respect to a no-signal specification. However, our baseline specification remains clearly preferred.

The second perturbation involves signals on future technology. This last exercise is motivated by a growing literature, which puts emphasis on news about future productivity as an important source of business cycle variability. This idea was revived and first implemented empirically by Beaudry and Portier (2004). In Christiano, Ilut, Motto and Rostagno (2008), we studied the economics of signals about future technical progress across various models, and Jaimovich and Rebelo (2009) have proposed modifications to agents' preferences which can better account for consumption-labour comovements. Schmitt-Grohé and Uribe (2008) have employed Bayesian techniques to estimate a real model with news about three technological shocks, finding strong evidence in favour of anticipated stationary changes in productivity. To build confidence in our findings, we re-estimate a version of our baseline model in which signals are received on the future realisations of three technology shocks only: the permanent technology shock, $\mu_{z^*,t}$, the temporary technology shock, ϵ_t and the marginal efficiency of investment shock, $\zeta_{i,t}$. The bottom entry on the left column of each Table reports the marginal data density that we obtain from this estimation. Comparing this latter statistic with the marginal data density of our baseline specification we note that this alternative source of news produces a noticeable deterioration in the fit (by around 80 and 90 units for the EA and the US model, respectively). This result is surprising, particularly in view of the stong conclusions of Schmitt-Grohé and Uribe (2008). Our estimates of the model with signals on future technology assign a negligible role to the two neutral technology shocks – contemporaneous and anticipated – and a preponderant role to the marginal efficiency of investment shock. However, despite the anticipated component, $\zeta_{i,t}$ continues having a conter-cyclical impact on the stock market, which explains the deterioration in the marginal data density.

We read this result as lending further credence to the notion that model-based inferences about shocks are often not robust to the information sets that are used to inform the empirical exercise. A stronger implication could be that data sets restricted to real variables might bias the shock accounting exercise towards real shocks. But the need to account for a broader set of facts, including financial facts, introduces severe constraints on the dynamic structure of the shocks that lay claim to becoming the main explanatory factors of economic fluctuations. Technology shocks – with or without signals – do not seem to satisfy those constraints.

7 The 'Financial accelerator' and the 'Bank funding' Channels

In our baseline model, shocks propagate to observable variables through a multitude of frictions, real and nominal. However, as we argued in section 2, two channels are central to our model building enterprise: the 'financial accelerator channel' and the 'bank funding channel'. Here we quantify their respective contributions to the fit of the model and we explore the economics of that contribution.

Recall from section 2 that the 'financial accelerator channel' can be further disaggregated into two complementary mechanisms: a pure BGG-type 'accelerator' effect and what we referred to as the 'Fisher deflation channel'. We define here a variant of the baseline model which allows us to identify the latter mechanism in isolation. This is done by starting off from our baseline specification and assuming – in line with BGG – that the liabilities issued to households to finance entrepreneurial loans are *state contingent*. In this model variant, the interest rate paid on T_t, when it matures at the end of the $t+1$ production period, is conditional on time $t+1$ shocks and satisfies the following condition: $\widetilde{R}^T_{t+1} = \frac{1+R^T_{t+1}}{\pi_{t+1}}$, where R^T_{t+1} is the interest rate paid on the baseline non-state-contingent specification of the contract. We estimate this alternative model over the same sample period and with the same data set used for the baseline model, and we compute its marginal data density. The value that we obtain is the entry under the '*No Fisher Effect*' header in the middle of the first columns in Table 7.a and Table 7.b. Note, again, that the test unambiguously favors the baseline specification embodying the 'Fisher deflation channel' (top value on the first column) over the alternative with a financial contract designed in real terms.

The 'bank funding channel' is what is left when the *Financial Accelerator Model* is stripped away from the baseline model. Here, though, Bayesian model comparisons based on marginal data densities are hampered by the fact that the baseline model is estimated on a larger data set. We circumvent this difficulty by re-estimating the baseline model – preserving all of its endogenous channels – on smaller data sets, and then using the marginal data densities obtained from those estimations to evaluate the relative performance of the two models. We report the results of this exercise along the top four rows in the right-hand section of Table 7.a and Table 7.b. Here, the pertinent comparisons are those between the first row (baseline model), the third row (*Financial Accelerator Model*) and the fourth row (variant of the *Financial Accelerator Model* estimated with signals on the risk shock). Note that all versions of the *Financial Accelerator Model* incorporate the same specification of the financial contract – inclusive of the pure 'accelerator' effect and the 'Fisher deflation channel' – as the baseline model. So, their relative performance quantifies the contribution of the 'bank funding channel' to model fit.

The results of these comparisons can be summarised as follows. Generally, the 'bank funding channel' makes a positive contribution to the fit of the model. This contribution is very substantial when credit is included in the test and the *Financial Accelerator Model* is estimated without signals on the risk shock. It is tenuous or nil when credit is omitted and signals are activated in the *Financial Accelerator Model*. The latter conclusion should probably come as no surprise, given the tight link between credit creation and bank funding in the model. An exception to this general pattern is the *Financial Accelerator Model* estimated with signals and without credit for the EA, which prevails over the baseline specification. In order to understand this result, we re-estimated all the model variants over the extended data sample which is used to construct the charts but is longer than the one used to estimate the models. Importantly, this longer sample includes the most severe phase of the financial crisis – 2008Q3-2009Q2 – which largely originated in disruptions to the banks' liquidity provision. Indeed, a re-run of the Bayesian model comparison using estimates for the latter extended period reinforces the advantage of the baseline model – where it already existed according to Tables 7.a and 7.b – over the alternatives, and overturned the EA result which we discussed above.[36] Thus, we conclude along two lines: (i) the 'bank funding channel' improves the empirical properties of our model, and (ii) our tests might actually understate its value added by disregarding observations collected over the most severe phase of the current crisis, when funding problems were most severe. We shall return to this latter theme in the following section.

The impulse responses of Figures 10-14 help dissect the mechanics of propagation. We plot the responses of the baseline model (black solid line) against those generated by its '*No Fisher Effect*' variant (dotted line), the *Financial Accelerator Model* (thin-starred line) and the *Simple Model* (grey line). In this way, we obtain four measures of impact. The distance between the lines corresponding to the baseline model and the *Simple Model* –

[36] Over the extended sample, the marginal data densities are as follows. For the EA, the baseline model estimated on the data set of the Financial Accelerator Model plus credit yields a marginal data density equal to 4089.46, higher than the corresponding statistic for the Financial Accelerator Model estimated with signals and with credit (4086.56). For the US, the former is equal to 3814.84, the latter is equal to 3793.87.

where available – can be interpreted as the *overall* dynamic effect of the financial frictions that we introduce. The distance between the *Financial Accelerator Model* and the *Simple Model* will measure the contribution of the 'financial accelerator channel', once bank funding constraints are ignored. Against the 'financial accelerator channel', the difference between the baseline model and its *No Fisher Effect* variant will help quantify the separate contribution of the 'Fisher deflation channel'. Finally, the difference between the baseline model and the *Financial Accelerator Model* will illustrate the contribution of the 'bank funding channel'. For the risk shock we visualize one more line, to quantify the differential role of the 'bank funding channel' in propagating a signal process. We shall discuss that line below.

We synthesise the pictures with few observations. First, overall, financial frictions act as an 'accelerator' mechanism in the face of shocks which move inflation and the economy in the same direction. However – our second observation – they work as cyclical smoothers in the face of shocks that move output and inflation in opposite directions. Compare the baseline model with the *Simple Model* (when the comparison is possible at all). The financial frictions that we embody in our model make the dynamic response to a monetary policy shock sharper and more drawn out than otherwise (Figure 14), but they smooth the reaction to a transitory technology shock (Figure 13). The '*No Fisher Effect*' line in deviation from the baseline model line explains why. Start with the baseline model: when payments owed by banks to households, against an entrepreneurial loan, are not contingent on the realization of shocks that can modify the profitability of the entrepreneurial project before it matures – the baseline specification of the contract (thick solid line) – a surprise innovation to the price level changes the real value of the transfer made from entrepreneurs to households. Other things the same, this alters entrepreneurs' net worth and – in the end – their demand for capital. Note, once more, that this channel – the 'Fisher deflation channel' – is distinct from the pure, BGG-type 'accelerator' effect. The latter effect stems from the sensitivity of the price of capital, entrepreneurs' receipts and entrepreneurs' net worth to aggregate demand: it is what is left in the '*No Fisher Effect*' model after making the transfer from entrepreneurs to households state contingent. Note also that the two effects can reinforce or offset each other. When the inflation surprise that the shock brings about has the same sign as the surpise to aggregate demand, the 'Fisher deflation channel' *magnifies* the economic transmission of the shock. This is evident in Figure 14. When the inflation response has a sign opposite to the direction of the economy, the nominal rigidity associated with the 'Fisher deflation channel' *dampens* the macroeconomic transmission of the shock. Indeed, in Figure 13 the 'Fisher deflation channel' which is embedded in the baseline model – and in the *Financial Accelerator Model* as well – cuts into entrepreneurs' profits and net worth accumulation at a time in which both could have been stronger, given the strength of aggregate demand. In fact, they are stronger when the 'Fisher deflation channel' is stripped away (see '*No Fisher Effect*' dotted line). The non-state contingency of the financial contract operates in this case as an automatic stabiliser.

There is one interesting exception to this general pattern: the marginal efficiency of investment shock (Figure 11). This shock looks like a demand shock – inflation and output co-move – but is amplified in the *Simple Model*, where financial frictions are absent. As we noted already, this is due to the 'negative beta' implications that $\zeta_{i,t}$, introduces for the stock market. This effect turns entrepreneurial net worth into an asset which – counterfactually – pays off more in downturns and less in booms. A counter-cyclical net worth cushions the cyclical impact that the shock generates through the financial contract, which explains why in Figure 11 propagation is weaker with – than without – financial frictions.

The third observation is that the 'bank funding channel' is an important avenue of transmission for financial shocks, σ_t and γ_t, and to some extent – in the US model – also for the marginal efficiency of investment shock and the monetary policy shock. Recall that in the model banks need to fund their operations via collecting different forms of deposits. These alternative funding sources carry different costs in terms of physical input and utilisation of central bank reserves (recall (24)). The higher the degree of transaction services provided by each type of deposits, the higher the associated cost to the bank. The interaction between households' preferences for different types of transactions and liquidity balances and the varying costs to the bank for producing such financial instruments determines the bank's intermediation margin. This margin corresponds to the difference between the lending rate charged by the bank, which will affect firms' production costs, and the interest rates paid on the two types of bank liabilities held by households, D_t^h and D_t^m, which influence consumption. This gives rise also to a gap between the interest rate controlled by the central bank and rates relevant for private sector decisions.

Comparing the estimation results which we obtain when the 'bank funding channel' is present with those that we obtain from estimating model variants without such a channel, we detect a noticeable change in the coefficients which determine the price and wage dynamics (compare estimates in Table 4 with the ones in Table A.2). In particular, the weight attached to lagged inflation in the price-setting equation (parameter ι in 8) drops in the US (EA) estimation from 0.85 (0.1) for the *Financial Accelerator Model* to 0.64 (0.07) for the baseline model. The corresponding weight on lagged inflation in the wage setting equation (parameter ι_w in 32) drops in the US (EA) eatimation from 0.72 (0.59) to 0.36 (0.27). Also, the Calvo parameters are larger in the *Financial Accelerator Model* compared to the baseline model.[37]

We interpret this finding as suggesting that the modelling of the 'bank funding channel' is a valid alternative to some of the ad-hoc persistence mechanisms introduced in estimated general equilibrium optimising models via indexation mechanisms. The dimension on which these two alternative approaches can substitute for each other in inducing the degree of persistence which is observed in the data is the link between the marginal rate of substitution in consumption and the rate at which firms can borrow. The extent of this impact is shock specific (see Figures 11-14), and it is largest for two shocks that specifically hit the 'bank funding channel', x_t^b and ξ_t.

Figure 15 displays the transmission mechanism of these two shocks. A rise in x_t^b corresponds to improved efficiency in the bank's funding activity. Similarly, a rise in ξ_t corresponds to a lower demand for liquidity buffers by banks, which in turn generates an increased balance-sheet capacity and a greater scope for expanding loan supply in the model. Both effects are expansionary for real economic activity. The two shocks, however, have different implications for inflation. This is explained by that fact that the higher funding efficiency brought about the rise in x_t^b allows for higher lending capacity, and at the same time for a decline in the intermediation cost. Note that these impulses are not triggered by central bank decisions to change the policy rate, but find their source within banks' funding activity itself.

Shocks such as x_t^b and ξ_t, which hit banks' liquidity provisions, are rare and thus, from a longer-term vantage point, seemingly unimportant. Indeed, the unconditional variance decomposition of macroeconomic variables that we provide in Tables 5.a-b and 6.a-b would tend to support this statement. The explanatory power for output of x_t^b and χ_t – which governs households' demand for liquid securities relative to other forms of money – is nil at all frequencies and across the two economies, and that of ξ_t, while positive, is negligible. The

[37] Note that, adding signals to the *Financial Accelerator Model*, has some impact on the estimates, but the differences mentioned in the main text persist.

next section, however, sheds a new light on this simple accounting. It shows that liquidity shocks look very different *in times of crisis.* As these are rare events, conventional statistical measures of relevance condemn liquidity shocks to being unimportant sources of fluctuations for the economy at large (Tables 5 and 6). However, when these events materialize, shocks that originate in banks' technology for transforming cash reserves into insight money can become responsible for major swings in output and economic conditions.

8 The 2007-2009 Financial Crisis

What caused the financial crisis that started in the summer of 2007 and – as we write – is still sweeping across the world? How did generalised conditions of illiquidity spread to asset pricing and from there to the broader economy? Would a different policy reaction have mitigated the macroeconomic fallout of the financial panic? In this section we study the recent episode of illiquidity and financial fragility, with a positive and a normative perspective. We use our baseline model as an instrument of interpretation and as a tool to run policy counterfactuals.

8.1 Interpreting the Crisis

We start with the interpretation. We do so by extending the in-sample shock accounting analysis of Figures 8 and 9 to all the shocks activated in estimation, and we concentrate on two variables. The first variable, the expected *equity premium*, measures the anticipated net excess return on capital in our model, and is treated as unobservable in the estimation. We obtain this measure from a straightforward transformation of a latent state variable in the system. This variable is defined as the expected rate of change of the stock market value of one share held by each entrepreneur active in time t, V_t (see the discussion around 30), in deviation from the expected return on an alternative investment in the risk-free financial securities available to households, R^T_{t+1}. Appendix E provides the algebra. The in-sample shock disaggregation of the equity premium sheds light on the principal asset-price channel by which the various sources of volatility transmit to the economy in our baseline model exercise. As a by-product, the exercise also extracts an in-sample full-information econometric estimate of the equity premium which can be used to inform the debate on the volatility of excess returns on stocks. The second variable that we analyse is GDP growth, a direct statistic for the macroeconomic fallout of the financial crisis.

We display the shock decompositions of the expected equity premium and the year-on-year demeaned per-capita GDP growth in Figures 17.a-b and Figures 18.a-b, respectively. To simplify the visual representation, we organize our 16 shocks into five broad categories. The 'Demand' category includes the shocks to government consumption, g_t, and to the preference for current utility, $\zeta_{c,t}$. 'Technology and mark-ups' include technology and pricing shocks affecting the supply of the final output good, as well as the shock to the relative price of petroleum: ϵ_t, $\mu^*_{z,t}$, $\mu_{\Upsilon,t}$, λ_{ft} and τ^{oil}_t. The 'Capital formation' group is composed of the two financial shocks, σ_t and γ_t, which move investment demand, and the shock to the marginal efficiency of investment, ζ_{it}, which moves investment supply.[38] The three liquidity shocks, x^b_t, χ_t and ξ_t, are grouped together in the 'Bank funding' category. Finally, the shock moving the inflation objective, π^{target}_t, and the unforecastable component of the monetary policy

[38] As the shock to the term structure, $\hat{\eta}^L_t$, is recursive in the model we do not consider it in the following analysis.

reaction function, ε_t, make up the 'Monetary policy' category. In the pictures, each shock category is represented as a bar of a different colour. For each quarter, the algebraic sum of the bars is equal to corresponding value along the black solid line, which in the pictures represents the projected value of the equity premium (Figures 17.a-b for the EA and US, respectively) or the observed value of demeaned per-capita GDP growth (Figures 18.a-b).

Start from the equity premium analysis. The lower panel of Figures 17.a (EA) and 17.b (US) show, for each quarter t, the shock disaggregation of the *expected* excess net return on investment (the equity premium, thick solid line). In the same panel, we also report the net excess return *realised* between $t-1$ and t (the starred line), although – to save on space – we do not show the contributions of the various shocks to this latter measure. In the upper panels of Figure 17.a and Figure 17.b we single out the contribution to the expected risk premium coming from the risk shock in isolation, both as a whole statistical process (leftmost panel) and in its near-term (middle panel) and more distant-future (rightmost panel) signal components.[39] The pictures suggest three considerations.

The first consideration concerns a puzzle that has long been identified in the finance literature: business conditions should be linked to expected excess returns, yet the successful predictors in standard predictive return regressions are not macroeconomic, but financial – for example, default premia. See, among others, Lettau and Ludvigson (2005). We believe the upper panels help reconcile this puzzle. They show that the prime driver of the expected equity premia in our model is a measure of financial risk, the risk shock, which is *also* – as we showed above – the principal force behind business conditions. So, indicators of financial stress can be a good source of explanatory power for expected excess stock returns *because* they possess powerful explanatory power for the state of the macro-economy more broadly. In a financial crisis, the perceived-risk component, in the form of news about future risk conditions, become a strong determinant of the market's assessment about its future return prospects (see the two right panels on the upper row). This result comforms well with the findings of a new strand of the finance literature (Kurz and Motolese, 2011, for example) which stresses the role of beliefs and market sentiment in the determination of excess asset returns. In addition, the structural decomposition of the equity premium helps answer the question whether excess returns are positive after adjusting for risk or whether they are simply compensation for a risk that has not yet shown itself and will eventually materialise. On this question see, for example, by Graham and Harvey (2001). The upper panels of the two Figures clearly show that the rise in expected stock market returns over the crisis are largely explained by an increase in the demand for risk remmuneration.

The second consideration regards the role of the structural determinants other than the risk shock in explaining the expected equity premium. While shocks modifying capital formation – foremost, the risk shock – are clearly the driving force behind expected equity premia (upper panels), liquidity shocks have risen in importance since 2007. This is particularly apparent in the US model (Figure 17.b). Over the most acute phase of the financial panic, when the dramatic losses realised by the market made the expected market returns increase sharply, the 'bank funding' shocks category explains a non-negligible fraction of the expected rebound in the premium.

The atypical contribution coming from liquidity shocks over the recent financial crisis is confirmed by the analysis of GDP growth (Figure 18.a and Figure 18.b). We recall that the 'bank funding' shocks measure stress in any of the bank's three funding sources: the issuance of transactions deposits included in M1 (or M2, for the US), the issuance of other

[39] Note that the solid lines in each of the three upper panels of Figure 17.a and Figure 17.b represent the same statistic as the thick solid line in the lower panel.

short-term deposits and marketable securities (or, for the US, repurchase agreements and commercial paper), and central bank refinancing (federal funds balances, in the US). In the immediate aftermaths of the inter-bank money market turmoil of the summer of 2007, the model interprets the sharp contraction in M1 in the EA (not shown) and the dramatic collapse of the wholesale liquidity market in the US (see, again, the three bottom righmost panels of Figure 9) as indicative of severe impairements in the liquidity production function of the bank. Later on, starting in mid-2008, and despite a recovery in M1, the EA banks face fresh difficulties in accessing the market for short-term securities – M3-M1 growth starts contracting in 2008Q3. Finally, after the failure of Lehman Brothers, banks in both economies launch themselves into an extraordinary rush to central bank money. At this point, the model reconciles the decline in deposits and the hoarding of central bank reserves with shifts in x_t^b, and ξ_t of a magnitude that can generate a widespread credit crunch. Indeed, the model estimates that, between the summer of 2008 and the second quarter of 2009, bank funding problems (the orange bars) may have detracted between 0.5 and 1 percent in the EA, and between 1/3 and 1.5 percentage points in the US off GDP growth.

According to our analysis monetary policy has been consistently expansionary over the period 2008-2009. This result is, at first sight, surprising. A number of studies have argued that, with the money market interest rates constrained at values very close to zero, monetary policy might have been more contractionary than it would have elected to be in a hypothetical situation in which nominal interest rates could be reduced to negative levels. The rationale behind our results reside in the characteristic specification of the feed-back condition, (34). Unlike in conventional Taylor-type policy feed-back rules, (34) makes the short-term interest rate a function of banks' demand for central bank reserves. As explained earlier, in ordinary circumstances, this specification allows for some degree of price-taking behaviour in liquidity-providing operations on the side of the central bank. In other words, under normal money market conditions, a positive reaction coefficient α_ξ in the central bank's feed-back function means that a rise in banks' demand for central bank money is allowed to exert some upward pressure on the short-term interest rate, bringing it to a level over and above the one that would be dictated, in similar macroeconomic conditions, by a conventional Taylor rule.[40] Over the crisis, the demand for reserves expanded to unprecedented levels. This, other things equal, would have led to a higher short-term interest rate. However, the reaction of central banks – in both economies – was such that the abnormal demand for reserves was met by an extraordinary degree of liquidity accommodation. The model interprets this deviation from norm as a negative – i.e. expansionary – monetary policy shock. Figures 18a and 18b document the extent to which this sequence of expansionary policy shocks (red bars) have helped compensate the drain that the liquidity shocks (orange bars) would otherwise have exerted on the economy.

8.2 A Policy Counterfactual: Quantitative Easing

Figure 18.b goes some way toward corroborating a conjecture that has been advanced by some observers. For example, Thornton (2009) and Hetzel (2009) have argued that, between the summer of 2007 and the fall of 2008, the Fed's efforts to alleviate the early signs of the financial turmoil concentrated on channeling credit to specific institutions and markets. But, in executing a series of targeted *sterilised* interventions, the Federal Reserve failed to expand the total supply of credit to the economy as a whole. The overall supply of credit to the financial markets could only have been increased by appropriate deliberate adjustments to

[40] See footnote 17 for an intuition.

the monetary base. However, the monetary base did not start increasing convincingly until November 2008, when the financial panic was already in full speed. Hetzel (2009) shows that a subdued monetary base in the first half of 2008 translated into a weak and at times faltering growth of M2.[41]

This interpretation begs the following question. Would the recession have been milder if the Federal Reserve had pursued a policy of quantitative easing sooner? This sub-section conducts a controlled experiment using our baseline model to answer this question. Our conterfactual is constructed in two stages.

First, we re-estimate the US model under the alternative monetary policy specification described in (35). To recall, under this alternative monetary policy rule the central bank is postulated to adjust the growth rate of the monetary base so as to hit a target specified in terms of forecast inflation deviations, realised inflation changes, GDP growth and banks' desire for reserves. Under (35), the central bank pre-set a volume of base money and operates as a price-taker with respect to the interest rate at which that volume is absorbed by the economy. We interpret the parameterisation that we obtain by re-estimating the US model under (35) as the quantitative-policy equivalent to the Taylor-type monetary policy feed-back rule that underlies our baseline empirical model. The estimated policy parameters are documented below.

$$\hat{x}_t = 0.44\hat{x}_{t-1} - (1-0.44)\left[64.75(E_t(\hat{\pi}_{t+1}) - \hat{\pi}_t^{target}) + 21.71\log\left(\frac{GDP_t}{\mu_{z^*}GDP_{t-1}}\right)\right. \tag{46}$$
$$\left. + 22.10(\hat{\pi}_t - \hat{\pi}_{t-1}) - 40.39\xi_t\right] + \varepsilon_t,$$

The second step of our procedure involves projecting the model forward over the period covering 2007Q4-2009Q2 under (46), conditioning on the realised values of all the variables treated as observables in estimation. In other words, in this second step the model is brought to match the evolution of the 16 observable variables over 2007Q4-2009Q2, which the model can do by generating an appropriate unique sequence of shock disturbances, one sequence for each one of the 16 economic shocks activated in estimation.

In a third step, we re-simulate the model over the same period, conditioning this time: (1) on the sequences of disturbances for the $16-1$ non-policy shocks identified in the second step; (2) and on a counterfactual evolution for M2 between 2007Q4 and 2009Q2. In other words, the third step amounts to indentifying a sequence of seven monetary policy disturbances, ε_t, in (46) such that the endogenous path for M2 follows a pre-defined counterfactual trajectory and the $16-1$ non-policy shock disturbances take on the values computed in step two. As we mentioned earlier, M2 was weak over the first phase of the financial turmoil which started in the summer 2007, and this fact has been interpreted as an indication that the total amount of central bank credit to the economy was subdued. Our counterfactual exercise aswers the question stated at the beginning of this sub-section in the following reformulation: what if the Federal Reserve had switched to a money-based rule right at the beginning of the financial turmoil in the summer of 2007, and had manipulated the growth rate of base money so as to engineer a more expansionary growth path for M2 in the 7 quarters that followed?

The alternative path of M2 (dotted line) relative to history (solid line) is reported in the top left panel of Figure 19. The policy counterfactual assumes that the central bank would

[41] Cecchetti (2008) argues that the targeted lending porgrams initiated by the Federal Reserve in the fall of 2007 were intended to ensure "*that liquidity would be distributed to those institutions that needed it most*". Taylor and Williams (2008), however, find that a cornerstone facility within the targeted sterilised lending policy of the Federal Reserve in the first half of 2008, the Term Auction Facility, was ineffective in compressing the term money market spreads.

set a minimum *floor* to the growth rate of M2 equal to the average growth rate of real M2 realised since the beginning of our estimation sample plus the steady state rate of inflation.[42] The central bank would then stand ready to adjust the money base – through an appropriate sequence of innovations, ε_t – so as to enforce that minimum rate of growth. This is the level at which M2 growth is stabilised over the phases in which the dotted line is horizontal in the first panel of Figure 19. Any market demand for a higher M2 supply (the two spikes of the solid line in the top left panel for Figure 19) are fully accommodated.

While this alternative policy commitment would not have involved large policy interventions, it would have alleviated somewhat the severity of the recession. The cumulative growth rate of GDP over the seven quarters would have been 2 percentage point higher than it was in actuality (left bottom panel), and the total supply of credit to the economy would have been larger (top right panel). What is interesting to note is that this stronger countercyclical impact of policy would not have implied a violation of the zero lower bound on the short-term interest rate (right bottom panel). This is due to the support that a higher base money growth exerts on inflation expectations in the model.

In line with the theoretical results in Christiano and Rostagno (2001) and the simulations that we document in Christiano, Motto and Rostagno (2003), we conclude that an explicit switch to quantitative easing in the last quarter of 2008 would have helped stabilise the economy.

9 Concluding Remarks

The events of the past two years make it clear that, to be useful, quantitative equilibrium models must be expanded to make it possible to address a broader range of policy questions. One important question that has been asked recently is, how can an injection of central bank liquidity when short-term interest rates are constrained be expansionary? How can other policy interventions, for example using regulatory instruments, attenuate the tendency of the economy to over-leverage during booms and deleverage during busts? To answer these questions requires a model in which liquidity conditions are relevant for economic decisions and the financial system uses capital to produce intermediation. This paper presents a model which meets the former requirement, but not the second.[43] A straightforward extension, however, of the framework that we have presented in this paper is possible, and we will pursue it in future research.

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10 Appendix A: First-Order Conditions

The equations that characterize the model's equilibrium are listed below. Our model solution requires that the model variables be stationary, so we first describe how we scaled the variables in order to induce stationarity. The model has two sources of growth: a deterministic trend in the price of investment goods, and a stochastic trend in neutral technology.

Real variables are scaled as follows:

$$\begin{aligned}
\bar{k}_{t+1} &= \frac{\bar{K}_{t+1}}{z_t^* \Upsilon^t},\ i_t = \frac{I_t}{z_t^* \Upsilon^t},\ Y_{z,t} = \frac{Y_t}{z_t^*},\ z_t^* = z_t \Upsilon^{\left(\frac{\alpha}{1-\alpha}t\right)}, \\
c_t &= \frac{C_t}{z_t^*},\ u_{c,t}^z = z_t^* u_{c,t},\ g_t = \frac{G_t}{z_t^*},
\end{aligned}$$

where $u_{c,t}$ denotes the derivative of present discounted utility with respect to C_t and z_t^* is defined as $z_t^* = z_t \Upsilon^{\left(\frac{\alpha}{1-\alpha}t\right)}$. The scaling here indicates that the capital stock and investment grow at a faster rate than does the output of goods and of consumption. Also, the marginal utility of consumption is falling at the same rate as output and consumption grow.

Prices are scaled as follows:

$$q_t = \Upsilon^t \frac{Q_{\bar{K}',t}}{P_t},\ r_t^k = \Upsilon^t \tilde{r}_t^k,\ \tilde{w}_t = \frac{W_t}{z_t^* P_t}.$$

This indicates that price and rental rate of capital, both expressed in units of consumption goods, are trending down with the growth rate of investment-specific technical change. At the same time, the real wage grows at the same rate as output and consumption.

Monetary and financial variables are scaled as follows:

$$\begin{aligned}
m_{,t}^{Broad} &= \frac{M_t^{Broad}}{z_t^* P_t},\ m_{t+1}^b = \frac{M_{t+1}^b}{z_t^* P_t},\ m_t = \frac{M_t}{M_t^b}, \\
d_t^m &= \frac{D_t^m}{M_t^b},\ b_t^{Tot} = \frac{B_t^{Tot}}{P_t z_t^*},\ n_{t+1} = \frac{N_{t+1}}{z_t^* P_t},\ \lambda_{z,t} = \lambda_t P_t z_t^*, \\
x_t &= \frac{X_t}{M_t^b},\ e_{z,t}^r = \frac{E_t^r}{P_t z_t^*},\ m_t^{\text{Narrow}} = \frac{M_t^{\text{Narrow}}}{P_t z_t^*},\quad res_t = \frac{Res_t}{P_t z_t^*}
\end{aligned}$$

All these variables, when expressed in real terms, growth at the same rate as output.

Other scaling conventions used are:

$$\begin{aligned}
\tilde{p}_t &= \frac{\tilde{P}_t}{P_t},\ p_{i,t+j} = \frac{P_{i,t+j}}{P_{t+j}},\ \mu_{z,t}^* = \mu_{z,t} \Upsilon^{\frac{\alpha}{1-\alpha}}, \\
p_t^* &= \frac{P_t^*}{P_t},\ w_t = \frac{\tilde{W}_t}{W_t},\ w_t^* = \frac{W_t^*}{W_t},
\end{aligned}$$

The complete list of conditions, expressed in scaled form, is reported below.

- Goods Production
  - A measure of marginal cost:

$$s_t = \left(\frac{1}{1-\alpha}\right)^{1-\alpha} \left(\frac{1}{\alpha}\right)^{\alpha} \frac{\left(r_t^k \left[1 + \psi_k R_t\right]\right)^{\alpha} \left(\tilde{w}_t \left[1 + \psi_l R_t\right]\right)^{1-\alpha}}{\epsilon_t} \tag{A.1}$$

– Another measure of marginal cost:

$$s_t = \frac{r_t^k \left[1 + \psi_k R_t\right]}{\alpha \epsilon_t \left(\Upsilon \frac{\mu_{z,t}^* l_t}{u_t \bar{k}_t}\right)^{1-\alpha}} \tag{A.2}$$

– Conditions associated with Calvo sticky prices:

$$p_t^* - \left[(1-\xi_p) \left(\frac{1 - \xi_p \left(\frac{\tilde{\pi}_t}{\pi_t}\right)^{\frac{1}{1-\lambda_{f,t}}}}{1-\xi_p} \right)^{\lambda_{f,t}} + \xi_p \left(\frac{\tilde{\pi}_t}{\pi_t} p_{t-1}^* \right)^{\frac{\lambda_{f,t}}{1-\lambda_{f,t}}} \right]^{\frac{1-\lambda_{f,t}}{\lambda_{f,t}}} = 0 \tag{A.3}$$

$$E_t \left\{ \lambda_{z,t} Y_{z,t} + \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}} \right)^{\frac{1}{1-\lambda_{f,t}}} \beta \xi_p F_{p,t+1} - F_{p,t} \right\} = 0 \tag{A.4}$$

$$E_t \left\{ \lambda_{f,t} \lambda_{z,t} Y_{z,t} s_t + \beta \xi_p \left(\frac{\tilde{\pi}_{t+1}}{\pi_{t+1}} \right)^{-\frac{\lambda_{f,t}}{\lambda_{f,t}-1}} K_{p,t+1} - K_{p,t} \right\} = 0 \tag{A.5}$$

where $K_{p,t}$, is a function of $F_{p,t}$ via the following relationship:

$$K_{p,t} = F_{p,t} \left[\frac{1 - \xi_p \left(\frac{\tilde{\pi}_t}{\pi_t}\right)^{\frac{1}{1-\lambda_{f,t}}}}{(1-\xi_p)} \right]^{1-\lambda_{f,t}}$$

and,

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

and,

$$Y_{z,t} = (p_t^*)^{\frac{\lambda_f}{\lambda_f - 1}} \left\{ \epsilon_t \nu_t^l \left(u_t \frac{\bar{k}_t}{\Upsilon \mu_{z,t}^*} \right)^{\alpha} \left[(w_t^*)^{\frac{\lambda_w}{\lambda_w - 1}} H_t \right]^{1-\alpha} - \phi \right\} \tag{A.6}$$

recalling that p_t^* is defined as:

$$p_t^* = \frac{\left[\int_0^1 P_{j,t}^{\frac{\lambda_{f,t}}{\lambda_{f,t}-1}} dj \right]^{\frac{1-\lambda_{f,t}}{\lambda_{f,t}}}}{P_t}$$

and that aggregate homogeneous labor, l_t, can be written in term of the aggregate, H_t, of household differentiated labor, $h_{j,t}$,

$$l_t \equiv \int_0^1 l_{j,t} dj = (w_t^*)^{\frac{\lambda_w}{\lambda_w - 1}} H_t, \text{ where } H_t \equiv \int_0^1 h_{j,t} dj$$

- Capital Producers

– Supply of capital:

$$E_t\left[\lambda_{z,t}q_tF_{1,t}-\lambda_{z,t}\frac{1}{\mu_{\Upsilon,t}}+\beta\frac{\lambda_{z,t+1}}{\mu^*_{z,t+1}\Upsilon}q_{t+1}F_{2,t+1}\right]=0 \tag{A.7}$$

where

$$F_{1,t}=-S'(\frac{\zeta_{i,t}\,i_t\mu^*_{z,t}\Upsilon}{i_{t-1}})\frac{\zeta_{i,t}\,i_t\mu^*_{z,t}\Upsilon}{i_{t-1}}+1-S(\frac{\zeta_{i,t}\,i_t\mu^*_{z,t}\Upsilon}{i_{t-1}})$$

and,

$$F_{2,t+1}=S'(\frac{\zeta_{i,t+1}\,i_{t+1}\mu^*_{z,t+1}\Upsilon}{i_t})\left(\frac{\zeta_{i,t+1}\,i_{t+1}\mu^*_{z,t+1}\Upsilon}{i_t}\right)^2$$

– Capital accumulation:

$$\bar{k}_{t+1}=(1-\delta)\frac{1}{\mu^*_{z,t}\Upsilon}\bar{k}_t+\left[1-S\left(\frac{\zeta_{i,t}\,i_t\mu^*_{z,t}\Upsilon}{i_{t-1}}\right)\right]i_t \tag{A.8}$$

- Entrepreneurs

  – Capital utilization:

$$r^k_t=\tau^{oil}_t a'(u_t) \tag{A.9}$$

  – Rate of return on capital:

$$R^k_t=\frac{\left[u_tr^k_t-\tau^{oil}_t a(u_t)\right]+(1-\delta)q_t}{\Upsilon q_{t-1}}\pi_t+\tau^k\delta-1 \tag{A.10}$$

  – Standard debt contract offered to entrepreneurs to be optimal (subject to constraints):

$$\begin{aligned}E_t\{[1-\Gamma_t(\bar{\omega}_{t+1}))]\frac{1+R^k_{t+1}}{1+R^e_{t+1}}+\frac{\Gamma'_t(\bar{\omega}_{t+1},)}{\Gamma'_t(\bar{\omega}_{t+1}))-\mu G'_t(\bar{\omega}_{t+1}))}&\times\\ \left[\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\left(\Gamma_t(\bar{\omega}_{t+1}))-\mu G_t(\bar{\omega}_{t+1}))\right)-1\right]\}=0\end{aligned} \tag{A.11}$$

  – Zero profit condition for banks on entrepreneurial loans:

$$\left(1+R^k_{t+1}\right)\left[\Gamma_t(\bar{\omega}_{t+1})-\mu G_t(\bar{\omega}_{t+1})\right]=1+R^e_{t+1}\left(q_t\bar{k}_{t+1}-n_{t+1}\right) \tag{A.12}$$

  – Law of motion for net worth:

$$\begin{aligned}n_{t+1}\;=\;&\frac{\gamma_t}{\pi_t\mu^*_{z,t}}\{\left(1+R^k_t\right)\bar{k}_tq_{t-1}+ \qquad\qquad (A.13)\\ &-\left[1+R^e_t+\frac{\mu\int_0^{\bar{\omega}_t}\omega dF_t(\omega_t)\left(1+R^k_t\right)\bar{k}_tq_{t-1}}{\bar{k}_tq_{t-1}-n_t}\right]\left(\bar{k}_tq_{t-1}-n_t\right)\}+w^e\end{aligned}$$

- Banks

– Banking services production function:

$$x_t^b\left(e_{v,t}\right)^{-\xi_t}\frac{e_t^r}{z_t^*}=\frac{m_t^b\left(1-m_t+\varsigma d_{m,t}\right)}{\pi_t\mu_{z,t}^*}+\psi_l w_t l_t+\psi_k\frac{r_t^k k_t}{\mu_{z,t}^*\Upsilon} \quad (A.14)$$

where

$$e_{z,t}^r=\frac{m_t^b}{\pi_t\mu_{z,t}^*}\left(1-\tau\right)\left(1-m_t\right)-\tau\left(\psi_l w_t l_t+\frac{\psi_k r_t^k k_t}{\mu_{z,t}^*\Upsilon}\right)$$

– Ratio of bank excess reserves to their value-added:

$$e_{v,t}=\frac{\left(1-\tau\right)\frac{m_t^b}{\pi_t\mu_{z,t}^*}\left(1-m_t\right)-\tau\left(\psi_l w_t l_t+\frac{\psi_k r_t^k}{\mu_{z,t}^*\Upsilon}k_t\right)}{\left(\frac{1}{\mu_{z,t}^*\Upsilon}(1-\nu_t^k)k_t\right)^{\alpha}\left((1-\nu_t^l)l_t\right)^{1-\alpha}} \quad (A.15)$$

– Banking efficiency condition:

$$R_{at}=\frac{\left(1-\tau\right)h_{e^r,t}-1}{\tau h_{e^r,t}+1}R_t \quad (A.16)$$

where

$$h_{e^r,t}=\left(1-\xi_t\right)x_t^b\left(e_{v,t}\right)^{-\xi_t}$$

– Another banking efficiency condition:

$$E_t\left\{\frac{\lambda_{z,t+1}}{\mu_{z,t+1}^*\pi_{t+1}}\left[R_{t+1}^T-R_{t+1}^m-\frac{\varsigma R_{t+1}}{h_{e^r,t+1}\tau+1}\right]\right\}=0 \quad (A.17)$$

– Choice of labor:

$$w_t=\frac{R_t}{\left(1+\psi_l R_t\right)}\frac{\left(1-\alpha\right)\xi_t x_t^b\left(e_{v,t}\right)^{1-\xi_t}\left(\frac{\mu_{z,t}^*\Upsilon(1-\nu_t^l)l_t}{(1-\nu_t^k)k_t}\right)^{-\alpha}}{1+\tau h_{e^r,t}} \quad (A.18)$$

- Households

– Marginal utility of consumption:

$$E_t\left\{u_{c,t}^z-\frac{\mu_{z,t}^*\zeta_{c,t}}{c_t\mu_{z,t}^*-bc_{t-1}}+b\beta\frac{\zeta_{c,t+1}}{c_{t+1}\mu_{z,t+1}^*-bc_t}\right\}=0 \quad (A.19)$$

– Consumption decision:

$$0=E_t\{u_{c,t}^z-(1+\tau^C)\lambda_{z,t}-\zeta_{c,t}\upsilon c_t^{-\sigma_q}\left(\frac{\pi_t\mu_{z,t}^*}{m_t^b}\right)^{1-\sigma_q}\times$$
$$\left[(1+\tau^C)\left(\frac{1}{m_t}\right)^{(1-\chi_t)\theta}\left(\frac{1}{1-m_t}\right)^{(1-\chi_t)(1-\theta)}\left(\frac{1}{dm_t}\right)^{\chi_t}\right]^{1-\sigma_q}\}$$

(A.20)

– Conditions associated with Calvo sticky wages:

$$w_t^* = [(1-\xi_w)\left(\frac{1-\xi_w\left(\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}}(\mu_{z^*})^{1-\vartheta}(\mu_{z^*,t})^{\vartheta}\right)^{\frac{1}{1-\lambda_w}}}{1-\xi_w}\right)^{\lambda_w} \tag{A.21}$$

$$+\xi_w\left(\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}}(\mu_{z^*})^{1-\vartheta}(\mu_{z^*,t})^{\vartheta}w_{t-1}^*\right)^{\frac{\lambda_w}{1-\lambda_w}}]^{\frac{1-\lambda_w}{\lambda_w}}$$

$$E_t\{(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}}H_t\frac{(1-\tau^l)\lambda_{z,t}}{\lambda_w}$$

$$+\beta\xi_w(\mu_{z^*})^{\frac{1-\vartheta}{1-\lambda_w}}(\mu_{z^*,t+1})^{\frac{\vartheta}{1-\lambda_w}-1}\left(\frac{1}{\pi_{w,t+1}}\right)^{\frac{\lambda_w}{1-\lambda_w}}\frac{\tilde{\pi}_{w,t+1}^{\frac{1}{1-\lambda_w}}}{\pi_{t+1}}F_{w,t+1}-F_{w,t}\}=0 \tag{A.22}$$

$$E_t\{\left[(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}}H_t\right]^{1+\sigma_L}\zeta_{c,t} \tag{A.23}$$

$$+\beta\xi_w E_t\left(\frac{\tilde{\pi}_{w,t+1}}{\pi_{w,t+1}}(\mu_{z^*})^{1-\vartheta}(\mu_{z^*,t+1})^{\vartheta}\right)^{\frac{\lambda_w}{1-\lambda_w}(1+\sigma_L)}K_{w,t+1}$$

$$-K_{w,t}\}=0$$

where $K_{w,t}$ is a function of $F_{w,t}$ via the following relationship:

$$\frac{1}{\psi_L}\left[\frac{1-\xi_w\left(\frac{\tilde{\pi}_{w,t}}{\pi_{w,t}}(\mu_{z^*})^{1-\vartheta}(\mu_{z^*,t})^{\vartheta}\right)^{\frac{1}{1-\lambda_w}}}{1-\xi_w}\right]^{1-\lambda_w(1+\sigma_L)}\tilde{w}_tF_{w,t}-K_{w,t}=0$$

and,

$$\tilde{\pi}_{w,t}=\left(\pi_t^{target}\right)^{\iota_w}(\pi_{t-1})^{1-\iota_w}$$

and,

$$\pi_{w,t}=\frac{\tilde{w}_t\mu_{z^*,t}\pi_t}{\tilde{w}_{t-1}}$$

recalling that $w_t^*\equiv W_t^*/W_t$ and:

$$W_t^*=\left[\int_0^1 W_t(j)^{\frac{\lambda_w}{1-\lambda_w}}dj\right]^{\frac{1-\lambda_w}{\lambda_w}}$$

– Choice of T_t:

$$E_t\left\{-\lambda_{z,t}+\frac{\beta}{\mu_{z,t+1}^*\pi_{t+1}}\lambda_{z,t+1}\left(1+R_{t+1}^T\right)\right\}=0 \tag{A.24}$$

– Choice of M_t:

$$E_t\{\zeta_{c,t}\upsilon\left[\left(1+\tau^c\right)c_t\left(\frac{1}{m_t}\right)^{(1-\chi_t)\theta}\left(\frac{1}{1-m_t}\right)^{(1-\chi_t)(1-\theta)}\left(\frac{1}{d_t^m}\right)^{\chi_t}\right]^{1-\sigma_q} \tag{A.25}$$

$$\times\left(\frac{\pi_t\mu_t^*}{m_t^b}\right)^{2-\sigma_q}\left[\frac{(1-\chi_t)\,\theta}{m_t}-\frac{(1-\chi_t)\,(1-\theta)}{1-m_t}\right]-\zeta_{c,t}H'\left(\frac{m_t m_t^b \pi_{t-1}\mu_{zt-1}^*}{m_{t-1}m_{t-1}^b}\right)\frac{\pi_t\mu_{zt}^*\pi_{t-1}\mu_{zt-1}^*}{m_{t-1}m_{t-1}^b}$$

$$+\beta\zeta_{c,t+1}H'\left(\frac{m_{t+1}m_{t+1}^b\pi_t\mu_{zt}^*}{m_t m_t^b}\right)\frac{m_{t+1}m_{t+1}^b\left(\pi_t\mu_{zt}^*\right)^2}{\left(m_t m_t^b\right)^2}-\lambda_{z,t}R_t^a\}=0$$

– Choice of D_{t+1}^m :

$$E_t\{\beta\zeta_{c,t+1}\upsilon_t\chi_{t+1}\left[\left(1+\tau^C\right)c_{t+1}\left(\frac{1}{m_{t+1}}\right)^{\left(1-\chi_{t+1}\right)\theta_t} \tag{A.26}$$

$$\times\left(\frac{1}{(1-m_{t+1})}\right)^{\left(1-\chi_{t+1}\right)(1-\theta_t)}\left(\frac{1}{d_{t+1}^m}\right)^{\chi_{t+1}}\right]^{1-\sigma_q}\frac{1}{d_{t+1}^m}\left(\frac{1}{m_{t+1}^b}\right)^{2-\sigma_q}\left(\pi_{t+1}\mu_{z,t+1}^*\right)^{1-\sigma_q}$$

$$+\frac{\beta}{\pi_{t+1}\mu_{z,t+1}^*}\lambda_{z,t+1}\left(1+R_{t+1}^m\right)-\lambda_{z,t}\}=0$$

– Choice of M_{t+1}^b:

$$E_t\{\beta\zeta_{c,t+1}\upsilon_t\left(1-\theta_t\right)\left(1-\chi_{t+1}\right) \tag{A.27}$$

$$\times\left[\left(1+\tau^c\right)c_{t+1}\left(\frac{1}{m_{t+1}}\right)^{\left(1-\chi_{t+1}\right)\theta}\left(\frac{1}{1-m_{t+1}}\right)^{\left(1-\chi_{t+1}\right)(1-\theta)}\left(\frac{1}{d_{t+1}^m}\right)^{\chi_{t+1}}\right]^{1-\sigma_q}$$

$$\times\left(\frac{1}{m_{t+1}^b}\right)^{2-\sigma_q}\left(\pi_{t+1}\mu_{z,t+1}^*\right)^{1-\sigma_q}\frac{1}{1-m_{t+1}}$$

$$+\beta\frac{1}{\pi_{t+1}\mu_{z,t+1}^*}\lambda_{z,t+1}\left(1+R_{t+1}^a\right)-\lambda_{z,t}\}=0$$

- Monetary Policy

  – Policy rule, in linearised form:

$$\hat{R}_{t+1}^e=\rho_i\hat{R}_t^e+(1-\rho_i)\alpha_\pi\frac{\pi}{R^e}\left[E_t\left(\hat{\pi}_{t+1}\right)-\hat{\pi}_t^{target}\right]+(1-\rho_i)\frac{\alpha_{\Delta y}}{4R^e}\log\left(\frac{GDP_t}{\mu_{z^*}GDP_{t-1}}\right)$$
$$+(1-\rho_i)\alpha_{\Delta\pi}\frac{\pi}{R^e}\left(\hat{\pi}_t-\hat{\pi}_{t-1}\right)+(1-\rho_i)\frac{\alpha_{\Delta c}}{R^e}\log\left(\frac{B_t^{Tot}}{\mu_{z^*}B_{t-1}^{Tot}}\right)+(1-\rho_i)\frac{\alpha_\xi}{R^e}\hat{\xi}_t+\frac{1}{400R^e}\varepsilon_t \tag{A.28}$$

where GDP_t and B_t^{Tot} are defined in the paper.

  – Law of motion of the monetary base:

$$m_{t+1}^b=\frac{1}{\pi_t\mu_{z,t}^*}m_t^b(1+x_t) \tag{A.29}$$

- Closing Conditions

  – Resource constraint:

$$\frac{\mu G_t(\bar{\omega}_t)\left(1+R_t^k\right)q_{t-1}\bar{k}_t}{\mu_{z,t}^*}\frac{1}{\pi_t}+\tau_t^{oil}a(u_t)\frac{\bar{k}_t}{\Upsilon\mu_{z,t}^*}+g_t+c_t+\frac{i_t}{\mu_{\Upsilon,t}}+\Theta\frac{1-\gamma_t}{\gamma_t}\left[n_{t+1}-w^e\right]$$
$$=\ (p_t^*)^{\frac{\lambda_{f,t}}{\lambda_{f,t}-1}}\left\{\epsilon_t\nu_t^l\left(u_t\frac{\bar{k}_t}{\Upsilon\mu_{z,t}^*}\right)^{\alpha}\left[(w_t^*)^{\frac{\lambda_w}{\lambda_w-1}}H_t\right]^{1-\alpha}-\phi\right\} \tag{A.30}$$

- Other equations

  – Definition of (scaled) broad money, M_t^{Broad} :

$$m_t^{Broad}=m_{t+1}^b\left(1+d_{t+1}^m\right)+\psi_l w_t l_t+\psi_k\frac{r_t^k u_t}{\Upsilon\mu_{z,t}^*}\bar{k}_t \tag{A.31}$$

  – Definition of (scaled) total bank loans:

$$b_t^{Tot}=\psi_l w_t l_t+\psi_k\frac{r_t^k u_t\bar{k}_t}{\mu_{z,t}^*\Upsilon}+\left(q_t\bar{k}_{t+1}-n_{t+1}\right) \tag{A.32}$$

  – Definition of average credit spread:

$$P_t^e=\frac{\mu\int_0^{\bar{\omega}_t}\omega dF_t(\omega_t)\left(1+R_t^k\right)\bar{k}_t q_{t-1}}{\bar{k}_t q_{t-1}-n_t} \tag{A.33}$$

  – Definition of (scaled) narrow money, M_t^{Narrow} :

$$m_t^{\text{Narrow}}=m_{t+1}^b+\psi_l w_t l_t+\psi_k\frac{r_t^k u_t\bar{k}_t}{\Upsilon\mu_{z,t}^*} \tag{A.34}$$

  – Definition of (scaled) reserves, Res_t :

$$res_t=\frac{m_t^b}{\pi_t}\left(1-m_t+x_t\right) \tag{A.35}$$

The first order expansion of the model about a steady state in which wages and prices are not distorted implies that the six price and wage equations reduce to simply two equations, and the unknowns associated with these equations reduce to just $\tilde{w}_t$ and π_t.

11 Appendix B: Signals

In the spirit of Gilchrist and Leahy (2002), as adopted in Christiano, Ilut, Motto and Rostagno (2008), we specify the risk shock process with signals:

$$\hat{\sigma}_t=\rho\hat{\sigma}_{t-1}+\xi_t^0+\xi_{t-1}^1+\xi_{t-2}^2+...+\xi_{t-p}^p, \tag{B.1}$$

where ξ_{t-j}^j is orthogonal to $\hat{\sigma}_{t-s}$, $s>0$. The variable, ξ_{t-j}^j is realized at time $t-j$ and represents news about $\hat{\sigma}_t$. The superscript on the variable indicates how many dates in the future the news applies to. The subscript indicates the date that the news is realized. The model with news in effect has p additional parameters:

$$\sigma_{\sigma,1}^{2}=Var\left(\xi_{t-1}^{1}\right),\ \sigma_{\sigma,2}^{2}=Var\left(\xi_{t-2}^{2}\right),...,\sigma_{\sigma,p}^{2}=Var\left(\xi_{t-p}^{p}\right).$$

Note that the presence of news does not alter the fact that (B.1) is a scalar first order moving average representation for $\hat{\sigma}_t$. Obviously, the number of signals in $\hat{\sigma}_t$ is not identified from observations on $\hat{\sigma}_t$ alone. However, the cross equation restrictions delivered by an economic model can deliver identification of the σ_j^2's.

We now set this process up in state space/observer form. Suppose, to begin, that $p=2$. Then,

$$\hat{\sigma}_t=\rho\hat{\sigma}_{t-1}+\xi_t^0+\xi_{t-1}^1+\xi_{t-2}^2. \tag{B.2}$$

It is useful to define the auxiliary variables, u_{t-1}^1 and u_{t-2}^2. Write:

$$\begin{bmatrix}\hat{\sigma}_t\\ u_t^2\\ u_t^1\end{bmatrix}=\begin{bmatrix}\rho & 0 & 1\\ 0 & 0 & 0\\ 0 & 1 & 0\end{bmatrix}\begin{bmatrix}\hat{\sigma}_{t-1}\\ u_{t-1}^2\\ u_{t-1}^1\end{bmatrix}+\begin{bmatrix}\xi_t^0\\ \xi_t^2\\ \xi_t^1\end{bmatrix}. \tag{B.3}$$

It is easy to confirm that this is the same as (B.2). Write the first equation:

$$\hat{\sigma}_t=\rho\hat{\sigma}_{t-1}+u_{t-1}^1+\xi_t^0. \tag{B.4}$$

To determine u_{t-1}^1 evaluate (B.3) at the previous date:

$$\begin{aligned}u_{t-1}^2 &= \xi_{t-1}^2\\ u_{t-1}^1 &= u_{t-2}^2+\xi_{t-1}^1.\end{aligned}$$

The second of the above two expressions indicates that we must evaluate (B.3) at an earlier date:

$$\begin{aligned}u_{t-2}^2 &= \xi_{t-2}^2\\ u_{t-2}^1 &= u_{t-3}^2+\xi_{t-2}^1.\end{aligned}$$

Combining the first of these equations with the second of the previous set of two equations, we obtain:

$$u_{t-1}^1=\xi_{t-2}^2+\xi_{t-1}^1.$$

Substituting this into (B.4), we obtain (B.2), which is the result we sought. We can refer to u_{t-1}^1 as the "state of signals about $\hat{\sigma}_t$ as of $t-1$". We can refer to ξ_{t-2}^2 as the "signal about $\hat{\sigma}_t$ that arrives at time $t-2$". We can refer to ξ_{t-1}^1 as the "signal about $\hat{\sigma}_t$ that arrives at time $t-1$".

We now consider the case of general p. Thus, we have

$$\begin{aligned}\hat{\sigma}_t &= \rho\hat{\sigma}_{t-1}+\xi_t^0+u_{t-1}^1\\ u_{t-1}^1 &= u_{t-2}^2+\xi_{t-1}^1\\ u_{t-2}^2 &= u_{t-3}^3+\xi_{t-2}^2\\ &\ldots\\ u_{t-(p-1)}^{p-1} &= u_{t-p}^p+\xi_{t-(p-1)}^{p-1}\\ u_{t-p}^p &= \xi_{t-p}^p.\end{aligned}$$

According to this setup, there are p signals about $\hat{\sigma}_t$. The first arrives in $t-p$, the second in $t-p+1$ and the p^{th} in $t-1$. This is set up in state space form as follows:

$$\begin{bmatrix} \hat{\sigma}_t \\ u_t^p \\ u_t^{p-1} \\ \vdots \\ u_t^2 \\ u_t^1 \end{bmatrix} = \begin{bmatrix} \rho_1 & 0 & 0 & \cdots & 0 & 1 \\ 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \cdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} \hat{\sigma}_{t-1} \\ u_{t-1}^p \\ u_{t-1}^{p-1} \\ \vdots \\ u_{t-1}^2 \\ u_{t-1}^1 \end{bmatrix} + \begin{bmatrix} \xi_t^0 \\ \xi_t^p \\ \xi_t^{p-1} \\ \vdots \\ \xi_t^2 \\ \xi_t^1 \end{bmatrix}$$

We can write this in compact notation as follows:

$$\Psi_{\hat{\sigma},t} = P_{\hat{\sigma}} \Psi_{\hat{\sigma},t-1} + \varepsilon_{\hat{\sigma},t},$$

where

$$\Psi_{\hat{\sigma},t} = \begin{bmatrix} \hat{\sigma}_t \\ u_t^p \\ u_t^{p-1} \\ \vdots \\ u_t^2 \\ u_t^1 \end{bmatrix}, \; P_{\hat{\sigma}} = \begin{bmatrix} \rho_1 & 0 & 0 & \cdots & 0 & 1 \\ 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 \end{bmatrix}, \; \varepsilon_{\hat{\sigma},t} = \begin{bmatrix} \xi_t^0 \\ \xi_t^p \\ \xi_t^{p-1} \\ \vdots \\ \xi_t^2 \\ \xi_t^1 \end{bmatrix}.$$

Note,

$$\varepsilon_{\hat{\sigma},t} = \begin{bmatrix} \xi_t^0 \\ \xi_t^p \\ \xi_t^{p-1} \\ \vdots \\ \xi_t^2 \\ \xi_t^1 \end{bmatrix} = D\tilde{\varepsilon}_t,$$

where

$$\tilde{\varepsilon}_t \equiv \begin{bmatrix} \xi_t^0 \\ \xi_t^p \\ \xi_t^{p-1} \\ \vdots \\ \xi_t^2 \\ \xi_t^1 \end{bmatrix}.$$

Here, D is the $p+1$ by $p+1$ identity matrix, augmented by inserting a row of zeros after the first row. In this way, D is $p+2$ by $p+1$. We now describe the variance-covariance matrix of $\tilde{\varepsilon}_t$.

We place structure on this by restricting both the pattern of the variances and the covariances. The variances are restricted as follows:

$$\sigma_{\sigma,1}^2 = \sigma_{\sigma,2}^2 = ... = \sigma_{\sigma,p}^2 = \sigma_\sigma^2.$$

We restrict the covariances so that signals about shocks j periods apart in time, have correlation, ρ_σ^j. To impose this restriction, it is convenient to first reorder the elements in $\tilde{\varepsilon}_t$:

$$s_t = \begin{pmatrix} \xi_t^p \\ \vdots \\ \xi_t^1 \\ \xi_t^0 \end{pmatrix}.$$

We impose the following structure on the variance-covariance of s_t :

$$V = E s_t s_t' = \begin{bmatrix} 1 \times \sigma_\sigma^2 & \rho_\sigma \times \sigma_\sigma^2 & \rho_\sigma^2 \times \sigma_\sigma^2 & \cdots & \rho_\sigma^{p-1} \times \sigma_\sigma^2 & \rho_\sigma^p \times \sigma_\sigma \sigma_{\xi^0} \\ \rho_\sigma \times \sigma_\sigma^2 & 1 \times \sigma_\sigma^2 & \rho_\sigma \times \sigma_\sigma^2 & \cdots & \rho_\sigma^{p-2} \times \sigma_\sigma^2 & \rho_\sigma^{p-1} \times \sigma_\sigma \sigma_{\xi^0} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \rho_\sigma^{p-1} \times \sigma_\sigma^2 & \rho_\sigma^{p-2} \times \sigma_\sigma^2 & \rho_\sigma^{p-3} \times \sigma_\sigma^2 & \cdots & 1 \times \sigma_\sigma^2 & \rho_\sigma \times \sigma_\sigma \sigma_{\xi^0} \\ \rho_\sigma^p \times \sigma_\sigma \sigma_{\xi^0} & \rho_\sigma^{p-1} \times \sigma_\sigma \sigma_{\xi^0} & \rho_\sigma^{p-2} \times \sigma_\sigma \sigma_{\xi^0} & \cdots & \rho_\sigma \sigma_\sigma \sigma_{\xi^0} & 1 \times \sigma_{\xi^0}^2 \end{bmatrix}.$$

To map this structure back into the variance-covariance matrix of $\tilde{\varepsilon}_t$, let H denote the $p+1$ by $p+1$ elementary matrix formed by moving the last row of the $p+1$ identity matrix into the first row. Then,

$$\tilde{\varepsilon}_t = H s_t,$$

and the variance covariance matrix of $\varepsilon_{\hat{\sigma},t}$ is

$$DHVH'D'.$$

12 Appendix C: Steady State Parameters

Values of parameters that control the nonstochastic part of our model economies are displayed in Table 1. The left and right columns report results for the EA and US, respectively.

The values of the parameters that control the financial frictions (e.g., γ, μ, $F(\bar{\omega})$ and $Var(\log \omega)$) were primarily determined by our desire to match $Z - R^e$, the equity to debt ratio and the rate of return on capital. The value of the quarterly survival rate of entrepreneurs, γ, that we use for both the EA and US models is fairly similar to the 97.28 percent value used in BGG. The value of μ is larger than the one used by BGG. The value of $F(\bar{\omega})$ that we use for our US model is lower than the 0.75 quarterly percent value used in BGG. The interval defined by the values of $Var(\log \omega)$ is close to the value of 0.28 used by BGG.

Several additional features of the parameter values in Table 1 are worth emphasizing. During the calibration, we imposed $\psi_k = \psi_l$, i.e., that the fraction of capital rental and labor costs that must be financed in advance are equal. Note, however, that these fractions are higher in the EA than in the US. This result reflects our finding (see below) that velocity measures in the EA are smaller than their counterparts in the US.

Consider the tax rates in Panel E of Table 1. We obtained the labor tax rate for the EA by first finding the labor tax rate data for 12 EA countries from the OECD in 2002.[44] We then computed a weighted average of the tax rates, based on each country's share in EA GDP. The result, 45 percent, is reported in Table 1. The tax rate on capital is taken from Eurostat and corresponds to the EA implicit tax rate on capital over the period 1995-2001.

We now turn to the US tax rates. We compute effective tax rates by extending the data compiled by Mendoza, Razin and Tesar (1994) to 2001. The differences in tax rates between the EA and the US are notable. The relatively high tax on consumption in the EA reflects the value-added tax in the EA. The relatively high tax on capital income in the US has been noted elsewhere. For example, Mendoza et al. find that in 1988 the tax rate on capital income was 40 percent in the US, 24 percent in Germany, 25 percent in France and 27 percent in Italy. The value for the US tax rate on capital income that we use is similar to Mulligan (2002)'s estimate, who finds that the US capital income tax rate was about 35

[44] See 'Taxing Wages', OECD Statistics, Organisation for Economic Co-operation and Development, 2004.

percent over the period 1987-1997. McGrattan and Prescott (2004) also report a value for the US capital tax rate similar to ours. According to them, the corporate income tax rate was 35 percent over the period 1990-2001.[45] Regarding the labor tax rate, our estimates imply a lower value for the US than the EA. This pattern is consistent with the findings of Prescott (2003), whose estimates of the labor tax rate in Germany, France and Italy are higher than for the US.

Consistent with the analysis of Prescott (2002), our model parameters imply that the wedge formed from the ratio of the marginal product of labor to the marginal household cost of labor is greater in the EA than in the US. This wedge is, approximately,

$$\frac{1+\tau_c}{1-\tau_w}\lambda_w\lambda_f.$$

Our model parameters imply that this wedge is 2.75 in the EA and 1.74 in the US.

Steady state properties of the EA and US versions of our model are provided in Tables 2 and 3. Details of our data sources are provided in the footnotes to the tables. Consider Table 2 first. The model understates somewhat the capital output ratio in both regions. This reflects a combination of the capital tax rate, as well as the financial frictions. Following BGG, we take the empirical analog of $N/(K-N)$ to be the equity to debt ratio of firms. Our EA model implies this ratio is around unity. Our US model implies a much higher value for this ratio. This is consistent with the analysis of McGrattan and Prescott (2004), who find that the equity to debt ratio in the US averaged 4.7 over the period 1960-1995 and then rose sharply thereafter. Finally, note that around one percent of labor and capital resources are in the banking sector in our EA and US models. The table reports that the empirical counterpart of this number is 5.9 percent. Although this suggests the model greatly understates amount of resources going into banking, this is probably not true. Our empirical estimate is the average share of employment in the finance, insurance and real estate sectors. These sectors are presumably substantially greater than the banking sector in our model.

Now consider the results in Table 3. The numbers in the left panel of that table pertain to monetary velocity measures. Note how the various velocity measures tend to be lower in the EA than in the US. The steady state of the model is reasonably consistent with these properties of the data. Note that according to the model, the velocity of credit in the EA is substantially smaller than it is in the US. This is consistent with the finding in Table 2, which indicates that the equity to debt ratio in the EA is much smaller than the corresponding value in the US.

The right panel of Table 3 reports various rates of return. The model's steady state matches the data reasonably well, in the cases where we have the data. In the case of the EA, the rate on demand deposits, R^a, corresponds to the overnight rate (the rate paid on demand deposits in the EA) and the rate of return on capital, R^k, is taken from estimates of the European Commission. As regards the US, the rate of return on capital is taken from Mulligan (2002), who shows that the real return was about 8 percent over the period 1987-1999.

There is considerable uncertainty about the spread between the 'cost of external finance', Z, and the return on household time deposits, R^e. Given that there is substantial uncertainty about the correct measure of the premium, we report a range based on findings in the literature and our own calculations. In the case of the US, Table 3 suggests a spread in the range of 198-298 basis points. This encompasses the values suggested by BGG, Levin,

[45] McGrattan and Prescott (2004) report that the tax rate on capital has been coming down. For the period, 1960-1969 they report an average value of 45%.

Natalucci and Zakrajsek (2004) and De Fiore and Uhlig (2005).[46] In the case of the EA the table suggests a range of 70-270 basis points. Although the results for the US and the EA might not be perfectly comparable, the evidence reported in the table suggests that the spread is probably higher in the US than in the EA. This is consistent with the findings of Carey and Nini (2004) and Cecchetti (1999), who report that the spread is higher in the US than in the EA by about 30-60 basis points. In order to match this evidence, we have chosen a calibration of the model that delivers a spread in the US that is 45 basis points higher than in the EA.

13 Appendix D: Data

13.1 Euro area

Official long time series for the euro area are not available. We mostly relied on the AWM database, which aggregates data for individual countries in a consistent manner. For details on the construction of the AWM database, see Euro Area Wide Model (AWM) by G. Fagan, J. Henry and R. Mestre (2001).

Below, if not otherwise specified, data are taken from the AWM database and extended using Eurostat series.

Data are expressed in per-capita terms using working age population, in millions. Annual data for population are linearly interpolated to obtain quarterly frequency. Source: Ameco and OECD.

- GDP, Y_t: Gross Domestic Product, in millions of euro, deflated by the GDP deflator.
- Consumption: Consumption Expenditures (including non-durables, durables and services),[47] in millions of euro, deflated by the GDP deflator.
- Investment, I_t: Gross Investment, in millions of euro, deflated by the investment deflator.
- Inflation, Π_t: quarter-on-quarter log difference of the GDP deflator.
- Hours worked, H_t: From 1995Q1 onwards, official annual hours worked are published by Eurostat. We have interpolated the data to quarterly frequency by using the pattern of hours worked for euro area countries that publish quarterly hours worked (Germany, Italy, France, Finland, which together make up 80% of employment in the euro area). The series has been then backcasted by using data on hours worked of euro

[46] Bernanke, Gertler and Gilchrist (1999) measure the external finance premium as approximately the historical average spread between the prime lending rate and the six-month Treasury bill rate, which amounts to 200 basis points. Levin, Natalucci and Zakrajsek (2004) report a spread of 227 basis points for the median firm included in their sample. De Fiore and Uhlig (2005) report that the spread between the prime rate on bank loans to business and the commercial paper is 298 basis points over the period 1997-2003. Carlstrom and Fuerst (1997) report a somewhat lower spread of 187 basis points.

[47] No breakdown in non-durable, durables and services is available for the historical series for consumption.

area countries for which data are available (same countries as above). Source: Eurostat, National Statistical Offices and our calculations.

- Wages, W_t: hourly compensation is computed as total compensation (from income side of national accounts) divided by number of employees, times total employment, divided by hours worked (as defined above). It is converted to real terms by using the GDP deflator.

- Short-term interest rate, R_t^{short}: 3-month Euribor.

- Networth, N_t: the Dow Jones EUROSTOXX, available from 1986Q4, is backcasted using the MSCI Europe price index; the series is deflated by the GDP price deflator. Source: Thomson Datastream and our calculations.

- Credit Spread, $Spread^{Credit}$: From 1996 onwards, it is computed as the weighted average of spreads between: bank lending rates and "risk-free" rates of corresponding maturity; corporate bond yields and "risk-free" rates of corresponding maturities. We use the outstanding stocks of each credit instrument as weight in order to aggregate the spreads. The series is backcasted by aggregating bank lending spreads for individual euro area countries using the share of each country in euro area GDP as weight. Source: ECB, Global Financial Data and our computations.

- Credit, L_t: Loans to the private sector, notional stock, converted to millions of euro, deflated by the GDP deflator. Source: ECB.

- Term Spread, $Spread_t^{Term}$: 10-year government bond yield minus short-term rate (as defined above).

- Narrow liquidity, M_t^{Narrow}: M1, notional stock, converted to millions of euro, deflated by the GDP price deflator. Source: ECB.

- Marketable instruments, $M_t^{\mathrm{Marketable}}$: M3 minus M1, both in notional stocks, deflated by the GDP deflator. Source: ECB.

- Reserves, Res_t: Liquidity provision by the Eurosystem since 1999, and we back-date the series using an appropriately rescaled aggregate of central bank liabilities vis-à-vis banks for Germany, France, Spain, the Netherlands, Finland and Portugal. Source: ECB, National Central Banks and our computations.

- Relative price of investment, $\Pi_t^{Investment}$: first difference of the log of (investment deflator divided by GDP deflator).

- Relative price of oil, Π_t^{Oil}: first difference of the log of (oil price divided by GDP deflator). Oil price is the euro value of the Brent. Source: IFS, BIS.

GDP, consumption, investment , wages, networth, credit, narrow liquidity, marketable instruments, reserves, and hours are logged and (with the exception of hours) first differenced. In the charts shown in the paper the series are expressed in percentage by multiplying them by 100. Interest rates, spreads and inflation are expressed on a quarterly basis corresponding to their appearence in the model, and in the charts they are converted to annual basis by multiplying them by 400. The time series of the variables are plotted in Figure 1a.

13.2 United States

Data are axpressed in per-capita terms using population over 16 (expressed in billions). Annual data for population are linearly interpolated to obtain quarterly frequency.[48] Source: OECD and our computations.

- GDP, Y_t: Gross Domestic Product, in billions of dollars, deflated by the Implicit Price Deflator of GDP. Source: US Department of Commerce - Bureau of Economic Analysis.
- Consumption, C_t: Personal Consumption Expenditures (non-durables plus services), in billions of dollars, deflated by Implicit Price deflator of GDP. Source: US Department of Commerce - Bureau of Economic Analysis.
- Investment, I_t: Fixed Private Investment plus Durable Consumption, in billions of dollars, deflated by its implicit price deflator. Source: US Department of Commerce - Bureau of Economic Analysis.
- Inflation: first difference of the log of the Implicit Price Deflator of GDP. Source: US Department of Commerce - Bureau of Economic Analysis.
- Hours worked, H_t: nonfarm business sector Index, hours of all persons. Source: US Department of Labor - Bureau of Labor Statistics.
- Wages, W_t: hourly compensation for nonfarm business sector for all persons, divided by the GDP price deflator. Source: US Department of Labor - Bureau of Labor Statistics and US Department of Commerce - Bureau of Economic Analysis.
- Short-term interest rate, R_t^{Short}: 3-month average of the daily effective federal funds rate. Source: Board of Governors of the Federal Reserve System.
- Networth, N_t: Dow Jones Wilshire 5000 index, deflated by the GDP price deflator. Board of Governors of the Federal Reserve System and US Department of Commerce - Bureau of Economic Analysis
- Credit Spread, $Spread_t^{Credit}$: US Industrial BBB corporate bond yield (period average), backcasted by using BAA Corporate Bond yields, minus short-term interest rate (as defined above). Source: Bloomberg, Board of Governors of the Federal Reserve System and our computations.

[48] We don not use the monthly series of civilian noninstitutional population published by the US Bureau of Labor Statistics as it displays breaks due to methodological revisions.

- Credit, L_t: Credit market instruments liabilities of nonfarm nonfinancial corporate business plus credit market instruments liabilities of nonfarm noncorporate business, in billions of dollars, deflated by the GDP price deflator. Source: Flow of Funds Accounts of the Federal Reserve Board and US Department of Commerce - Bureau of Economic Analysis.

- Term Spread, $Spread_t^{Term}$: 10-year government bond yield (constant maturity) minus short-term rate (as defined above). Source: Board of Governors of the Federal Reserve System.

- Narrow liquidity, M_t^{Narrow}: M2, in billions of dollars, deflated by the GDP price deflator. Source: Board of Governors of the Federal Reserve System and US Department of Commerce - Bureau of Economic Analysis.

- Marketable instruments, $M_t^{\text{Marketable}}$: Commercial papers plus Repos, issued by US financial institutions, deflated by the GDP price deflator. Source: Flow of Funds Accounts of the Federal Reserve Board and US Department of Commerce - Bureau of Economic Analysis.

- Reserves, Res_t: Total banks' reserves, deflated by the GDP price deflator. Source: Board of Governors of the Federal Reserve System and US Department of Commerce - Bureau of Economic Analysis.

- Relative price of investment, $\Pi_t^{Investment}$: first difference of the log of (investment deflator divided by GDP deflator). Source: US Department of Commerce - Bureau of Economic Analysis.

- Relative price of oil, Π_t^{Oil}: first difference of the log of (oil price divided by GDP deflator). Oil price is the Crude oil West Texas FOB. Source: Datastream and US Department of Commerce - Bureau of Economic Analysis.

GDP, consumption, investment , wages, networth, credit, narrow liquidity, marketable instruments, reserves, and hours are logged and (with the exception of hours) first differenced. In the charts shown in the paper the series are expressed in percentage by multiplying them by 100. Interest rates, spreads and inflation are expressed on a quarterly basis corresponding to their appearence in the model, and in the charts they are converted to annual basis by multiplying them by 400. The time series of the variables used in the estimation are plotted in Figure 1b.

13.3 Measurement equation

The following measurement equation relates observable variables to the corresponding model variables. Data are demeaned by removing their sample mean, with the exception of inflation and the short-term interest rate (R_{t+1}^e), which are demeaned by subtracting their steady-state values, as reported in Tables 2 and 3 in the paper.

A hat over a variable, say y_t, stands for:

$$\hat{y}_t = \frac{y_t - \bar{y}}{\bar{y}}$$

where a bar over a variable indicates the steady state. Both y_t and $\bar{y}$ should be understood as opportunely scaled in order to induce stationarity, as described in Appendix A.

$$\begin{bmatrix} \Delta\log(Y_t) \\ \Delta\log(C_t) \\ \Delta\log(I_t) \\ \Delta\log(W_t) \\ \log(H_t) \\ \Pi_t \\ R_t^{short} \\ \Delta\log(N_t) \\ Spread_t^{Credit} \\ \Delta\log(L_t) \\ Spread_t^{Term} \\ \Delta\log(M_t^{\text{Narrow}}) \\ \Delta\log(M_t^{\text{Marketable}}) \\ \Delta\log(Res_t) \\ \Pi_t^{Investment} \\ \Pi_t^{Oil} \end{bmatrix} - \begin{bmatrix} \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \pi^* \\ \bar{R}^e \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \\ \text{sample mean} \end{bmatrix} = \begin{bmatrix} \widehat{gdp}_t - \widehat{gdp}_{t-1} + \hat{\mu}_{z_t^*,t} \\ \hat{c}_t - \hat{c}_{t-1} + \hat{\mu}_{z_t^*,t} \\ \hat{\imath}_t - \hat{\imath}_{t-1} + \hat{\mu}_{z_t^*,t} \\ \hat{w}_t - \hat{w}_{t-1} + \hat{\mu}_{z_t^*,t} \\ \hat{h}_t \\ \hat{\pi}_t \\ \bar{R}^e\hat{R}^e_{t+1} \\ \hat{n}_{t+1} - \hat{n}_t + \hat{\mu}_{z_t^*,t} \\ P_t^e \\ \hat{b}_t^{Tot} - \hat{b}_{t-1}^{Tot} + \hat{\mu}_{z_t^*,t} \\ \bar{R}^L\hat{R}^L_t - \bar{R}^e\hat{R}^e_{t+1} \\ \hat{m}_t^{\text{Narrow}} - \hat{m}_{t-1}^{\text{Narrow}} + \hat{\mu}_{z_t^*,t} \\ \hat{d}^m_{t+1} - \hat{d}^m_t + \hat{\mu}_{z_t^*,t} \\ \widehat{res}_t - \widehat{res}_{t-1} + \hat{\mu}_{z_t^*,t} \\ -\left(\hat{\mu}_{\Upsilon,t} - \hat{\mu}_{\Upsilon,t-1}\right) \\ \hat{\tau}^{oil}_t - \hat{\tau}^{oil}_{t-1} \end{bmatrix}$$

14 Appendix E: The Market for Capital and Credit

In this Appendix we derive long-linear approximations to the capital producers' supply of capital, the entrepreneurs'demand for capital and demand for credit, and the bank's supply of credit. We start from the capital producers and from their optimal capital pricing condition (40). By log-linearizing that condition, ignoring innovations to shocks different from the marginal productivity of investment shock and changes in the stock of capital occurred in the past, we find:

$$\hat{q}_t = S''\left(\mu_z^*\Upsilon\right)^2 \frac{\bar{k}}{i}\left[(1+\beta) + \beta\frac{1-\delta}{\mu_z^*\Upsilon}\right]\widehat{\bar{k}}_{t+1} - \beta S''\left(\mu_z^*\Upsilon\right)^2\frac{\bar{k}}{i}E_t\widehat{\bar{k}}_{t+2} + S''\left(\mu_z^*\Upsilon\right)^2 E_t\left(\hat{\zeta}_{i,t} - \beta\hat{\zeta}_{i,t+1}\right).$$

Note that an investment boom today strains capital production, and thus exerts upward pressure on the price of capital (first term on the right side of the equal sign). At the same time, higher costs today detract from production costs tomorrow (second term), which – discounted back to present – partly offsets the current price increase. Collecting terms, the above expression simplifies to:

$$\hat{q}_t = C\widehat{\bar{k}}_{t+1} - \beta D E_t\widehat{\bar{k}}_{t+2} + D\frac{i}{\bar{k}}E_t\left(\hat{\zeta}_{i,t} - \beta\hat{\zeta}_{i,t+1}\right). \tag{E.1}$$

where a 'hat' on top of a variable signifies percent deviation from the variable's steady state value. The two coefficient, C and D satisfy the following equalities: $C = D\left[1+\beta+\beta\frac{1-\delta}{\mu_z^*\Upsilon}\right] > 0$, and $D = \frac{\bar{k}}{i}S''\left(\mu_z^*\Upsilon\right)^2 > 0$. Note that (E.1) defines a positively sloped linear relation between the relative price of capital in deviation from its unit steady state and the stock of capital supplied by capital producers. The sensitivity of adjustment costs to changes in the rate of investment, S'', determines the slope of the curve.

Next, we proceed to the derivation of the demand for capital. We go back to the standard debt contract maximisation problem stated in (22). We reproduce the maximisation problem here, for ease of reference, after substituting out B_{t+1}:

$$\max_{\bar{\omega}_{t+1},\bar{K}_{t+1}} E_t\{ \ [1-\Gamma(\bar{\omega}_{t+1})]\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)\frac{Q_{\bar{K}',t}\bar{K}_{t+1}}{N_{t+1}}+\eta_{t+1}[\frac{Q_{\bar{K}',t}\bar{K}_{t+1}}{N_{t+1}}\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)(\Gamma(\bar{\omega}_{t+1})$$
$$-\mu G(\bar{\omega}_{t+1}))-\frac{Q_{\bar{K}',t}\bar{K}_{t+1}}{N_{t+1}}+1]\} \quad .$$

The gross share of entrepreneurial profits accruing to the bank, $\Gamma(\bar{\omega}_{t+1})$, and the entrepreneurs' probability of default, $G(\bar{\omega}_{t+1})$, are defined in the text.

The first order necessary condition for an optimal choice of capital by entrepreneurs is:

$$E_t\left\{[1-\Gamma(\bar{\omega}_{t+1},\sigma_t)]\frac{1+R^k_{t+1}}{1+R^e_{t+1}}+\eta_{t+1}\left[\frac{1+R^k_{t+1}}{1+R^e_{t+1}}(\Gamma(\bar{\omega}_{t+1},\sigma_t)-\mu G(\bar{\omega}_{t+1},\sigma_t))-1\right]\right\}=0. \tag{E.2}$$

where we highlight the dependence of $\Gamma(\bar{\omega}_{t+1})$, and $G(\bar{\omega}_{t+1})$ on the risk shock, σ_t, which controls the dispersion of the entrepreneurial profits. Note the date on σ_t. It corresponds to the date when the capital purchase is actually made. The productivity cutoff, $\bar{\omega}_{t+1}$, has date $t+1$ because its value is determined by date $t+1$ events.

The first order condition for the bank's optimal choice of $\bar{\omega}_{t+1}$ – a stand-in variable for the contractual, no-default interest rate on entrepreneurial debt, Z_{t+1} – yields:

$$E_t\left\{\eta_{t+1}-\frac{\Gamma'(\bar{\omega}_{t+1},\sigma_t)}{\Gamma'(\bar{\omega}_{t+1},\sigma_t)-\mu G'(\bar{\omega}_{t+1},\sigma_t)}\right\}=0. \tag{E.3}$$

Finally, assuming the zero-profit condition for banks binds (i.e. $\eta_{t+1}>0$), the complementary slackness condition for the contract is:

$$E_t\left\{\frac{Q_{\bar{K}',t}\bar{K}_{t+1}}{N_{t+1}}\left[\left(\frac{1+R^k_{t+1}}{1+R^e_{t+1}}\right)(\Gamma(\bar{\omega}_{t+1},\sigma_t)-\mu G(\bar{\omega}_{t+1},\sigma_t))-1\right]+1\right\}=0. \tag{E.4}$$

The demand for capital can be derived as follows. First, we combine (E.2) and (E.3), and, linearizing the resulting expression around the steady state, we obtain:

$$E_t\left\{X\left(\bar{\omega}\widehat{\bar{\omega}}_{t+1}\right)-Y\left(\frac{R^k\hat{R}^k_{t+1}}{1+R^k}-\frac{R^e\hat{R}^e_{t+1}}{1+R^e}\right)-Z\sigma\hat{\sigma}_t\right\}=0. \tag{E.5}$$

The three coefficients, X, Y, Z, are convolutions of primitive coefficients which we quantify by calibrating the steady state properties of our baseline model: the two functions, $\Gamma(\bar{\omega}_{t+1},\sigma_t)$ and $G(\bar{\omega}_{t+1},\sigma_t)$, along with their first, second and cross-derivatives with respect to the cutoff payoff of the entrepreneurial project and the risk shock, all evaluated in steady state. These coefficients are: $X=(1-\Gamma)\frac{1+R^k}{1+R^e}[\Gamma_{\omega\omega}-\eta(\Gamma_{\omega\omega}-\mu G_{\omega\omega})]>0$, $Y=\eta\Gamma_\omega>0$, $Z=\frac{1+R^k}{1+R^e}(-\Gamma_\omega\Gamma_\sigma+\eta\Gamma_\omega(\Gamma_\sigma-\mu G_\sigma)-(1-\Gamma)[\Gamma_{\omega\sigma}-\eta(\Gamma_{\omega\sigma}-\mu G_{\omega\sigma})])<0$ and $\eta=\frac{\Gamma_\omega}{[\Gamma_\omega-\mu G_\omega]}$. We then scale (E.4) by making use of the standard transformations: $\bar{K}_{t+1}=z^*_t\Upsilon^t\bar{k}_{t+1}$, $\bar{N}_{t+1}=z^*_tP_tn_{t+1}$, $Q_{\bar{K}',t}=q_t\Upsilon^{-t}P_t$. We obtain:

$$E_t\left\{\frac{q_t\bar{k}_{t+1}}{n_{t+1}}\frac{1+R^k_{t+1}}{1+R^e_{t+1}}(\Gamma(\bar{\omega}_{t+1},\sigma_t)-\mu G(\bar{\omega}_{t+1},\sigma_t))-\frac{q_t\bar{k}_{t+1}}{n_{t+1}}+1\right\}=0. \tag{E.6}$$

Linearizing (E.6) and using (E.5) to eliminate $\bar{\omega}\widehat{\bar{\omega}}_{t+1}$ allows us to define a negative relation between the relative price of capital, $\hat{q}_t$, in deviation from its unit steady state value, and the stock of capital purchases that entrepreneurs decide to finance with a loan, $\widehat{\bar{k}}_{t+1}$:

$$\hat{q}_t = -\widehat{\bar{k}}_{t+1} + \hat{n}_{t+1} + A\left(\frac{\bar{k}-n}{n}\right)E_t\left(\frac{R^k\hat{R}^k_{t+1}}{1+R^k} - \frac{R^e\hat{R}^e_{t+1}}{1+R^e}\right) - B\left(\frac{\bar{k}-n}{n}\right)\sigma\hat{\sigma}_t, \tag{E.7}$$

where $A = 1 + \frac{(\Gamma_\omega - \mu G_\omega)}{(\Gamma - \mu G)}\frac{Y}{X} > 0$ and $B = -\left(\frac{Z}{X} + \frac{(\Gamma_\sigma - \mu G_\sigma)}{(\Gamma - \mu G)}\right) > 0$. We interpret the above expression as a demand for capital condition. Note that shocks to the value of equity, $\hat{n}_{t+1}$, which constitutes purchasing power for entrepreneurs in the time-t market for capital, and shocks to entrepreneurial risk, $\hat{\sigma}_t$, act as shifters in the $\hat{q}_t - \widehat{\bar{k}}_{t+1}$ space. Notice also the role of expectations of future returns on capital, $\hat{R}^k_{t+1}$, in moving (E.7). To understand how these expectations are formed at time t, we first scale and then linearise the expression that defines R^k_{t+1}, (17) in the main text, ignoring the presence of tax on capital, and obtain:

$$R^k\hat{R}^k_{t+1} = \frac{\pi}{\Upsilon}\left[r^k\hat{r}^k_{t+1} + \left(r^k + 1 - \delta\right)\hat{\pi}_{t+1} + (1-\delta)\,\hat{q}_{t+1} - \left(r^k + 1 - \delta\right)\hat{q}_t\right], \tag{E.8}$$

Note that $\hat{r}^k_{t+1}$, the percent deviation of the real capital rental rate from its steady state, is a function of $\widehat{\bar{k}}_{t+1}$ (see (6) in the main text).

To obtain a credit demand condition, we go back to our definition of the external finance premium in (18). Note that the premium which is relevant for pricing the loan that the entrepreneur is about to take on at the end of time t, B_{t+1}, is the *expected* external finance premium that the bank will apply – after observing the time $t+1$ shocks – at the end of the contract. So, we take expectations of the premium and we linearize it around its steady state:

$$\hat{P}^e_{t+1} = -\left(\frac{n}{\bar{k}-n}\right)\left(\hat{q}_t + \widehat{\bar{k}}_{t+1} - \hat{n}_{t+1}\right) + \frac{G_\sigma\sigma\hat{\sigma}_t}{G} + E_t\left(\frac{R^k\hat{R}^k_{t+1}}{1+R^k} + \frac{G_\omega}{G}\bar{\omega}\widehat{\bar{\omega}}_{t+1}\right). \tag{E.9}$$

Note, once more, that at $t+1$ – when the current loan contract will mature – the premium charged on the time-t loan will be set conditional on the realisation of $\widehat{\bar{\omega}}_{t+1}$, evaluated on the basis of the time-t default probability function, $G(\bar{\omega}_{t+1}, \sigma_t)$. Next, we use our definition of credit in deviation of steady state, $\left(\frac{\bar{k}-n}{\bar{k}}\right)\hat{b}_{t+1} + \frac{n}{\bar{k}}\hat{n}_{t+1} = \hat{q}_t + \widehat{\bar{k}}_{t+1}$, and (E.5) to substitute out $\hat{q}_t + \widehat{\bar{k}}_{t+1}$ and $\bar{\omega}\widehat{\bar{\omega}}_{t+1}$, respectively, from (E.9). The resulting expression is what we interpret as the entrepreneurs'demand for credit:

$$\hat{P}^{e,D}_{t+1} = -\frac{n}{\bar{k}}\hat{b}_{t+1} + \frac{n}{\bar{k}}\hat{n}_{t+1} + E_t\left[H\left(\frac{R^k\hat{R}^k_{t+1}}{1+R^k}\right) - (H-1)\frac{R^e\hat{R}^e_{t+1}}{1+R^e} + J\sigma\hat{\sigma}\right], \tag{E.10}$$

where: $H = 1 + \frac{G_\omega}{G}\frac{Y}{X} > 1$ and $J = \frac{G_\omega}{G}\frac{Z}{X} + \frac{G_\sigma}{G} < 0$. Note that positive shocks to entrepreneurial equity and to expectations of future returns on capital shift the demand rightward in a $\hat{P}^e_{t+1} - \hat{b}_{t+1}$ space.

We finally derive the supply of credit from the scaled version of the bank's zero-profit condition, (E.6). We linearize (E.6) and we use (E.9) to eliminate $\bar{\omega}\widehat{\bar{\omega}}_{t+1}$. We obtain:

$$\hat{P}^{e,S}_{t+1} = S\frac{n}{\bar{k}}\hat{b}_{t+1} - S\frac{n}{\bar{k}}\hat{n}_{t+1} - E_t\left[S\left(\frac{R^k\hat{R}^k_{t+1}}{1+R^k}\right) + (1+S)\frac{R^e\hat{R}^e_{t+1}}{1+R^e} - T\sigma\hat{\sigma}_t\right], \tag{E.11}$$

where $S = \frac{G_\omega(\Gamma - \mu G)}{G(\Gamma_\omega - \mu G_\omega)} - 1 > 0$ and $T = \frac{G_\sigma}{G} - \frac{G_\omega(\Gamma_\sigma - \mu G_\sigma)}{G(\Gamma_\omega - \mu G_\omega)} > 0$. The above expression defines a positively sloped schedule in a $\hat{P}^e_{t+1} - \hat{b}_{t+1}$ space. Negative shocks to equity, $\hat{n}_{t+1}$, or expectations of future negative shocks to the return on capital determine an upward shift in the supply of credit, as banks seek compensation for a reduced collateral value securing the loan, or for increased macroeconomic risk.

In conclusion, note the presence of the risk shock as an independent shifter of the two conditions establishing an equilibrium in the credit market, (E.10) and (E.11). The estimated coefficients attached to the risk shock in the two conditions are remarkably large. This helps explain our result that adding credit to the estimation shifts emphasis to this shock as an important pro-cyclical force of economic motion.

14.1 The excess return on capital

In the text, we discuss one measure for the anticipated excess return on capital, the *equity premium*. Here, we derive this measure as the difference between the expected rate of change in value of a share of representative entrepreneurial equity and the risk-free interest rate:

$$R^{ep}_t = E_t \left[\frac{V_{t+1}}{V_t} - \left(1 + R^e_{t+1}\right) \right]. \tag{E.12}$$

In (E.12) we used the equality between the risk-free rate at which the household can invest in illiquid financial assets, R^T_{t+1}, and the interest rate which the bank considers its opportunity cost to entrepreneurial loans, R^e_{t+1}. Furthermore, in (E.12), V_{t+1} denotes the average expected profits to be made by entrepreneurs during period $t+1$, net of repayments to banks:

$$E_t \left[V_{t+1}\right] = E_t \left[\left(1 + R^k_{t+1}\right) Q_{\bar{K}',t} \bar{K}_{t+1} - \left\{1 + R^e_{t+1} + P^e_{t+1}\right\} \left(Q_{\bar{K}',t} \bar{K}_{t+1} - \bar{N}_{t+1}\right) \right], \tag{E.13}$$

where P^e_{t+1} is defined in (18). Comparing (E.13) and (17), note that $V_{t+1} = \frac{\bar{N}_{t+2} - W^e}{\gamma_{t+1}}$, i.e. it is the expected value of equity at $t+1$ for an entrepreneur active in t and purchasing capital at the end of that period, and thus it corrects for composition effects due to entrepreneurs' turnover (γ_{t+1}) and for transfers to start-ups (W^e). Linearising the expression in (E.12) we obtain:

$$R^{ep} \hat{R}^{ep}_{t+1} = E_t \left\{ \pi \mu^*_z \left[\frac{n}{n - w^e} \hat{n}_{t+2} - \hat{\gamma}_{t+1} - \frac{n}{n - w^e} \hat{n}_{t+1} + \hat{\gamma}_t + \hat{\pi}_{t+1} + \hat{\mu}^*_{z,t+1} \right] - R^e \hat{R}^e_{t+1} \right\}, \tag{E.14}$$

where $R^{ep} = \pi \mu^*_z - (1 + R^e)$ is the steady state value of the equity risk premium. This is the equity premium measure simulated in Figure 17.a and Figure 17.b.

15 Appendix F: Comparing RMSEs

To understand the methodology, let $RMSE^{BVAR}$ and $RMSE^{Model}$ denote the RMSEs from the BVAR and the baseline model, respectively, for some forecast horizon. It can be shown (see Christiano, 1989) that, for T large,

$$RMSE^{BVAR} - RMSE^{Model} \sim N(0, \frac{V}{T}),$$

where T is the number of observations used in computing the RMSE. The grey area in the panels of Figure 4 represents:

$$RMSE^{BVAR} \pm 1.96\sqrt{\frac{\hat{V}}{T}}.$$

where $\hat{V}$ is an asymptotically valid estimator of V. If $RMSE^{Model}$ lies outside the grey area, then the null hypothesis that the two models produce the same RMSE is rejected at the 5% level, in favor of the alternative that one or the other model produces a lower RMSE.

16 Appendix G: Laplace Approximation to the Marginal Data Density

A typical problem is to compute the marginal data density:

$$f(y) = \int f(y|\theta) f(\theta) d\theta,$$

where $\theta \in R^N$ is an $N-$dimensional vector of parameters. Let

$$g(\theta) \equiv \log f(y|\theta) f(\theta).$$

Let θ^* denote the mode of $g(\theta)$. Write

$$g(\theta) = g(\theta^*) + g_\theta(\theta^*)(\theta - \theta^*) - \frac{1}{2}(\theta - \theta^*)' g_{\theta\theta}(\theta^*)(\theta - \theta^*),$$

where

$$g_{\theta\theta}(\theta^*) = -\frac{\partial^2 \log f(y|\theta) f(\theta)}{\partial\theta\partial\theta'}|_{\theta=\theta^*}.$$

Note that the fact that θ^* is the mode implies $g_{\theta\theta}(\theta^*)$ is positive definite. Then,

$$f(y|\theta) f(\theta) \simeq f(y|\theta^*) f(\theta^*) \exp\left\{-\frac{1}{2}(\theta - \theta^*)' g_{\theta\theta}(\theta^*)(\theta - \theta^*)\right\},$$

after imposing $g_\theta(\theta^*) = 0$. Note that

$$\frac{1}{(2\pi)^{\frac{N}{2}}} |g_{\theta\theta}(\theta^*)|^{\frac{1}{2}} \exp\left\{-\frac{1}{2}(\theta - \theta^*)' g_{\theta\theta}(\theta^*)(\theta - \theta^*)\right\}$$

is the multinormal density for an N-dimensional random variable, θ, with variance covariance matrix, $g_{\theta\theta}(\theta^*)^{-1}$, and mean θ^*. As a result, it's integral over all values of θ is unity:

$$\int \frac{1}{(2\pi)^{\frac{N}{2}}} |g_{\theta\theta}(\theta^*)|^{\frac{1}{2}} \exp\left\{-\frac{1}{2}(\theta - \theta^*)' g_{\theta\theta}(\theta^*)(\theta - \theta^*)\right\} d\theta = 1.$$

Then,

$$\begin{aligned}\int f(y|\theta) f(\theta) d\theta &\simeq \int f(y|\theta^*) f(\theta^*) \exp\left\{-\frac{1}{2}(\theta - \theta^*)' g_{\theta\theta}(\theta^*)(\theta - \theta^*)\right\} d\theta \\ &= \frac{f(y|\theta^*) f(\theta^*)}{\frac{1}{(2\pi)^{\frac{N}{2}}} |g_{\theta\theta}(\theta^*)|^{\frac{1}{2}}} \int \frac{1}{(2\pi)^{\frac{N}{2}}} |g_{\theta\theta}(\theta^*)|^{\frac{1}{2}} \exp\left\{-\frac{1}{2}(\theta - \theta^*)' g_{\theta\theta}(\theta^*)(\theta - \theta^*)\right\} d\theta \\ &= \frac{f(y|\theta^*) f(\theta^*)}{\frac{1}{(2\pi)^{\frac{N}{2}}} |g_{\theta\theta}(\theta^*)|^{\frac{1}{2}}}.\end{aligned}$$

Thus,

$$f(y) = \int f(y|\theta) f(\theta) d\theta \simeq (2\pi)^{\frac{N}{2}} \frac{f(y|\theta^*) f(\theta^*)}{|g_{\theta\theta}(\theta^*)|^{\frac{1}{2}}}.$$

We use the above approximation for model comparison.

Table 1: Model Parameters, EA and US (Time unit of Model: quarterly)			
		Euro Area	US
Panel A: Household Sector			
β	Discount rate	0.999	0.9966
σ_L	Curvature on Disutility of Labor	1.00	1.00
υ	Weight on Utility of Money	0.001	0.002
σ_q	Curvature on Utility of money	-6.00	-7.00
θ	Power on Currency in Utility	0.74	0.87
χ	Power on Saving Deposits in Utility	0.49	0.40
b	Habit persistence parameter	0.56	0.63
λ_w	Steady state markup, suppliers of labor	1.05	1.05
Panel B: Goods Producing Sector			
μ_z	Growth Rate of the economy (APR)	1.50	1.36
ψ_k	Fraction of capital rental costs that must be financed	0.92	0.75
ψ_l	Fraction of wage bill that must be financed	0.92	0.75
δ	Depreciation rate on capital	0.02	0.025
α	Power on capital in production function	0.36	0.40
λ_f	Steady state markup, intermediate good firms	1.20	1.20
Φ	Fixed cost, intermediate goods	0.29	0.07
Panel C: Entrepreneurs			
γ	Percent of Entrepreneurs Who Survive From One Quarter to the Next	97.80	97.62
μ	Fraction of Realized Profits Lost in Bankruptcy	0.94	0.94
$F(\bar{\omega})$	Percent of Businesses that go into Bankruptcy in a Quarter	0.15	0.26
$Var(log(\omega))$	Variance of (Normally distributed) log of idiosyncratic productivity parameter	0.06	0.24
Panel D: Banking Sector			
ξ	Power on Excess Reserves in Deposit Services Technology	0.94	0.96
x^b	Constant in Front of Deposit Services Technology	102	90.5
Panel E: Policy			
τ	Bank Reserve Requirement	0.02	0.01
τ^c	Tax Rate on Consumption	0.20	0.05
τ^k	Tax Rate on Capital Income	0.28	0.32
τ^l	Tax Rate on Labor Income	0.45	0.24
x	Growth Rate of Monetary Base (APR)	3.37	3.71

Table 2: Steady State Properties, Model versus Data, EA and US

Variable	Model, EA	Data, EA 1998:1-2003:4	Model, US	Data, US 1998:1-2003:4
$\frac{k}{y}$	8.70	12.5[1]	6.98	10.7[2]
$\frac{i}{y}$	0.21	0.20[3]	0.22	0.25[4]
$\frac{c}{y}$	0.56	0.57	0.58	0.56
$\frac{g}{y}$	0.23	0.23	0.20	0.20
r^k	0.042		0.059	
$\frac{N}{K-N}$ ('Equity to Debt')	1.15	1.08-2.19[5]	3.40	1.3-4.7[6]
Transfers to Entrepreneurs (as % of Goods Output)	1.36		2.78	
Banks Monitoring Costs (as % of Output Goods)	0.53		0.34	
Output Goods (in %) Lost in Entrepreneurs Turnover	0.21		1.31	
Percent of Aggregate Labor and Capital in Banking	0.93		0.95	5.9[7]
Inflation (APR)	1.84	1.84[8]	2.32	2.32[9]

Note: [1]Capital stock includes also government capital, as disaggregated data are not available. Source: Euro Area Wide Model (AWM), G.Fagan, J.Henry and R.Mestre (2001). [2]Capital stock includes private non-residential fixed assets, private residential, stock of consumer durables and stock of private inventories. Source: BEA. [3]Investment includes also government investment and does not include durable consumption, as disaggregated data are not available. Source: AWM. [4]Investment includes residential, non-residential, equipment, plants, business durables, change in inventories and durable consumption. Source: BEA. [5]The equity to debt ratio for corporations in the euro area is 1.08 in 1995, 2.19 in 1999 and drops to 1.22 in 2002. Taking into account the unusual movements in asset prices in the second half of the 1990s, the steady-state equity to debt ratio is probably closer to the lower end of the range reported in the Table. Debt includes loans, debt securities issued and pension fund reserves of non-financial corporations. Equity includes quoted and non-quoted shares. Source: Euro area Flow of Funds. [6]E.McGrattan and E.Prescott (2004) estimates the equity to debt ratio for the corporate sector over the period 1960-2001. Over the period 1960-1995 the ratio is quite stable and averaged at 4.7. In 1995 it started exhibiting an extraordinary rise. The unprecedented sharp rise that occurred in the second half of the 1990s makes the calibration of such ratio for the purpose of our analysis very difficult. For comparison, Masulis (1988) reports an equity to debt ratio for US corporations in the range of 1.3-2 for the period 1937-1984. [7]Based on analysis of data on the finance, insurance and real estate sectors over the period 1987-2002. [8]Average inflation (annualised), measured using GDP deflator. [9]Average inflation (annualised), measured using GDP Price Index over the period 1987-2003.

Table 3: Money and Interest Rates. Model versus Data, EA and US

Money	Model, EA	Data, EA	Model, US	Data, US	Interest Rates (APR)	Model, EA	Data, EA	Model, US	Data, US
Narrow Liquidity Velocity	3.32	3.31	3.65	1.92	Deposits, R^a	0.82	0.76	0.41	
Broad Liquidity Velocity	1.31	1.32	1.54	1.56	Long-term Assets	3.78	4.86	5.12	5.99
Base Velocity	14.56	14.83	12.06	18.07	Rate of Return on Capital, R^k	8.21	8.32	10.52	10.32
Currency/Base	0.69	0.69	0.86	0.86	Cost of External Finance, Z	4.37	4.3-6.3	6.16	7.1-8.1
Currency/Total Deposits	0.07	0.06	0.12	0.08	Gross Rate on Work. Capit. Loans	4.08		4.18	7.07
Credit Velocity	0.80	1.05	1.70	1.70	Other Financial Securities, R^e	3.78	3.60	5.12	5.12

Notes to Table :

Data for the Euro area: the sample is 1998:4-2003:4

(1) 'Narrow Liquidity' is M1, and 'Broad Liquidity' is M3. (2) The interest rate on 'Deposits' is the overnight rate. (3) The interest rate on 'Longer-term Assets' is the rate on 10-years Government Bonds. (4) The 'Rate of Return on Capital' is the Net Return on Net Capital Stock. Source: European Commission. (5) 'Cost of External Finance': We consider 3 different measures. First, we construct a weighted average of the spread between short-term bank lending rates to enterprises and the risk-free rate of corresponding maturity, the spread between long-term bank lending rates and the risk-free rate of corresponding maturity, the spread between yields on corporate bonds and the risk-free rate of corresponding maturity. We use outstanding amounts as weights. The spread is 67 b.p. Second, we consider an alternative measure for the spread suggested by De Fiore and Uhlig (2005), which amounts to 267 b.p. Third, we consider the spread between BAA and AAA, which amounts at 135 b.p. Adding these spreads to our measure of the risk-free rate gives the range displayed in the table. (6) The Rate on 'Other Financial Securities' is the 3-month Euribor.

Data for the US: the sample is 1987:1-2003:4.

(1) 'Narrow Liquidity' is M2, and 'Broad Liquidity' is M2 + Commercial Paper + Repos. (2) The interest rate on 'Longer-term Assets' is the rate on 10-years Government Bonds. (3) 'Rate of Return on Capital ': it is based on Mulligan's (2002) estimate of the real return over the period 1987-1999, to which we added average inflation. (4) Cost of 'External Finance': Bernanke, Gertler and Gilchrist (1999) suggest a spread of 200 b.p. over the risk-free rate. Levin, Natalucci and Zakrajsek (2004) find a spread of 227 b.p. for the median firm in their sample over 1997-2003. De Fiore and Uhlig (2005) find a spread of 298 b.p. Adding these spreads to our measure of the risk-free rate gives the range displayed in the table. (5) The rate on 'Working Capital Loans' is the rate on commercial and industrial loans. Source: Survey of terms of business lending, Federal Reserve Board of Governors. (6) The Rate on 'Other Financial Securities' is the Federal Funds Rate.

Table 4: Baseline Model, Parameter Estimates, Euro area and US

		Prior			Posterior Euro area			Posterior US		
		Type	Mean	Std. dev.	Mode	Std. dev. (Hess.)	90% Prob. Interval	Mode	Std. dev. (Hess.)	90% Prob. Interval
ξ_p	Calvo prices	Beta	0.75[1] 0.375	0.05	0.712	0.027	0.67-0.76	0.693	0.041	0.63-0.76
ξ_w	Calvo wages	Beta	0.75[1] 0.375	0.1	0.703	0.032	0.65-0.76	0.699	0.029	0.65-0.75
H''	Curvature on currency demand[2]	Normal	2.0	2.0	0.036	0.007	0.02-0.05	/	/	/
ι	Weight on steady state inflation	Beta	0.5	0.15	0.923	0.037	0.86-0.98	0.362	0.178	0.07-0.66
ι_w	Weight on steady state inflation	Beta	0.5	0.15	0.726	0.100	0.56-0.89	0.641	0.160	0.38-0.90
ϑ	Weight on technology growth	Beta	0.5	0.15	0.914	0.039	0.85-0.98	0.930	0.032	0.88-0.98
S''	Investment adjust. cost	Normal	10.0	5	31.43	3.424	25.8-37.1	26.64	3.089	21.6-31.7
σ_a	Capacity utilization	Gamma	6	5	23.60	6.455	12.98-34.2	19.718	4.903	11.7-27.8
α_π	Weight on inflation in Taylor rule	Normal	1.75	0.1	1.821	0.089	1.68-1.98	1.849	0.095	1.69-2.00
$\alpha_{\Delta y}$	Weight on output growth in Taylor rule	Normal	0.25	0.1	0.307	0.103	0.14-0.48	0.321	0.100	0.16-0.48
$\alpha_{\Delta\pi}$	Weight on change in infl. in Taylor rule	Normal	0.3	0.1	0.201	0.097	0.04-0.36	0.192	0.099	0.03-0.35
$\alpha_{\Delta c}$	Weight on credit growth in Taylor rule[2]	Normal	0.05	0.025	0.069	0.023	0.03-0.11	/	/	/
α_ξ	Weight on ξ_t shock in Taylor rule	Normal	0	10	-13.26	2.788	-17.8- -8.7	-13.03	6.171	-23.2- -2.89
ρ_i	Coeff. on lagged interest rate	Beta	0.8	0.05	0.825	0.017	0.80-0.85	0.880	0.013	0.86-0.90
ρ	Correlation of signals (ρ_σ)	Normal	0	0.5	0.284	0.102	0.12-0.45	0.696	0.060	0.60-0.80
ρ	Banking technol. shock (x_t^b)	Beta	0.5	0.2	0.972	0.010	0.96-0.99	0.988	0.007	0.97-0.99
ρ	Bank reserve demand shock (ξ_t)	Beta	0.5	0.2	0.033	0.017	0.005-0.061	0.858	0.043	0.79-0.93
ρ	Term premium shock (η_t^L)	Beta	0.5	0.2	0.943	0.012	0.92-0.96	0.896	0.035	0.84-0.95
ρ	Price of Investment shock ($\mu_{\Upsilon,t}$)	Beta	0.5	0.2	0.977	0.010	0.96-0.99	0.983	0.007	0.97-0.99
ρ	Money demand shock (χ_t)	Beta	0.5	0.2	0.994	0.004	0.988-0.999	0.977	0.012	0.96-0.99
ρ	Government consumption shock (g_t)	Beta	0.5	0.2	0.987	0.010	0.97-0.99	0.938	0.025	0.90-0.98
ρ	Persistent product. shock ($\mu_{z,t}^*$)	Beta	0.5	0.2	0.061	0.049	0.-0.14	0.169	0.073	0-0.29
ρ	Transitory product. shock (ϵ_t)	Beta	0.5	0.2	0.970	0.011	0.95-0.99	0.883	0.024	0.84-0.92
ρ	Financial wealth shock (γ_t)[3]	Beta	0.5	0.1	0.817	0.027	0.77-0.86	0.529	0.025	0.49-0.57
ρ	Riskiness shock (σ_t)[3]	Beta	0.5	0.2	0.911	0.018	0.88-0.94	0.821	0.033	0.77-0.88
ρ	Consump. prefer. shock ($\zeta_{c,t}$)	Beta	0.5	0.2	0.889	0.030	0.84-0.94	0.902	0.016	0.88-0.93
ρ	Margin. effic. of invest. shock ($\zeta_{i,t}$)[3]	Beta	0.5	0.05	0.591	0.049	0.51-0.67	0.344	0.071	0.23-0.46
ρ	Oil price shock (τ_t^{oil})	Beta	0.5	0.2	0.954	0.019	0.92-0.99	0.946	0.017	0.92-0.97
ρ	Price mark-up shock ($\lambda_{f,t}$)[3]	Beta	0.5	0.2	0.984	0.010	0.97-0.99	0.689	0.048	0.61-0.77

Table 4, continued

		Prior			Posterior Euro area			Posterior US		
		Type	Mode	Df.	Mode	Std. dev. (Hess.)	90% Prob. Interval	Mode	Std. dev. (Hess.)	90% Prob. Interval
σ	Banking technol. shock (x_t^b)	Inv. Gamma	0.1	5 d	0.095	0.008	0.08-0.11	0.083	0.006	0.07-0.09
σ	Bank reserve demand shock (ξ_t)	Inv. Gamma	0.001	5 d	0.125	0.020	0.09-0.16	0.018	0.0013	0.016-0.020
σ	Term premium shock (η_t^L)^4	Inv. Gamma	0.01	5 d	0.003	0.001	0.002-0.003	0.004	0.0016	0.002-0.007
σ	Investm. specific shock ($\mu_{\Upsilon,t}$)	Inv. Gamma	0.003	5 d	0.003	0.0002	0.003-0.004	0.003	0.0002	0.003-0.004
σ	Money demand shock (χ_t)	Inv. Gamma	0.001	5 d	0.025	0.002	0.022-0.029	0.032	0.002	0.028-0.036
σ	Government consumption shock (g_t)	Inv. Gamma	0.01	5 d	0.013	0.001	0.011-0.014	0.021	0.002	0.018-0.023
σ	Persistent product. shock ($\mu_{z,t}^*$)	Inv. Gamma	0.001	5 d	0.005	0.0004	0.004-0.005	0.007	0.001	0.006-0.008
σ	Transitory product. shock (ϵ_t)	Inv. Gamma	0.001	5 d	0.004	0.0003	0.004-0.005	0.005	0.0004	0.005-0.006
σ	Financial wealth shock (γ_t)^4	Inv. Gamma	0.001	5 d	0.005	0.0004	0.004-0.005	0.005	0.0004	0.004-0.006
σ	Risk shock (σ_t)	Inv. Gamma	0.01	5 d	0.041	0.007	0.03-0.05	0.050	0.007	0.04-0.06
σ	Signal on Risk shock (σ_{signal})	Inv. Gamma	$0.01/\sqrt[2]{8}$	5 d	0.023	0.002	0.02-0.03	0.027	0.003	0.02-0.03
σ	Consump. prefer. shock ($\zeta_{c,t}$)	Inv. Gamma	0.001	5 d	0.013	0.002	0.01-0.02	0.021	0.002	0.018-0.024
σ	Margin. effic. of invest. shock ($\zeta_{i,t}$)^4	Inv. Gamma	0.001	5 d	0.018	0.002	0.016-0.021	0.018	0.001	0.015-0.020
σ	Oil price shock (τ_t^{oil})	Inv. Gamma	0.01	5 d	0.150	0.011	0.13-0.17	0.133	0.010	0.12-0.15
σ	Monetary policy shock (ε_t)	Inv. Gamma	0.25	10 d	0.446	0.035	0.39-0.50	0.520	0.040	0.46-0.59
σ	Price markup shock ($\lambda_{f,t}$)	Inv. Gamma	0.0005	5 d	0.010	0.001	0.008-0.012	0.017	0.003	0.011-0.022
	Meas. Error, Real Credit Growth	Weibull	0.0007 0.0010	5	0.00066	0.00014	0.0004-0.0009	0.00095	0.00021	0.0060-0.0013
	Meas. Error, Real Net Worth Growth	Weibull	0.0090 0.0100	5	0.0141	0.00113	0.0122-0.0156	0.01791	0.00083	0.0165-0.0193
	Meas. eroor, External Finance Premium	Weibull	0.0001 0.0001	5	0.00010	0.00002	0.00007-0.00013	0.00009	0.00002	0.00006-0.0001

(^{1}) Upper numbers refer to EA, lower numbers to US.

(^{2}) This parameter is set equal to zero in the US model.

(^{3}) The std. dev. of the prior distribution for the autocorrelation parameters of $\lambda_{f,t}$, γ_t, σ_t and $\zeta_{i,t}$ are set equal to 0.05, 0.025, 0.1 and 0.1, respectively, in the US.

(^{4}) The mode of the prior distributions for the standard deviations of γ_t, $\zeta_{i,t}$ and η_t^L are set equal to 0.01, 0.01 and 0.001, respectively, in the US model.

Table 5a: EA, Variance Decomposition at Business Cycle Frequency in Alternative Models (in percent)

	$\lambda_{f,t}$	ξ_t	xb_t	$\mu_{\Upsilon,t}$	χ_t	g_t	$\mu_{z,t}$	γ_t	ϵ_t	$Mon.Pol.$	$\zeta_{c,t}$	$\zeta_{i,t}$	τ_t^{oil}	$Term\ Spread$	σ_t	π_t^*	$Meas.Err.$
Stock Market	2	1	0	0	0	0	0	22	0	2	0	2	0	0	69	0	1
	(3)	(–)	(–)	(0)	(–)	(0)	(0)	(77)	(0)	(5)	(0)	(3)	(0)	(–)	(11)	(0)	(1)
Inflation	39	1	1	0	0	1	1	3	20	2	10	13	4	0	4	2	0
	(38)	(–)	(–)	(0)	(–)	(1)	(1)	(4)	(21)	(4)	(13)	(13)	(3)	(–)	(2)	(2)	(0)
	[40]	[–]	[–]	[0]	[–]	[1]	[1]	[–]	[23]	[5]	[5]	[20]	[3]	[–]	[–]	[2]	[0]
Hours	22	2	0	0	0	3	1	4	5	2	12	31	0	0	16	0	0
	(25)	(–)	(–)	(0)	(–)	(3)	(2)	(9)	(5)	(3)	(12)	(29)	(0)	(–)	(11)	(0)	(0)
	[22]	[–]	[–]	[1]	[–]	[5]	[2]	[–]	[7]	[6]	[10]	[46]	[1]	[–]	[–]	[0]	[0]
Credit (real)	11	0	0	0	0	0	0	22	3	0	1	2	1	0	60	0	0
GDP	17	2	0	0	0	2	3	6	11	3	10	20	1	0	23	0	0
	(24)	(–)	(–)	(0)	(–)	(3)	(4)	(13)	(14)	(6)	(12)	(22)	(1)	(–)	(1)	(0)	(0)
	[19]	[–]	[–]	[1]	[–]	[4]	[3]	[–]	[17]	[6]	[9]	[40]	[1]	[–]	[–]	[0]	[0]
Real Wage	47	0	1	0	0	0	28	0	16	0	0	3	3	0	1	0	0
	(33)	(–)	(–)	(0)	(–)	(0)	(46)	(0)	(13)	(0)	(1)	(3)	(2)	(–)	(0)	(0)	(0)
	[30]	[–]	[–]	[0]	[–]	[1]	[46]	[–]	[15]	[1]	[1]	[6]	[2]	[–]	[–]	[0]	[0]
Investment	4	0	0	0	0	0	0	16	0	1	0	42	0	0	36	0	0
	(5)	(–)	(–)	(0)	(–)	(0)	(0)	(35)	(1)	(2)	(1)	(55)	(0)	(–)	(1)	(0)	(0)
	[9]	[–]	[–]	[1]	[–]	[0]	[0]	[–]	[4]	[1]	[1]	[83]	[0]	[–]	[–]	[0]	[0]
Real M1	39	19	4	0	9	0	0	2	10	7	2	1	3	0	3	0	0
Real (M3-M1)	7	20	29	0	6	0	1	4	3	4	13	7	1	0	6	1	0
Consumption	24	3	1	0	0	4	1	1	25	5	29	2	3	0	1	0	0
	(29)	(–)	(–)	(0)	(–)	(4)	(1)	(1)	(24)	(7)	(30)	(2)	(2)	(–)	(0)	(0)	(0)
	[18]	[–]	[–]	[0]	[–]	[6]	[1]	[–]	[24]	[9]	[37]	[4]	[2]	[–]	[–]	[0]	[0]
Premium	0	1	0	0	0	0	0	12	0	1	0	1	0	0	85	0	0
	(1)	(–)	(–)	(0)	(–)	(0)	(0)	(39)	(0)	(2)	(0)	(1)	(0)	(–)	(56)	(0)	(0)
Term Structure	16	6	0	0	0	0	0	4	5	14	6	12	1	24	11	0	0
Interest Rate	18	8	0	0	0	0	1	5	10	17	11	15	2	0	10	1	0
	(22)	(–)	(–)	(0)	(–)	(1)	(1)	(9)	(13)	(21)	(16)	(14)	(2)	(–)	(1)	(1)	(0)
	[24]	[–]	[–]	[0]	[–]	[1]	[1]	[–]	[13]	[29]	[6]	[23]	[2]	[–]	[–]	[1]	[0]
Rel. Price Investment	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0
	(0)	(–)	(–)	(100)	(–)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(–)	(0)	(0)	(0)
	[0]	[–]	[–]	[100]	[–]	[0]	[0]	[–]	[0]	[0]	[0]	[0]	[0]	[–]	[–]	[0]	[0]
Rel. Price Oil	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0
	(0)	(–)	(–)	(0)	(–)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(100)	(–)	(0)	(0)	(0)
	[0]	[–]	[–]	[0]	[–]	[0]	[0]	[–]	[0]	[0]	[0]	[0]	[100]	[–]	[–]	[0]	[0]
Real Reserves	19	7	8	0	14	1	0	3	11	15	5	8	2	0	6	1	0

Legend: For each variable, figures for the baseline model are in the first row. The alternative models, if present, are in the following rows. Financial Accelerator model is denoted by (). Simple model is denoted by []. Note: Periodic components with cycles of 8-32 quarters, obtained using the model spectrum.

Table 5b: US, Variance Decomposition, Business Cycle Frequency, in Alternative Models (in percent)

	$\lambda_{f,t}$	ξ_t	xb_t	$\mu_{\Upsilon,t}$	χ_t	g_t	$\mu_{z,t}$	γ_t	ϵ_t	$Mon.Pol.$	$\zeta_{c,t}$	$\zeta_{i,t}$	τ_t^{oil}	$Term\ Spread$	σ_t	π_t^*	$Meas.Err.$
Stock Market	0	0	0	0	0	0	0	9	0	1	0	1	0	0	83	0	4
	(1)	(–)	(–)	(0)	(–)	(0)	(0)	(87)	(0)	(1)	(0)	(1)	(0)	(–)	(6)	(0)	(2)
Inflation	42	1	0	0	0	2	1	1	23	4	13	4	3	0	6	1	0
	(45)	(–)	(–)	(0)	(–)	(1)	(1)	(5)	(33)	(2)	(6)	(4)	(2)	(–)	(0)	(0)	(0)
	[50]	[–]	[–]	[0]	[–]	[2]	[1]	[–]	[17]	[4]	[5]	[14]	[6]	[–]	[–]	[1]	[0]
Hours	6	1	0	0	0	8	2	4	15	6	21	17	1	0	19	0	0
	(12)	(–)	(–)	(0)	(–)	(6)	(2)	(21)	(26)	(4)	(12)	(15)	(1)	(–)	(1)	(0)	(0)
	[5]	[–]	[–]	[1]	[–]	[13]	[4]	[–]	[10]	[6]	[10]	[50]	[1]	[–]	[–]	[0]	[0]
Credit (real)	4	0	0	0	0	0	0	18	2	0	1	0	1	0	73	0	0
GDP	5	0	0	0	0	7	6	2	9	6	18	14	1	0	30	0	0
	(12)	(–)	(–)	(0)	(–)	(7)	(4)	(18)	(20)	(4)	(14)	(16)	(2)	(–)	(1)	(0)	(0)
	[5]	[–]	[–]	[1]	[–]	[12]	[6]	[–]	[15]	[5]	[10]	[44]	[3]	[–]	[–]	[0]	[0]
Real Wage	32	0	0	0	0	1	37	0	18	1	2	2	3	0	4	0	0
	(29)	(–)	(–)	(0)	(–)	(1)	(42)	(1)	(21)	(0)	(1)	(2)	(2)	(–)	(0)	(0)	(0)
	[32]	[–]	[–]	[0]	[–]	[1]	[42]	[–]	[13]	[1]	[1]	[6]	[5]	[–]	[–]	[0]	[0]
Investment	0	0	0	0	0	0	1	6	0	1	0	34	0	0	57	0	0
	(1)	(–)	(–)	(0)	(–)	(0)	(0)	(53)	(1)	(0)	(0)	(43)	(0)	(–)	(1)	(0)	(0)
	[1]	[–]	[–]	[1]	[–]	[0]	[0]	[–]	[5]	[1]	[3]	[87]	[0]	[–]	[–]	[0]	[0]
Real M2	36	0	4	0	12	1	0	1	17	14	6	1	4	0	3	0	0
Real (CP+Repos)	20	1	20	0	1	1	2	1	13	8	20	3	2	0	7	0	0
Consumption	8	1	1	0	0	4	1	0	19	10	46	1	4	0	4	0	0
	(18)	(–)	(–)	(0)	(–)	(4)	(0)	(3)	(32)	(6)	(29)	(1)	(5)	(–)	(0)	(0)	(0)
	[6]	[–]	[–]	[0]	[–]	[6]	[2]	[–]	[19]	[8]	[51]	[3]	[5]	[–]	[–]	[0]	[0]
Premium	0	0	0	0	0	0	0	3	0	0	0	0	0	0	96	0	0
	(0)	(–)	(–)	(0)	(–)	(0)	(0)	(51)	(0)	(0)	(0)	(0)	(0)	(–)	(48)	(0)	(0)
Term Structure	24	0	0	0	0	1	1	2	14	12	10	5	2	15	15	0	0
Interest Rate	24	0	0	0	0	2	2	2	19	13	19	4	3	0	10	1	0
	(31)	(–)	(–)	(0)	(–)	(2)	(2)	(10)	(30)	(8)	(10)	(5)	(3)	(–)	(0)	(0)	(0)
	[31]	[–]	[–]	[0]	[–]	[3]	[2]	[–]	[15]	[16]	[7]	[20]	[5]	[–]	[–]	[1]	[0]
Rel. Price Investment	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0
	(0)	(–)	(–)	(100)	(–)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(–)	(0)	(0)	(0)
	[0]	[–]	[–]	[100]	[–]	[0]	[0]	[–]	[0]	[0]	[0]	[0]	[0]	[–]	[–]	[0]	[0]
Rel. Price Oil	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0
	(0)	(–)	(–)	(0)	(–)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(100)	(–)	(0)	(0)	(0)
	[0]	[–]	[–]	[0]	[–]	[0]	[0]	[–]	[0]	[0]	[0]	[0]	[100]	[–]	[–]	[0]	[0]
Reserves (real)	15	34	5	0	11	1	1	0	10	13	4	2	1	0	3	0	0

Legend: For each variable, figures for the baseline model are in the first row. The alternative models, if present, are in the following rows. Financial Accelerator model is denoted by (). Simple model is denoted by []. Note: Periodic components with cycles of 8-32 quarters, obtained using the model spectrum.

Table 6a: EA, Variance Decomposition at Low Frequency in Alternative Models (in percent)

	$\lambda_{f,t}$	ξ_t	xb_t	$\mu_{\Upsilon,t}$	χ_t	g_t	$\mu_{z,t}$	γ_t	ϵ_t	$Mon.Pol.$	$\zeta_{c,t}$	$\zeta_{i,t}$	τ_t^{oil}	$Term\ Spread$	σ_t	π_t^*	$Meas.Err.$
Stock Market	1	1	0	0	0	0	0	27	0	2	0	3	0	0	63	0	2
	(2)	(–)	(–)	(0)	(–)	(0)	(0)	(83)	(0)	(4)	(0)	(4)	(0)	(–)	(3)	(0)	(2)
Inflation	26	2	0	0	0	1	1	10	14	3	13	13	3	0	8	5	0
	(25)	(–)	(–)	(0)	(–)	(1)	(1)	(14)	(16)	(6)	(18)	(13)	(2)	(–)	(0)	(4)	(0)
	[33]	[–]	[–]	[0]	[–]	[1]	[1]	[–]	[19]	[7]	[6]	[24]	[3]	[–]	[–]	[6]	[0]
Hours	31	2	0	0	0	2	1	9	1	2	8	30	0	0	13	0	0
	(38)	(–)	(–)	(0)	(–)	(2)	(2)	(14)	(1)	(3)	(8)	(28)	(0)	(–)	(2)	(0)	(0)
	[37]	[–]	[–]	[1]	[–]	[3]	[2]	[–]	[2]	[5]	[6]	[43]	[1]	[–]	[–]	[0]	[0]
Credit (real)	3	0	0	0	0	0	0	16	1	0	0	2	0	0	77	0	0
GDP	15	1	0	0	0	1	4	13	9	2	4	15	1	0	35	0	0
	(23)	(–)	(–)	(0)	(–)	(2)	(5)	(26)	(13)	(3)	(7)	(18)	(1)	(–)	(1)	(0)	(0)
	[25]	[–]	[–]	[1]	[–]	[2]	[5]	[–]	[23]	[4]	[5]	[34]	[1]	[–]	[–]	[0]	[0]
Real Wage	51	0	1	0	0	0	14	3	17	0	0	5	3	0	5	0	0
	(44)	(–)	(–)	(0)	(–)	(1)	(26)	(5)	(15)	(1)	(0)	(6)	(2)	(–)	(0)	(0)	(0)
	[38]	[–]	[–]	[0]	[–]	[1]	[31]	[–]	[19]	[1]	[0]	[8]	[2]	[–]	[–]	[0]	[0]
Investment	7	1	0	0	0	0	0	24	1	1	0	24	0	0	42	0	0
	(9)	(–)	(–)	(0)	(–)	(0)	(1)	(52)	(1)	(2)	(1)	(33)	(0)	(–)	(1)	(0)	(0)
	[19]	[–]	[–]	[2]	[–]	[0]	[1]	[–]	[10]	[2]	[2]	[64]	[0]	[–]	[–]	[0]	[0]
Real M1	35	7	5	0	13	0	0	7	11	3	3	2	4	0	10	1	0
Real (M3-M1)	6	6	33	0	2	0	1	10	3	1	13	8	1	0	14	2	0
Consumption	15	1	1	0	0	5	2	7	25	2	19	5	3	0	14	0	0
	(23)	(–)	(–)	(0)	(–)	(5)	(2)	(9)	(24)	(2)	(26)	(6)	(2)	(–)	(0)	(0)	(0)
	[14]	[–]	[–]	[1]	[–]	[9]	[2]	[–]	[25]	[4]	[35]	[8]	[2]	[–]	[–]	[0]	[0]
Premium	0	0	0	0	0	0	0	15	0	1	0	1	0	0	82	0	0
	(1)	(–)	(–)	(0)	(–)	(0)	(0)	(64)	(0)	(3)	(0)	(1)	(0)	(–)	(30)	(0)	(0)
Term Structure	12	2	0	0	0	0	0	10	4	5	7	12	1	24	22	0	0
Interest Rate	13	2	0	0	0	1	1	16	8	5	13	15	3	0	21	2	0
	(16)	(–)	(–)	(0)	(–)	(1)	(1)	(23)	(11)	(6)	(23)	(14)	(2)	(–)	(0)	(2)	(0)
	[24]	[–]	[–]	[1]	[–]	[1]	[1]	[–]	[14]	[14]	[7]	[33]	[2]	[–]	[–]	[3]	[0]
Rel. Price Investment	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0
	(0)	(–)	(–)	(100)	(–)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(–)	(0)	(0)	(0)
	[0]	[–]	[–]	[100]	[–]	[0]	[0]	[–]	[0]	[0]	[0]	[0]	[0]	[–]	[–]	[0]	[0]
Rel. Price Oil	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0
	(0)	(–)	(–)	(0)	(–)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(100)	(–)	(0)	(0)	(0)
	[0]	[–]	[–]	[0]	[–]	[0]	[0]	[–]	[0]	[0]	[0]	[0]	[100]	[–]	[–]	[0]	[0]
Real Reserves	12	7	9	0	14	1	0	11	9	5	6	9	3	0	14	1	0

Legend: For each variable, figures for the baseline model are in the first row. The alternative models, if present, are in the following rows. Financial Accelerator model is denoted by (). Simple model is denoted by []. Note: Periodic components with cycles of 33-60 quarters, obtained using the model spectrum.

Table 6b: US, Variance Decomposition at Low Frequency in Alternative Models (in percent)

	$\lambda_{f,t}$	ξ_t	xb_t	$\mu_{\Upsilon,t}$	χ_t	g_t	$\mu_{z,t}$	γ_t	ϵ_t	$Mon.Pol.$	$\zeta_{c,t}$	$\zeta_{i,t}$	τ_t^{oil}	$Term\ Spread$	σ_t	π_t^*	$Meas.Err.$
Stock Market	0	0	0	0	0	0	0	12	0	1	0	2	0	0	74	0	10
	(0)	(–)	(–)	(0)	(–)	(0)	(0)	(90)	(0)	(1)	(0)	(2)	(0)	(–)	(2)	(0)	(5)
Inflation	16	2	0	0	0	2	2	2	19	8	25	4	3	0	13	3	0
	(21)	(–)	(–)	(0)	(–)	(2)	(2)	(18)	(27)	(4)	(15)	(5)	(3)	(–)	(0)	(1)	(0)
	[26]	[–]	[–]	[0]	[–]	[3]	[2]	[–]	[18]	[9]	[9]	[22]	[7]	[–]	[–]	[5]	[0]
Hours	3	1	0	0	0	8	3	4	5	7	19	17	1	0	31	0	0
	(10)	(–)	(–)	(0)	(–)	(6)	(6)	(34)	(3)	(5)	(13)	(20)	(2)	(–)	(0)	(0)	(0)
	[3]	[–]	[–]	[1]	[–]	[11]	[6]	[–]	[2]	[8]	[8]	[59]	[2]	[–]	[–]	[0]	[0]
Credit (real)	1	0	0	0	0	0	0	8	1	0	1	1	0	0	88	0	0
GDP	1	0	0	0	0	4	10	4	7	4	9	11	1	0	47	0	0
	(5)	(–)	(–)	(0)	(–)	(3)	(8)	(43)	(14)	(2)	(8)	(15)	(3)	(–)	(1)	(0)	(0)
	[2]	[–]	[–]	[1]	[–]	[8]	[11]	[–]	[20]	[4]	[9]	[41]	[3]	[–]	[–]	[0]	[0]
Real Wage	19	0	0	0	0	1	32	1	21	1	2	4	6	0	12	0	0
	(15)	(–)	(–)	(0)	(–)	(1)	(42)	(12)	(19)	(1)	(1)	(5)	(4)	(–)	(0)	(0)	(0)
	[21]	[–]	[–]	[0]	[–]	[1]	[42]	[–]	[17]	[1]	[0]	[10]	[7]	[–]	[–]	[0]	[0]
Investment	0	0	0	1	0	0	2	10	0	1	0	21	0	0	64	0	0
	(0)	(–)	(–)	(0)	(–)	(0)	(1)	(75)	(1)	(0)	(0)	(21)	(0)	(–)	(1)	(0)	(0)
	[1]	[–]	[–]	[2]	[–]	[1]	[2]	[–]	[10]	[2]	[9]	[72]	[1]	[–]	[–]	[0]	[0]
Real M2	14	0	7	0	19	1	1	2	15	7	9	2	6	0	16	1	0
Real (CP+Repos)	6	1	29	0	1	1	3	2	9	3	29	3	2	0	12	1	0
Consumption	2	0	1	0	0	6	4	2	15	4	30	4	5	0	27	0	0
	(7)	(–)	(–)	(0)	(–)	(6)	(2)	(22)	(24)	(2)	(22)	(7)	(7)	(–)	(1)	(0)	(0)
	[2]	[–]	[–]	[0]	[–]	[7]	[4]	[–]	[15]	[4]	[55]	[9]	[4]	[–]	[–]	[0]	[0]
Premium	0	0	0	0	0	0	0	5	0	0	0	0	0	0	95	0	0
	(0)	(–)	(–)	(0)	(–)	(0)	(0)	(77)	(0)	(0)	(0)	(0)	(0)	(–)	(22)	(0)	(0)
Term Structure	8	0	0	0	0	1	1	4	12	5	17	5	2	17	26	0	0
Interest Rate	7	0	0	0	0	3	4	4	15	5	32	4	3	0	21	1	0
	(12)	(–)	(–)	(0)	(–)	(2)	(3)	(28)	(23)	(2)	(19)	(6)	(3)	(–)	(1)	(1)	(0)
	[14]	[–]	[–]	[1]	[–]	[3]	[3]	[–]	[15]	[10]	[13]	[33]	[6]	[–]	[–]	[3]	[0]
Rel. Price Investment	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0
	(0)	(–)	(–)	(100)	(–)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(–)	(0)	(0)	(0)
	[0]	[–]	[–]	[100]	[–]	[0]	[0]	[–]	[0]	[0]	[0]	[0]	[0]	[–]	[–]	[0]	[0]
Rel. Price Oil	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0
	(0)	(–)	(–)	(0)	(–)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(100)	(–)	(0)	(0)	(0)
	[0]	[–]	[–]	[0]	[–]	[0]	[0]	[–]	[0]	[0]	[0]	[0]	[100]	[–]	[–]	[0]	[0]
Reserves (real)	2	68	3	0	7	1	1	1	4	2	4	1	1	0	6	0	0

Legend: For each variable, figures for the baseline model are in the first row. The alternative models, if present, are in the following rows. Financial Accelerator model is denoted by (). Simple model is denoted by []. Note: Periodic components with cycles of 33-60 quarters, obtained using the model spectrum.

Table 7a: EA, Log Marginal Likelihood

Model Variants \ Dataset	Baseline	Financial Accelerator & Credit	Financial Accelerator
Baseline	4941.24	3909.54	3632.17
Baseline without Signals	4598.17	3618.00	3615.22
Financial Accelerator	–	3628.02	3616.19
Financial Accelerator with signals	–	3957.02	3633.06
Baseline with No Fisher Effect	4867.09	–	–
Baseline with Signals on Financial Wealth Shock (γ) and No Signals on Risk Shock (σ)	4895.65	–	–
Baseline with Signals on Technology Shocks and No Signals on Risk Shock (σ)	4860.26	–	–

Table 7b: US, Log Marginal Likelihood

Model Variants \ Dataset	Baseline	Financial Accelerator & Credit	Financial Accelerator
Baseline	4642.80	3711.11	3434.27
Baseline without Signals	4315.72	3373.59	3382.42
Financial Accelerator	–	3376.16	3383.09
Financial Accelerator with signals	–	3691.09	3433.47
Baseline with No Fisher Effect	4615.50	–	–
Baseline with Signals on Financial Wealth Shock (γ) and No Signals on Risk Shock (σ)	4594.50	–	–
Baseline with Signals on Technology Shocks and No Signals on Risk Shock (σ)	4551.81	–	–

Figure 1a: EA, Actual (solid line) and Fitted (dotted line) Data

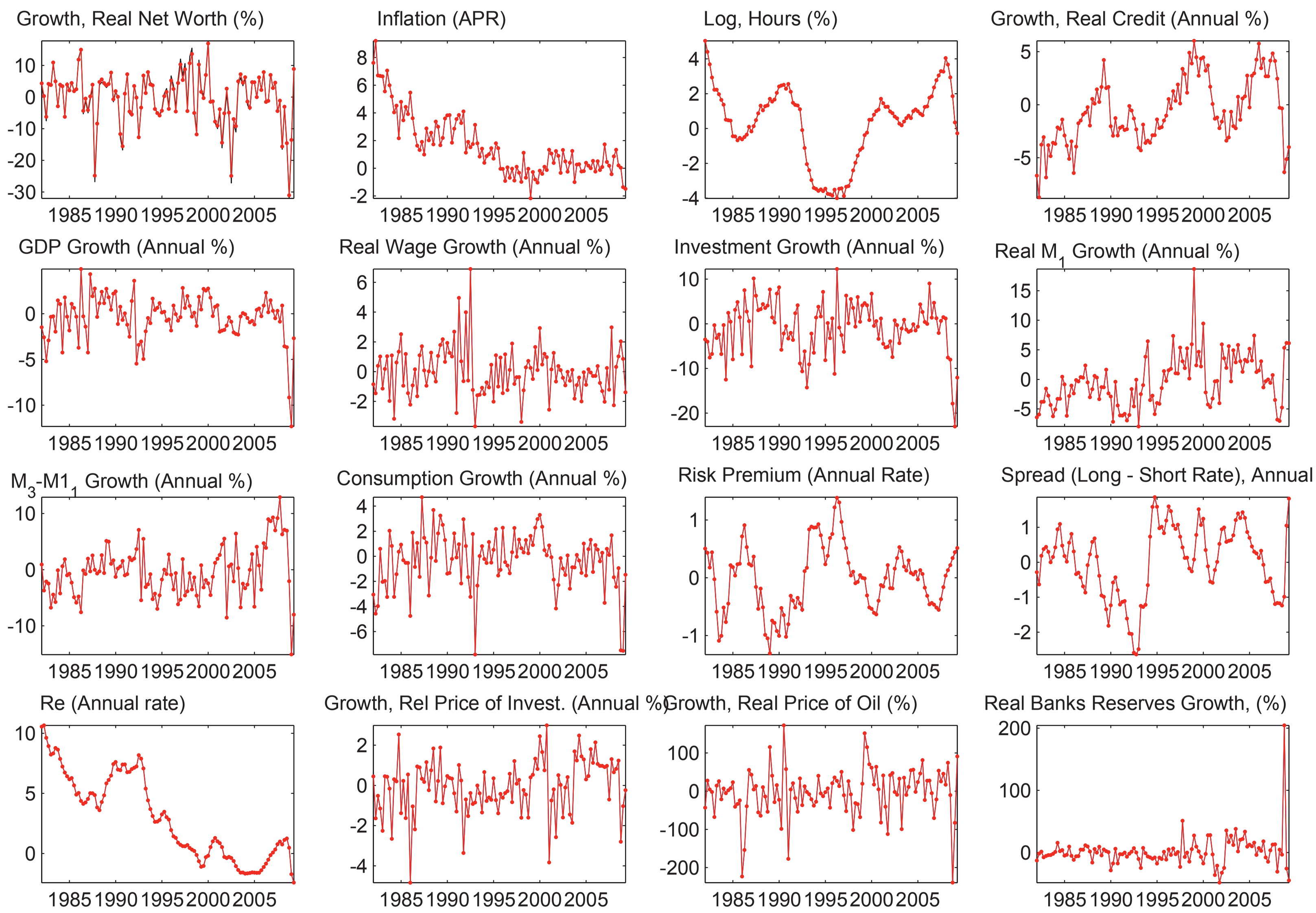


Figure 1b: US, Actual (solid line) and Fitted (dotted line) Data

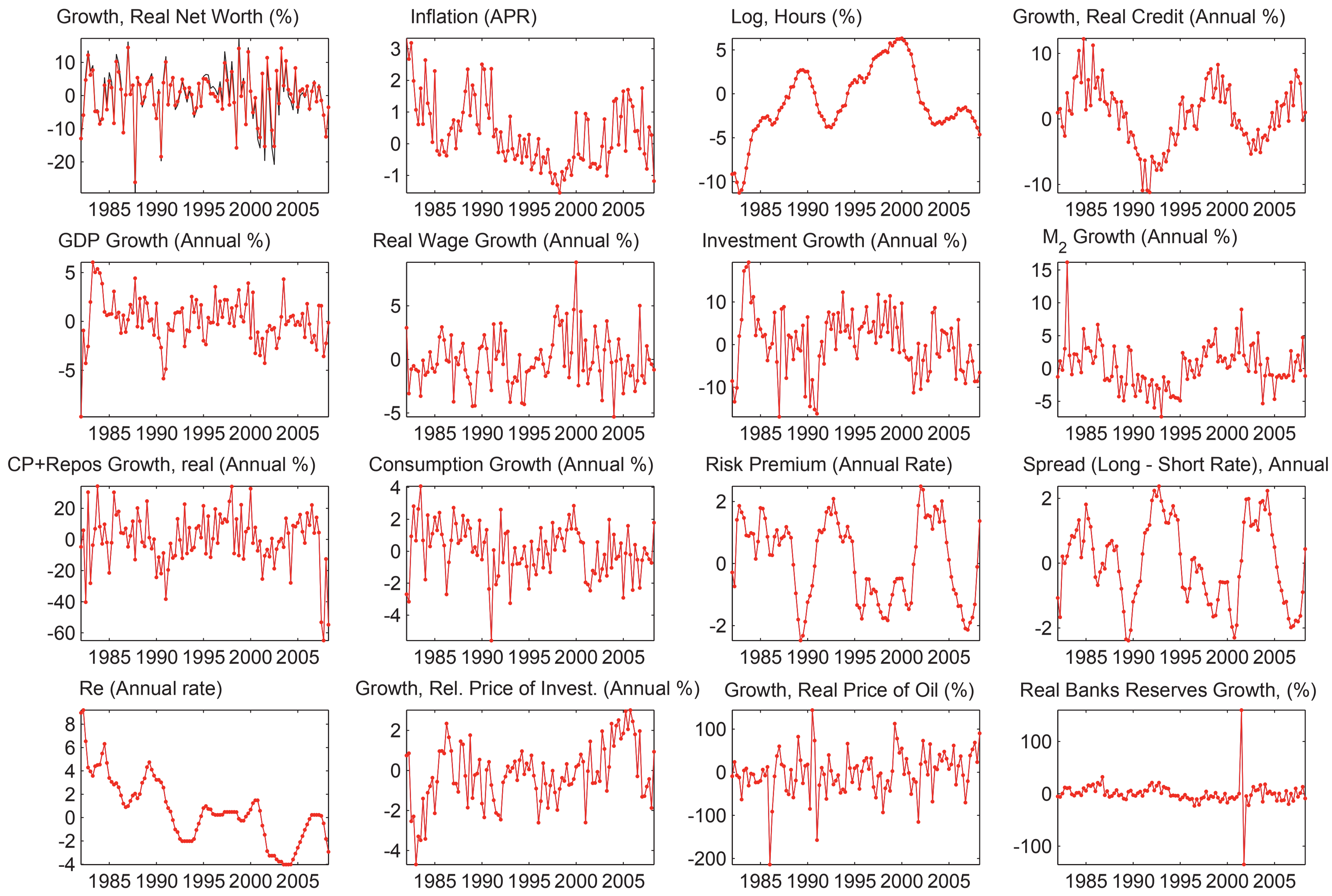


Figure 2a: Priors and Posteriors (US - thick line, EA - thin line). Model Parameters

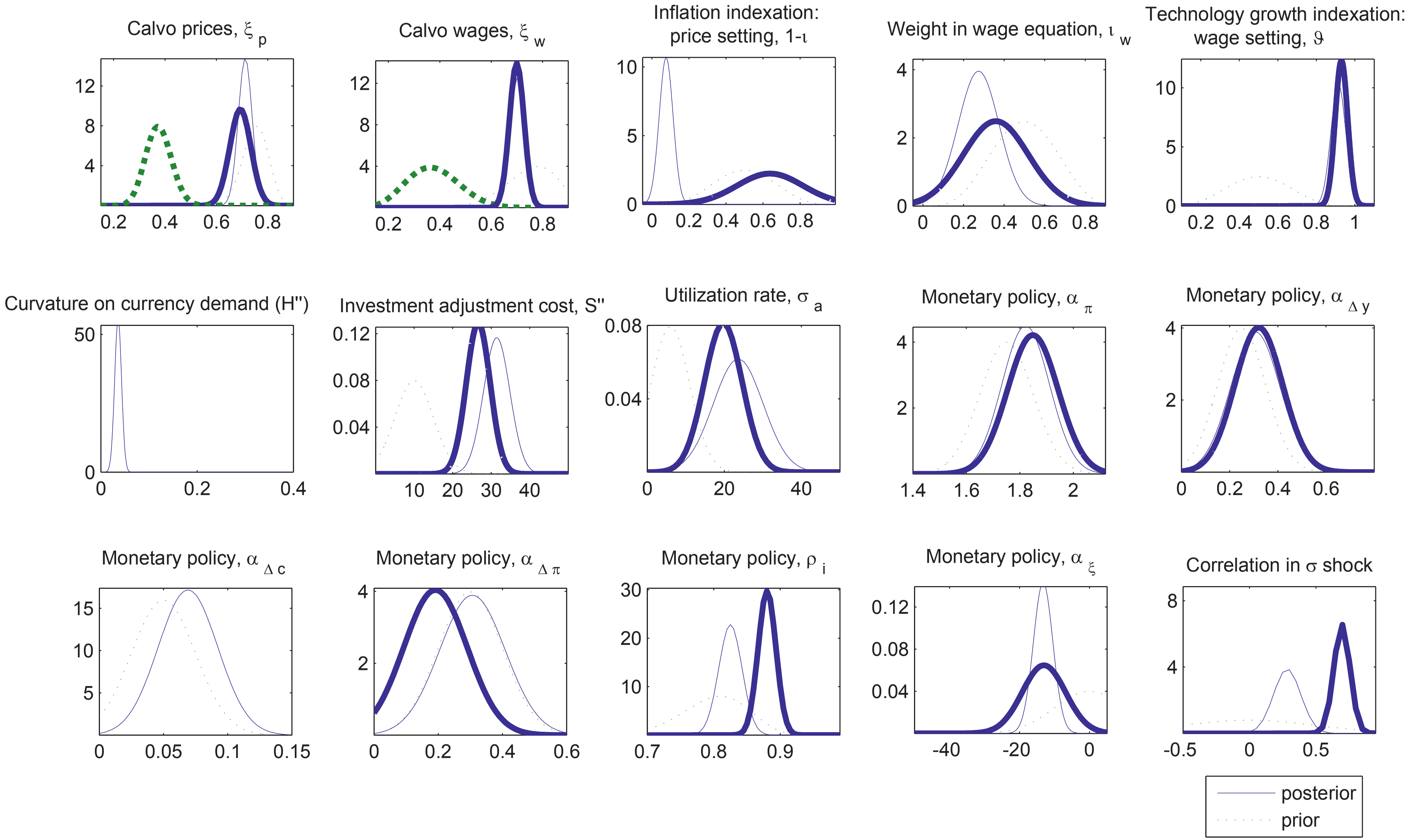
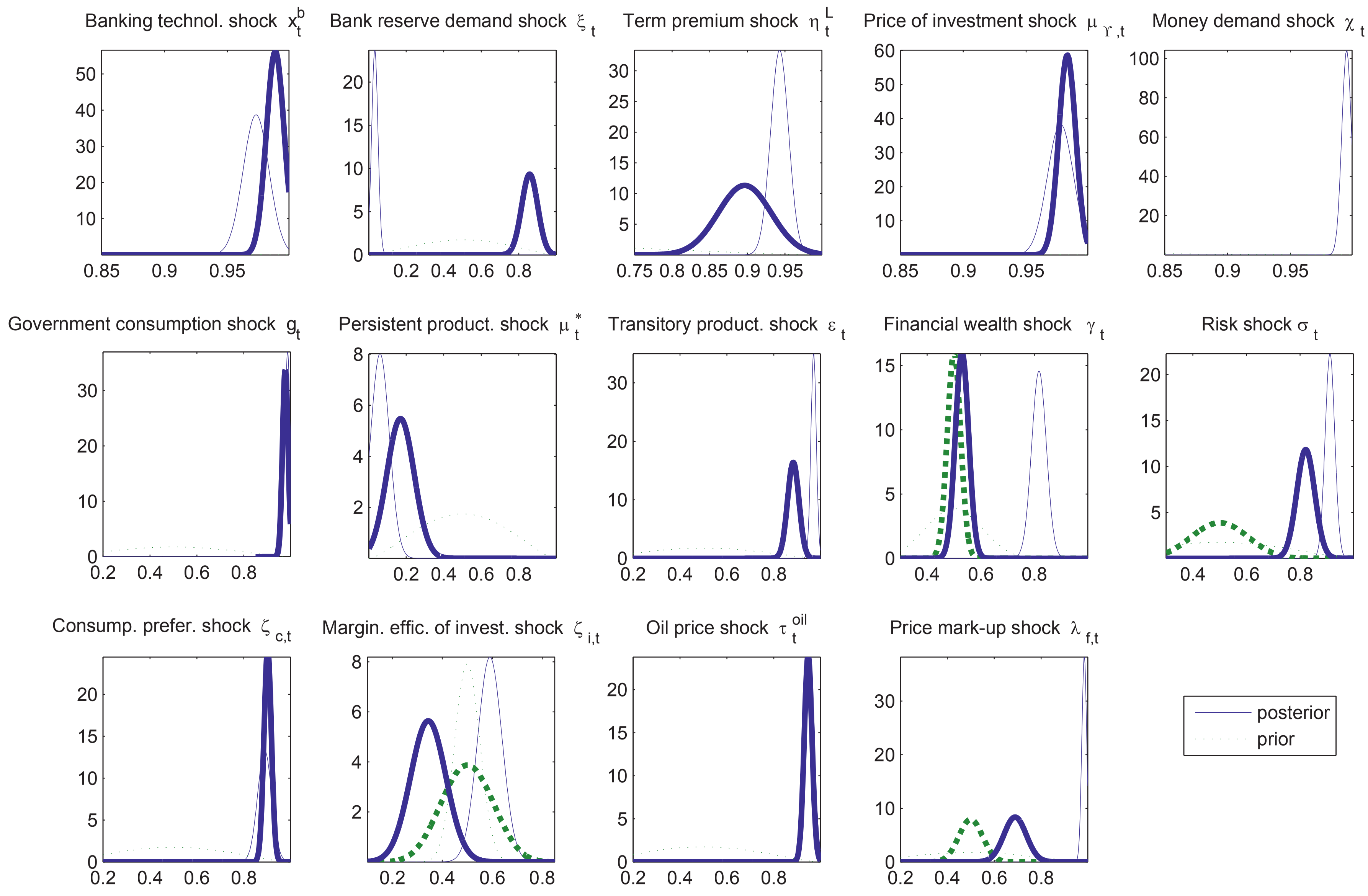


Figure 2b: Priors and Posteriors (US - thick line, EA - thin line). Autoregressive coefficients



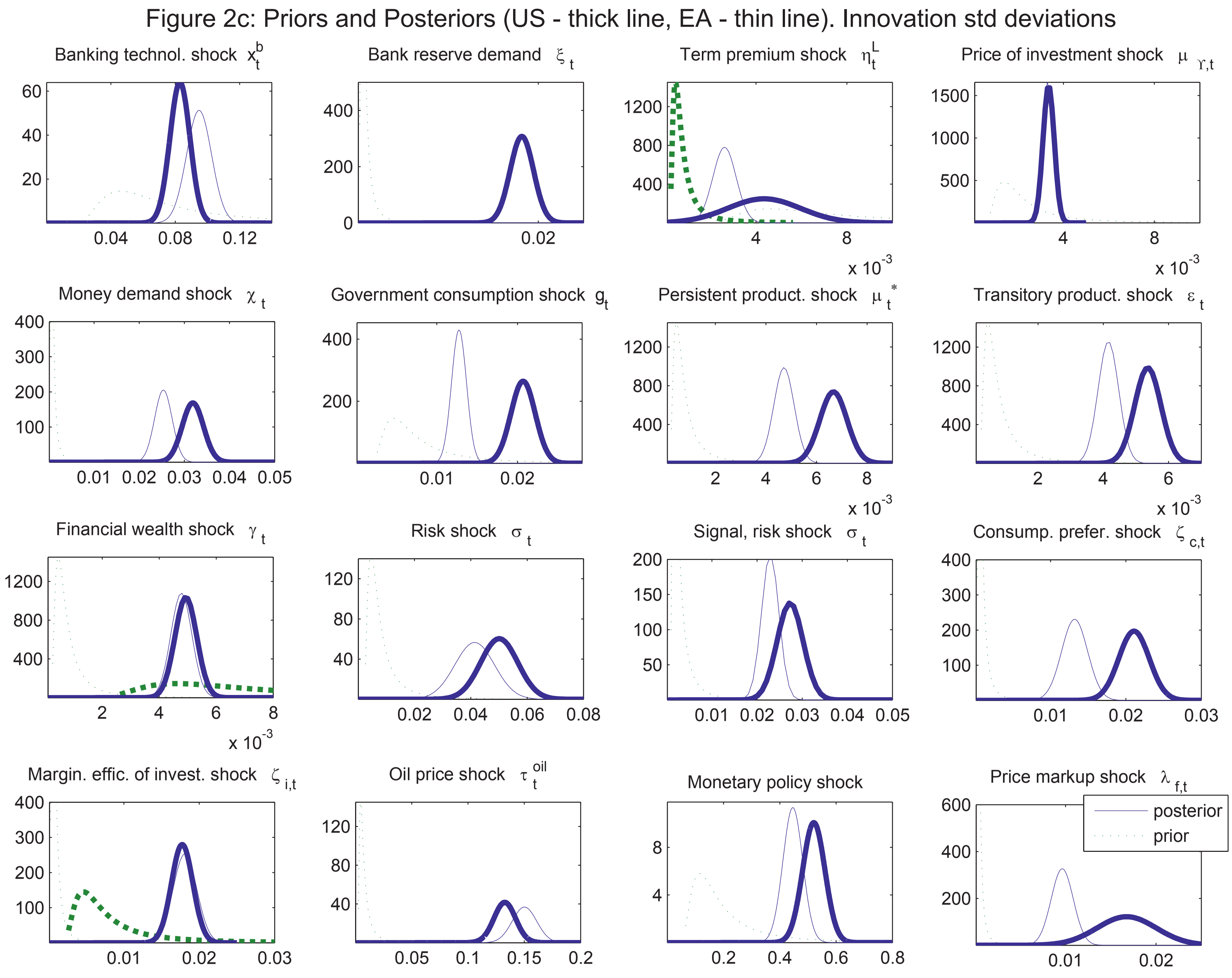


Figure 2c: Priors and Posteriors (US - thick line, EA - thin line). Innovation std deviations
Banking technol. shock x_t^b
Bank reserve demand ξ_t
Term premium shock η_t^L
Price of investment shock $\mu_{\Upsilon,t}$
Money demand shock χ_t
Government consumption shock g_t
Persistent product. shock μ_t^*
Transitory product. shock ε_t
Financial wealth shock γ_t
Risk shock σ_t
Signal, risk shock σ_t
Consump. prefer. shock $\zeta_{c,t}$
Margin. effic. of invest. shock $\zeta_{i,t}$
Oil price shock τ_t^{oil}
Monetary policy shock
Price markup shock $\lambda_{f,t}$
posterior
prior
x 10^{-3}

Figure 3a: EA, Cross-correlations: Baseline Model and Data

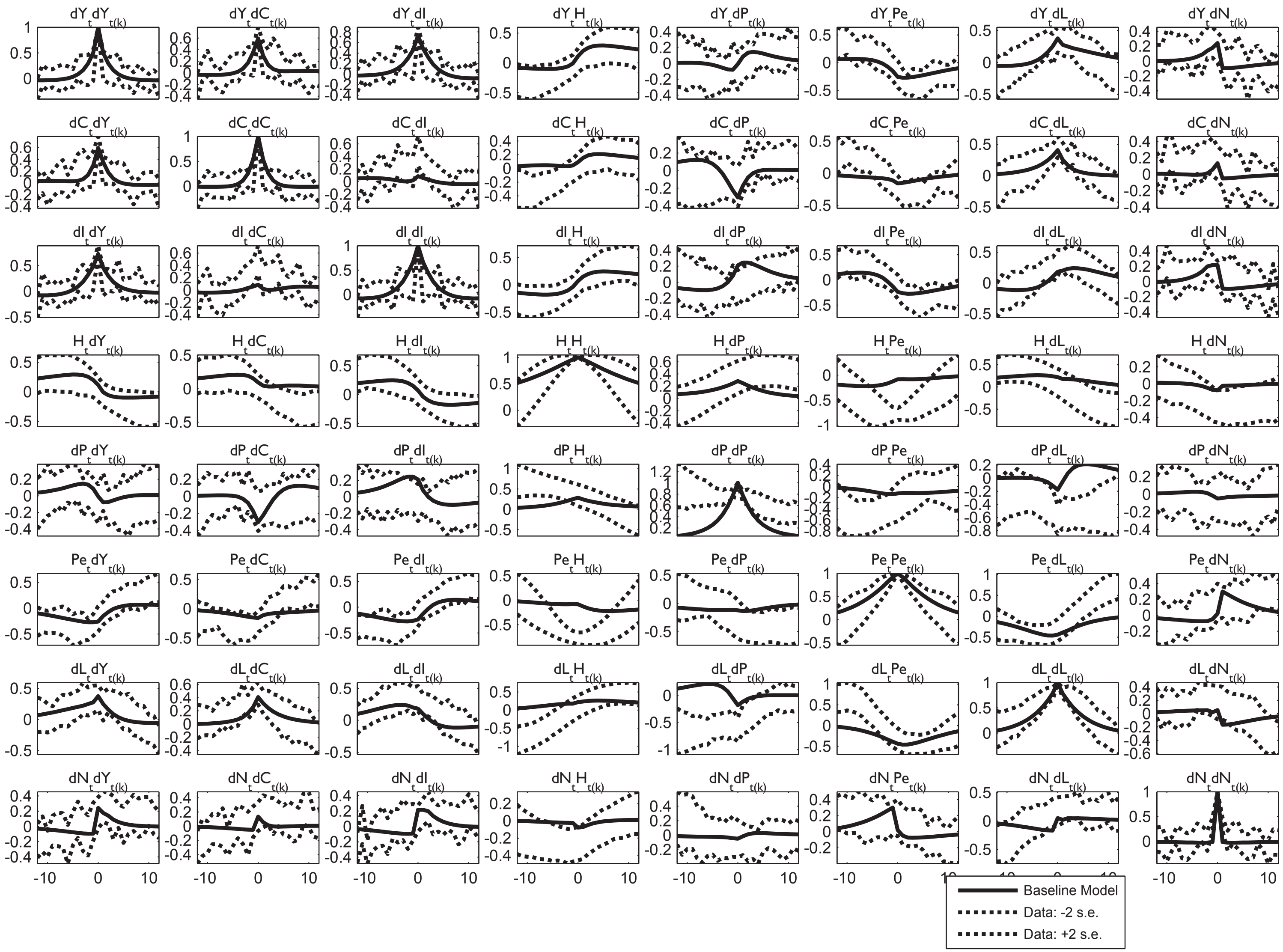


Figure 3b: US, Cross-correlations: Model and Data

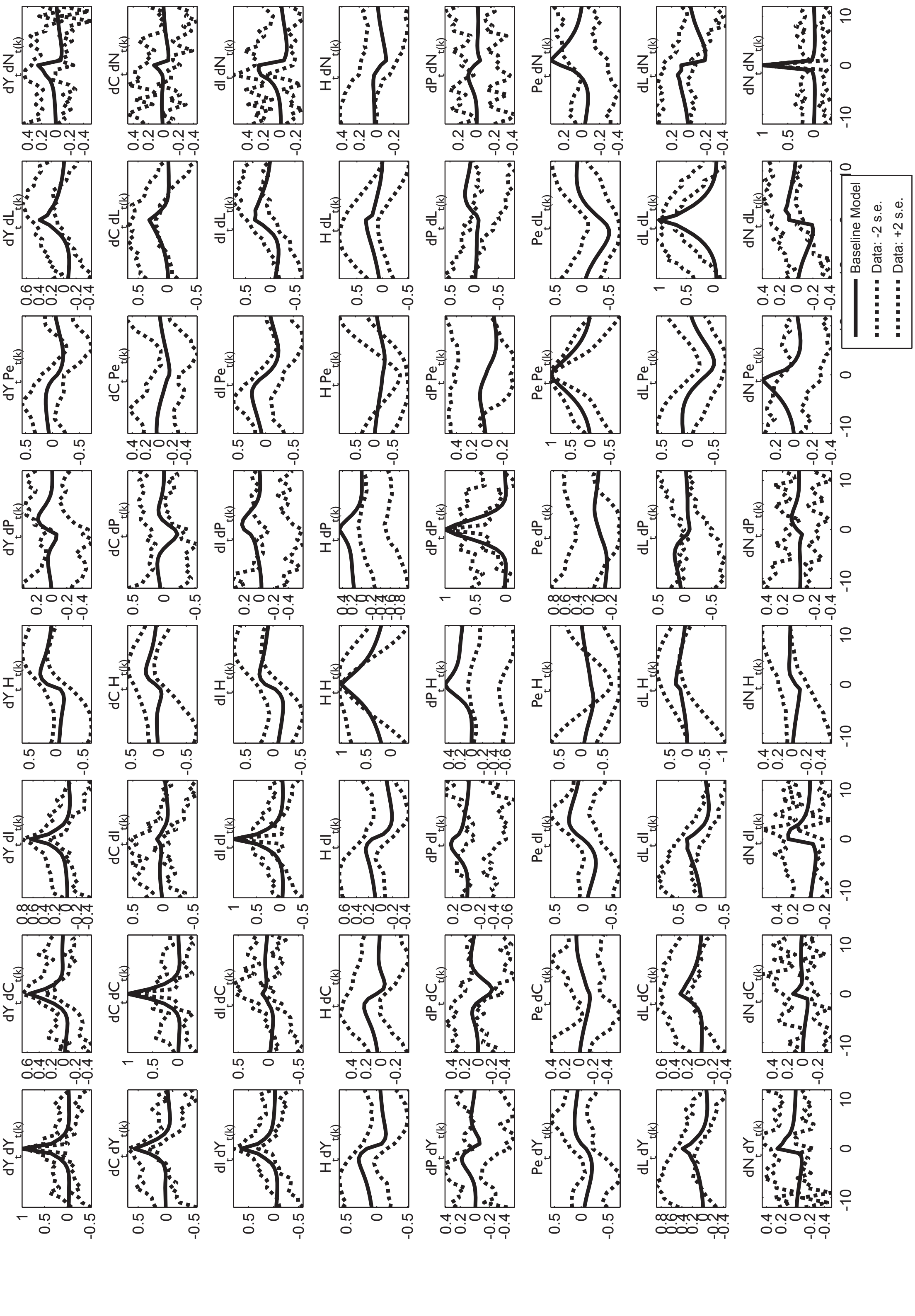


Figure 4: RMSE, Confidence band represents 2 std and is centred around BVAR (in percent)

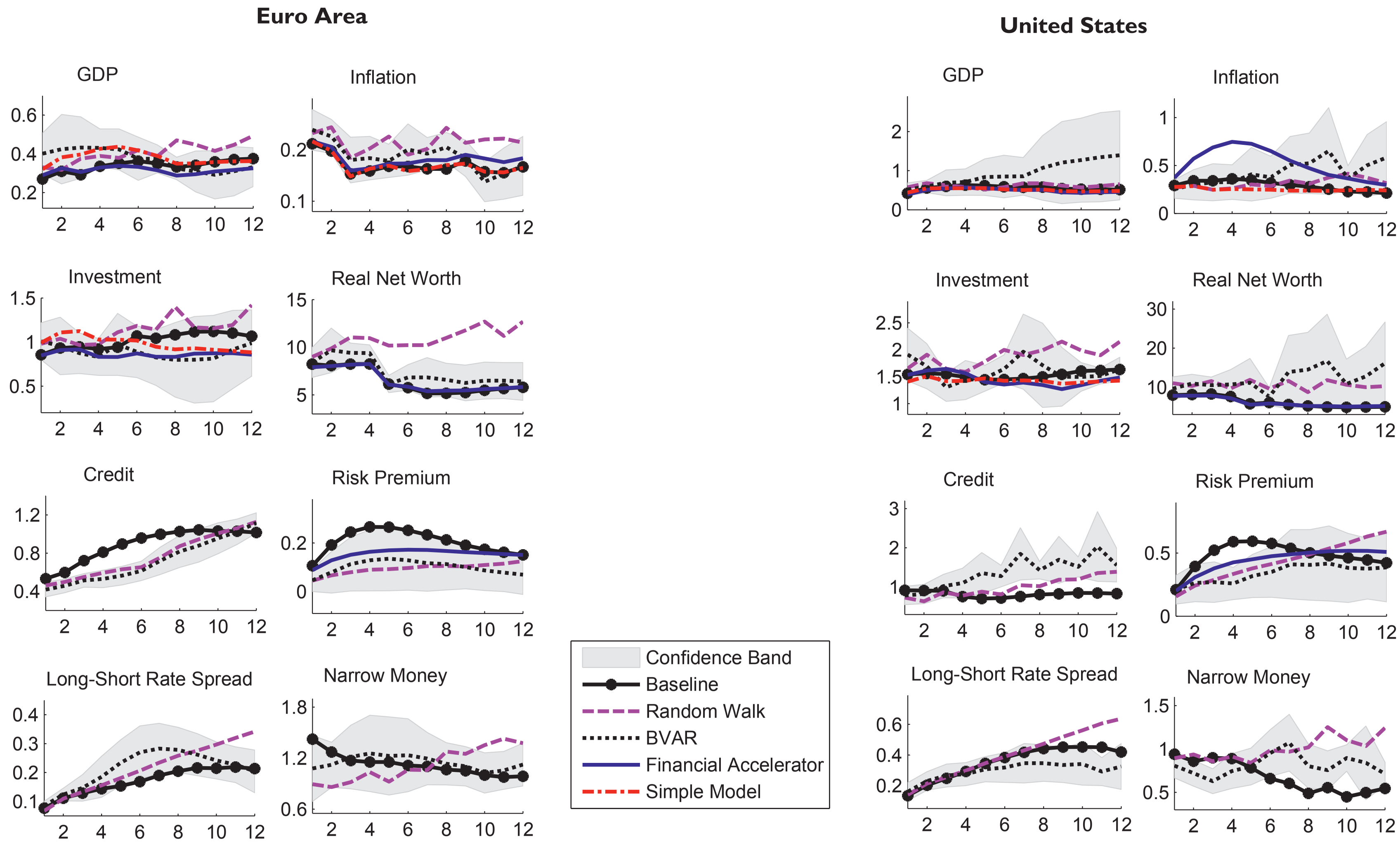


Figure 5: Cross-correlations: Models and Data (both HP filtered)

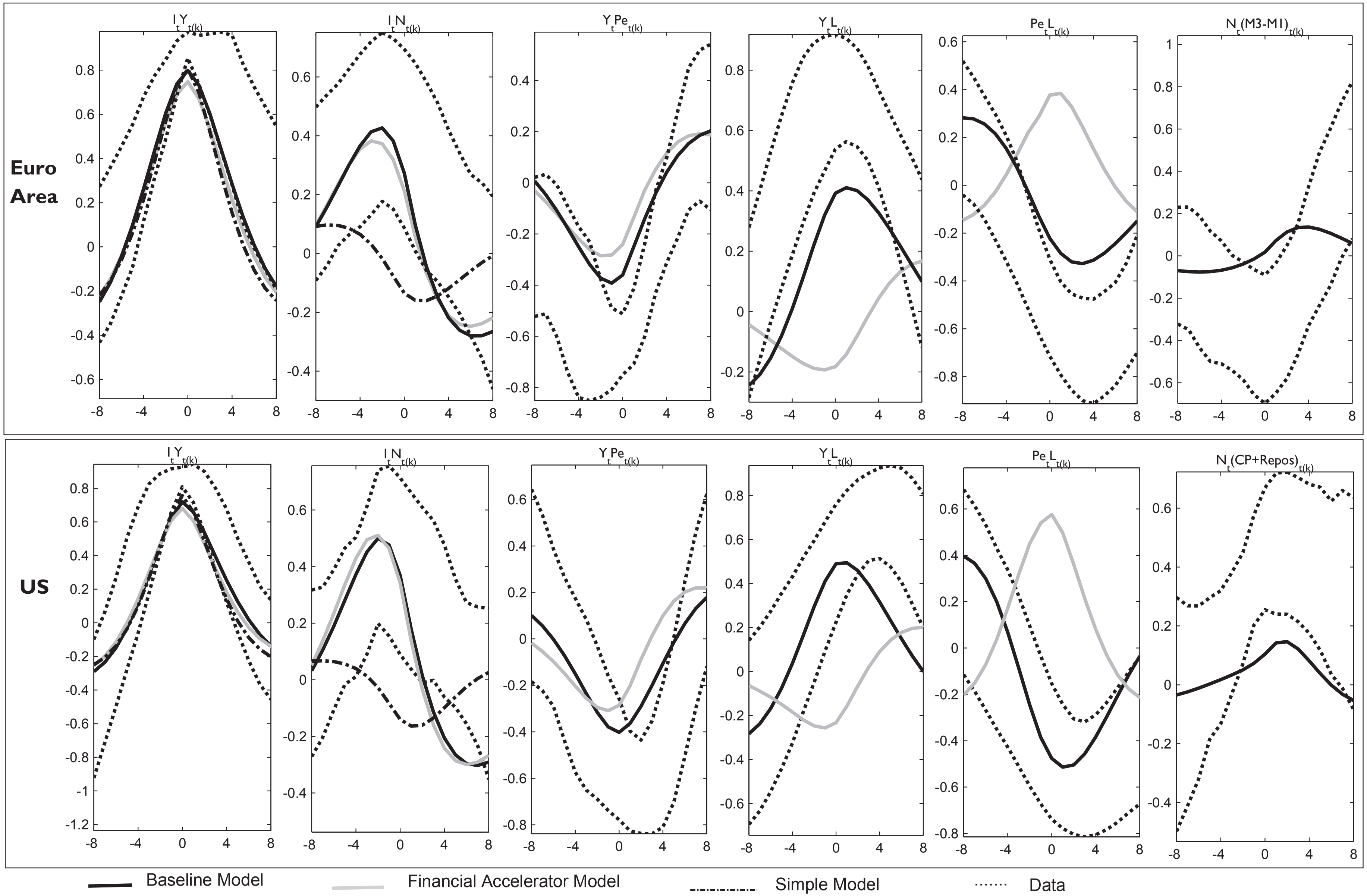


Figure 6. The Market for Capital: Demand and Supply

Figure 6a. Simple Model

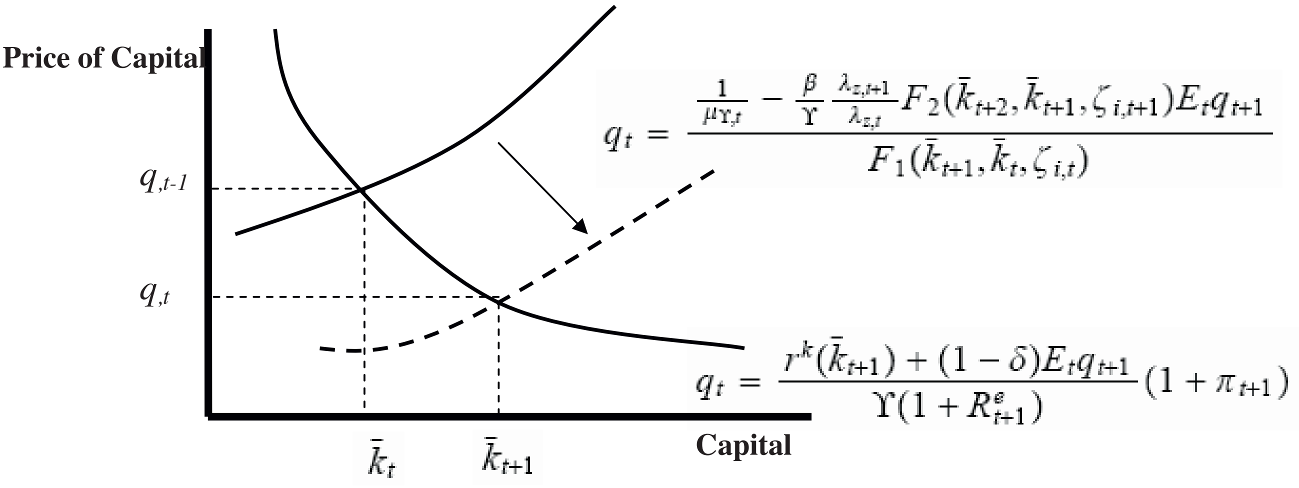


Figure 6b. Financial Accelerator Model and Baseline Model

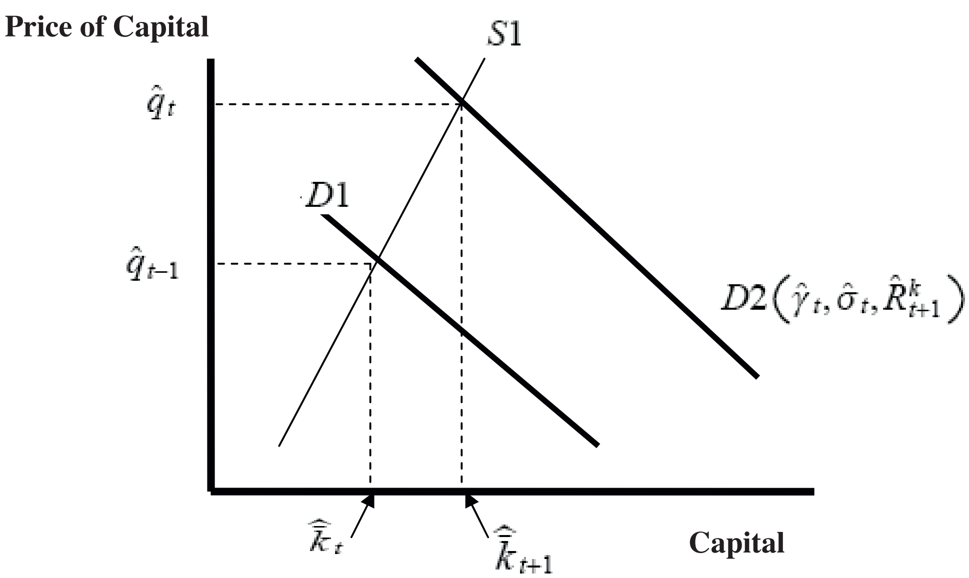


Figure 7a. Capital and Credit Markets in the Financial Accelerator Model after a γ shock

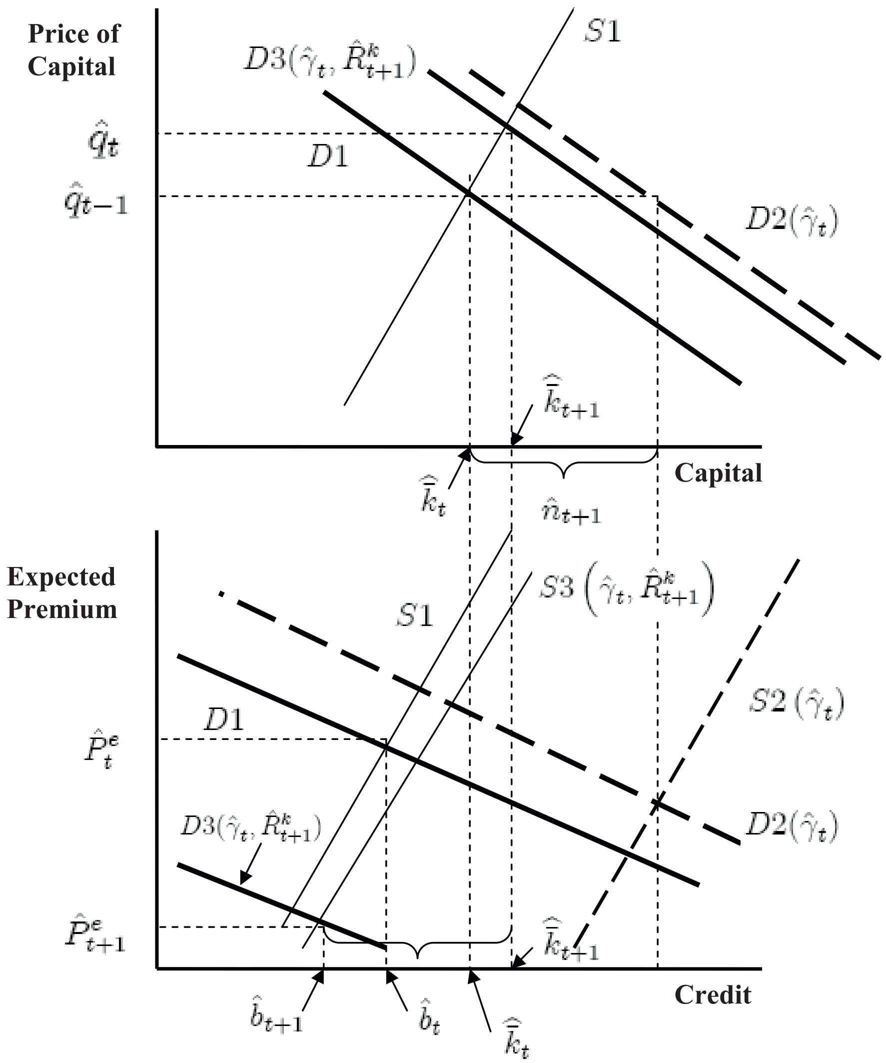


Figure 7b. Capital and Credit Markets in the baseline model after a risk shock

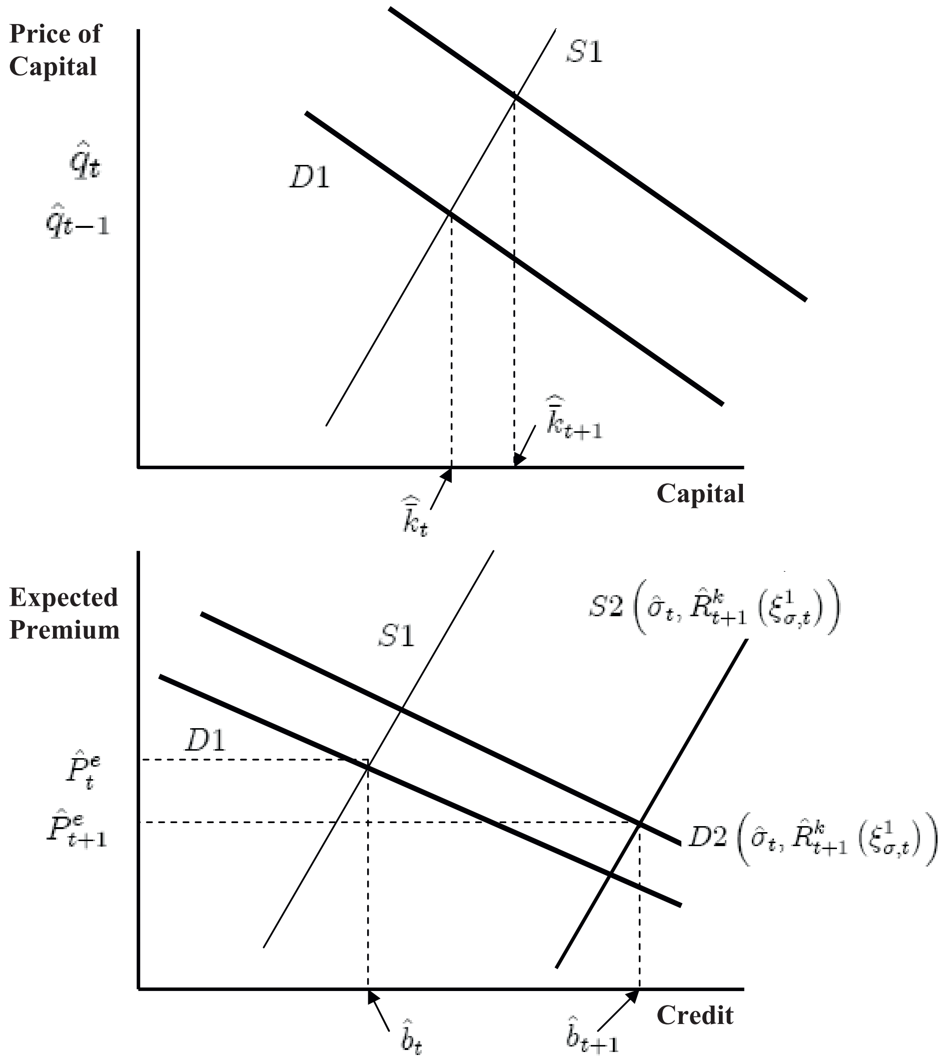


Figure 8a. EA, Driving Forces in Alternative Models

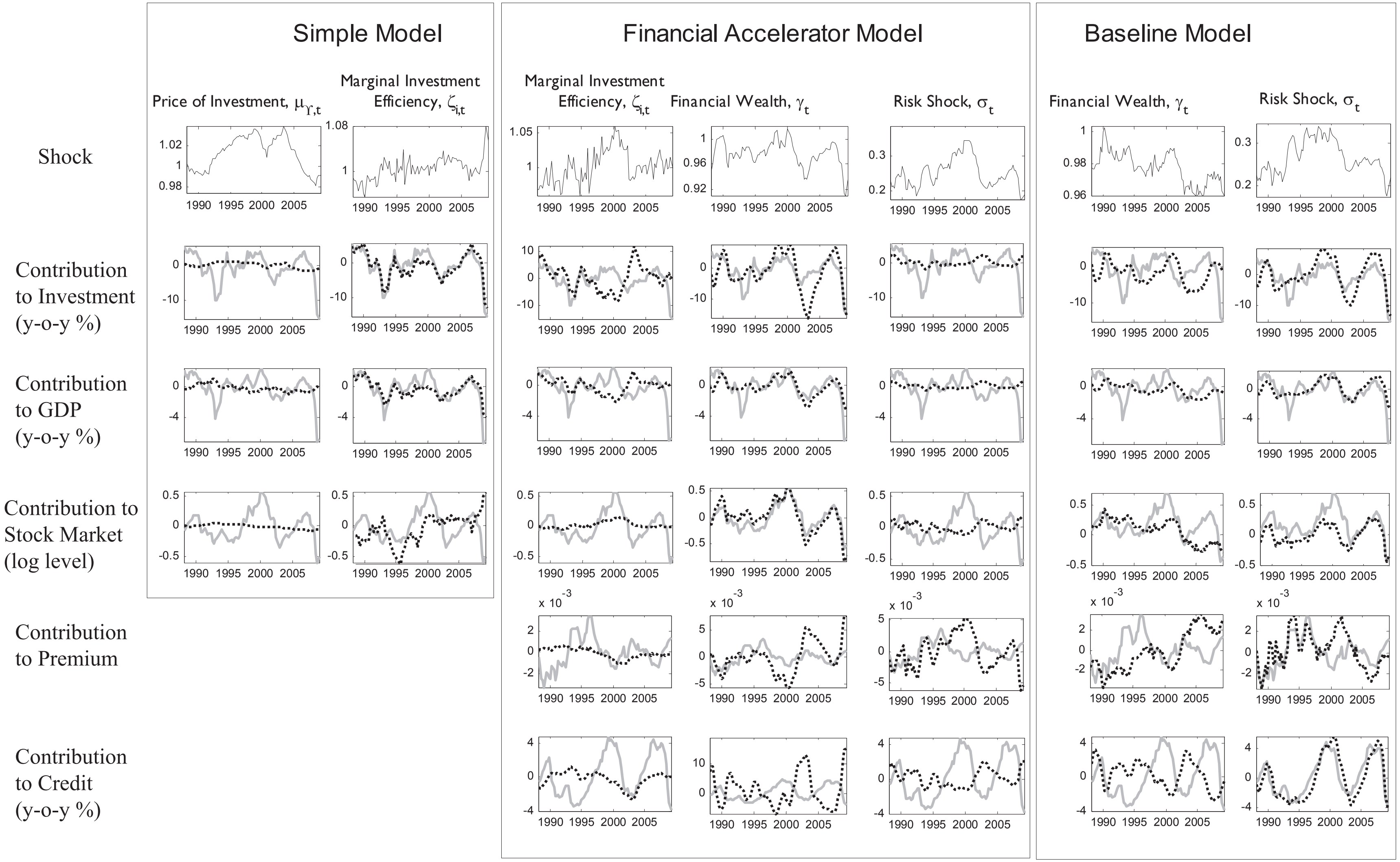


Figure 8b. US, Driving Forces in Alternative Models

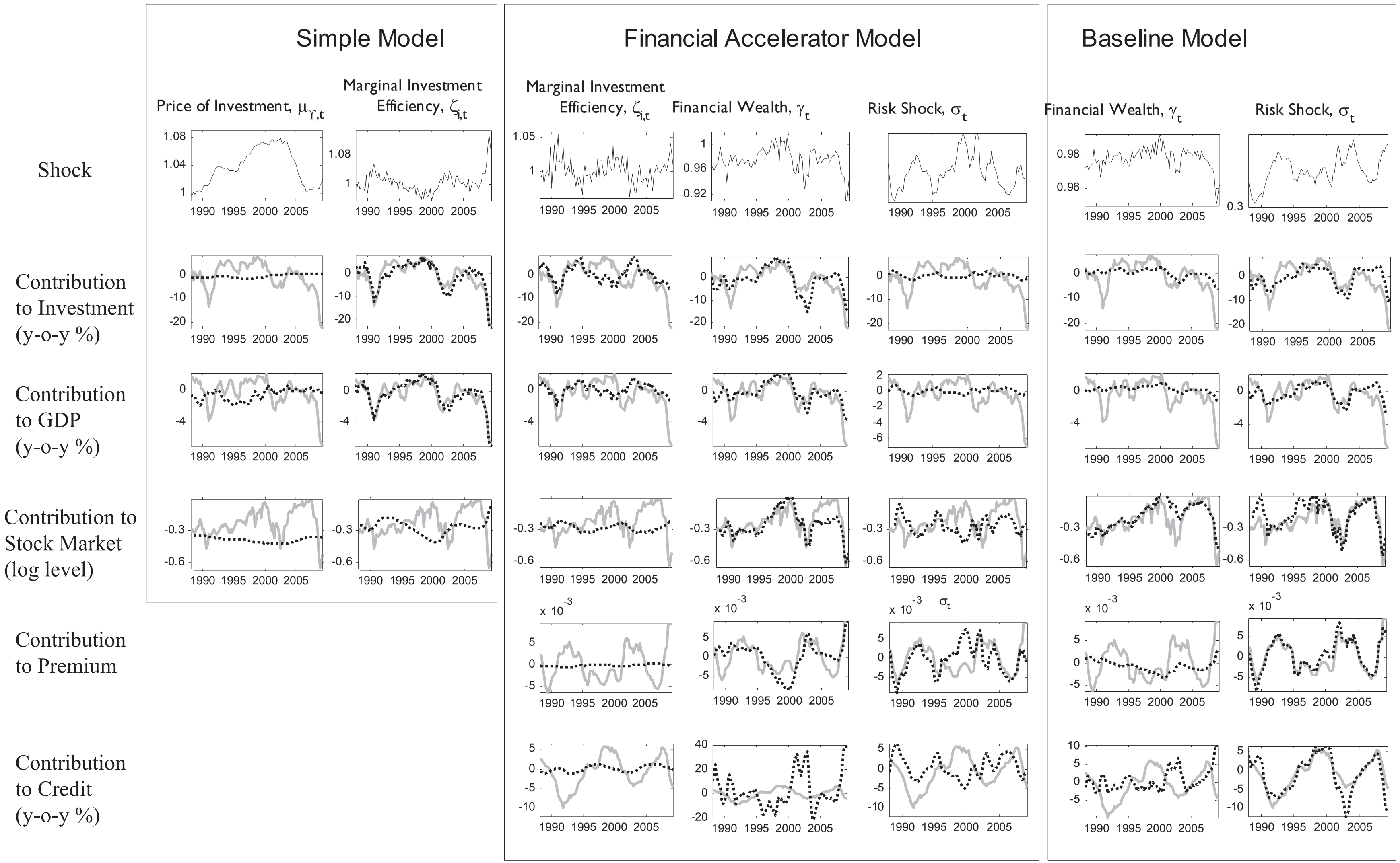


Figure 9: Contributions of Risk Shock Signals: data (thick line), signal contribution (dotted line)

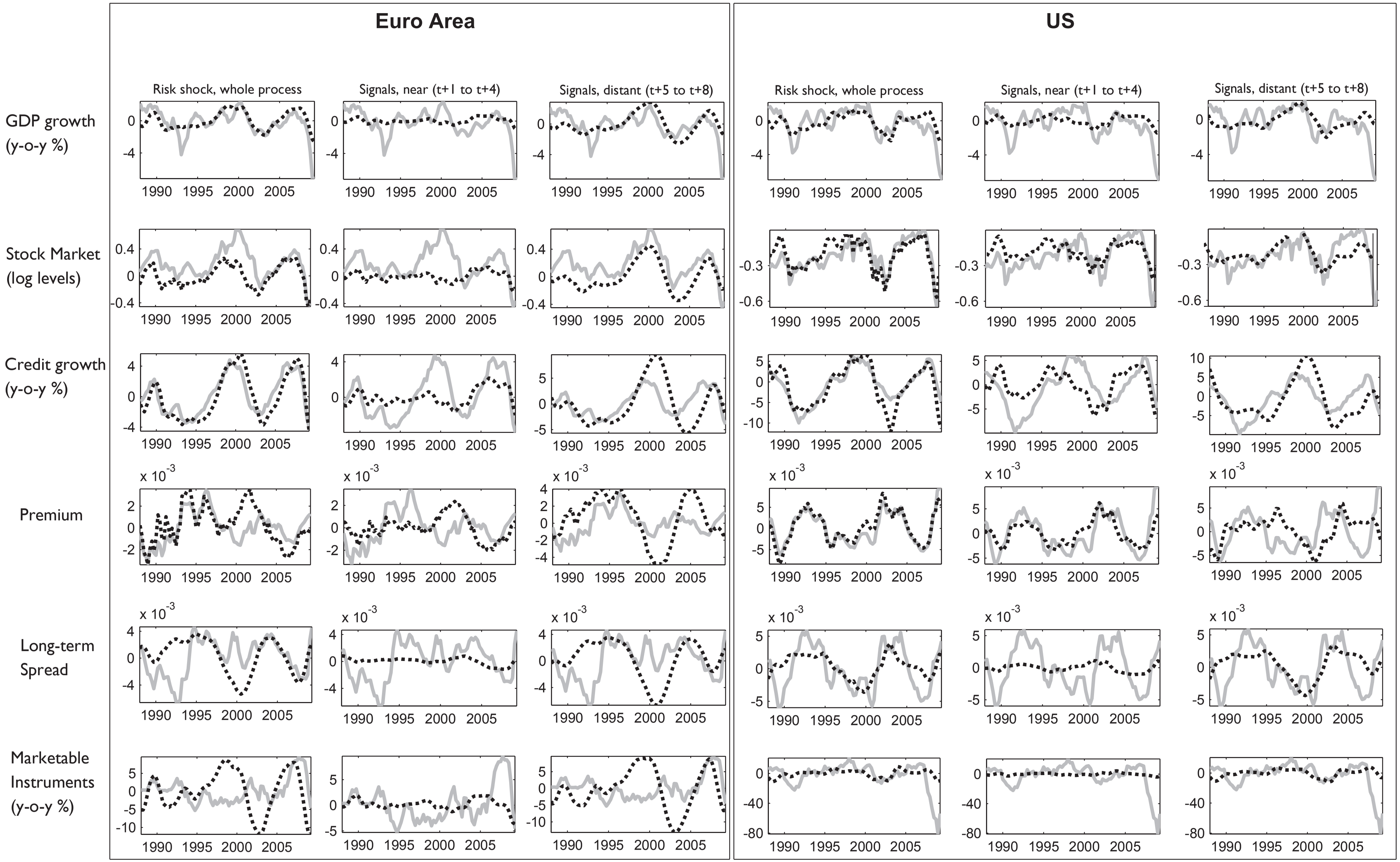


Figure 10. Impulse Response to a Risk Shock

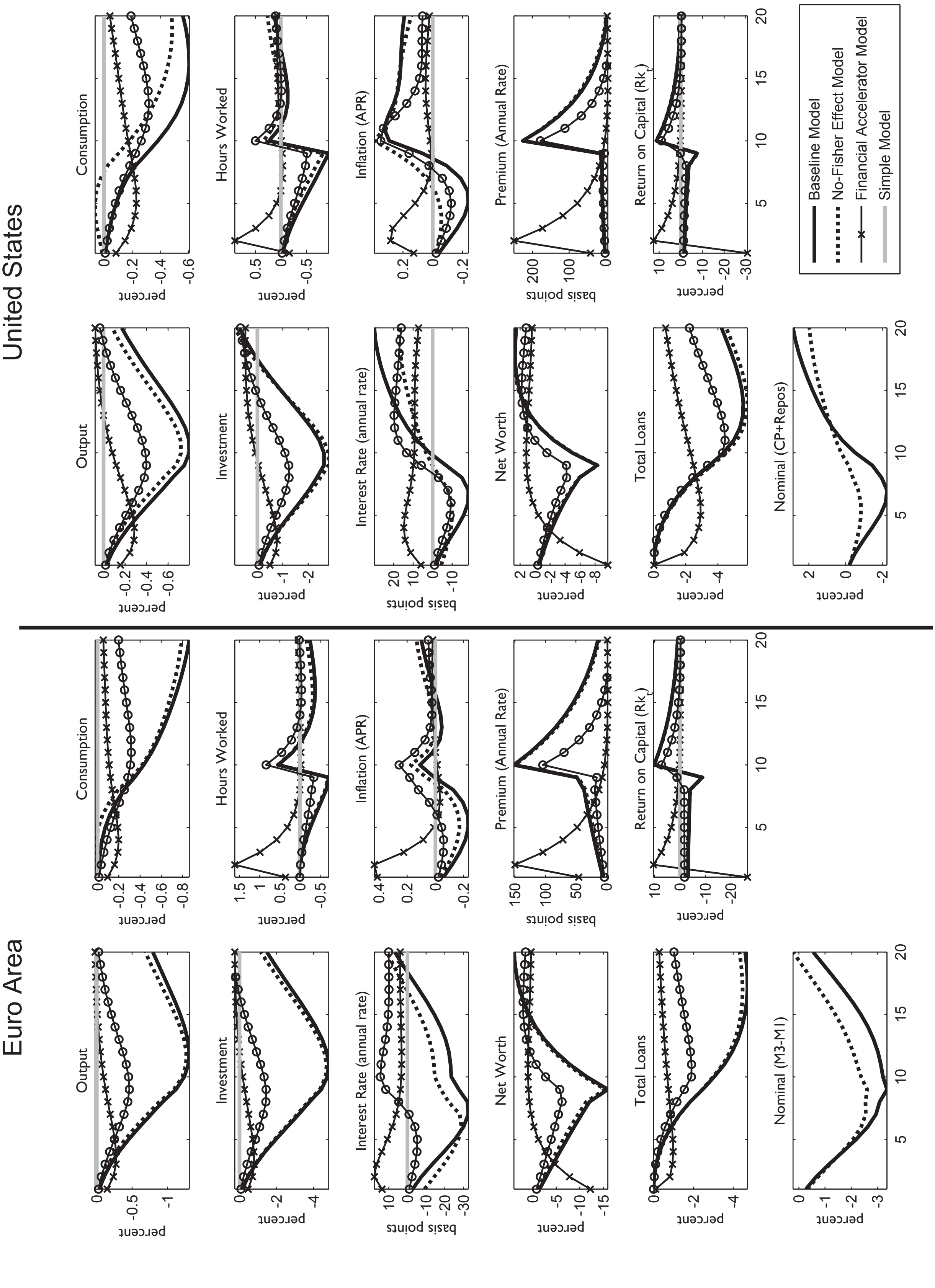


Figure 11. Impulse Response to a Shock in Marginal Efficiency of Investment ($\zeta_{i,t}$)

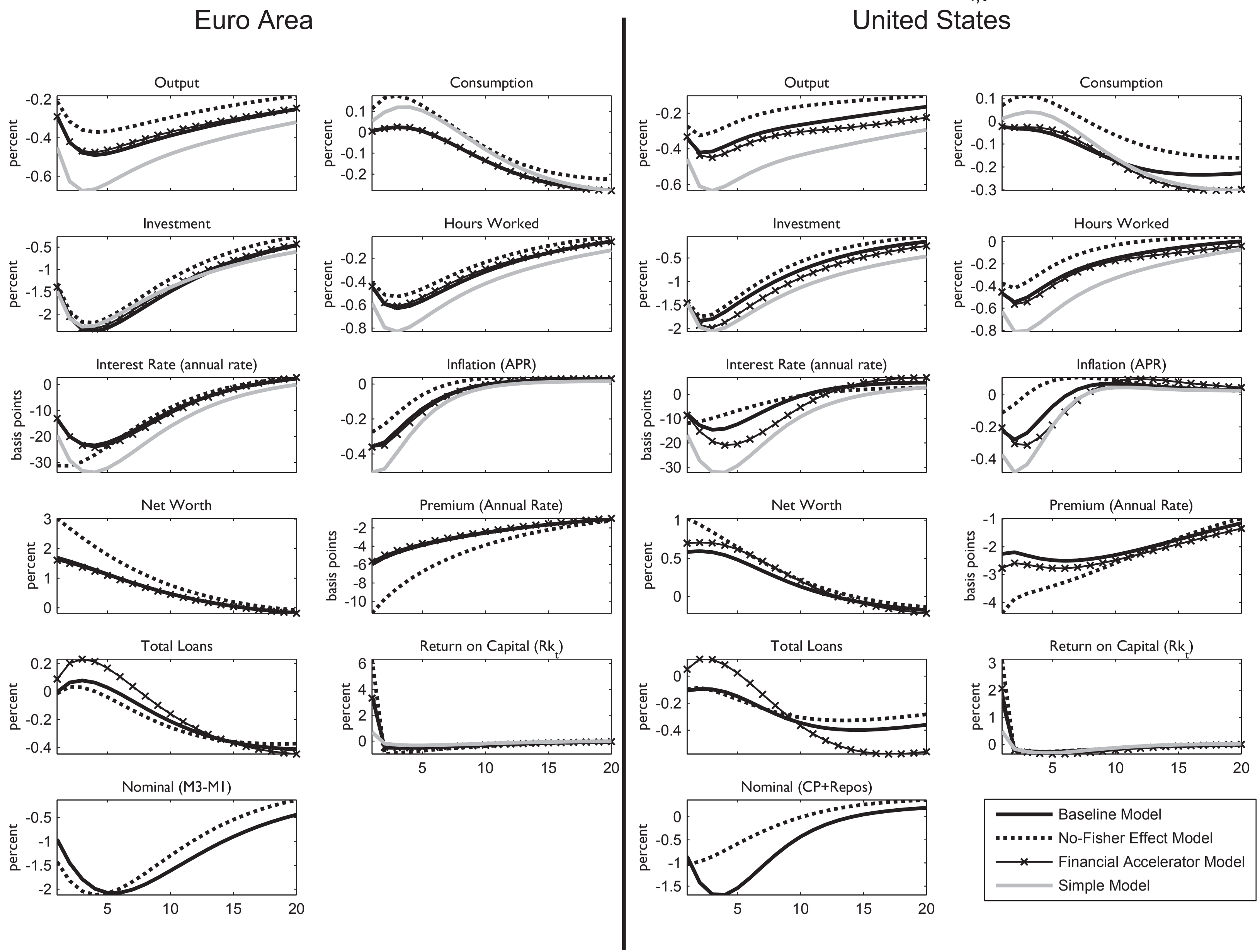


Figure 12. Impulse Response to a Financial Wealth Shock (γ_t)

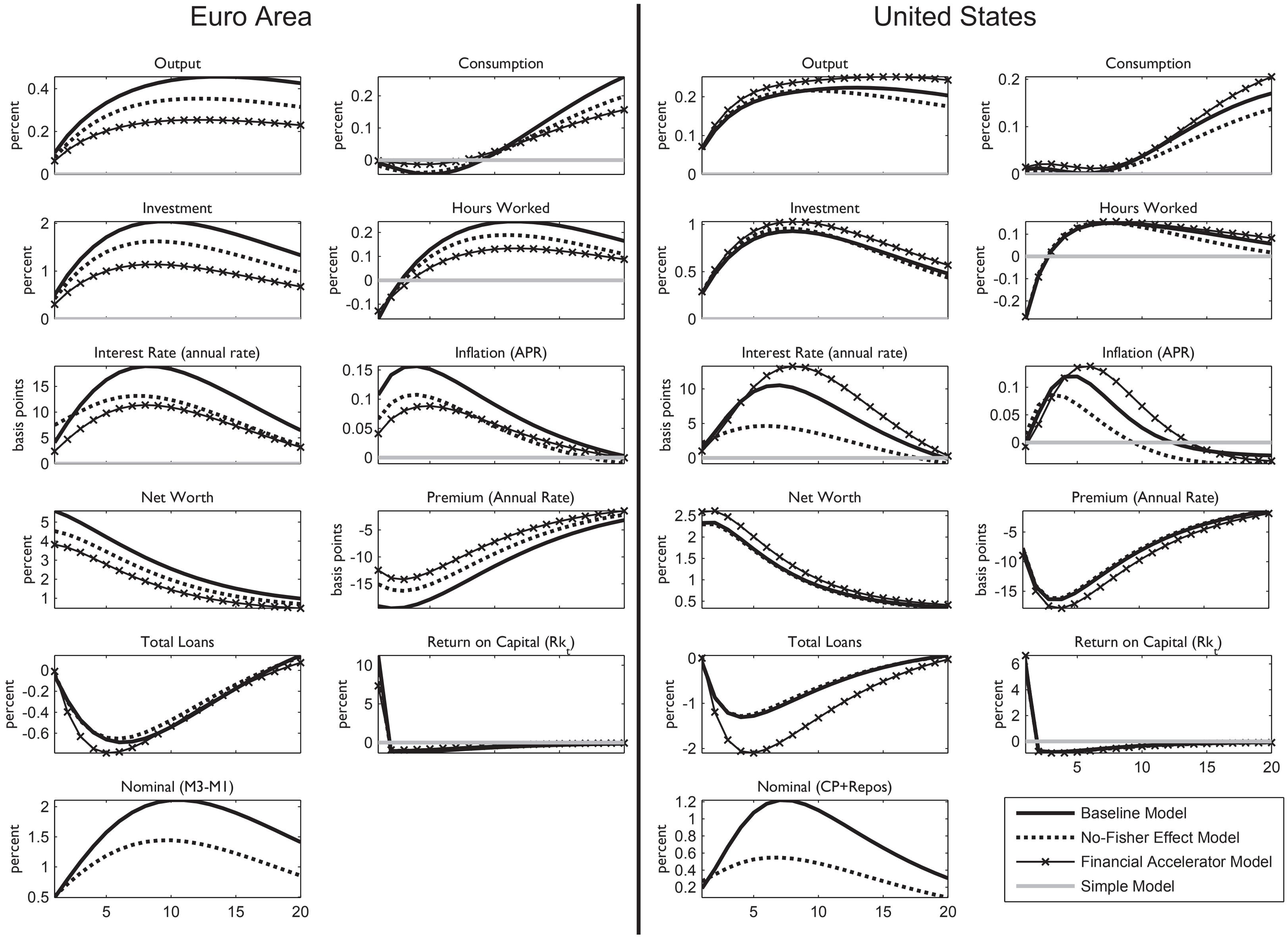


Figure 13. Impulse Response to a Transitory Technology Shock

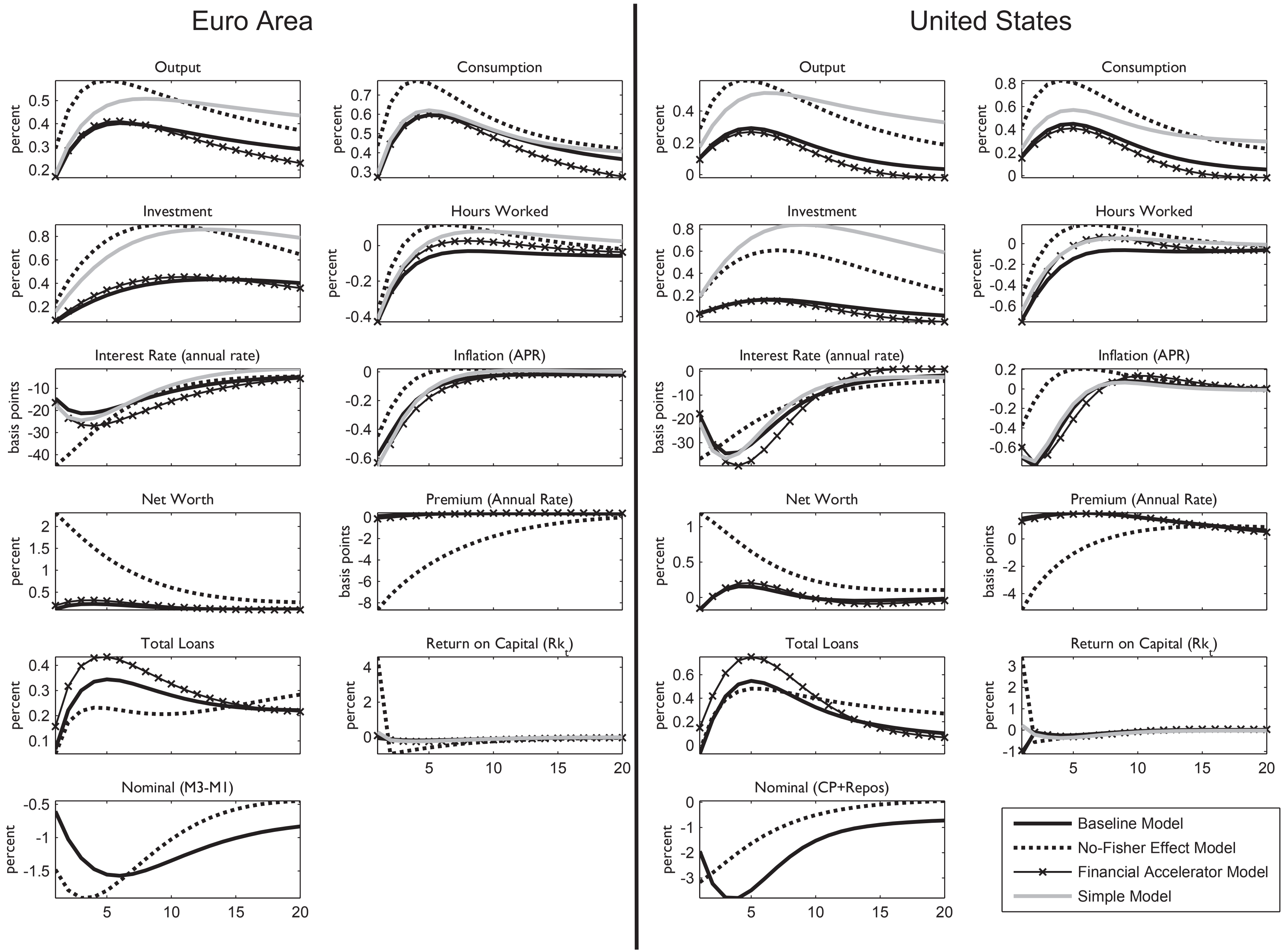


Figure 14. Impulse Response to a Monetary Policy Shock

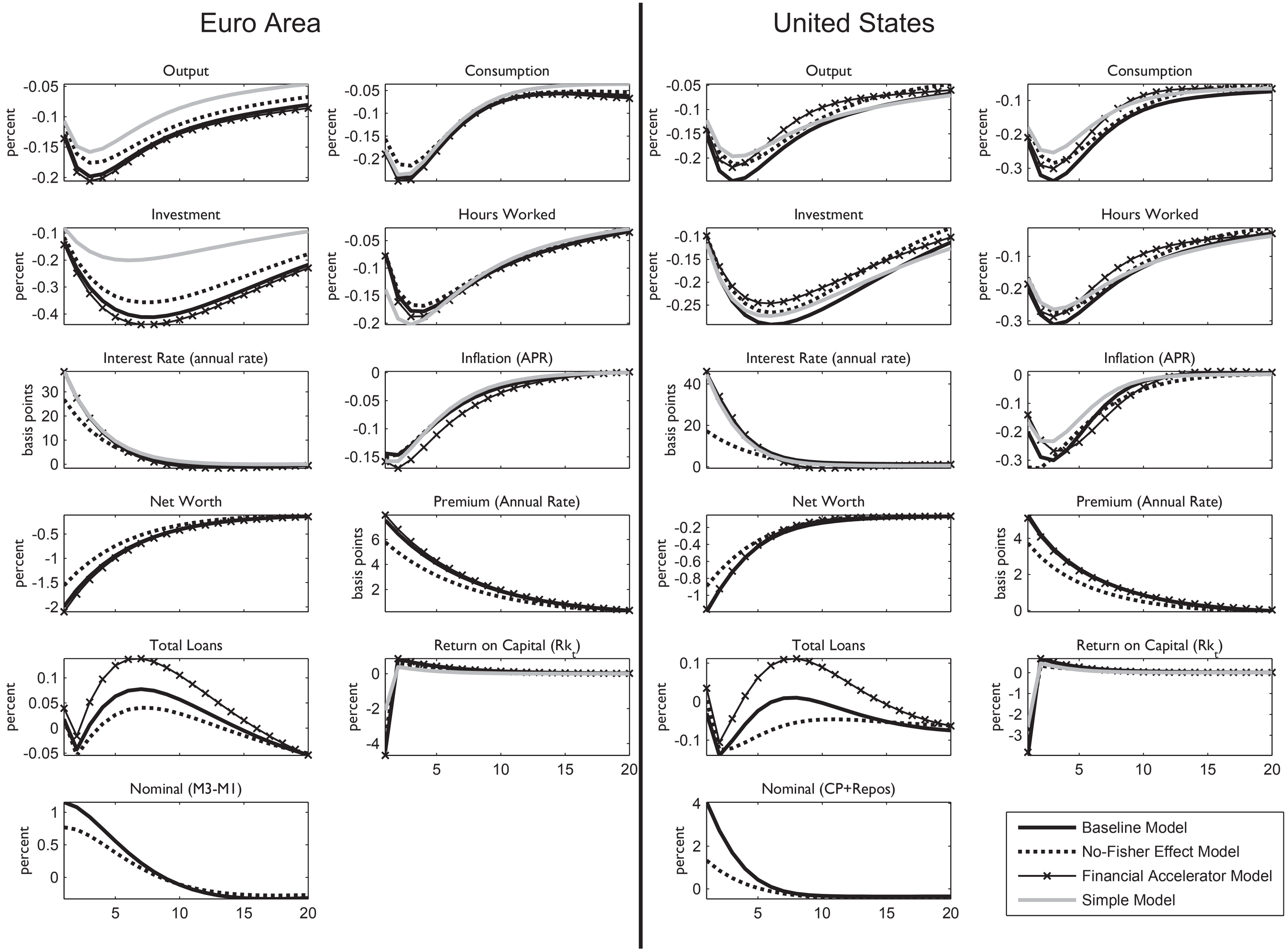
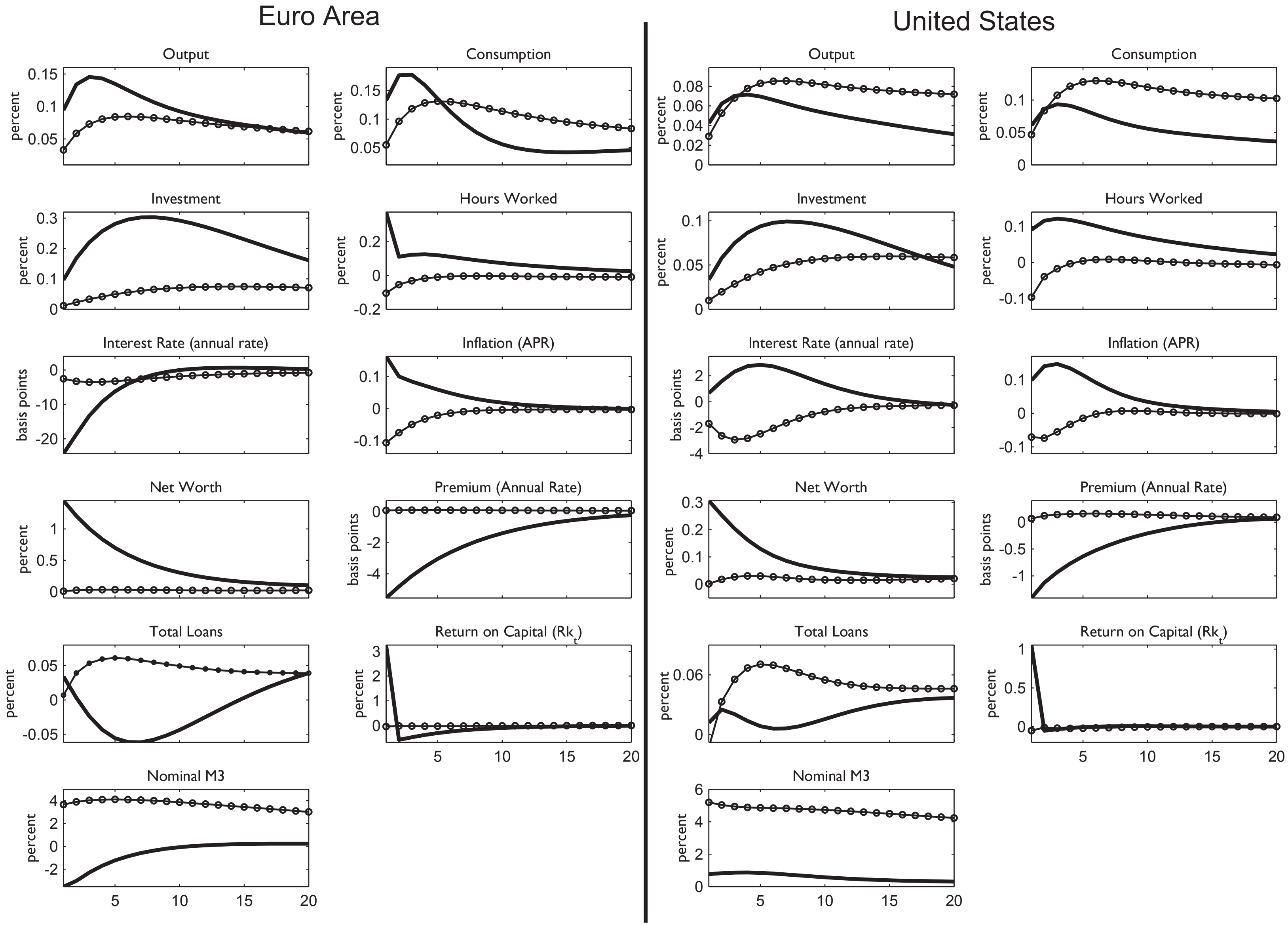


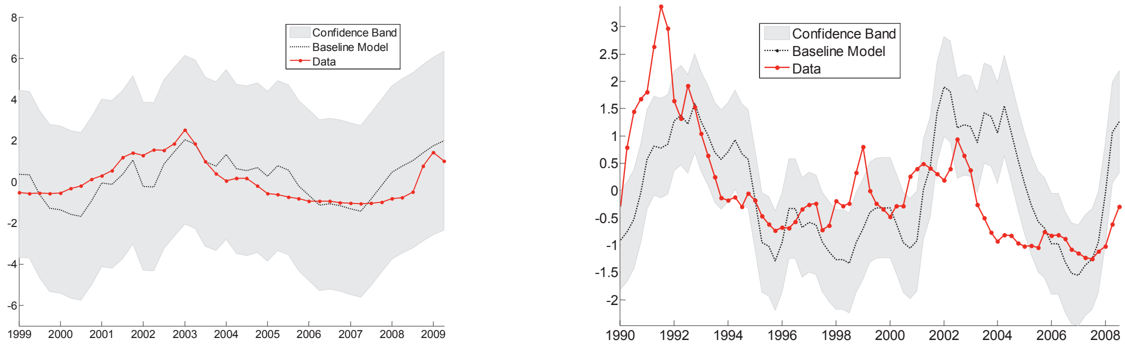
Figure 15. Impulse Response to Banks' Funding Shocks (ξ_t and x_t^b) in Baseline Model



Note: Response to ξ_t is solid line; response to x_t^b is line with circles

Figure 16. Comparing Expected Defaults Data with Model Predictions

Euro Area United States



This figure shows data on Expected Default Probability for the Non-Financial Corporate sector computed by Moody's KMV (solid line with circles) and model predictions (dotted line) with estimated confidence band (grey area). Data and Model objects are demeaned and standardised.

Figure 17a: EA, Contribution to the Equity Premium
(y-o-y, % change; solid: expected; starred: realised)

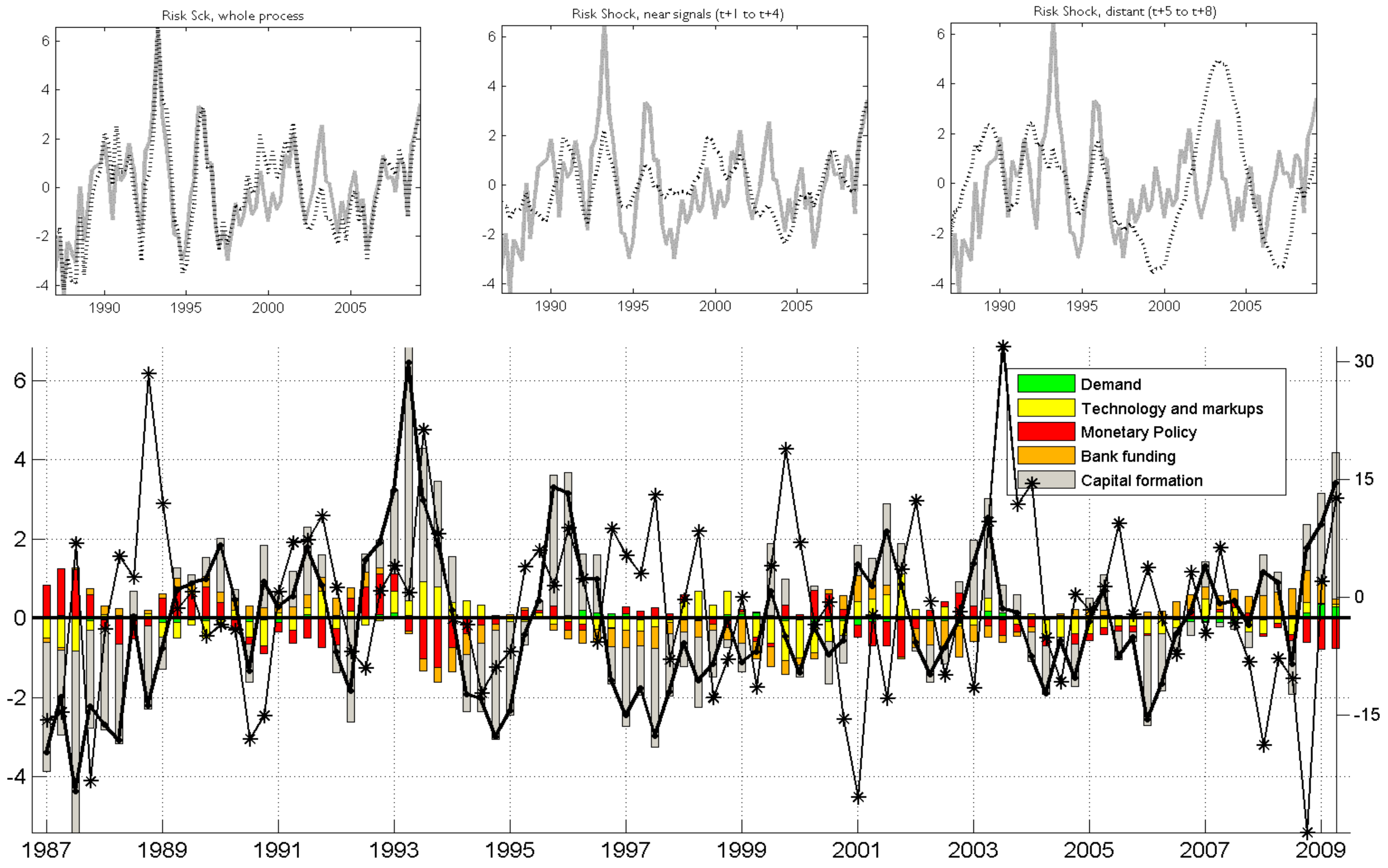


Figure 17b: US, Contribution to Equity Premium
(% change; solid, expected; starred, realised)

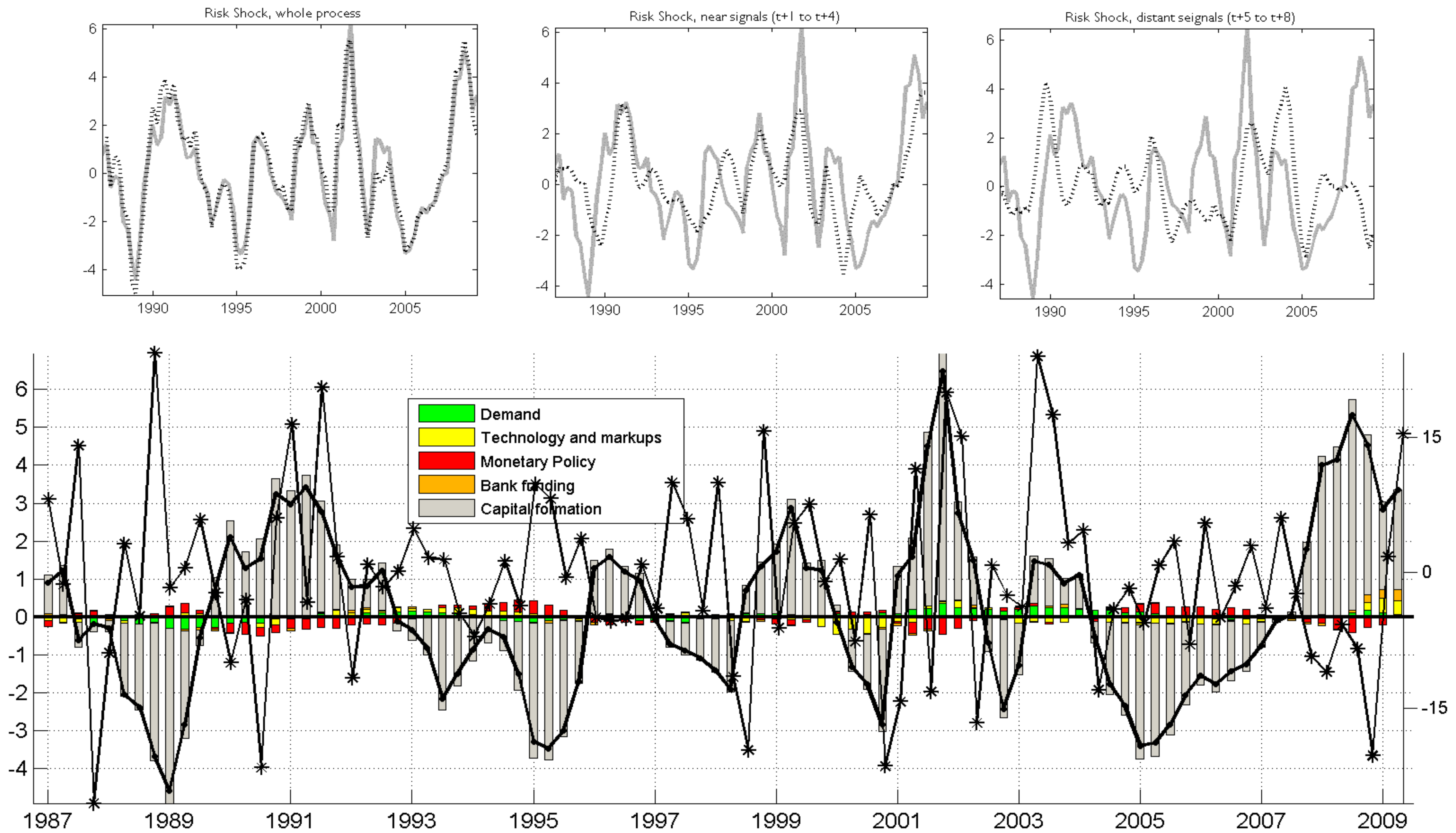


Figure 18a, EA, Contribution to GDP Growth (y-o-y % change)

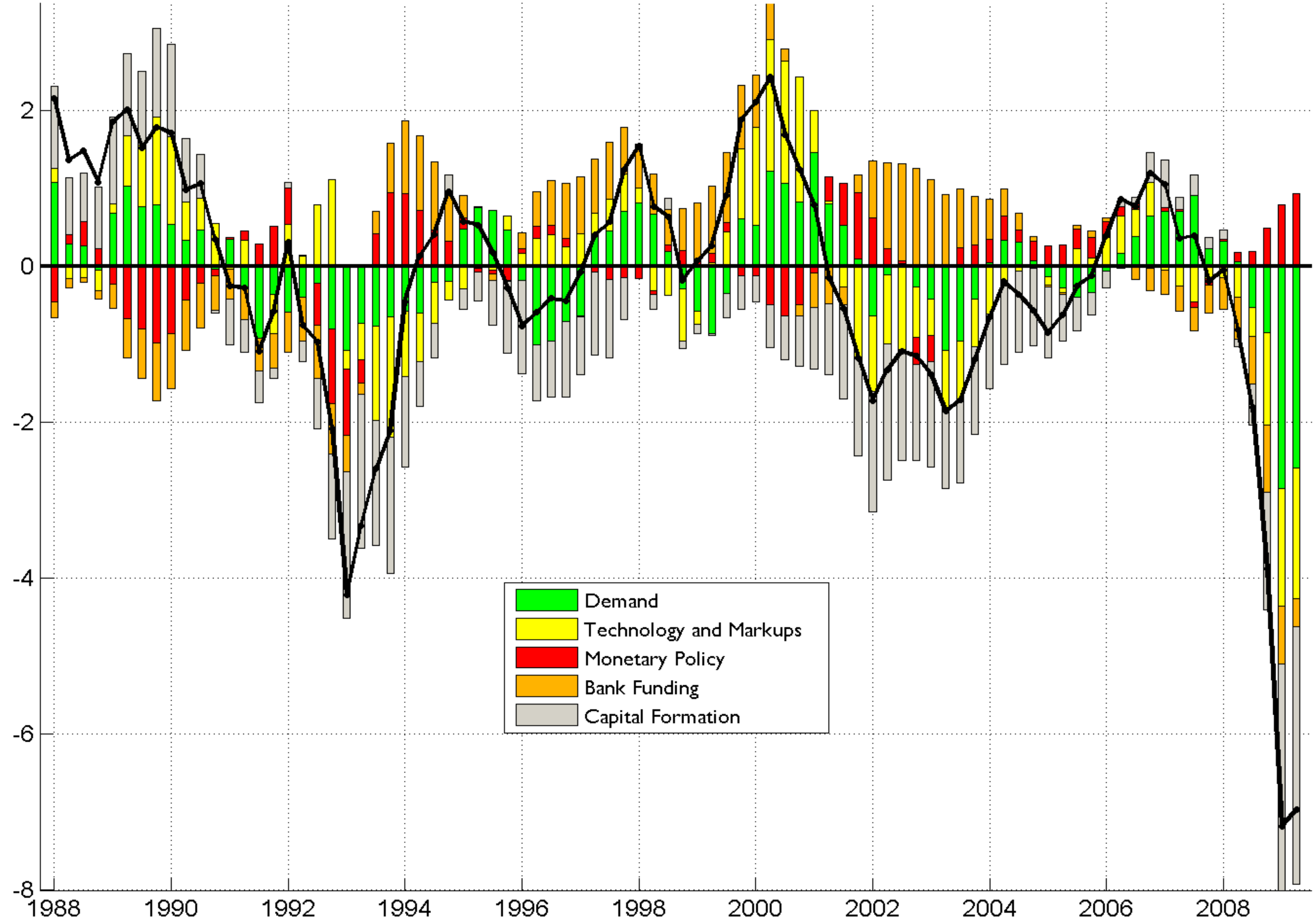


Figure 18b: US, Contribution to GDP Growth (y-o-y % change)

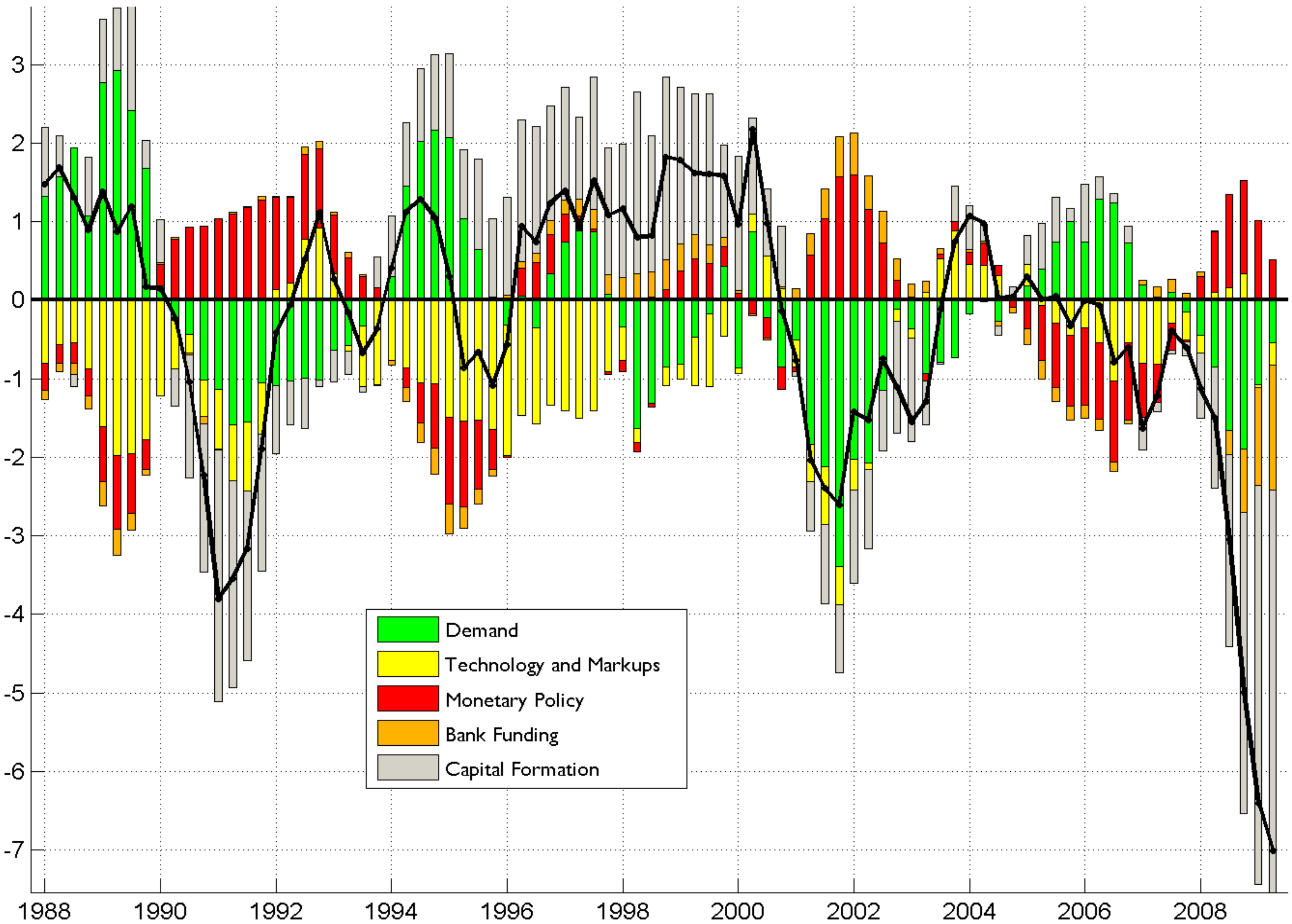


Figure 19: The US Crisis under a Money-based Monetary Policy Rule

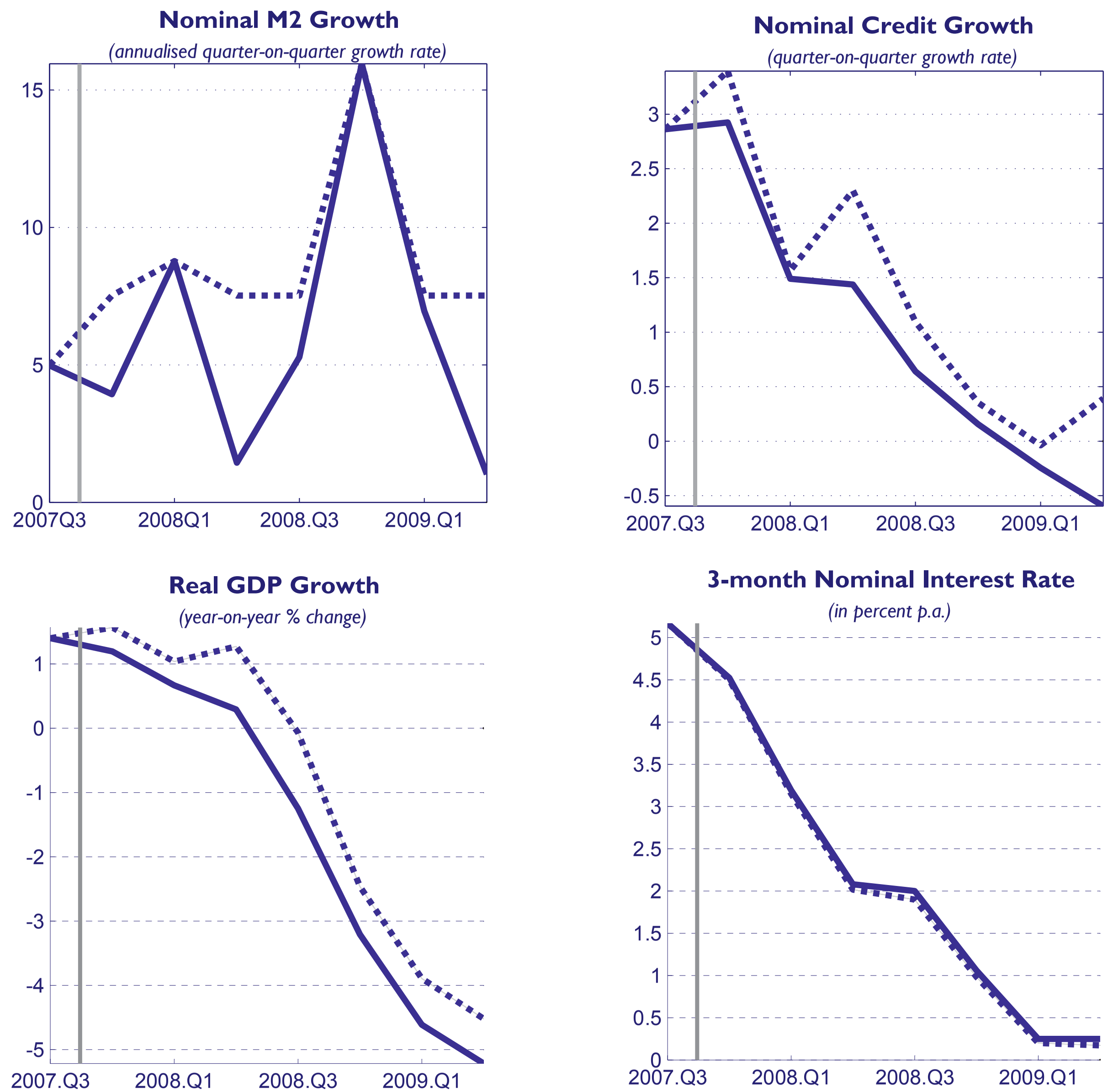


Table A.1: Simple Model, Parameter Estimates, Euro area and US

		Prior			Posterior Euro area		Posterior US	
		Type	Mean	Std. dev.	Mode	Std. dev. (Hess.)	Mode	Std. dev. (Hess.)
ξ_p	Calvo prices	Beta	0.75[1] 0.375	0.05	0.684	0.034	0.684	0.045
ξ_w	Calvo wages	Beta	0.75[1] 0.375	0.1	0.761	0.049	0.719	0.030
ι	Weight on steady state inflation	Beta	0.5	0.15	0.903	0.046	0.402	0.203
ι_w	Weight on steady state inflation	Beta	0.5	0.15	0.505	0.135	0.682	0.145
ϑ	Weight on technology growth	Beta	0.5	0.15	0.918	0.037	0.930	0.032
S''	Investment adjust. cost	Normal	10.0	5	18.27	3.904	14.71	3.939
σ_a	Capacity utilization	Gamma	6	5	30.36	8.032	14.54	3.727
α_π	Weight on inflation in Taylor rule	Normal	1.75	0.1	1.856	0.092	1.854	0.094
$\alpha_{\Delta y}$	Weight on output growth in Taylor rule	Normal	0.25	0.1	0.296	0.099	0.332	0.010
$\alpha_{\Delta\pi}$	Weight on change in infl. in Taylor rule	Normal	0.3	0.1	0.260	0.095	0.191	0.099
ρ_i	Coeff. on lagged interest rate	Beta	0.8	0.05	0.832	0.017	0.851	0.016
ρ	Price of Investment shock ($\mu_{\Upsilon,t}$)	Beta	0.5	0.2	0.981	0.008	0.988	0.006
ρ	Government consumption shock (g_t)	Beta	0.5	0.2	0.987	0.008	0.947	0.020
ρ	Persistent product. shock ($\mu^*_{z,t}$)	Beta	0.5	0.2	0.067	0.047	0.187	0.076
ρ	Transitory product. shock (ϵ_t)	Beta	0.5	0.2	0.974	0.012	0.936	0.023
ρ	Consump. prefer. shock ($\zeta_{c,t}$)	Beta	0.5	0.2	0.867	0.049	0.894	0.021
ρ	Margin. effic. of invest. shock ($\zeta_{i,t}$)[2]	Beta	0.5	0.05	0.510	0.046	0.459	0.076
ρ	Oil price shock (τ_t^{oil})	Beta	0.5	0.2	0.938	0.021	0.928	0.018
ρ	Price mark-up shock ($\lambda_{f,t}$)[2]	Beta	0.5	0.2	0.963	0.022	0.692	0.049

Table A.1, continued

		Prior			Posterior Euro area		Posterior US	
		Type	Mode	Df.	Mode	Std. dev. (Hess.)	Mode	Std. dev. (Hess.)
σ	Investm. specific shock ($\mu_{\Upsilon,t}$)	Inv. Gamma	0.003	5 d	0.003	0.0002	0.003	0.0002
σ	Government consumption shock (g_t)	Inv. Gamma	0.01	5 d	0.014	0.0010	0.024	0.0017
σ	Persistent product. shock ($\mu^*_{z,t}$)	Inv. Gamma	0.001	5 d	0.005	0.0004	0.007	0.0005
σ	Transitory product. shock (ϵ_t)	Inv. Gamma	0.001	5 d	0.004	0.0003	0.004	0.0003
σ	Consump. prefer. shock ($\zeta_{c,t}$)	Inv. Gamma	0.001	5 d	0.012	0.0015	0.016	0.0014
σ	Margin. effic. of invest. shock ($\zeta_{i,t}$)[3]	Inv. Gamma	0.001	5 d	0.015	0.0012	0.018	0.0016
σ	Oil price shock (τ_t^{oil})	Inv. Gamma	0.01	5 d	0.152	0.0111	0.134	0.0097
σ	Monetary policy shock (ε_t)	Inv. Gamma	0.25	10 d	0.568	0.0485	0.574	0.0446
σ	Price markup shock ($\lambda_{f,t}$)	Inv. Gamma	0.0005	5 d	0.007	0.0011	0.015	0.0031

([1]) Upper numbers refer to EA, lower numbers to US.

([2]) The std. dev. of the prior distribution for the autocorrelation parameters of $\lambda_{f,t}$ and $\zeta_{i,t}$ are set equal to 0.05 and 0.1, respectively, in the US model.

([3]) The mode of the prior distributions for the standard deviations of $\zeta_{i,t}$ is set equal to 0.01 in the US model.

Table A.2: Financial Accelerator Model, Parameter Estimates, Euro area and US

		Prior			Posterior Euro area		Posterior US	
		Type	Mean	Std. dev.	Mode	Std. dev. (Hess.)	Mode	Std. dev. (Hess.)
ξ_p	Calvo prices	Beta	0.75[1] 0.375	0.05	0.711	0.031	0.702	0.0337
ξ_w	Calvo wages	Beta	0.75[1] 0.375	0.1	0.741	0.036	0.771	0.029
ι	Weight on steady state inflation	Beta	0.5	0.15	0.902	0.047	0.159	0.077
ι_w	Weight on steady state inflation	Beta	0.5	0.15	0.419	0.120	0.285	0.236
ϑ	Weight on technology growth	Beta	0.5	0.15	0.925	0.034	0.917	0.038
S''	Investment adjust. cost	Normal	10.0	5	30.42	3.409	29.31	3.357
σ_a	Capacity utilization	Gamma	6	5	31.29	8.148	18.85	5.570
α_π	Weight on inflation in Taylor rule	Normal	1.75	0.1	1.866	0.088	1.817	0.096
$\alpha_{\Delta y}$	Weight on output growth in Taylor rule	Normal	0.25	0.1	0.302	0.099	0.310	0.099
$\alpha_{\Delta \pi}$	Weight on change in infl. in Taylor rule	Normal	0.3	0.1	0.230	0.096	0.181	0.100
ρ_i	Coeff. on lagged interest rate	Beta	0.8	0.05	0.842	0.015	0.877	0.014
ρ	Price of Investment shock ($\mu_{\Upsilon,t}$)	Beta	0.5	0.2	0.978	0.009	0.983	0.007
ρ	Government consumption shock (g_t)	Beta	0.5	0.2	0.978	0.017	0.930	0.027
ρ	Persistent product. shock ($\mu^*_{z,t}$)	Beta	0.5	0.2	0.066	0.047	0.166	0.075
ρ	Transitory product. shock (ϵ_t)	Beta	0.5	0.2	0.953	0.019	0.816	0.059
ρ	Financial wealth shock $(\gamma_t)^2$	Beta	0.5	0.1	0.674	0.063	0.598	0.024
ρ	Riskiness shock $(\sigma_t)^2$	Beta	0.5	0.2	0.724	0.034	0.722	0.037
ρ	Consump. prefer. shock ($\zeta_{c,t}$)	Beta	0.5	0.2	0.940	0.021	0.921	0.023
ρ	Margin. effic. of invest. shock $(\zeta_{i,t})^2$	Beta	0.5	0.05	0.576	0.048	0.434	0.089
ρ	Oil price shock (τ_t^{oil})	Beta	0.5	0.2	0.937	0.022	0.929	0.021
ρ	Price mark-up shock $(\lambda_{f,t})^2$	Beta	0.5	0.2	0.965	0.018	0.627	0.048

Table A.2, continued

		Prior			Posterior		Posterior	
		Type	Mode	Df.	Mode	Euro area Std. dev. (Hess.)	Mode	US Std. dev. (Hess.)
σ	Investm. specific shock ($\mu_{\Upsilon,t}$)	Inv. Gamma	0.003	5 d	0.003	0.0002	0.003	0.0002
σ	Government consumption shock (g_t)	Inv. Gamma	0.01	5 d	0.013	0.0009	0.021	0.0015
σ	Persistent product. shock ($\mu^*_{z,t}$)	Inv. Gamma	0.001	5 d	0.005	0.0004	0.007	0.0060
σ	Transitory product. shock (ϵ_t)	Inv. Gamma	0.001	5 d	0.005	0.0004	0.008	0.0006
σ	Financial wealth shock (γ_t)^3	Inv. Gamma	0.001	5 d	0.010	0.0017	0.014	0.0012
σ	Risk shock (σ_t)	Inv. Gamma	0.01	5 d	0.074	0.0060	0.076	0.0061
σ	Consump. prefer. shock ($\zeta_{c,t}$)	Inv. Gamma	0.001	5 d	0.019	0.0043	0.021	0.0034
σ	Margin. effic. of invest. shock ($\zeta_{i,t}$)^3	Inv. Gamma	0.001	5 d	0.018	0.0014	0.019	0.0017
σ	Oil price shock (τ_t^{oil})	Inv. Gamma	0.01	5 d	0.152	0.0111	0.135	0.0010
σ	Monetary policy shock (ε_t)	Inv. Gamma	0.25	10 d	0.502	0.0407	0.519	0.0389
σ	Price markup shock ($\lambda_{f,t}$)	Inv. Gamma	0.0005	5 d	0.008	0.0012	0.022	0.0046
	Meas. Error, Real Net Worth Growth	Weibull	0.0090 0.0100	5	0.012	0.0014	0.0148	0.0013
	Meas. eroor, External Finance Premium	Weibull	0.0001 0.0001	5	0.00010	0.00002	0.00009	0.00002

([1]) Upper numbers refer to EA, lower numbers to US.

([2]) The std. dev. of the prior distribution for the autocorrelation parameters of $\lambda_{f,t}$, γ_t, σ_t and $\zeta_{i,t}$ are set equal to 0.05, 0.025, 0.1 and 0.1, respectively, in the US.

([3]) The mode of the prior distributions for the standard deviations of γ_t, and $\zeta_{i,t}$ are set equal to 0.01 in the US model.

Table A.3: Log Marginal Likelihood for Alternative Number of Signals in σ Shock in Baseline Model

Number of Signals (p) \ Country	EA	US
p=1	4871.80	4560.96
p=2	4823.00	4573.10
p=3	4893.87	4599.88
p=4	4884.69	4616.16
p=5	4904.09	4626.02
p=6	4919.61	4633.05
p=7	4931.70	4638.74
Memo item: Baseline Model (p=8)	**4941.24**	**4642.80**