Financial Intermediaries and Bond Risk Premia*

Rodrigo Guimaraes† Bank of England

Gabriele Zinna‡ Bank of England

September 2013

PRELIMINARY AND INCOMPLETE - PLEASE DO NOT QUOTE

Abstract

A rapidly growing literature emphasizes the behavior of financial intermediary balance sheets (FIBS) as a key variable in explaining agregate dynamics, and particularly their impact on risk premia. The role of monetary policy in the build up of financial fragility and risk taking behavior has also been a topic of significant interest, in both academic and policy circles. This paper provides an empirical assessment of the impact of FIBS changes on risk premia and the interaction between monetary policy and FIBS. We use an affine dynamic term structure model specification of the stochastic discount factor with unspanned macro and balance sheet variables to show that Shadow Banks' asset growth has a significant impact on prices of risk. Our framework has the advantage of separately identifying time-varying prices of risk and exposures to risk. Our framework also allows us to investigate the propagation of monetary policy, balance sheet and risk premia shocks. Our results support the counter-cyclical effect of FIBS on risk premia, in that Shadow Banks contributed to first compress the risk premia in the run up to the crisis and then increase them after the crisis. Using standard identification techniques we find evidence for significant feedback effects of term premia and Shadow Bank asset growth, but no significant role for monetary policy shocks in explaining FIBS expansion. Instead we find evidence that monetary policy reacts to financial risk taking behaviour in a "lean against the wind" fashion.

Keywords: risk premia; financial intermediaries; stochastic discount factors; monetary policy; affine term structure; unspanned risks; Bayesian econometrics.

JEL Classification: G10; G12; G23; E43; E52

* *Acknowledgements:* First version December 2012. The authors are indebted for discussions with David Aikman, Gabor Pinter, Antoine Lallour, David Murphy, Allan Taylor and comments from participants at Bank of England seminar, and the VIII Seminar on Risk, Financial Stability and Banking. We would also like to thank Haroon Mumtaz and Marcelo Ferman for kindly sharing some of their codes. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of England and the Monetary or Financial Policy Comittee.

† Bank of England, Threadneedle Street, London EC2R 8AH, UK. Email: Rodrigo.Guimaraes@bankofengland.co.uk.

‡ Bank of England, Threadneedle Street, London EC2R 8AH, UK. Email: Gabriele.Zinna@bankofengland.co.uk.

1 Introduction

The important role played by some financial intermediaries in the great recession has sparked a reassessment of the role of financial intermediary balance sheets (FIBS) for the macroeconomy and asset pricing. A rapidly growing theoretical and empirical literature has focused on explicitly modelling and expanding the role of financial intermediaries for the macroeconomy and asset prices, with a particular emphasis on non-traditional banking, or shadow banking sector.[1] A common feature in this incipient line of research is that the decision of these financial intermediaries to expand or contract their balance sheets is an important determinant of the economy's aggregate liquidity, credit and risk premia. The common prediction is for a negative correlation between FIBS size and risk premia: in periods of expanding FIBS the required risk premia embedded in asset prices will be lower.

The recent global financial crisis has also brought the relationship between monetary policy and financial intermediaries risk taking and balance sheets to the forefront of the economic policy debate. One narrative that has gained prominence is the "search-for-yield" or "risk taking channel",[2] which focuses on the role of loose monetary policy as the root cause in the buildup in FIBS and their fragility. Another popular view emphasizes the exogenous compression of risk premia through global imbalances or savings glut[3] as the origin of excess risk taking, which would suggest that exogenous changes in term premia played an important role in the dynamics of balance sheets.[4] An alternative hypothesis focuses on financial deregulation and innovation as driving the build up in FIBS risks,[5] which would suggest that innovations to FIBS are mostly exogenous relative to monetary policy and term premia, and might itself be driving risk premia lower.

In this paper, we use an affine specification of the stochastic discount factor to allow for time-varying riskpremia and to investigate the empirical importance of financial intermediaries in explaining the pricing of risks. This framework also allows us to attempt to quantify the relation between

[1] For a theoretical perspective see He & Krishnamurthy (12, 13), Muir (12), Adrian & Boyarchenko (12), Brunermeier & Sannikov (12, 13), Parlour, Stanton & Walden (11), and Phelan (12), among many others. Empirical papers include Adrian, Moench & Shin (10), He, Khang & Krishnamurthy (10), Adrian, Muir & Etula (12), Gorton & Metrick (2012), Adrian, Colla & Shin (11), among others.

[2] See for example Rajan (2005), Borio & Zhu (2008) and Adrian & Shin (2011).

[3] See Caballero, Farhi & Gourrinchas (2008) and Bernanke (2005).

[4] While some use the term 'search for yield' to denote the effect on risk taking from either short or long term yields, we here use it to refer to impact on risk taking of short term interest rates and monetary policy. We refer to the effect of long term yield term premia compression as the global imbalances or savings glut hypothesis.

[5] See Acharya, Schnabl & Suarez (2013). For a succint summary of some of the key changes in financial regulation see Sherman (2009). Philippon & Reshef (2013) calculate an index of finanical deregulation for a panel of OECD countries, while Philippon & Reshef (2012) focus on the US deregulation in more detail.

shocks to expected short term rates, term premia and FIBS. Being able to jointly model the expected and risk premia components of yields with both macro and FIBS data is crucial to analyze both the effect of FIBS on risk premia and differentiate between the different hypotheses on the main drivers of the build up in risk in the financial sector prior to the crisis.

We build on the results of Adrian, Etula & Muir (2012, AEM), who find that financial intermediary balance sheet data has significant forecasting power for financial asset price returns and can successfully price the cross section of equity returns and bond market returns. Their empirical exercise assumes constant price of risk. Not only is there robust evidence from across asset classes of strong time-variation in prices of risk (Cochrane (2011)), but the implication of many of these models is precisely about changes in the price of risk.[6]

We take the same intuition of AEM that financial intermediaries are a good proxy for innovations in the stochastic discount factor, and investigate it's usefulness in a well known model with time-varying risk premia. We follow the methodology of Joslin, Priebisch and Singleton (2012, JPS) and use an unspanned Gaussian affine dynamic terms structure model (GADTSM) with macro variables and FIBS variables to study the impact of FIBS on bond risk premia. The model of JPS allow us to assess the importance of variables for which we might not have observable asset prices, but have reasons to believe can be important in explaining the dynamics of risk factors and the price of risk. This is precisely the case with FIBS.

We find that FIBS play an important role in the counter-cyclical behavior of prices of risk. Confirming the intuition from recent theoretical and empirical literature, the model implies that the expansion of balance sheets of financial intermediaries is associated with lower prices of risk. The estimates suggest that FIBS played an important role in compressing returns in the few years leading into the 1990 recession and for most part of the decade ahead of the Great Recession. They also imply that during the Great Recession it has played a major role in explaining high expected excess holding period returns on bonds.

Another benefit of using this framework relative to AEM, is that we can attempt to quantify the effects of monetary policy and term premia shocks on FIBS, and feedback from FIBS on the rest of the economy. Using Shadow Banks' asset growth as a proxy for FIBS, we find no evidence that

[6] See Adrian, Crump & Moench (2011) for comparisson of methodology in AEM and the dynamic affine SDF approaches.

monetary policy shocks have a significant effect on FIBS, but find a significant effect of shocks to Shadow Banks' asset growth on expected short rate. This suggests that monetary policy reacts to changes in FIBS rather than causing them. We also find weak evidence of an effect from term premia on FIBS, but the response of growth and inflation to the term premia shock suggests this might be capturing positive news, such as expected TFP shocks (consistent with Kurmann & Otrok (2012)). We confirm these results with other measures of FIBS. However, one caveat is that since this exercise is purely about the reaction to shocks, it says nothing about the potential effect of prolonged periods of low interest rates, which has been argued could have distorting effects irrespective of whether they reflect cumulative policy shocks or neutral policy.

The rest of the paper is structured as follows. In Section 2 we do a quick review of the literature on the importance of financial intermediaries that motivates our study and will provide the alternative hypothesis we wish to test. We then describe the model in Section 3 and the estimation and data used in Section 4. The main empirical results are discussed in Section 5.

2 Financial Intermediaries, Macroeconomy and Asset Pricing

There is a fast growing theoretical and empirical literature on the importance of financial intermediaries for macroeconomics, asset pricing and policy. On theoretical front the most relevant papers are those of He & Krishnamurthy (2012, 2013), Brunnermeier & Sannikov (2013), Adrian & Boyarchenko (2012), Garleanu, Panageas & Yu (2013), Muir (2013), Parlour, Stanton & Walden (2011), Danielsson, Shin & Zigrand (2012), Phelan (2012), Rampini & Visnawathan (2012) and Acharya & Visnawathan (2011). All of these studies combine general equilibrium considerations and asset pricing implications. There is also a rapidly growing literature focusing on the implications for macro instability with less of focus on asset pricing (e.g. Di Tella (2012), Ajello (2012)). The mechanisms, relevant constraints and channels are diverse, but the underlying intuition is that financial intermediaries are an important marginal investor in the economy for a wide set of asset prices, and changes in their balance sheet size can be a good proxy of their effective risk appetite. This suggests that using their balance sheet information can be a better proxy for the artificial representative agent's intertemporal marginal rate of substitution than aggregate consumption.

The most relevant theoretical paper for us is Adrian & Boyarchenko (2012). In their model, financial intermediaries play two roles: amplify shocks (as in He & Krishnamurthy (2012) and, Brunnermeier & Sannikov (2013)) and generate aggregate risk. The equilibrium can be written as a function of two state variables: financial intermediaries total assets and net wealth. In their model, the size of financial intermediaries balance sheet assets, or equivalently leverage, will determine prices of risk. Despite the underlying fundamental shocks being homoscedastic, this generates stochastic volatility and time-varying prices of risk in asset prices. While their model is not specifically about shadow banks, the empirical facts used to motivate their theory, and that match their predictions, are shadow banks rather than traditional commercial banks.

There is already a large body of research dissecting the evolution of the financial crisis that is relevant to our work. Among them Adrian et al (various), He, Khan & Krishnamurthy (2010), Gorton & Metrick (2012), Bruno & Shin (2013) and many others. The main observations from these studies was the central role played by the shadow banking sector in the recent crisis. Shadow banking provides maturity and credit transformation similar to deposit taking commercial banks, but without public sources of backstops and funding is more reliant on short term markets, such as repos (Adrian, Covitz, & Liang (2012))

Within the empirical literature, two studies are particularly relevant for our analysis. The first is Adrian, Moench & Shin (2010) who show that different financial intermediary balance sheet variables have substantial forecasting power for most assets. They consider a large number of alternative measures extracted from the US Flow of Funds statistics and different asset classes. They conclude that Shadow Banks asset growth (SBAG), defined as sum of Funding Corporations, Finance Companies and Asset Backed Securities Issues in the Flow of Funds, and Securities Broker Dealer's leverage (BDL) have substantial forecasting power across asset classes. They find that SBAG is better for treasuries and corporate bonds while BDL performs better for equities.

The second is Adrian, Etula & Muir (2012, AEM) who argue that financial intermediary leverage (measured by BDL) is priced and is a good proxy for the SDF (He & Krishnamurthy (2013)). They find that exposure to BDL can explain the pricing of the cross-section average return of portfolios, albeit less success in the time series. However, they use a methodology that imposes a constant price of risk, which doesn't allow them to test a key part of the theoretical prediction coming out of the literature cited above.

Lastly, our paper is also related to the analysis of the impact of monetary policy on financial intermediaries' balance sheet. Within a traditional monetary VAR framework, Nelson, Pinter &

Theodoridis (2013) investigate the impact of monetary policy shocks on different FIBS measures in the US. They show that traditional commercial banks reaction to monetary policy is sharply different from that of the shadow banking proxies. This highlights the difference in mechanisms that work through traditional bank lending behavior and that of the shadow banking sector. In this paper we focus on shadow banking as we are more interested on risk premia impact that recent theory has put forward, and whether this part of the financial system seems to be driven or not by monetary policy (as opposed to traditional bank lending channel). Adrian, Moench & Shin (2010) also conduct a similar VAR exercise with FIBS. Relative to Nelson, Pinter & Theodoridis (2013) and Adrian, Moench & Shin (2010) our framework allows for the analysis of the response of expectation and risk premia components along with identification of monetary policy.

3 Dynamic Term Structure Models and Macro Risk

In equilibrium, continuously-compounded zero-coupon yields are the expectation under the risk-adjusted probability measure ($\mathbb{Q}$) of future short rates, or the expectation under the actual probability measure ($\mathbb{P}$) of the stochastic discount factor (SDF), or Arrow-Debreu state-price densities (see Duffie (2001)). The nominal yield curve is the expected path of the nominal SDF. If we denote by $M_{t,T} = \Pi_{i=1}^{T-t} M_{t+i}$ the SDF and $y_{t,T-t}$ the zero-coupon yields between at date t with time to maturity $T-t$, and r_t the short-term risk free interest rate, then in equilibrium we have:

$$y_{t,T-t} = -\frac{1}{T} \ln E_t^P \left[M_{t,T} \right] = -\frac{1}{T} \ln E_t^Q \left[\exp \left(-\sum_{s=t}^{T-1} r_s \right) \right], \text{ for } T > t \tag{1}$$

The SDF is the representative agent's intertemporal marginal rate of substitution process. Dynamic term structure models specify a parametric model for the evolution of the conditional expectation of the SDF. The main intuition of the literature reviewed in the previous section is that FIBS measures might provide a better proxy of the representative agent for pricing purposes than aggregate consumption (see AEM). The model of JPS allows us to test this intuition within a full fledged model of the SDF without having to specify the role of FIBS in full detail.

We first describe the basic Affine Dynamic Term Structure Model (ADTSM). We then give the intuition for the distinction between spanned and unspanned risks before describing the methodology of JPS to model unspanned macro risks that we adopt to measure the impact of FIBS.

3.1 Affine Dynamic Term Structure Model

From equation (1) it is clear that to price the entire term structure of yields we only need the risk-adjusted dynamics of the risk-free interest rate. We adopt the affine framework of Duffie & Kan (1996) and specify short term risk-free rates as a linear function of pricing factors and the (risk-adjusted) $\mathbb{Q}$-dynamics of the pricing factors as standard linear VAR:

$$r_t = \delta_0 + \delta_1 X_t \tag{2}$$

$$X_{t+1} = \mu^Q + \Phi^Q X_t + \Sigma_X \varepsilon_{t+1}^Q \tag{3}$$

where $\varepsilon_{t+1}^Q \mid X_t \sim MVN\,(0, I)$ under the risk-adjusted probabilities $\mathbb{Q}$.

With (2) and (3) we can easily calculate yields with any maturity using Equation (1). These two assumptions imply that bond prices are exponential-affine functions of the pricing variables:

$$P_{t,n} = \exp(A_n + B_n X_t) \tag{4}$$

where the loadings $A_n = \mathcal{A}\left(\delta_0, \delta_1, \mu^Q, \Phi^Q, \Sigma_X, n\right)$, $B_n = \mathcal{B}\left(\delta_0, \delta_1, \mu^Q, \Phi^Q, \Sigma_X, n\right)$ satisfy a set of recursive equations derived in Appendix A.

These models are referred to as Gaussian-ADTSM because continuously compounded yields are affine functions of the factors:

$$y_{t,n} = A_n^Q + B_n^Q X_t \tag{5}$$

with $A_n^Q = -\frac{A_n}{n}, B_n^Q = -\frac{B_n}{n}$.

Although (2) and (3) are enough for pricing we need to specify the dynamics under the actual, or objective, probability measure ($\mathbb{P}$) in order to estimate the model, and therefore to extract the risk premia. This involves specifying the price of risk, or Arrow-Debreu state-price density, which determines the translation from actual to the risk-adjusted probabilities. We follow Duffee (2002) and specify the price of risk as linear function of the factors:

$$\Lambda_t = \Sigma_X^{-1} \left(\lambda_0 + \lambda_1 X_t\right) \tag{6}$$

In a yields-only framework, the specification of Duffee (2002) offers the most flexible parametrization while maintaining the same linear functional form for $\mathbb{P}$-dynamics:

$$X_{t+1} = \mu + \Phi X_t + \Sigma_X \varepsilon_{t+1}^P$$

where $\varepsilon_{t+1}^P \mid X_t \sim MVN\,(0, I)$ under the actual probabilities $\mathbb{P}$,[7] $\mu^Q = \mu - \lambda_0$ and $\Phi^Q = \Phi - \lambda_1$.

With these assumptions the Expectation Hypothesis (EH) equivalent yields, term premia and actual expected future rates are also affine functions of the state variables using the same recursive coefficients (see Appendix A). This analytical tractability is what has always made these models popular. More recently, Joslin, Singleton & Zhu (2011, JSZ) have greatly enhanced the empirical tractability of these models by proposing a more efficient identification strategy, which greatly reduces the numerical intensity of the estimation and allows greater investigation into the robustness of results.

3.2 Unspanned Macro Risks in ADTSM

With the assumptions above all of the information required to price and forecast bonds should be included in the cross-section (and time series) of yields. A flexible way to relax this assumption without having to modify the pricing of bonds is the *unspanned* framework proposed by JPS: additional observable variables are allowed to influence the forecasting and price of risk of the yield curve pricing factors without the need to specify a price of risk for that variable. In this way we avoid the 'pretence of knowledge' of being able to price any derivative on a variable just because we believe it contains information relevant for yields. This was the case in the *spanned* framework (which includes almost all of the macro-finance literature following Ang & Piazzesi (2003)) were the model would imply a precise price for any derivative written on the macro variables included because the model would imply a price of risk for that variable. Because of the linearity of (5), the spanned assumption would further imply the counter-factual result that all the information of macro variables that matters for yields should be spanned by the yield curve (see JPS and Joslin, Le & Singleton (2011)).

The choice of spanned versus unspanned factor is not only about the counter-factual implications arising from the linearity of yields on the factors. Even if we knew that a factor has a price of risk,

[7] In a Gaussian setting the change of measure $\left(\frac{d\mathbb{Q}}{d\mathbb{P}} = \Lambda_t\right)$ twists the shocks between the two measures by changing the drift, or mean, without affeting the variance ($\varepsilon_{t+1}^Q = \varepsilon_{t+1}^P + \Lambda$). See Duffie (2001).

if we do not observe proxies for it's risk adjusted dynamics we will not be able to estimate them precisely.[8] In economic terms, the risk adjusted measure is a modelling artifact that allows us to express equilibrium conditions, such as asset prices, as expected values with respect to Arrow-Debreu adjusted real probabilities. In a general equilibrium model the intertemporal marginal rate of substitution, or stochastic discount factor, will typically be a function of a few state variables. These will either be a subset of variables needed to describe the whole economy, or potentially complex nonlinear functions of the observed 'fundamentals' in the economy. In the absence of specific model predictions for the price of risk for any variable, or empirical proxies for their risk adjusted process (i.e. observed prices of assets whose payoffs are known functions of the variable of interest), it is problematic to include variables directly into the risk-adjusted dynamics. Furthermore, in the case ADTSM of bond yields this typically leads to a significant deterioration in the pricing performance, as shown by JPS. This however does not preclude any observed variable of having forecast power for the state variables of the SDF beyond that contained in their own current and lagged variables. Furthermore, investigating the real world comovement of additional variables is a valid econometric question that does not rely on economic restrictions.

That is, while we can use observed time series of any variable to infer their real world dynamics, we can only infer theory-implied risk adjusted dynamics either based on specific theoretical restrictions or with proxies for risk-adjusted dynamics of those variables. In the absence of theoretical predictions about the price of risk of a (macro) variable or observation of prices of assets written on that variable, we should not include those variables in the $\mathbb{Q}$-VAR, but we can expand the $\mathbb{P}$-VAR . This is the case of FIBS and other macro variables, and the unspanned framework of JPS is exactly the expansion of GADTSM to allow us to ask real world links without assuming risk-adjusted properties.

In the unspanned framework of JPS pricing remains as before (short-rate and $\mathbb{Q}$-VAR dynamics are a function of X only), but we have an expanded $\mathbb{P}$-VAR with observable variables interacting

[8] As an example, Guimarães (2013) conducts the following experiment with UK real yield curve, which is available for a long time span and does not suffer the liquidity issues that have been documented for US TIPS. After estimating the joint real and nominal yield curve dynamics using a flexible ADTSM and survey forecasts of both nominal interest rates and inflation rates, the observed real yields are progressively removed and the model is re-estimated with all remaining data (nominal yields and survey forecasts and inflation forecasts) and starting from the maximum likelihood estmate for the full data (that is, giving the maximum likelihood a better chance of finding the correct inflation risk premia than an econometrician who does not have the real yield data). The estimated real yields are up to 300 to 500 basis points away from observed yields.

with the pricing factors:

$$\underbrace{\begin{bmatrix} X_{t+1} \\ M_{t+1} \end{bmatrix}}_{Z_{t+1}} = \underbrace{\begin{bmatrix} \mu \\ \mathcal{K}^P_{0,m} \end{bmatrix}}_{K^P_0} + \underbrace{\begin{bmatrix} \Phi & \mathcal{K}^P_{1,xm} \\ \mathcal{K}^P_{1,mx} & \mathcal{K}^P_{1,m} \end{bmatrix}}_{K^P_1} \underbrace{\begin{bmatrix} X_t \\ M_t \end{bmatrix}}_{Z_t} + \underbrace{\begin{bmatrix} \Sigma_X & \Sigma_{mx} \\ \Sigma_{mx} & \Sigma_m \end{bmatrix}}_{\Sigma} \underbrace{\begin{bmatrix} \varepsilon^P_{t+1} \\ u^P_{t+1} \end{bmatrix}}_{\epsilon^P_{t+1}} \tag{7}$$

where M includes any observable or latent factor that is not spanned by the yield curve. In this setting pricing, pricing ($\mathbb{Q}$-dynamics) is not directly affected by M, but the forecast (i.e. the $\mathbb{P}$-dynamics) of future yields and pricing factors is. And since the risk premia is the difference between the two measures, the time-varying risk premia will be affected by M :

$$\tilde{\Lambda}_t = \Sigma_X^{-1} \left\{ \mu - \mu^Q + \left(\Phi - \Phi^Q \right) X_t + \mathcal{K}^P_{1,xm} M_t \right\} \tag{8}$$

We can still use the same affine recursions to calculate bond yields, expected values and term premia. All we have to do is to rewrite the system in terms of the expanded vector of variables $Z_t = [X_t', M_t']'$, which we derive in Appendix A.1:

$$\begin{aligned} \tilde{\Lambda}_t &= \Sigma_X^{-1} \left\{ \underbrace{\mu - \mu^Q}_{\lambda_0} + \underbrace{\begin{bmatrix} \Phi & \mathcal{K}^P_{1,xm} \end{bmatrix} - \begin{bmatrix} \Phi^Q & 0 \end{bmatrix}}_{\tilde{\lambda}_1} \begin{bmatrix} X_t \\ M_t \end{bmatrix} \right\} \\ &= \Sigma_X^{-1} \left(\lambda_0 + \tilde{\lambda}_1 Z_t \right) \end{aligned} \tag{9}$$

The zero coefficients in the expanded system is why some have interpreted JPS as saying M cannot affect yields (imposing zero restriction in $\mathbb{Q}$-VAR), but this is just an expositional artifact. We are just abstaining from deriving prices of risk for M, not saying that M cannot affect bond pricing. For any observable for which we actually observed a price (for example, we observe some inflation-linked bond prices so we can infer the price of inflation risk) we can include them in the risk-adjusted dynamics.

4 Methodology and Data

The ADTSM is naturally cast as a state-space model. In this setting, the transition equation describes the evolution of the risk factors (X, M) under the objective probability measure, whereas the the measurement equation maps the 'pricing' risk factors (X) into the term structure of observed interest rates $\left(y_t^{obs}\right)$. We assume that all yields are observed with error, so that the equation for each yield is:

$$y_{t,n}^{obs} = y_{t,n} + \eta_{t,n} \tag{10}$$

where $y_{t,n}$ is the model implied yield from equation (5) and $\eta_{t,n}$ is the zero mean observation error, which is IID across time and yields. We specify the $\eta_{t,n}$ to be normally distributed with common variance across different maturities σ_η.

Because the factors are latent, we need to impose restrictions to guarantee the model is identified. We follow the identification method of JSZ, which greatly improves the estimation of ADTSM by concentrating the likelihood of yields and factors. This is explained in Appendix B.

The likelihood of the model is given by:

$$\begin{aligned}\ell\left(Y_t, Z_t|Z_{t-1};\Theta\right) &= \ell\left(Y_t|Z_t, Z_{t-1};\Theta\right) \times \ell\left(Z_t|Z_{t-1};\Theta\right) \\ &= \ell\left(Y_t|X_t, X_{t-1};\lambda^{\mathbb{Q}}, r_\infty^{\mathbb{Q}}, \Sigma_X, \sigma_\eta\right) \times \ell\left(Z_t|Z_{t-1};K_0^{\mathbb{P}}, K_1^{\mathbb{P}}, \Sigma\right)\end{aligned} \tag{11}$$

where the conditional density of the states only depends on $K^{\mathbb{P}}$ and Σ. Of interest is also that, due to the identification of JSZ, the density $\ell\left(Z_t|Z_{t-1};\Theta\right)$ of the yields only depends on the risk neutral parameters $\left(\lambda^{\mathbb{Q}}, k_\infty^{\mathbb{Q}}\right)$, Σ_X and σ_η. Therefore, there is an almost exact separation, whereby Σ_X are the only parameters entering both the state and yield density. As a result, for any Σ the $K^{\mathbb{P}}$ that maximize the likelihood are simply the OLS estimates. The original maximization problem therefore consists of maximizing the likelihood over the $\lambda^{\mathbb{Q}}, k_\infty^{\mathbb{Q}}$, Σ_X and σ_η.

Estimation of this model by maximum likelihood can be done with Kalman filter or by assuming that a portfolio of yields is observed without error, which removes the need to filter latent factors, as shown by JSZ and JPS. JSZ have shown that assuming the first few principal components are observed without error is an efficient way of finding the maximum likelihood. We follow their approach in assuming the first 3 principal components are observed without error, but embbed this within Bayesian setting to account for estimation uncertainty. The post-estimation calculations we are interested in comparing for different models, such as term premia, excess retursn, Sharpe ratios and impulse response functions, are highly non-linear functions of the estimated parameters. Approaches such as the delta-method are only valid asymptotically and can perform poorly in small samples, particularly given the estimation concerns due to high persistence of yields. As a result, more complex bootstrapping methods are generally used. But traditional bootstrapping methods also have drawbacks and, more fundamentally, are highly computationally intensive. In contrast, evaluating estimation uncertainty is rather straightforward in a Bayesian context, and convergence and monitoring of sampling properties is better established than bootstrapping. Specifically, the object of interest, e.g. impulse response function, can be computed for each draw and its posterior distribution can therefore be easily obtained.

The Bayesian methods not only allows us to quantify model uncertainty, but also to perform model selection. In particular, alternative model specifications can be compared by means of the marginal likelihood, which can be easily computed for a VAR following Chib (1995). And because models with different number of unspanned factors, but with the same number of pricing factors, mainly differ for their forecasting performance ($\mathbb{P}$-VAR), it is therefore sufficient to evaluate the marginal likelihood of the different $\mathbb{P}$-VAR specifications.

We choose flat priors and use the maximum likelihood estimates to help tune the priors and proposal densities and initalize the $\mathbb{Q}$-parameters. In this way none of our main results differ meaningfully from the maximum likelihood estimates, but we are able to properly account for estimation uncertainty.

4.1 Bayesian Inference

Maximum likelihood estimation relies on complicated numerical optimization and are limited by the risk of reaching local optima. In contrast, Bayesian estimation tries to find the posterior distribution of parameters and states given the whole set of observations, $p(\Theta, Z|Y)$, where Θ denotes the parameters, Z denotes the latent states, and $Y = \{y_t^{obs}\}_{t=1}^T$ denotes the data. Direct sampling from the posterior distribution $p(\Theta, Z|Y)$ is often not feasible due to its high dimensionality or complicated form. The MCMC method solves the problem of simulating from this complicated target distribution by simulating from simpler conditional distributions. Precisely, by applying the Bayes' rule, the posterior density can be decomposed as follows

$$p(\Theta, Z|Y) \propto p(Y|Z, \Theta)p(Z|\Theta)p(\Theta), \tag{12}$$

where $p(Y|Z,\Theta)$ is the likelihood function given the states and the parameters, $p(Z|\Theta)$ is the probability distribution of states conditional on the parameters, and $p(\Theta)$ is the prior density of the parameters. We can then iteratively draw from the full conditionals $p(\Theta|Z,Y)$ and $p(Z|\Theta,Y)$. However, in our model setup the states Z are observable and observed without error, so that the problem simply consists of drawing from $p(\Theta|Z,Y)$.

We therefore draw the parameters conditional on factors and yields. Moreover, the parameter space Θ can be further decomposed into smaller blocks. The complete conditional distribution of $K^{\mathbb{P}}$ is known in closed form and can be directly sampled, so it simply consists of a Gibbs step in the MCMC. In contrast, the conditional posteriors of the other parameters are not known in closed form so that we use the Metropolis-Hastings algorithms. These algorithms sample a candidate draw from a proposal density, and then accept reject the candidate draw based on an acceptance criterion (Johannes and Polson, 2009). In sum, our algorithm consists of a combination of Gibbs steps and Metropolis-Hastings steps. In order to learn about what the data can tell us about bond risk premia, we impose flat priors. We use as starting values the maximum likelihood estimates of the model. Details on the algorithm are left to the Appendix, along with a discussion of the convergence diagnostics.

4.2 Data

We use quarterly data for the United States from 1972 to 2012. Our choice of frequency and sample are driven by availability and quality of the balance sheet data from the Flow of Funds database. In light of the results of AMS we start by focusing mainly on the two measures of FIBS identified as the most useful in forecasting asset returns: Shadow Banks asset growth (SBAG) and Securities Brokers and Dealers leverage (BDL). We adopt the same definitions as AMS for SBAG and BDL. Shadow Banks asset growth is defined as changes in total financial assets of ABS issuers, Finance Companies and Funding Corporations. Brokers and Dealers leverage is calculated as total financial assets divided by the difference between total financial assets and total liabilities (residual equity). Figure 1 shows the corresponding time series of SBAG and BDL.

From Panel A of Figure 1 we can see that including broker-dealers' asset growth in a broader definition of Shadow Banks would not change the behavior of SBAG significantly. The correlation between the two series is 0.91. Comparing the time series behavior of SBAG in Panel A and the growth of BDL in Panel B reveals two important differences. First, BDL is much more volatile and less persistent. Second, the timing of the reversal of each measure in the recent crisis suggest they proxy for very different aspects of financial intermediaries behavior: while SBAG began to fall in 2007 Q3, immediately after the global financial crisis began, BDL continued to grow rapidly until the failure of Lehman Brothers in 2008 Q3. Given that equity is calculated as residual between toal financial assets and total liabilities, BDL might be capturing stress in financial markets (particualrly funding, see Gorton & Metrick (2012)) rather than the decision to expand or contract their balance sheets, which is what the theory we are trying to test is based on.

This suspicion seems to be confirmed by analysis of equivalent measures of equity for other categories of financial institutions available from the Flow of Funds Statistics. In fact, for many of the main financial intermediries covered by the Flow of Funds, this residual definition of equity, as used to construct BDL, is negative for prolongued periods of time. As indicated by AEM in their choice of sample, this was the case for Broker-Dealers before 1960. They argue this suggests earlier data is of suspicious quality. However, this measure has also been negative for traditional depository institutions (including most recent quarters but also long periods in the 90s and 80s) as well as shadow banks (as recently as 2009, and most of the 90s). This suggests this measure is icking up valuation rather than balance sheet management. We nevertheless include BDL as measured in AEM an alternative measure of FIBS in our empirical work in light of the results of AEM and AMS.[9]

In addition to these 2 measures of FIBS we use nominal zero-coupon yields with maturities of $\{0.25, 1, 2, 3, 4, 5, 7, 10\}$ years, from Federal Reserve Board and Gurkaynak, Sack & Wright (2007), inflation and GDP growth.

We follow the identification strategy of JSZ and JPS outlined earlier with $Z_t = [X_t', M_t']'$, where $M_t = \begin{bmatrix} Inf_t & GDP_t & FIBS_t \end{bmatrix}$ and $X_t = \begin{bmatrix} PC1_t & PC2_t & PC3_t \end{bmatrix}'$.

5 Results

In this section we discuss the results of the estimation of the unspanned macro risk model of Section 3.2. We first describe the model fit. We then show the effect of the financial intermediary balance sheet quantities on measures of risk premia, such as the implied Sharpe Ratios and model-

[9] More recently the Flow of Funds have added a series with an estimate of equity for Securities Brokers and Dealers that seems to capture book equity and results in very different measures of leverage, more in line with other assessments of the leverage of this setor. Results with this measure, as well as other categories in the Flow of Funds are available from the authors on request and will be incorporated in future drafts.

implied excess returns. We then use a standard Choleski identification scheme on the expanded VAR to discuss the effect of shocks to expected monetary policy, term premia and balance sheets.

To quantify the impact of $FIBS_t$ we compare the Sharpe Ratio for a model without any FIBS data (M1) and models with each in turn (M2 and M3):

$$
\begin{aligned}
M1 &: M_t = \begin{bmatrix} Inf_t & GDP_t \end{bmatrix}' \\
M2 &: M_t = \begin{bmatrix} Inf_t & GDP_t & SBAG_t \end{bmatrix}' \\
M3 &: M_t = \begin{bmatrix} Inf_t & GDP_t & BDL_t \end{bmatrix}
\end{aligned}
$$

5.1 Model Fit and Selection

Table 1 shows the different model fit statistics for three alternative sets of macro variables and time periods. The first column of the table shows the conditional likelihood of the yields, which is given by the Gaussian likelihood of model residuals of yields. Within each sample period, the log-likelihood are nearly identical for the different sets of macro factors, which confirms the pricing independence of the unspanned framework of JPS. Recall that all three models have the first three principal components of yields as pricing factors. This is also reflected in the mean absolute errors of yields, shown in the second column, which are also the same up to a one-hundredth of one basis point annualized.

The third and fourth columns of Table 1 show the log marginal likelihood of the VAR computed as in Chib (1995) scaled by T and the log likelihood of the VAR divided by T, respectively. The log marginal likelihood allows us to compare the different models. For all three samples the models with FIBS are preferred to the model with only macro variables, and in all three samples the marginal likelihood of the model with shadow bank's asset growth (M2) is higher than for the model with broker-dealer leverage (M3).

In Table 2 we show the mean absolute errors (MAE) and the root mean squared errors (RMSE) for in-sample forecasts at different horizons for the 1yr, 5yr and 10yr yields. Given that in the unspanned model the role of non-yield variables operates exclusively through $\mathbb{P}$-dynamics, since the $\mathbb{Q}$-dynamics is unaffected (Table 1), this is a useful metric to gauge the importance of additional variables (see JPS). The model with shadow bank's asset growth (M2) outperforms the model with only macro (M1) and broker-dealer leverage (M3) for the 1, 4 and 8 quarter ahead forecast horizons.

The model with broker-dealers leverage (M3) does not produce smaller forecasting errors than the model with only macro variables (M1). Further results not shown here (including other measures of FIBS such as depository institutions and BD asset growth) confirm the superior performance of SBAG, which are on average 20% lower than the randow walk and 5% to 15% lower than the yields only model. These results taken together suggest that M2 likely provides a better estimate of bond risk premia. Since the implied bond yields are the same, the bond risk premia will depend on the implied expectations, hence an improved fit of actual dynamics should improve bond risk premia fit.

The relative performance of the model with shadow bank's asset growth (M2) and the model with broker-dealer leverage (M3) is in line with the results in AMS. They find that SBAG is the best overall predictor of returns of both government bonds of different maturities and corporate bonds with different ratings and sectors. The BDL is instead better for equity returns. Because of this, and the measurement issues with BDL mentioned earlier, in the remainder we focus the rest of the paper on the results for model M2.

Table 3 shows the parameter estimates and 95% credible intervals for the constant and lagged coefficients of the VAR dynamics under $\mathbb{P}$ (see Equation (7)) of model M2. Both macro variables and shadow banks asset growth have a significant impact on the level (PC1) and slope (PC2) of the yield curve, while they are insignificant for the curvature factor (PC3). The sign and significance of growth and inflation resemble the results of JPS. We next turn to analysis of the impact of SBAG on bond risk premia.

5.2 Time-varying Risk Premia and Balance Sheets

One of the major advantages of the framework adopted here is that it allows time-varying risk premia. Table 4 shows the market price of risk estimates for model M2, given by Equation (8). Both macro variables and shadow banks asset growth have a significant impact on the price of risk of level and slope factors of the yield curve, and insignificant for the curvature factor.

To see the impact of FIBS in an economic meaningful way we follow Duffee (2010) and examine term structure of bond (log) expected excess returns and maximal Sharpe ratios. The maximal (log) Sharpe ratio is given by:

$$SR_t = \sqrt{\tilde{\Lambda}_t' \tilde{\Lambda}_t}, \tag{13}$$

where $\tilde{\Lambda}_t$ is the market price of risk specified in Equation (9).

Figure 2 shows the model-implied Sharpe Ratio for model M2. As would be expected from theory, the Sharpe Ratio is counter-cyclical, higher at the trough of the cycle in the four downturns since late 1970. Figure 3 shows the difference between the Sharpe ratio for models M2 and M1 to capture the effect of SBAG in the model-implied risk premia. This difference does not capture the total effect of SBAG on risk, only the part that was not already captured by the yield pricing and macro factors. This figure shows the counter-cyclical impact on prices of risk of SBAG, particularly during the recent crisis period and in the period of high asset growth in the mid 1980s. Confirming the intuition of recent literature that motivated this study, the model implies that the expanding balance sheets of financial intermediaries is associated with a compression of prices of risk and that the sharp contraction in balance sheet in the recent recession was associated with a spike in risk premia.

The same analysis with model M3 reinforces our preference for SBAG as a proxy for financial intermediaries balance sheet expansion. The impact of BDL on market prices of risk are not statistically significant. Furthermore, the difference in Sharpe ratios between models M1 and M3 is positively correlated with BDL growth rate, contrary to implications from theory summarized earlier. Instead, this would be consistent with BDL being a proxy for both balance sheet choice and market stress or funding risks, being significantly affected by stress in funding markets, particularly by developments in repo markets.

We also examine the time series of model-implied excess returns. The log expected excess return for bond with maturity n-years is derived in Appendix A and is given by:

$$\ln E_t \left[xr_{t+1,n} \right] = \ln E_t P_{t+1,n-1} - p_{t,n} - r_t = B_{n-1} \Sigma_X \tilde{\Lambda}_t \tag{14}$$

The Sharpe Ratio is a measure of magnitude of prices of risk (without directional information), whereas excess returns combine the prices of risk ($\tilde{\Lambda}_t$) with the quantity of risk the bonds are exposed to. The loading B_{n-1} represent the exposure to each risk. The term structure of expected excess returns for 1 quarter holding periods is shown in Figure 4. In Figure 5 we show the marginal impact of shadow banks asset growth on expected excess returns, measured as the difference in excess returns of model M2 - M1. The estimates suggest that FIBS played an important role in compressing returns in the few years leading into the 1990 recession and for most part of the decade ahead of the Great Recession. They also imply that during the Great Recession it has played a major role in explaining high returns on bonds. In short, the excess return analysis confirms and complements the analysis of the Sharpe Ratio.

As a further check on the significance of our results on risk premia, we use the model implied Sharpe Ratio from model M2 to forecast excess equity portfolios. This exercise is similar to AEM, and we use the portfolios sorted by momentum and the Fama/French size and book-to-market portfolios.[10] The results are shown for excess quarterly returns for 1, 2 and 3 quarters ahead. Table 5 shows the results for the 10 momentum sorted portfolios. Our results are comparable to those of AEM. We find similar pattern of betas, t-statistics and adjusted R^2 increasing with higher momentum, except for portfolio 10. We find higher predictability for the 2 quarter ahead quarterly return, with the R^2 reaching 6%. For the size and book-to-market sorted portfolios predictive regressions, shown in Table 6, there is also evidence of predictability for two quarters ahead. Results shown in the internet appendix reveal that Shadow Banks asset growth (M2) has a larger incremental impact on longer non-overlapping forecast horizons relative to the model with only macro variables (M1).

5.3 Monetary Policy, Risk Taking and Balance Sheets

A second key advantage of the unspanned ADTSM framework used in this paper is that it allows us to conduct the same type of exercises in the Structural VAR literature on monetary policy with the risk and expectation components of yields. This is important for the current debate relating to the causes of the rapid expansion of FIBS. Different hypotheses differ on highlighting the role of monetary policy or compression of term premia (e.g. savings glut) in causing risk-taking behavior by financial intermediaries, or the behavior of financial intermediaries being driven by other exogenous factors (e.g. financial innovation and liberalization or changes in accounting and regulation).

Because in the GADTSM every quantity of interest is a linear combination of the factors, we can rotate the original vector of variables Z_t to express the VAR with both expected and risk premia components instead of pricing factors X_t (see Pericoli & Taboga (2012) and Ferman (2011)). On this rotated vector $\tilde{Z}_t = W_0 + W_1 Z_t$, for which the VAR dynamics follow by straightforward manipulations shown in Appendix D of the original VAR, we can apply any of the standard identification methods

[10] These are available from Kenneth French's wensite: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

used to identify structural shocks. Here we adopt the standard recursive identification using the Choleski decomposition of the covariance matrix of the rotated vector with the following ordering: GDP growth, inflation, expected 1 year risk-free rate, 5-year spot term premia, FIBS and 5-year spot yield. This ordering is similar to AMS, but in addition we have the term premium in our VAR. Our conclusions are robust to inverting the order of term premia and FIBS or choosing 10 year term premia.

Figure 6 shows the impulse responses to a 25 basis points shock to expected monetary policy, captured by the shock to expected interest rates up to 4 quarters ahead. The shock has the standard effect on GDP (initial fall) and inflation (delayed fall). The monetary policy shock actually has a small positive impact on shadow banks asset growth on impact, before becoming insignificant (the point estimate leading to a small fall in the few years after impact), which resembles the "price puzzle". The shock has the effect of raising spot term premium.

Figure 7 shows the impulse responses to a 25 basis points shock to 5-year spot term premia. Growth displays a strong positive reaction, while inflation falls. Both expected rates and asset growth responses are insignificant, though point estimates display a persistent rise. The shape of these impulse responses is consistent with term premia shock at least partly capturing good news about the economy, perhaps a "technological productivity news" shock (as in Kurmann & Otrok 2012). Whether it captures news shocks or not, it has the opposite sign on SBAG than the implied negative relation that would be consistent with "savings glut" phenomena driving SBAG.

Figure 8 shows the impulse responses to a 1 percentage point shock to SBAG. Expected interest rates increase on impact, consistent with monetary policy reacting to the expansion of FIBS in a 'leaning against the wind fashion'. Term premia fall in response to SBAG increase, which is consistent with the predicted impact on risk premia as discussed previously. There is no significant response of both growth and inflation.

The relation between monetary policy, term premium and SBAG is robust to sample period. The responses of GDP and inflation to the different shocks however vary substantially between the whole sample estimates and the great Moderation period (post 1984 sample), as used in AMS, in line with the findings of den Haan & Sterk (2010).

When we use BDL instead of SBAG, we find substantial differences across samples between all variables, not just with growth and inflation. Furthermore, the reaction of BDL to a contractionary monetary policy shock is a sharp contraction (2 pp in response to 25bps tightening) in line with the search-for-yield story in the Great Moderation sample. A term premium shock has opposite effects on BDL and a an expansionary shock to BDL leads to accommodative (loosening) monetary policy.

These differences in part reflect the difficulties and uncertainties with structural identification in VAR well known in monetary policy analysis. However, the magnitude of the responses and the previous estimation diagnostics for the model with BDL, combined with the measurement issues discussed in Section 4.2, leads us to place less weight on those results. As discussed earlier, given that this measure of BDL is in part reflecting market stress, particularly funding market stress, it is not surprising that monetary policy would have a higher impact.

Furthermore, the overall implications of the VAR analysis seem to be supported by general aspects of the historical evolution of these variables. The long run expansion of shadow bank's assets shown in Figure 9, and the high positive correlation with short term real rates (above 0.5 for the whole sample, and above 0.6 since 1984) is difficult to reconcile with the search-for-yield argument (which would imply negative correlation between short term rates and asset growth). In addition, the long term rise in size of the balance sheet relative to GDP and in leverage begin mid to late 1980s, substantially earlier than the global imbalances of "savings glut" phenomena. Rather, it seems more consistent with the timing of financial liberalization, deregulation and innovation that began in the early 1980s. Indeed the average value of Shadow Bank's asset over GDP share (shown in Figure) has a correlation of 0.94 with the US financial deregulation index of Philippon & Reshef (2012).[11]

6 Conclusion

In this paper we use an affine specification of the stochastic discount factor to allow for time-varying risk premia to investigate the importance of financial intermediaries in explaining the pricing of risks. We build on the results of Adrian, Etula & Muir (2012), who find that financial intermediary balance sheet data has significant forecasting power for financial asset price returns and can successfully price the cross section of equity returns and bond market returns. Their empirical exercise assumes constant price of risk (see Adrian, Crump & Moench (2011)).

We find that financial intermediary balance sheet changes, particularly Shadow Banks' asset growth, play an important role in the counter-cyclical behavior of prices of risk. Confirming the

[11] Calculated between 1970 and 2006, when the deregulation index ends.

intuition of recent literature, the model implies that the expanding balance sheets of financial intermediaries compresses market risk premia. The estimates suggest that Shadow Banks' asset growth played an important role in compressing returns in the few years leading into the 1990 recession and for most part of the decade ahead of the Great Recession. They also imply that during the Great Recession the contraction in shadow banking balance sheet has played a major role in explaining high excess holding period returns on bonds.

We use standard SVAR identification scheme with a dynamic term structure model that follows Joslin, Priebisch & Singleton (2012), to test the importance of financial intermediaries risk appetite and interaction with monetary policy, as well as exogenous shocks to term premia. The results suggest the opposite causation to the "risk taking channel" of monetary policy for the US: exogenous higher risk taking, measured by expansion to Shadow Bank's asset growth, leads to lower term premia and higher monetary policy rates while shocks to policy rate expectations have little, or even the opposite effect to that predicted by "search for yield", on Shadow Bank's asset growth.

The evidence presented here is not that "search for yield" or the "risk taking channel" does not exist. Rather, it is more casting doubt whether monetary policy shocks cause risk taking through balance sheet expansion of Shadow Banks. The "search for yield" phenomena might not be captured by short term reaction to monetary policy shocks, rather the consequence of extended periods of low or declining interest rates, which the exercises conducted in this paper would have little to say. Furthermore, the micro evidence for the risk taking channel is concerned with lending practices by commercial banks (e.g. Maddaloni & Peydró (2012)), which behaved very differently to shadow banks (see Nelson *et al* (2013)).

Nevertheless, the evidence we find and the timing and comovement of aggregate shadow banking balance sheet changes is easier to reconcile with factors other than monetary policy or savings glut, including deregulation and financial innovation, in explaining the long run expansion of shadow banks' balance sheets prior to the Great Recession.

References

Acharya, V., P. Schnabl and G. Suarez (2013), "Securitization without risk transfer", *Journal of Financial Economics*, vol. 107, 515–536

Acharya, V., and S. Visnawathan (2011). "Leverage, Moral Hazard and Liquidity." *Journal of Finance*, 66(1): 99-138.

Adrian, T. and N. Boyarchenko (2012) "Intermediary Leverage Cycles and Financial Stability." *Federal Reserve Bank of New York Staff Report* 567

Adrian, T., P. Colla, and H. Shin (2012) "Which Financial Frictions? Parsing the Evidence from the Financial Crisis of 2007-09," *NBER Macroeconomics Annual*, edited by Daron Acemoglu, Jonathan Parker, and Michael Woodford, forthcoming.

Adrian, T., R. Crump, and E. Moench (2012). "Pricing the Term Structure with Linear Regressions," *Journal of Financial Economics*, forthcoming.

Adrian, T., R. K. Crump and E. Moench (2011). "Efficient, Regression-Based Estimation of Dynamic Asset Pricing Models," *Federal Reserve Bank of New York Staff Report* 493.

Adrian, T., E. Etula, and T. Muir (2012). "Financial Intermediaries and the Cross-Section of Asset Returns," *Journal of Finance*, forthcoming.

Adrian, T., E. Etula, and J. Groen (2011), "Financial Amplification of Foreign Exchange Risk Premia," *European Economic Review* 55(3), pp. 354-370.

Adrian, T., E. Moench, and H. Shin (2010a) "Macro Risk Premium and Intermediary Balance Sheet Quantities." *IMF Economic Review* 58, 179-207.

Adrian, T., E. Moench, and H. Shin (2010b). "Financial Intermediation, Asset Prices, and Macroeconomic Dynamics", FRBNY Staff Report no. 422

Adrian, T. and H. Shin (2011). "Financial Intermediaries and Monetary Economics." *Handbook of Monetary Economics* 3A, ch. 12, ed. by Benjamin Friedman and Michael Woodford, pp. 601-650.

Adrian, T. and H. Shin (2010). "Liquidity and Leverage." *Journal of Financial Intermediation*, 19 (3), pp. 418-437.

Adrian, T., M. Brunnermeier, H. Nguyen. "Hedge Fund Tail Risk." Chapter in forthcoming NBER book *Quantifying Systemic Risk*, Joseph G. Haubrich and Andrew W. Lo, editors.

Ajello, A. (2012), "Financial Intermediation, Investment Dynamics and Business Cycle Fluctuations", mimeo Federal Reserve Board.

Ang, A. and M. Piazzesi (2003). "A No-Arbitrage Vector Regression of Term Structure Dynamics with Macroeconomic and Latent Variables", *Journal of Monetary Economics*, vol. 50 (4).

Ang, A., S. Dong and M. Piazzesi (2007). "No-Arbitrage Taylor Rules", NBER working paper 13448.

Bauer, M. (2011). "Bayesian Estimation of Dynamic Term Structure Models under Restrictions on Risk Pricing", *Federal Reserve Bank of San Francisco*working paper 2011-03.

Bauer, M., G. Rudebusch and J. Wu (2012). "Correcting Estimation Bias in Dynamic Term Structure Models", *Journal of Business and Economic Statistics*, vol. 30 (3).

Bernanke, B. (2005), "The Global Saving Glut and the U.S. Current Account Deficit," The Sandridge Lecture, April 14, 2005.

Bibkov, R. and M. Chernov (2009). "Unspanned Stochastic Volatility in Affine Models: Evidence from Eurodollar Futures and Options", *Management Science*, vol. 55 (8).

Borio, C and H Zhu (2008). "Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism?", BIS Working Papers, no 268.

Bruno, V. and H. Shin (2013). "Capital Flows and the Risk-Taking Channel of Monetary Policy", NBER working paper18942.

Brunnermeier, M. and Y. Sannikov (2013), "A Macroeconomic Model with a Financial Sector", *American Economic Review* forthcoming.

Brunnermeier, M., T. Eisenbach and Y. Sannikov (2013),"Macroeconomics with Financial Frictions: A Survey", in Advances in Economics and Econometrics, 10th World Congress of the Econometric Society. , ed. Daron Acemoglu, Manuel Arellano and Eddie Dekel. Cambridge University Press, Cambridge, UK.

Caballero, R., E. Farhi & P. Gourrinchas (2008), "An Equilibrium Model of "Global Imbalances" and Low Interest Rates", *American Economic Review*, vol. 98 (1), 358–393

Chib, S. (1995). "Marginal likelihood from the Gibbs output", *Journal of the American Statistical Association*, vol. 90, 1313–1321.

Chib, S. and B. Ergashev (2009), "Analysis of Multi-Factor Affine Yield Curve Models", *Journal of the American Statistical Association*, vol 104, 1324-1337.

Cochrane, J. (2011). "Discount Rates", *Journal of Finance*, vol. 66 (4).

Danielsson, J., H. Shin & J-P Zigrand (2012) "Procyclical Leverage and Endogenous Risk", mimeo LSE

Den Haan, W. and V. Sterk (2011). "The Myth of Financial Innovation and the Great Moderation", *The Economic Journal*, vol. 121, 707-39.

Di Tella, S. (2012). "Uncertainty Shocks and Balance Sheet Recessions", working paper, MIT

Duffee, G. (2010). "Sharpe ratios in term structure models", mimeo Johns Hopkins University.

Duffie, D. (2001). *Dynamic Asset Pricing Theory*, Princeton University Press, 3rd Ed.

Duffie, D., and R. Kan (1996). “A Yield-Factor Model of Interest Rates”, *Mathematical Finance*, vol. 6.

Feldhüter, P. (2008). "Can Affine Models Match the Moments in Bond Yields?", mimeo London Business School.

Ferman, M. (2011). "The Monetary Policy Transmission Mechanism in a Term-Structure Model with Unspanned Macro Risks", working paper LSE.

Garleanu, N., S. Panageas & J. Yu (2013). "Financial Entanglement: A Theory of Incomplete Integration, Leverage, Crashes, and Contagion", working paper UC Berkeley Haas.

Geweke, J. (1992). "Evaluating the Accuracy of Sampling-Based Approaches to the Calculation of Posterior Moments", in J.M. Bernardo, J.O. Berger, A.P. Dawid and A.F.M. Smith (eds.), *Bayesian Statistics 4*. Oxford: Oxford University Press

Gorton, G. and A. Metrick (2012), “Securitized Banking and the Run on Repo,” *Journal of Financial Economics*, vol. 104 (3), 425-451.

Guimarães, R. (2013), "Expectations, risk premia and information spanning in dynamic term structure model estimation", mimeo Bank of England.

He, Z., I. Khang and A. Krishnamurthy (2010). "Balance Sheet Adjustment in the 2008 Crisis", *IMF Economic Review* 1, pp. 118-156.

He, Z. and A. Krishnamurthy (2012). "A Model of Capital and Crises", *Review of Economic Studies* 79(2): pp. 735-777.

He, Z. and A. Krishnamurthy (2013). "Intermediary Asset Pricing", *American Economic Review* 103(2), pp. 1-43.

Johannes, M. and N. Polson (2009), "MCMC methods for Financial Econometrics", in Handbook of Financial Econometrics, edited by Y. Ait-Sahalia and L.P. Hansen, Volume 2, 1-72, North Holland.

Joslin, S., A. Le and K. Singleton (2011). "Why Gaussian Macro-Finance Term Structure Models Are (Nearly) Unconstrained Factor-VARs", *Journal of Financial Economics*, forthcoming.

Joslin, S., M. Priebisch and K. Singleton (2012). "Risk Premiums in Dynamic Term Structure Models with Unspanned Macro Risks", *Journal of Finance*, forthcoming.

Joslin, S., K. Singleton and H. Zhu (2011). "A New Perspective on Gaussian Dynamic Term Structure Models", *Review of Financial Studies*, vol.24 (3).

Kurmann, A. and C. Otrok (2012). "News Shocks and the Slope of the Term Structure of Interest Rates", *American Economic Journal: Macroeconomics,* forthcoming.

Maddaloni, A. and J-L Peydró (2011), "Bank Risk-taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro-area and the U.S. Lending Standards", *Review of Financial Studies*, vol. 24 (6).

Muir, T. (2013). "Financial Crises, Risk Premia, and the Term Structure of Risky Assets", mimeo Northwestern U.

Nelson, B., G. Pinter & K. Theodoridis (2013). "Monetary Policy and the Financial System: Some Evidence for the US", unpublished mimeo Bank of England.

Parlour, C., R. Stanton and J. Walden (2011). "Financial Flexibility, Bank Capital Flows, and Asset Prices", *Journal of Finance*, forthcoming.

Pericolli, M. and M. Taboga (2012), "Bond Risk Premia, Macroeconomic Fundamentals and the Exchange Rate" *International Review of Economics and Finance*, 22, 42-65.

Phelan, G. (2012), "Financial Intermediation, Leverage, and Macroeconomic Instability", mimeo Yale U..

Philippon, T., and A. Reshef. (2012), "Wages and Human Capital in the U.S. Financial Industry: 1909–2006." *Quarterly Journal of Economics*, vol. 127 (4), 1551–1609.

Philippon, T. and A. Reshef (2013), "An International Look at the Growth of Modern Finance", *Journal of Economic Perspectives,* vol. 27 (2), 73–96.

Rajan, R. (2005), "Has Financial Development Made the World Riskier?", NBER working paper No. 11728.

Rampini, A. and S. Viswanathan (2012). "Financial Intermediary Capital", working paper Duke Univ.

Sherman, M. (2009), "A Short History of Financial Deregulation in the United States", Center for Economic and Policy Research

Schularick, Moritz and Alan M. Taylor (2012), "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises, 1870-2008," *American Economic Review,* vol. 102 (2).

Wright, J. (2011). "Term Premia and Inflation Uncertainty: Empirical Evidence from an International Panel Dataset", *American Economic Review*, vol. 101 (4).

Table 1: Model Fit

	Yields ($\mathbb{Q}$)		Factors ($\mathbb{P}$)	
	logL	MAE	logML	logL
	1972Q1-2012Q2			
M1: Macro	57.87	1.47	23.74	26.33
M2: SB Asset Growth	57.87	1.47	27.88	30.81
M3: BD Leverage	57.87	1.47	25.82	28.78
	1972Q1-2007Q2			
M1: Macro	58.29	1.55	23.56	26.50
M2: SB Asset Growth	58.29	1.55	27.78	31.11
M3: BD Leverage	58.29	1.55	25.79	29.15
	1984Q1-2012Q2			
M1: Macro	58.67	1.19	23.89	27.72
M2: SB Asset Growth	58.67	1.19	27.86	32.13
M3: BD Leverage	58.67	1.19	25.83	30.20

The table reports: *logL* the log likelihood of the yields divided by the number of observations (T); *MAE* is the total mean absolute error, which is computed as the average of the mean absolute errors of the 1yr, 2yr, 3yr, 4yr, 5yr, 7yr, and 10yr maturities; *logML* is the log marginal likelihood of the VAR computed as in Chib (1995) scaled by T; and (logL) is the log likelihood of the VAR divided by T. *M1: Macro* denotes a restricted model which only includes macro factors in addition to the first three principal components. *M2: SB Asset Growth* includes principal components, macro variables and shadow banks' financial asset growth. *M3: BDL Leverage* includes principal components, macro variables and broker dealers' leverage. Each panel denotes a different sample.

Table 2: Pricing Errors

	MAE				RMSE			
	t,t	t,t+1	t,t+4	t,t+8	t,t	t,t+1	t,t+4	t,t+8
				M1: Macro				
1yr	1.30	16.1	32.8	46.1	1.87	23.8	41.1	55.3
5yr	1.60	13.7	24.7	32.9	2.26	17.6	31.9	41.5
10yr	1.77	11.7	21.4	26.7	2.40	15.3	28.0	34.9
				M2: SB Asset Growth				
1yr	1.30	16.0	31.3	43.5	1.87	23.2	39.1	52.5
5yr	1.60	13.2	23.6	30.6	2.26	17.2	30.4	38.8
10yr	1.77	11.3	20.6	25.0	2.40	15.1	26.9	32.4
				M3: BDL Leverage				
1yr	1.30	16.1	32.5	46.0	1.87	23.7	40.9	55.4
5yr	1.60	13.8	25.0	33.3	2.26	17.6	32.0	41.9
10yr	1.77	11.7	21.5	27.4	2.40	15.3	28.2	35.6

The table reports the mean absolute errors (MAE) and the root mean squared errors (RMSE) for in-sample forecasts at different horizons for the 1yr, 5yr and 10yr yields. Specifically, t,t denotes the contemporaneous pricing errors. In contrast, t,t+1, t,t+4 and t,t+8 denote the pricing errors resulting from the one-, four- and eight-quarter ahead yield forecasts, respectively. All figures are in annualized basis points. *M1: Macro* denotes a restricted model which only includes macro factors in addition to the first three principal components. *M2: SB Asset Growth* includes principal components, macro variables and shadow banks' financial asset growth. *M3: BD Leverage* includes principal components, macro variables and broker dealers' leverage. Each panel denotes a different sample.

Table 3: VAR Parameter Estimates

	$K_0^{\mathbb{P}}$	$K_1^{\mathbb{P}}$					
	const	PC1	PC2	PC3	INF	GDP	SBAG
PC1	-0.0038	0.8545	-0.4308	1.3744	0.4364	0.119	0.1617
	[-0.01;-0.00]	[0.82;0.89]	[-0.63;-0.23]	[0.65;2.10]	[0.33;0.54]	[0.04;0.20]	[0.11;0.21]
PC2	-0.0004	-0.024	0.7797	-0.4743	0.0635	0.0494	0.0188
	[-0.00;-0.00]	[-0.03;-0.02]	[0.73;0.83]	[-0.71;-0.25]	[0.04;0.09]	[0.03;0.07]	[0.01;0.03]
PC3	0.0003	0.0006	-0.0073	0.6816	-0.0007	-0.0011	-0.0011
	[0.00;0.00]	[-0.00;0.00]	[-0.02;0.00]	[0.63;0.74]	[-0.01;0.00]	[-0.01;0.00]	[-0.00;0.00]
INF	-0.0003	-0.0169	0.0866	0.6758	1.0224	0.0603	0.0144
	[-0.00;0.00]	[-0.02;-0.01]	[0.05;0.12]	[0.47;0.87]	[1.00;1.04]	[0.05;0.07]	[0.00;0.02]
GDP	0.0013	0.0029	-0.3337	-1.7582	-0.0145	0.8583	-0.0287
	[0.00;0.00]	[-0.01;0.02]	[-0.44;-0.22]	[-2.22;-1.27]	[-0.07;0.04]	[0.81;0.90]	[-0.06;-0.00]
AG	-0.0003	0.0043	-0.0569	-0.4947	0.0788	0.2295	0.8932
	[-0.00;0.00]	[-0.01;0.02]	[-0.18;0.06]	[-1.01;0.05]	[0.02;0.14]	[0.18;0.27]	[0.86;0.93]

The table reports posterior means and 95 percent credible intervals (in squared bracket) of the VAR parameters for model M2: SB Asset Growth, where PC1, PC2 and PC3 denote the first three principal components, and the remaining factors denote inflation (INF), real gross domestic product (GDP), and shadow banks financial asset growth (SBAG). The estimation is performed with the Bayesian algorithm described in Section 4, based on quarterly data from 1972-Q1 to 2012-Q2.

Table 4: Market Price of Risk Estimates

	$K_0^{\mathbb{P}}$-$K_0^{\mathbb{Q}}$	$K_1^{\mathbb{P}}$-$K_1^{\mathbb{Q}}$					
	const	PC1	PC2	PC3	INF	GDP	SBAG
PC1	-0.004	-0.1418	-0.0762	2.3364	0.4364	0.119	0.1617
	[-0.01;-0.00]	[-0.17;-0.11]	[-0.28;0.12]	[1.62;3.07]	[0.33;0.54]	[0.04;0.20]	[0.11;0.21]
PC2	-0.0005	-0.0303	-0.0568	0.4303	0.0635	0.0494	0.0188
	[-0.00;-0.00]	[-0.04;-0.02]	[-0.10;-0.01]	[0.20;0.66]	[0.04;0.09]	[0.03;0.07]	[0.01;0.03]
PC3	0.0003	-0.0046	-0.0059	0.007	-0.0007	-0.0011	-0.0011
	[0.00;0.00]	[-0.01;-0.00]	[-0.02;0.01]	[-0.05;0.06]	[-0.01;0.00]	[-0.01;0.00]	[-0.00;0.00]

The table reports posterior means and 95 percent credible intervals (in squared bracket) of the risk premium parameters for model M2: SB Asset Growth, where PC1, PC2 and PC3 denote the first three principal components, and the remaining factors denote inflation (INF), real gross domestic product (GDP), and shadow banks financial asset growth (SBAG). The estimation is performed with the Bayesian algorithm described in Section 4, based on quarterly data from 1972-Q1 to 2012-Q2.

Table 5: Predictive Regression Momentum Portfolios Returns

	Mom 1	Mom 2	Mom 3	Mom 4	Mom 5	Mom 6	Mom 7	Mom 8	Mom 9	Mom 10
E[R_e]	-3.93	3.01	4.73	5.86	4.48	5.36	6.28	7.98	8.42	11.99
	PANEL A: $R_{t,t+1} = \beta_0 + \beta_{SR} SR_t + \epsilon_t$									
β_{SR}	9.58	7.78	11.56	9.88	3.19	11.74	10.11	10.62	21.43	13.62
T-Stat	0.57	0.61	1.15	0.97	0.36	1.11	1.18	1.19	2.13	0.96
Radj(%)	-0.48	-0.46	-0.14	-0.16	-0.57	0.10	0.05	0.11	1.82	-0.04
	PANEL B: $R_{t+1,t+2} = \beta_0 + \beta_{SR} SR_t + \epsilon_{t+1,t+2}$									
β_{SR}	18.09	16.43	17.58	18.11	11.06	23.07	23.62	24.61	33.52	27.74
T-Stat	1.17	1.26	1.66	1.91	1.30	2.33	3.01	2.90	3.82	2.23
Radj(%)	-0.10	0.10	0.51	0.95	0.06	2.18	3.07	3.35	5.36	1.80
	PANEL C: $R_{t+2,t+3} = \beta_0 + \beta_{SR} SR_t + \epsilon_{t+2,t+3}$									
β_{SR}	18.93	13.63	15.86	18.28	11.60	16.52	19.44	19.90	24.33	17.30
T-Stat	1.07	1.04	1.53	1.92	1.28	1.56	2.15	2.17	2.40	1.21
Radj(%)	-0.05	-0.13	0.29	0.97	0.12	0.81	1.87	1.97	2.52	0.32

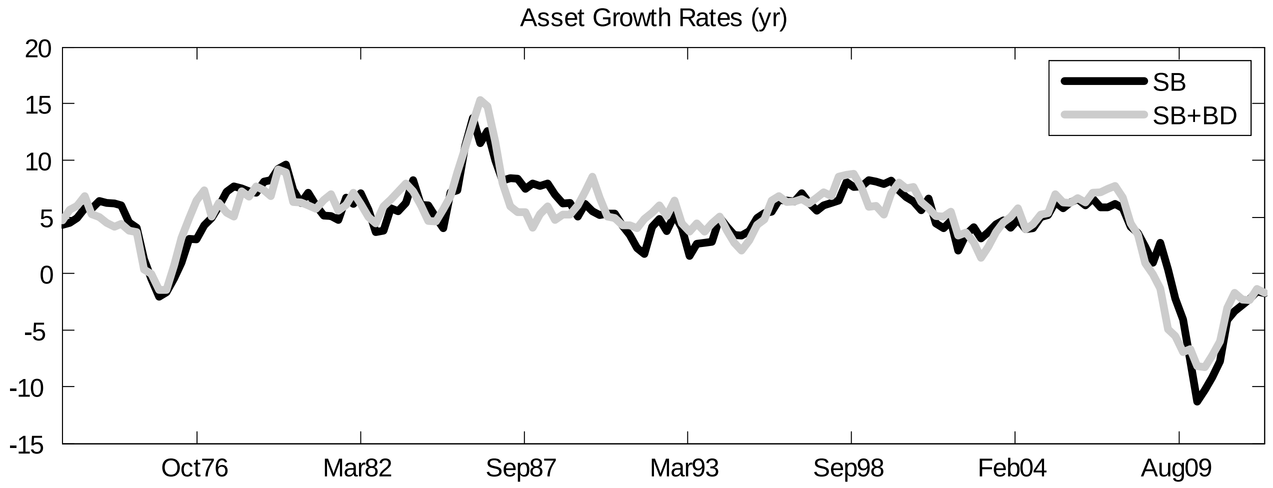
Time series predictive regressions of the momentum portfolios quarterly excess returns at 1-, 2-, and 3-quarter ahead on the Sharpe ratio (SR) of M2 (the model that includes Shadow Banks' asset growth). Data are quarterly, 1972Q1-2012Q2. Newey-West standard errors with optimal lag selection.

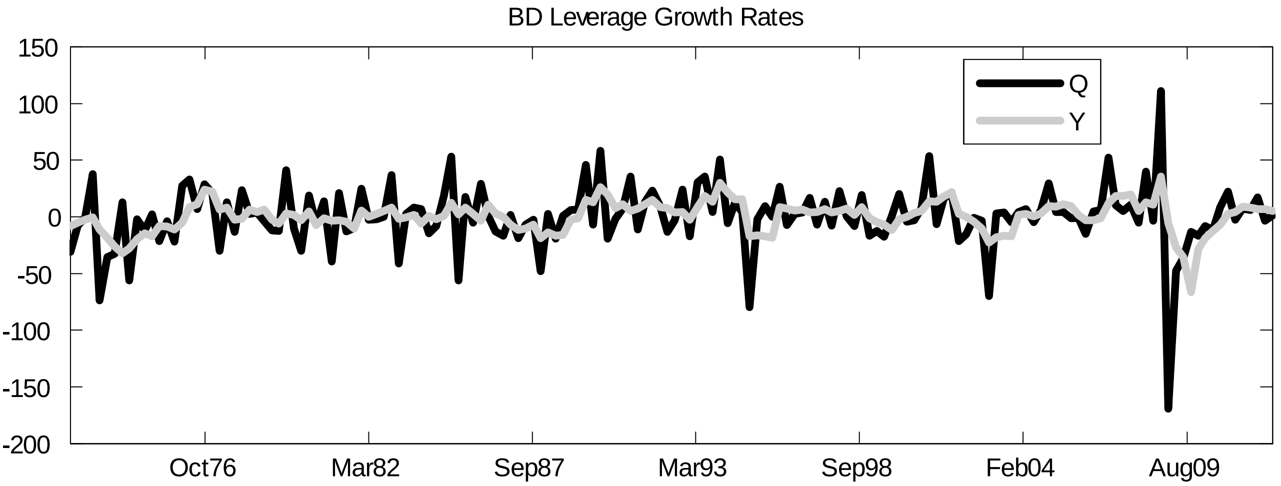
Table 6: Predictive Regressions Size Book-to-Market Portfolios

	PANEL A					PANEL B					PANEL C				
	$R_{t,t+1} = \beta_0 + \beta_{SR}SR_t + \epsilon_{t,t+1}$					$R_{t+1,t+2} = \beta_0 + \beta_{SR}SR_t + \epsilon_{t,t+2}$					$R_{t+2,t+3} = \beta_0 + \beta_{SR}SR_t + \epsilon_{t,t+3}$				
	Low	Book-to-Market			High	Low	Book-to-Market			High	Low	Book-to-Market			High
			β_{SR}					β_{SR}					β_{SR}		
Small	6.55	9.25	15.16	10.79	16.18	34.82	30.06	33.40	29.86	35.03	27.53	18.31	22.18	17.48	22.29
	11.17	14.92	12.90	16.44	16.72	33.58	34.08	29.86	30.75	30.65	24.56	21.94	18.45	23.50	18.51
Size	15.98	18.80	13.17	18.37	15.45	32.62	32.76	28.52	28.23	23.00	22.77	22.75	19.23	16.70	17.39
	9.39	10.85	17.48	14.19	22.50	25.06	22.51	26.24	20.43	25.95	18.03	18.26	20.92	11.15	18.64
Big	5.76	6.98	5.88	11.65	-0.75	17.71	17.06	18.72	25.43	11.78	13.25	18.22	18.77	17.48	20.00
			T-Stat					T-Stat					T-Stat		
Small	0.36	0.66	1.14	0.89	1.20	1.87	2.04	2.46	2.43	2.71	1.35	1.12	1.44	1.22	1.53
	0.74	1.23	1.11	1.52	1.39	2.30	2.85	2.79	3.08	2.67	1.54	1.63	1.58	2.36	1.57
Size	1.13	1.60	1.29	1.67	1.40	2.39	3.12	3.17	3.07	2.18	1.54	1.98	1.89	1.64	1.67
	0.67	0.97	1.57	1.34	1.89	1.93	2.25	2.71	2.10	2.42	1.32	1.63	2.01	1.15	1.76
Big	0.52	0.74	0.62	1.19	-0.07	1.62	1.87	2.15	2.83	1.29	1.26	1.97	2.01	2.04	2.19
			Radj(%)					Radj(%)					Radj(%)		
Small	-0.56	-0.42	0.08	-0.23	0.04	1.34	1.52	2.83	2.39	2.54	0.61	0.17	0.90	0.41	0.65
	-0.36	0.04	0.00	0.42	0.21	1.77	2.89	2.72	3.06	2.19	0.65	0.83	0.65	1.52	0.40
Size	0.01	0.65	0.16	0.79	0.27	2.03	3.27	3.06	2.73	1.37	0.66	1.24	1.04	0.54	0.51
	-0.37	-0.15	0.70	0.30	1.28	1.22	1.42	2.37	1.30	1.91	0.33	0.72	1.26	-0.06	0.68
Big	-0.47	-0.34	-0.40	0.22	-0.62	0.89	1.06	1.65	3.39	0.06	0.22	1.30	1.66	1.26	1.34

Time series predictive regressions of the size book-to-market portfolios quarterly excess returns at 1-, 2-, and 3-quarter ahead on the Sharpe ratio (SR) of M2 (the model that includes Shadow Banks' asset growth). Data are quarterly, 1972Q1-2012Q2. Newey-West standard errors with optimal lag selection.

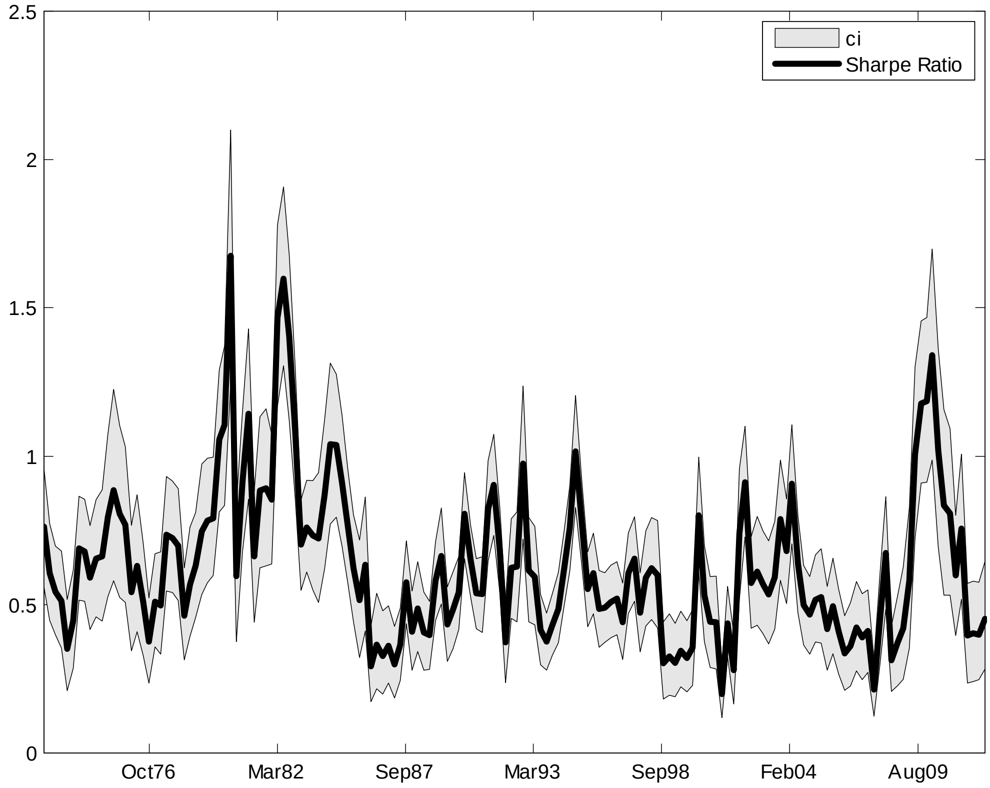
Figure 1: Financial Intermediary Balance Sheet Data





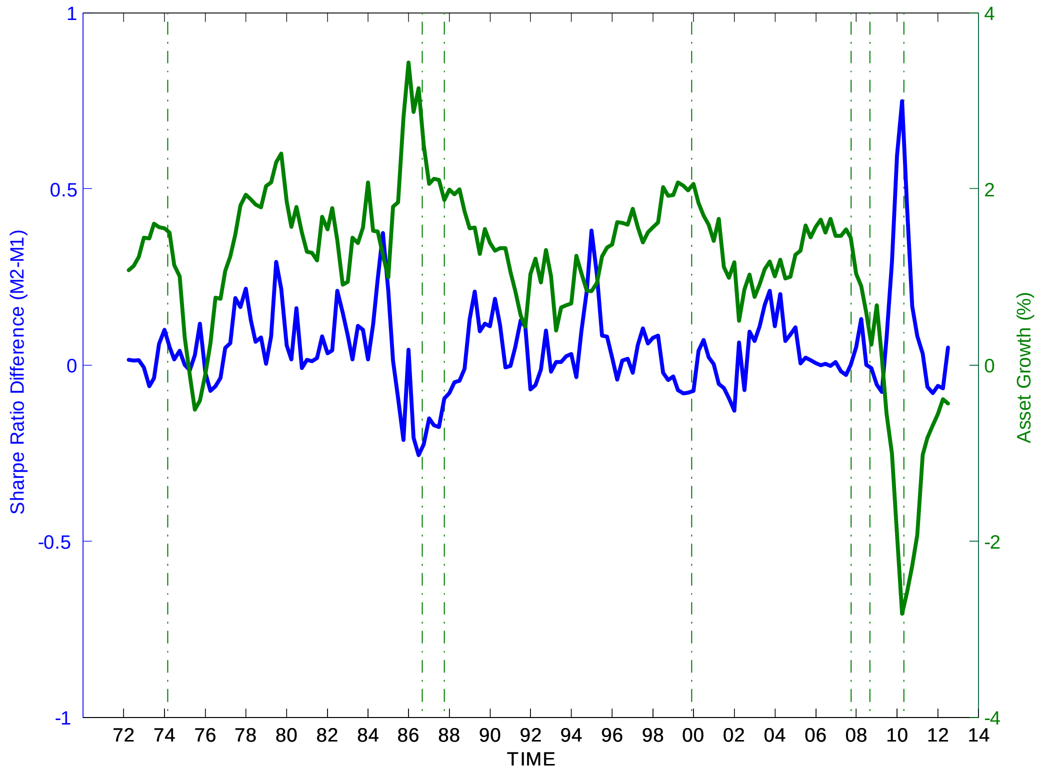
Panel A shows the time series of log-quarterly asset growth rates annualized (x4) for Shadow Banks (ABS issuers, Finance Companies and Funding Corporations) and Securities Broker-Dealers. Panel B shows the log growth rates (annual and quarterly annualized) of Broker Dealer's leverage. Data are quarterly from the US Flow of Funds statistics.

Figure 2: Sharpe Ratio



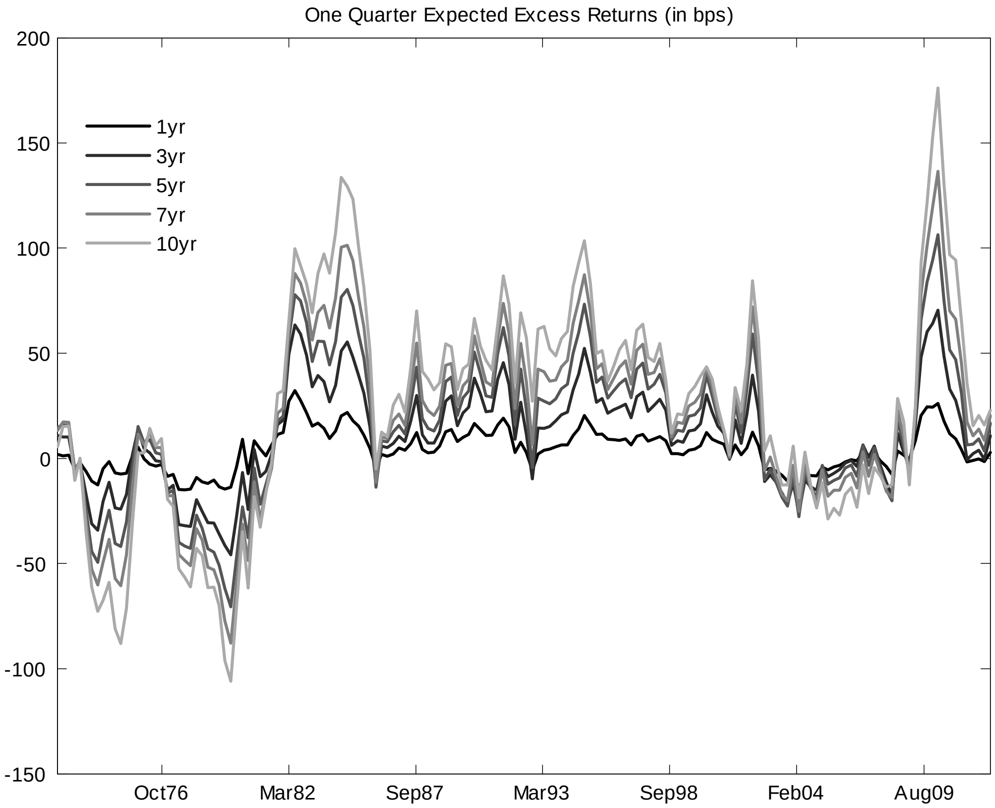
This chart shows the model-implied Sharpe Ratio for model M2 (3 principal components of yields, GDP growth, inflation rate and Shadow Banks' asset growth). The Sharpe Ratio is given by Equation 13 on page 16. The chart shows the posterior means and 95 percent credible intervals.

Figure 3: Shadow Banks' Asset Growth and Sharpe Ratio



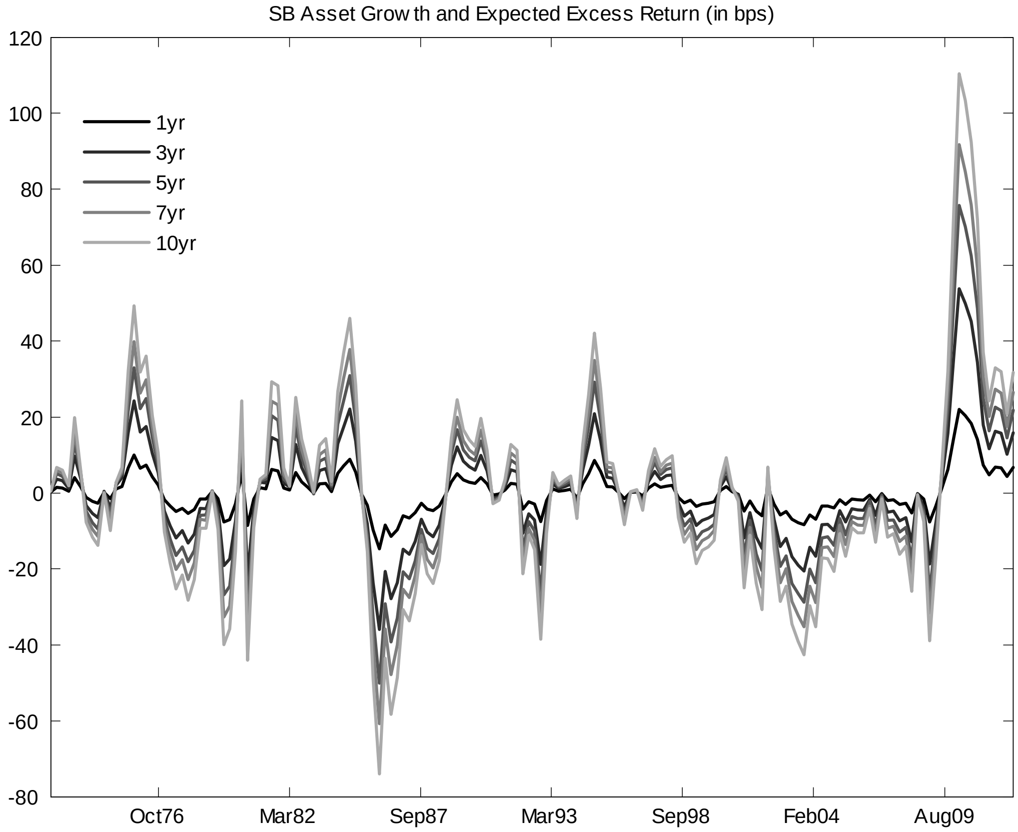
This chart shows the impact of shadow banks' asset growth on Sharpe Ratios in Blue (left hand scale) and shadow banks' asset growth in green (right hand scale). The effect of shadow banks' asset growth is capture by the difference between the Sharpe Ratio for models M2 (3 principal components of yields, GDP growth, inflation rate and Shadow Banks' asset growth) and M1 (3 principal components of yields, GDP growth and inflation rate). The Sharpe Ratio is given by Equation 13 on page 16.

Figure 4: Term Structure of Model Implied Expected Excess Returns



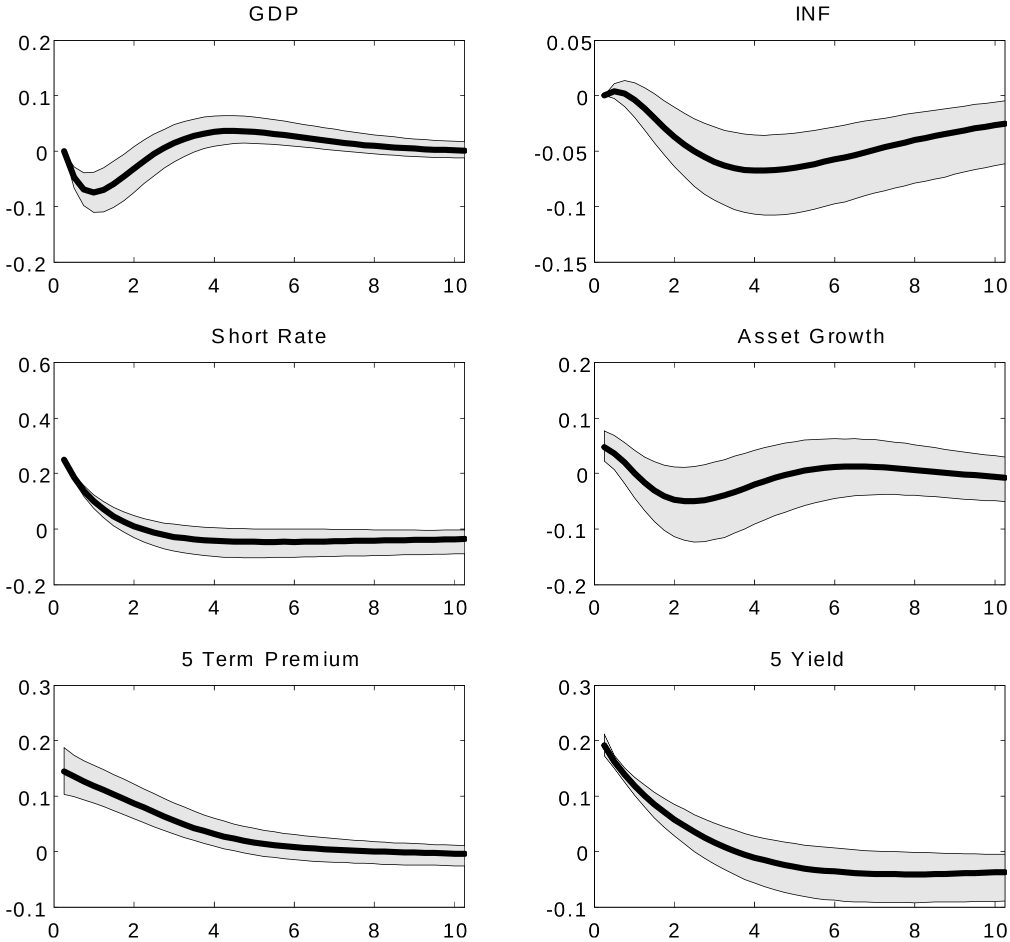
This chart shows the model implied term structure of expected excess returns for 1 quarter holding periods. The expected excess returns are given by Equation (14) in page 17.

Figure 5: Shadow Bank Asset Growth and the Term Structure of Expected Excess Returns



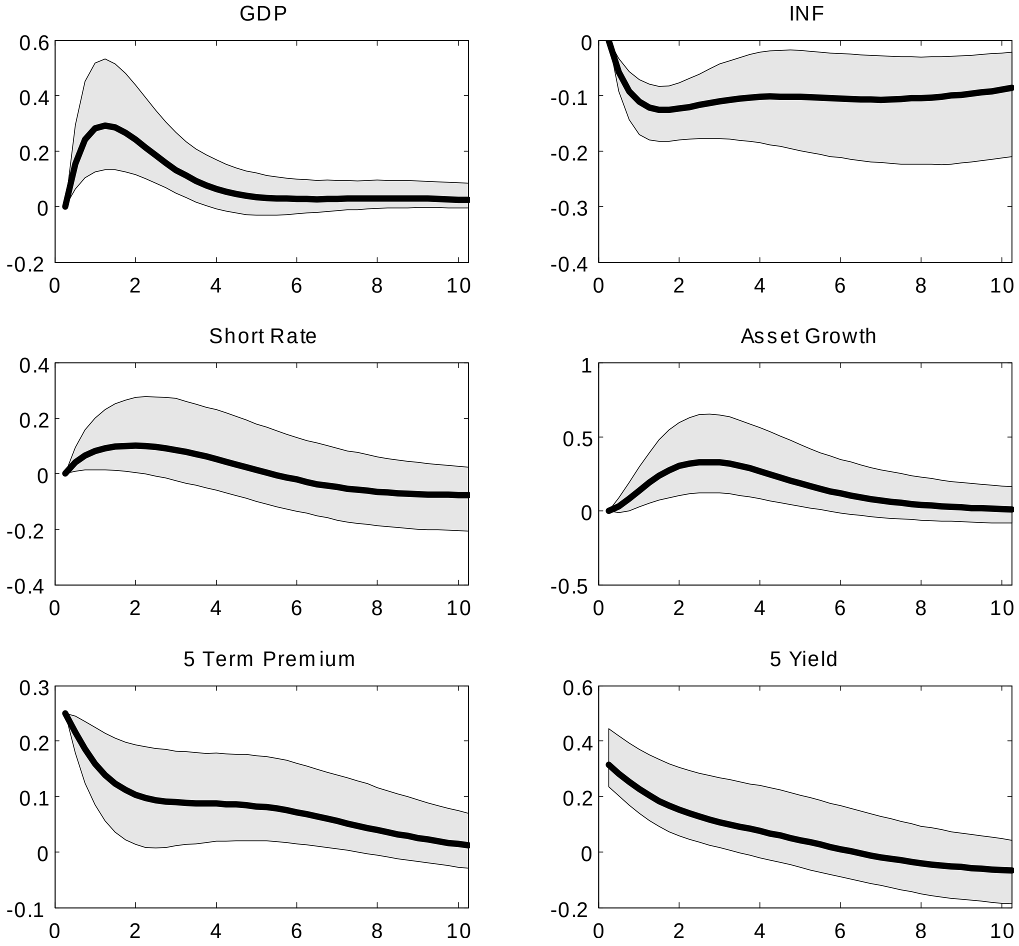
This chart shows the impact of shadow banks' asset growth on the term structure of model- implied expected excess returns. The effect of shadow banks' asset growth is capture by the difference between the expected excess returns for models M2 (3 principal components of yields, GDP growth, inflation rate and Shadow Banks' asset growth) and M1 (3 principal components of yields, GDP growth and inflation rate). The expected excess returns are given by Equation (14) in page 17.

Figure 6: Impulse Response Functions for Monetary Policy Shock



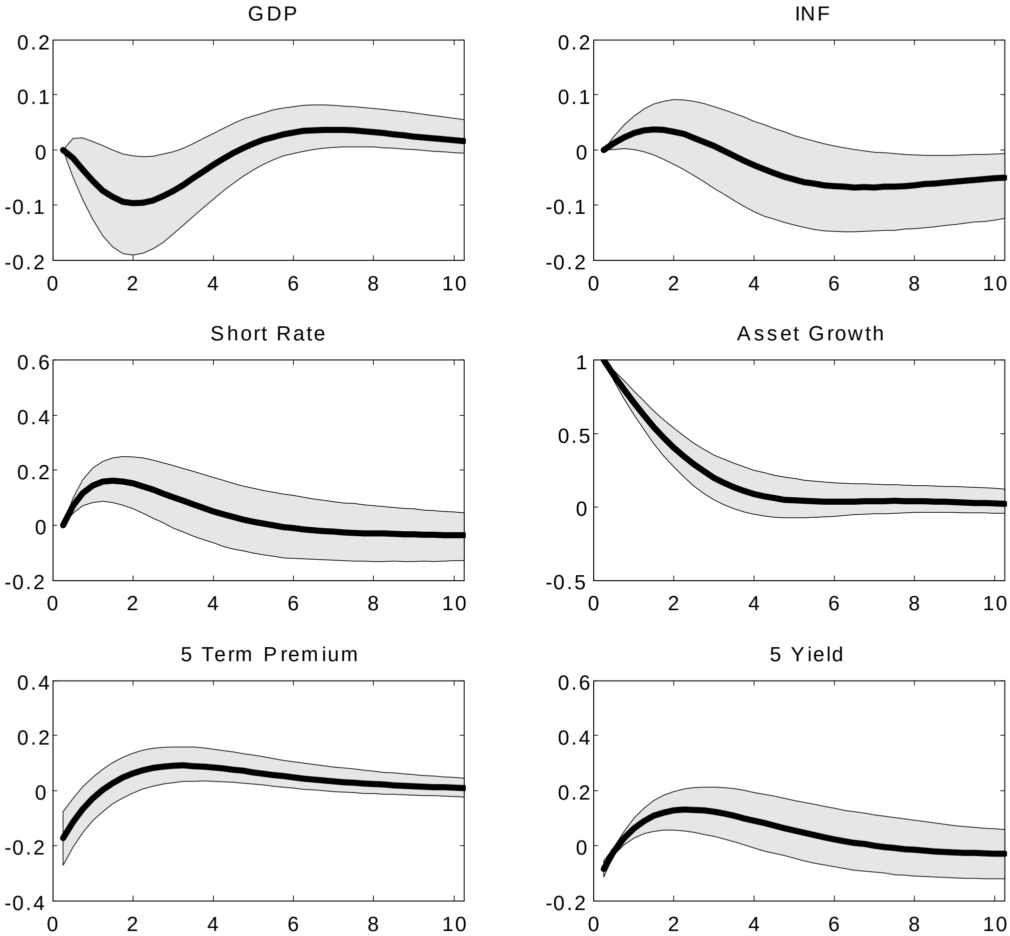
This chart shows the impulse response functions to a expected monetary policy shock on GDP growth (GDP), inflation (INF), expected policy rate (Short Rate), Shadow Banks' asset growth (Asset Growth), 5 year spot term premium and the 5 year spot yield. The scale of the x-axis is in number of years and the y-axis in percentage points. The identification scheme is discussed in Appendix D. The shock is normalized to 25 bps. The chart shows the posterior means and 95 percent credible intervals.

Figure 7: Impulse Response Functions for Term Premium Shock



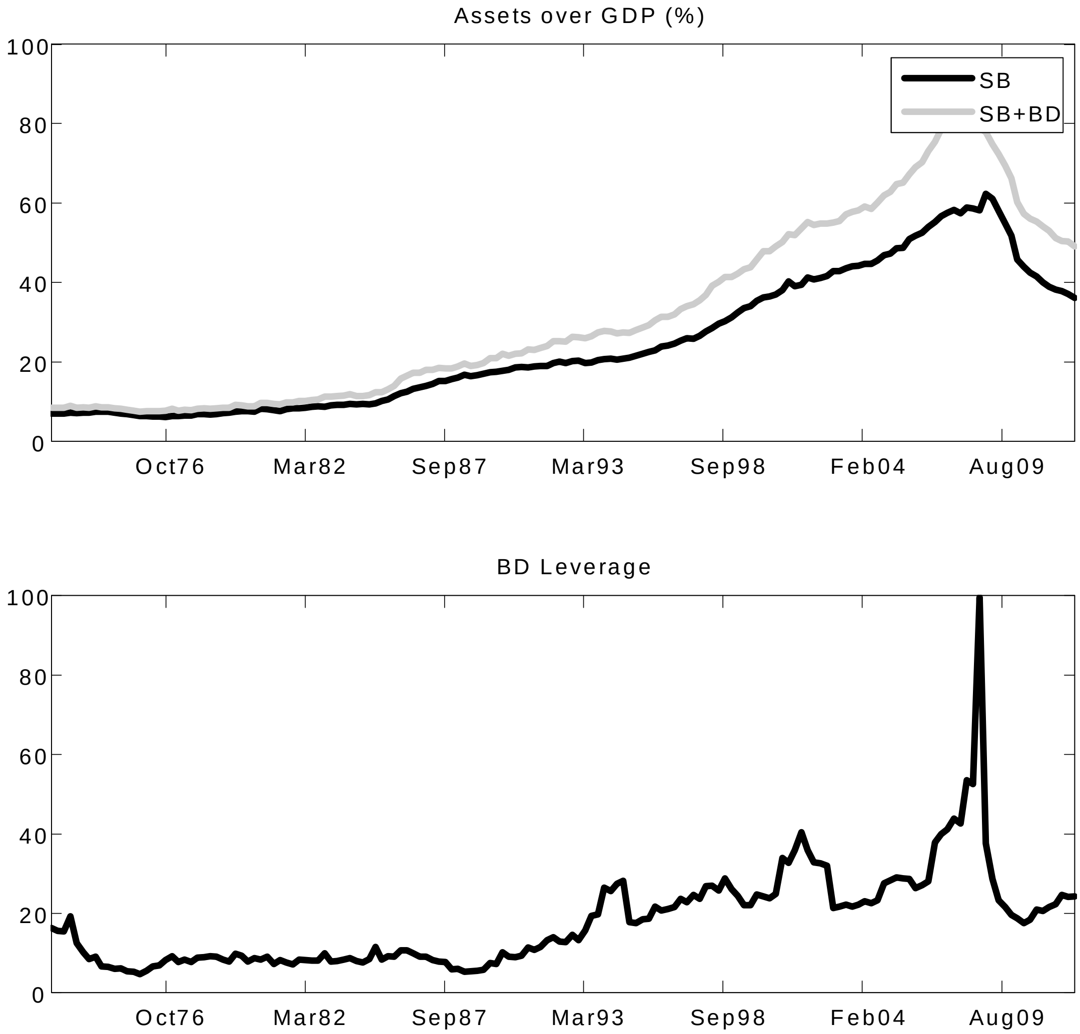
This chart shows the impulse response functions to a (5 year spot) term premium shock on GDP growth (GDP), inflation (INF), expected policy rate (Short Rate), Shadow Banks' asset growth (Asset Growth), 5 year spot term premium and the 5 year spot yield. The scale of the x-axis is in number of years and the y-axis in percentage points. The identification scheme is discussed in Appendix D. The shock is normalized to 25 bps. The chart shows the posterior means and 95 percent credible intervals.

Figure 8: Impulse Response Functions for Shadow Banks Asset Growth Shock



This chart shows the impulse response functions to a Shadow Banks' asset growth shock on GDP growth (GDP), inflation (INF), expected policy rate (Short Rate), Shadow Banks' asset growth (Asset Growth), 5 year spot term premium and the 5 year spot yield. The scale of the x-axis is in number of years and the y-axis in percentage points. The identification scheme is discussed in Appendix D. The shock is normalized to 1 pp. The chart shows the posterior means and 95 percent credible intervals.

Figure 9: Financial Intermediary Balance Sheet Data



Panel A shows the time series of assets as a percent of GDP for Shadow Banks (ABS issuers, Finance Companies and Funding Corporations) and Shadow Banks plus Securities Broker-Dealers. Panel B shows the time series of Broker Dealer's leverage (measured as total financial assets divided by total financial assets minus total liabilities). Data are quarterly from the US Flow of Funds statistics.

A Affine pricing recursions

If we assume that nominal bond prices are exponential-affine:

$$P_{t,n} = \exp(A_n + B_n X_t)$$

combined with the no-arbitrage condition

$$P_{t,n} = E_t^Q \left[e^{-r_t} P_{t+1,n-1} \right]$$

we obtain the recursion:

$$\begin{aligned}
A_n + B_n X_t &= \ln P_{t,n} \\
&= \ln E_t^Q \left[\exp\left\{ -r_t + A_{n-1} + B_{n-1} X_{t+1} \right\} \right] \\
&= \ln E_t^Q \left[\exp\left\{ -\left(\delta_0 + \delta_1 X_t\right) + A_{n-1} + B_{n-1}\left(\mu^Q + \Phi^Q X_t + \Sigma_X \varepsilon_{t+1}^Q\right) \right\} \right] \\
&= -\left(\delta_0 + \delta_1 X_t\right) + A_{n-1} + B_{n-1}\left(\mu^Q + \Phi^Q X_t\right) + \ln E_t^Q \left[\exp\left\{ B_{n-1} \Sigma_X \varepsilon_{t+1}^Q \right\} \right] \\
&= -\left(\delta_0 + \delta_1 X_t\right) + A_{n-1} + B_{n-1}\left(\mu^Q + \Phi^Q X_t\right) + \frac{1}{2} B_{n-1} \Sigma_X \Sigma_X' B_{n-1}'
\end{aligned}$$

Matching coefficients we obtain the recursions:

$$\begin{aligned}
A_n &= -\delta_0 + A_{n-1} + \frac{1}{2} B_{n-1} \Sigma_X \Sigma_X' B_{n-1}' + B_{n-1}\mu^Q \equiv \mathcal{A}\left(\delta_0, \delta_1, \mu^Q, \Phi^Q, \Sigma_X, n\right) \\
B_n &= -\delta_1 + B_{n-1}\Phi^Q \equiv \mathcal{B}\left(\delta_0, \delta_1, \mu^Q, \Phi^Q, \Sigma_X, n\right)
\end{aligned}$$

with initial conditions $A_0, B_0 = 0$. Instead of using the arbitrage condition expressed in term of risk-adjusted expectations side of (1) we can also derive the recursive loadings using $P_{t,n} = E_t \left[M_{t,t+1} P_{t+1,n-1} \right]$ and

$$M_{t,t+1} = \exp\left(-r_t - \frac{\Lambda_t' \Lambda_t}{2} - \Lambda_t' \varepsilon_{t+1}^P \right)$$

which would result in the same recursions with $\mu^Q = \mu - \lambda_0$ and $\Phi^Q = \Phi - \lambda_1$.
Given the exponential affine bond prices, continuously compounded zero-coupon yields will also be affine functions of the states:

$$y_{t,n} = A_n^Q + B_n^Q X_t$$

where

$$\begin{aligned}
A_n^Q &= -\frac{1}{n} \mathcal{A}\left(\delta_0, \delta_1, \mu^Q, \Phi^Q, \Sigma_X, n\right) \\
B_n^Q &= -\frac{1}{n} \mathcal{B}\left(\delta_0, \delta_1, \mu^Q, \Phi^Q, \Sigma_X, n\right)
\end{aligned}$$

Note that this establishes that these recursions solve the following Expectation-equation:

$$\ln E_t^Q \left[\exp\left(-\sum_{s=0}^{n-1} \left(\delta_0 + \delta X_{t+s}\right) \right) \right] = \mathcal{A}\left(\delta_0, \delta_1, \mu^Q, \Phi^Q, \Sigma_X, n\right) + \mathcal{B}\left(\delta_0, \delta_1, \mu^Q, \Phi^Q, \Sigma_X, n\right) X_t$$

To calculate yields under the actual measure we can therefore use the same recursions, since the only difference from the observed yields is the change in conditional mean parameters of VAR:

$$\begin{aligned} y_{t,n}^P &= -\frac{1}{n}\ln E_t^P\left[\exp\left(-\sum_{s=0}^{n-1} r_{t+s}\right)\right] \\ &= -\frac{1}{n}\ln E_t^P\left[\exp\left(-\sum_{s=0}^{n-1}\left(\delta_0+\delta X_{t+s}\right)\right)\right] \\ &= A_n^P + B_n^P X_t \end{aligned}$$

where $A_n^P = -\frac{1}{n}\mathcal{A}\left(\delta_0,\delta_1,\mu^Q,\Phi^Q,\Sigma_X,n\right)$ and $B_n^P = -\frac{1}{n}\mathcal{B}\left(\delta_0,\delta_1,\mu^Q,\Phi^Q,\Sigma_X,n\right)$.
It is worth pointing out that this is not the expectation of future interest rates because of a convexity term. The convexity term arises because yields are the expectations of a nonlinear function of future interest rates, which are stochastic, and is given by:

$$\begin{aligned} c_{t,n} &= y_{t,n}^P - y_{t,n}^{EH} \\ &= -\frac{1}{n}\ln E_t^P\left[\exp\left(-\sum_{s=0}^{n-1} r_{t+s}\right)\right] - \frac{1}{n}\ln E_t^P\left[\sum_{s=0}^{n-1} r_{t+s}\right] \\ &= A_n^P - A_n^{EH} + \left(B_n^P - B_n^{EH}\right)X_t \end{aligned}$$

where the "Expectation Hypothesis" (EH) yields are equivalent to treating interest rates as non-stochastic, which can done by simply imposing $\Sigma = 0$ in the same recursions:

$$\begin{aligned} A_n^{EH} &= -\frac{1}{n}\mathcal{A}\left(\delta_0,\delta_1,\mu^Q,\Phi^Q,0,n\right) \\ B_n^{EH} &= -\frac{1}{n}\mathcal{B}\left(\delta_0,\delta_1,\mu^Q,\Phi^Q,0,n\right) \end{aligned}$$

From these, spot term premia are easily calculated as an affine function of the state as well[12]

$$\begin{aligned} tp_{t,n} &= y_{t,n}^Q - y_{t,n}^P \\ &= \left(A_n^Q - A_n^P\right) + \left(B_n^Q - B_n^P\right)X_t \end{aligned} \qquad \text{(A.1)}$$

We can also easily calculate forward rates starting in n periods in the future maturing in $m > n$ periods, $y_{t,n-m} = (m-n)^{-1}\left(my_{t,m} - ny_{t,n}\right)$ which becomes

$$y_{t,n-m} = A_{n-m}^Q + B_{n-m}^Q X_t$$

with $A_{n-m}^Q = (m-n)^{-1}\left[mA_m^Q - nA_n^Q\right]$ and $B_{n-m}^Q = (m-n)^{-1}\left[mB_m^Q - nB_n^Q\right]$. Forward term premia can be calculated by substituting the corresponding forward yields in (A.1).

[12] We do not exclude convexity in this definition of term premia because the convexity term would be present even in the world where there is no compensation for risk.

Log expected excess returns for a bond of maturity n is given by

$$\begin{aligned}
E_t\left[xr_{t+1,n}\right] &\equiv \ln E_t P_{t+1,n-1} - p_{t,n} - r_t \\
&= A_{n-1} + B_{n-1}(\mu + \Phi X_t) + \frac{1}{2} B_{n-1}\Sigma_X\Sigma_X' B_{n-1}' \\
&\quad - (A_n + B_n X_t) - r_t \\
&= A_{n-1} + B_{n-1}(\mu + \Phi X_t) + \frac{1}{2} B_{n-1}\Sigma_X\Sigma_X' B_{n-1}^{r\prime} \\
&\quad - \left(-\delta_0 + A_{n-1} + \frac{1}{2} B_{n-1}\Sigma_X\Sigma_X' B_{n-1}^{r\prime} + B_{n-1}\mu^Q\right) \\
&\quad - \left(-\delta_1 + B_{n-1}\Phi^Q\right) X_t - r_t \\
&= B_{n-1}\left[\mu - \mu^Q + \Phi - \Phi^Q\right] X_t \\
&= B_{n-1}\left(\lambda_0 + \lambda_1 X_t\right) \\
&= -(n-1)\, B_{n-1}^Q \Sigma_X \Lambda_t
\end{aligned}$$

A.1 Unspanned ADTSM

Add bond pricing recursions for unspanned (as a function of Z_t) - exactly the same, just useful for notation clarity

B JSZ identification

JSZ propose a set of normalizations that not only allows for identification of the model described in Section 3.1, but also simplifies the task of finding a global maximum of the likelihood function. With this normalization, there is a near separation of the likelihood in $\mathbb{P}$ and $\mathbb{Q}$ parameters and it is easier to estimate each of them.

JSZ show that any canonical GADTSM (as described in section 3.2) is observationally equivalent to a canonical GADTSM where the parameters governing bond pricing, $\left(\delta_0, \delta, \mu^Q, \Phi^Q, \Sigma_X\right)$, are uniquely mapped into a smaller set of parameters $\left(k_\infty^{\mathbb{Q}}, \lambda^{\mathbb{Q}}, \Sigma_X\right)$, where $k_\infty^{\mathbb{Q}}$ is proportional to the long-run mean of the short-rate under $\mathbb{Q}$ and $\lambda^{\mathbb{Q}}$ is the N-vector of ordered eigenvalues. In the JSZ normalization, with parameter set $\Theta^{JSZ} = \left\{k_\infty^{\mathbb{Q}}, \lambda^{\mathbb{Q}}, \mu, \Phi, \Sigma_X\right\}$, (*i*) the risk-free rate (Equation (2)) becomes $r_t = \iota X_t$, where ι is a vector of ones; (*ii*) Σ_X is lower triangular with positive diagonal entries, (*iii*) and the $\mathbb{Q}$-drift is given by $\mu_1^Q = k_\infty^{\mathbb{Q}}$ and $\mu_i^Q = 0$ for $i \neq 1$, and $\Phi^Q = J\left(\lambda^Q\right)$ is in real Jordan form (see JSZ Appendix C for the real Jordan form for different assumptions on eigenvalues).

B.1 OLS estimates with PCs

Let $\mathcal{P}_t$ denote N portfolios of bond yields. Under the assumption that N portfolios of bonds are priced perfectly, $\mathcal{P}_t \equiv W y_t = W y_t^{obs} \equiv \mathcal{P}_t^{obs}$, then there is full separation of the likelihood and OLS recovers the ML estimates of $\{\mu, \Phi\}$. The observed yields are allowed to differ from their model-implied counterpart through a J-vector of measurement errors $u_t \sim N\left(0, \sigma_u^2 I_J\right)$. Note that here it is assumed for simplicity that the variance of the measurement errors is the same across all long-term yields used to fit the model.

The likelihood function of the model is then given by

$$\mathcal{L}\left(y_t^{obs}, \mathcal{P}_t | \mathcal{P}_{t-1}; \Theta, \sigma_u\right) = \mathcal{L}\left(y_t^{obs} | \mathcal{P}_t; k_\infty^{\mathbb{Q}}, \lambda^{\mathbb{Q}}, \Sigma_X, \sigma_u\right) \times \mathcal{L}\left(\mathcal{P}_t | \mathcal{P}_{t-1}; \mu, \Phi, \Sigma_X\right) \tag{B.1}$$

where y_t^{obs} is the vector of observed yields. A convenient feature of the normalization proposed by JSZ is that the ML estimate of μ and Φ, that is $\hat{\mu}$ and $\hat{\Phi}$, are obtained by OLS. Conditional on $\left\{\hat{\mu}, \hat{\Phi}\right\}$, an optimization algorithm searches for the values of $k_\infty^{\mathbb{Q}}$, $\lambda^{\mathbb{Q}}$, Σ_X, and σ_u in order to find the global maximum of the likelihood function. First, good starting values for the parameters in Σ can be obtained by running an OLS regression of $\mathcal{P}_t$ on $\mathcal{P}_{t-1}$, which can be taken to be the principal components of yields. Also, good starting values for $k_\infty^{\mathbb{Q}}$ and $\lambda^{\mathbb{Q}}$ are not difficult to obtain because these parameters are rotation-invariant and therefore carry economic interpretation.
A natural candidate for the portfolio of bonds are the PC of yields, since following Litterman & Scheinkman (1991) it has been well documented the first 3 PC typically explain well over 95% of variation in yields.

C Bayesian MCMC estimation

A number of studies, such us Ang, Dong and Piazzesi (2007), Feldhutter (2008) and Chib and Ergashev (2009), among others, have previously estimated multi-factor affine yield curve models by using MCMC methods. These methods consists of iteratively sampling from the conditional posteriors of each block of parameters. In this section we provide a detailed description of each block in turn.

Step 1: Drawing $K_0^{\mathbb{P}}$ and $K_1^{\mathbb{P}}$

As Z_t follows a VAR in equation 7, the draw of $K^{\mathbb{P}} = \left[K_0^{\mathbb{P}}, K_1^{\mathbb{P}}\right]$ is standard Gibbs sampling with conjugate normal priors and posteriors. The posterior of $K^{\mathbb{P}}$ conditional on the Z, Y and the other parameters is:

$$p(K^{\mathbb{P}}|\Theta\_, Z, Y) \propto \ell(Z|K^{\mathbb{P}}, \Sigma)p(K^{\mathbb{P}}), \tag{C.1}$$

where $\Theta\_$ denotes the other parameters, and $\ell(Z|K_0^{\mathbb{P}}, K_1^{\mathbb{P}}, \Sigma)$ is the likelihood function. Assume that the prior of the VAR coefficients is normal and given by

$$p(k^{\mathbb{P}}) \propto N(\underline{K}, \underline{H}), \tag{C.2}$$

where $k^{\mathbb{P}}$ is $\text{vec}\big(K^{\mathbb{P}}\big)$, $\underline{K}$ is a $(N \times (N+1)) \times 1$ vector which denotes the prior mean while $\underline{H}$ is a $[(N \times (N+1)) \times 1] \times [(N \times (N+1)) \times 1]$ diagonal matrix where the diagonal elements denote the variance of the prior. The conditional posterior distribution of the VAR parameters conditional on Σ is also normal, $\pi(k^{\mathbb{P}}) \sim N(\overline{K}, \overline{H})$, where

$$\overline{K} = \left(\underline{H}^{-1} + \Sigma^{-1} \otimes Z_t' Z_t\right)^{-1} \left(\underline{H}^{-1}\underline{K} + \Sigma^{-1} \otimes Z_t' Z_t \widehat{k}^{\mathbb{P}}\right)^{-1} \tag{C.3}$$

$$\overline{H} = \left(\underline{H}^{-1} + \Sigma^{-1} \otimes Z_t' Z_t\right)^{-1} \tag{C.4}$$

where $\widehat{k}^{\mathbb{P}}$ is a $(N \times (N+1)) \times 1$ vector which denotes the OLS estimates of the VAR coefficients. We use a flat prior so that $\underline{K}$ =0 and $\underline{H}$ =1000. Also, we only retain stationary draws.

Step 2: Drawing $\Sigma\Sigma'$

In contrast to the $K^{\mathbb{P}}$ matrix the variance covariance matrix $\Sigma\Sigma'$ enters the pricing recursions. For this reason, we use a Metropolis-Hastings algorithm similar to Ang, Dong and Piazzesi (2007) to draw $\Sigma\Sigma'$. We note that the posterior distribution of $\Sigma\Sigma'$ conditional on Z, Y and the other parameters is:

$$\begin{aligned} p(\Sigma\Sigma'|\Theta\_, Z, Y) &\propto \ell(Y|\Theta, X)p(Z|K^{\mathbb{P}}, \Sigma)p(\Sigma\Sigma') &\text{(C.5)} \\ &\propto \ell\left(Y_t|X_t, X_{t-1}; \lambda^{\mathbb{Q}}, k_{\infty}^{\mathbb{Q}}, \Sigma_X, \sigma_e\right)\ell(Z|K^{\mathbb{P}}, \Sigma)p(\Sigma\Sigma') &\text{(C.6)} \end{aligned}$$

where Σ_X and Σ are the Choleski factorizations of the $\Sigma\Sigma'$ and $\Sigma\Sigma'_X$, i.e. the variance covariance matrices of Z and X, respectively. This posterior suggests an Independence Metropolis draw from the proposal distribution $q(\Sigma\Sigma') = \ell(Z|K^{\mathbb{P}}, \Sigma)p(\Sigma\Sigma')$. Assume that the prior $p(\Sigma\Sigma')$ is an inverse Wishart density, $p(\Sigma\Sigma') \sim IW\left(\underline{S}, \underline{T}\right)$, then this implies that the proposal density is also distributed as an inverse Wishart $q(\Sigma\Sigma') \sim IW\left(S, df\right)$, with scale matrix $S = \underline{S} + \sum_{t=1}^{T} \epsilon_t \epsilon_t'$, where $\epsilon_t = Z_t - K_0^{\mathbb{P}} - K_1^{\mathbb{P}} Z_{t-1}$, and degree of freedom $df = \underline{T} + T$.
The proposed draw $(\Sigma\Sigma')^c$ for the $(j+1)$th draw is then accepted with probability

$$\alpha = \min\left\{\frac{\ell\left(Y_t|X_t, X_{t-1}; \lambda^{\mathbb{Q}}, k_{\infty}^{\mathbb{Q}}, (\Sigma_X)^c, \sigma_\eta\right)}{\ell\left(Y_t|X_t, X_{t-1}; \lambda^{\mathbb{Q}}, k_{\infty}^{\mathbb{Q}}, (\Sigma_X)^j, \sigma_\eta\right)}, 1\right\} \tag{C.7}$$

where $\ell\left(Y_t|X_t, X_{t-1}; \lambda^{\mathbb{Q}}, k_{\infty}^{\mathbb{Q}}, (\Sigma_X), \sigma_e\right)$ is the likelihood function. Thus, the acceptance probability is the ratio of the likelihoods evaluated at the candidate draw $(\Sigma_X)^c$ relative to the old draw $(\Sigma_X)^j$.

Step 3: Drawing $\lambda^{\mathbb{Q}}$ and $k_{\infty}^{\mathbb{Q}}$

The risk neutral parameters only enter the pricing of yields, for which the density is not known in closed form. For this reason, we use a Metropolis-Hastings. However, differently from the case of $\Sigma\Sigma'$, we use the Random-Walk Metropolis (RWM) algorithm. Intuitively, the RMW differs from the independence MH in that it draws the candidate parameter from a generic density, therefore ignoring the structural features of the target density (Johannes and Polson, 2009). Specifically, let denote by $\theta^{(j)}$ the (j)th draw of the parameter. At the $(j+1)$th iteration we draw a candidate parameter $\theta^{(c)}$ from the proposal normal density

$$\theta^{(c)} = \theta^{(j)} + v_\theta \epsilon \tag{C.8}$$

where $\epsilon \sim N(0,1)$ and v_θ is the scaling factor used to tune the acceptance probability around 10-50%. Let define $\Theta_{-\theta}$ as all the Θ parameters but θ, we accept the candidate draw with probability

$$a = min\left\{\frac{\ell\left(y_t^{obs}|X_t, X_{t-1}; \Theta_{-\theta}, \theta^{(c)}, \sigma_\eta\right)}{\ell\left(y_t^{obs}|X_t, X_{t-1}; \Theta_{-\theta}, \theta^{(j)}, \sigma_\eta\right)}, 1\right\} \tag{C.9}$$

Note that the proposal density has no impact on the acceptance probability. Also, we assume a flat prior, so that the accept/reject probability is simply the ratio of the likelihood evaluated at the candidate draw $\theta^{(c)}$ relative to the old draw $\theta^{(j)}$.We perform this RWM step for each parameter ($\lambda^{\mathbb{Q}}$ and $k_{\infty}^{\mathbb{Q}}$) in turn.

Step 4: Drawing σ_η

The observation errors η_t can be seen as the residuals from the regression 10. We specify an inverse Gamma conjugate prior for σ_η^2, $p\left(\sigma_\eta^2\right) \sim \Gamma^{-1}\left(\frac{T_0}{2}, \frac{\vartheta_0}{2}\right)$, so that the conditional posterior for σ_η^2 is inverse Gamma:

$$p\left(\sigma_\eta^2 | y_t^{obs}, X_t, X_{t-1}, \lambda^{\mathbb{Q}}, r_\infty^{\mathbb{Q}}, \Sigma_X\right) \sim \Gamma^{-1}\left(\frac{T_1}{2}, \frac{\vartheta_1}{2}\right) \tag{C.10}$$

where $T_1 = T_0 + M \times T$ and $\vartheta_1 = \vartheta_0 + \sum_{t=1}^{T} \eta_t' \eta_t$. We therefore assume that the M yields have common variance σ_η^2. We assume flat priors.

Implementation Details and Convergence Check

We perform 80,000 replications of which the first 40,000 are 'burned' to ensure convergence of the chain to the ergodic distribution. We save one every 10 draws of the last 40,000 replications of the Markov chain to limit the autocorrelation of the draws.

The Random Walk Metropolis algorithm converges for an acceptance level of accepted draws around 20-40% (Johannes and Polson, 2009). If the variance is too high (low) we would reject (accept) nearly every draw. In order to reach reasonable acceptance ratios, we follow the method of Feldhutter (2008), whereby we tune the variance over the first half of the burn-in period. Specifically, we check the acceptance ratio every 100 draws, and if the acceptance ratio for the last 100 draws is above 50% we double the standard deviation (v_θ). By contrast, we halve the standard deviation if the ratio is below 10%.

In order to check the convergence of the Markov chain we carried on several exercises. We implemented a preliminary Maximum Likelihood (ML) estimation of the model. Chib and Ergashev (2009) show that a ML estimation of the model may efficiently help the Bayesian algorithm, in particular by tuning the priors and proposal densities. We simply use the ML estimates to initialize the $\lambda^{\mathbb{Q}}$ and $k_\infty^{\mathbb{Q}}$ parameters. But we have also estimated the model from many initial values, and the results do not change. Tables I-III in the Internet Appendix show the parameter estimates with the numerical standard errors and the convergence diagnostic (CD) proposed by Geweke (1992). Values of CD below 2 indicate the series has likely converged. Except for two of the P-dynamics parameters for equation of PC3, all of the CD statistics are well below two.

D Impulse Response Functions

To be able to shock monetary policy expectations and term premia, we will rotate $Z_t \equiv [\ X_t \quad M_t'\ ]'$ so that the quantities shocked appear explicitly in the rotated state vector $\widetilde{Z}_t$. Let W_0 be a $3+N\times 1$ vector and W_1 be an invertible $3+N \times 3+N$, where N is the number of observable series (size of M) matrix such that

$$\widetilde{Z}_t \equiv W_0 + W_1 Z_t$$

Let the rotated state vector be given by $\widetilde{Z}_t \equiv \left[GDP_t \quad Inf_t \quad y_{m,t}^{EH} \quad tp_{k,t} \quad FIBS_t \quad y_{k,t}\right]'$. Calculations below shows that there exists a 6×1 vector W_0 and an invertible 6×6 matrix W_1 such that

$$\underbrace{\begin{bmatrix} GDP_t & Inf_t & y^{EH}_{m,t} & tp_{k,t} & FIBS_t & y_{n,t} \end{bmatrix}}_{\equiv \widetilde{Z}_t} \equiv W_0 + W_1 \underbrace{\begin{pmatrix} X_t \\ M_t \end{pmatrix}}_{\equiv Z_t} \tag{D.1}$$

The choices of W_0 and W_1 rely on the fact that in the unspanned DTSM $y^{EH}_{m,t}$ and $tp_{k,t}$ are linear functions of Z_t, namely $y^{EH}_{m,t} = A^{EH}_m + B^{EH}_m Z_t$ and $tp_{k,t} = \left(A_k - A^{EH}_k\right) + \left(\begin{bmatrix} B_k & 0 \end{bmatrix} - B^{EH}_k\right) Z_t$. Straightforward calculations show that $\widetilde{Z}_t$ evolves according to

$$\widetilde{Z}_{t+1} = \widetilde{K}^{\mathbb{P}}_0 + \widetilde{K}^{\mathbb{P}}_1 \widetilde{Z}_t + \sqrt{W_1 \Sigma W_1'} \epsilon^{\mathbb{P}}_{zt}$$

where $\widetilde{K}^{\mathbb{P}}_0$ and $\widetilde{K}^{\mathbb{P}}_1$ are known functions of W_0, W_1, $K^{\mathbb{P}}_0$ and $K^{\mathbb{P}}_1$.
We identify shocks using the recursiveness assumption and thus assume that $\sqrt{W_1 \Sigma W_1'}$ is the Choleski factor associated with matrix $W_1 \Sigma W_1'$. The ordering of the variables in $\widetilde{Z}_t$ is crucial. The dynamics following the shock can be obtained through the rotated matrices of VAR coefficients, namely $\widetilde{K}^{\mathbb{P}}_0$ and $\widetilde{K}^{\mathbb{P}}_1$ (See Ferman (2011) or Pericoli & Taboga (2012)).

Internet Appendix to
'Financial Intermediaries and Bond Risk Premia'

Table I: Σ Convergence Statistics

	mean	se	nse (%)	CD
$\Sigma_{1,1}$	0.490	0.020	0.032	1.019
$\Sigma_{2,1}$	0.032	0.006	0.009	0.323
$\Sigma_{3,1}$	-0.003	0.001	0.002	1.928
$\Sigma_{4,1}$	0.010	0.005	0.008	0.287
$\Sigma_{5,1}$	0.097	0.014	0.022	1.221
$\Sigma_{6,1}$	-0.008	0.016	0.025	0.266
$\Sigma_{2,2}$	0.105	0.004	0.006	0.761
$\Sigma_{3,2}$	0.010	0.001	0.002	0.314
$\Sigma_{4,2}$	0.009	0.005	0.008	0.731
$\Sigma_{5,2}$	-0.011	0.013	0.021	0.148
$\Sigma_{6,2}$	-0.005	0.016	0.025	0.912
$\Sigma_{3,3}$	0.024	0.001	0.002	0.583
$\Sigma_{3,4}$	0.019	0.005	0.008	1.069
$\Sigma_{3,5}$	0.005	0.014	0.022	0.936
$\Sigma_{3,6}$	-0.021	0.016	0.025	0.145
$\Sigma_{4,4}$	0.087	0.003	0.005	0.246
$\Sigma_{4,5}$	-0.043	0.013	0.021	1.716
$\Sigma_{4,6}$	-0.053	0.016	0.025	0.974
$\Sigma_{5,5}$	0.238	0.010	0.015	0.116
$\Sigma_{6,5}$	0.037	0.016	0.025	0.533
$\Sigma_{6,6}$	0.278	0.011	0.017	1.066

This table presents the posterior mean, the standard deviation (se), the numerical standard error (nse), and the absolute value of the convergence diagnostic (CD), as in Geweke (1992), for the Σ matrix. These estimates result from the Bayesian estimation, described in Section 4, based on quarterly data from 1972-Q1 to 2012-Q2.

Table II: $K^{\mathbb{P}}$ Convergence Statistics

	$K_0^{\mathbb{P}}$	$K_1^{\mathbb{P}}$					
	const	PC1	PC2	PC3	INF	GDP	AG
PC1	-0.004	0.854	-0.433	1.381	0.435	0.119	0.162
se	0.002	0.032	0.202	0.730	0.103	0.079	0.054
nse (%)	0.003	0.051	0.319	1.155	0.164	0.124	0.085
CD	1.520	0.897	0.220	1.187	1.456	0.530	1.359
PC2	0.000	-0.024	0.780	-0.477	0.064	0.050	0.019
se	0.000	0.007	0.047	0.232	0.024	0.018	0.012
nse (%)	0.001	0.012	0.074	0.367	0.038	0.029	0.019
CD	0.143	0.456	0.176	0.434	0.252	0.851	0.168
PC3	0.000	0.001	-0.007	0.682	-0.001	-0.001	-0.001
se	0.000	0.002	0.011	0.057	0.006	0.004	0.003
nse (%)	0.000	0.003	0.017	0.091	0.009	0.007	0.005
CD	2.011	0.900	0.747	2.080	0.732	0.635	1.638
INF	0.000	-0.017	0.086	0.671	1.022	0.060	0.014
se	0.000	0.006	0.038	0.198	0.019	0.015	0.010
nse (%)	0.001	0.010	0.059	0.313	0.030	0.023	0.016
CD	0.205	0.582	0.071	1.185	0.235	0.427	0.427
GDP	0.001	0.003	-0.333	-1.752	-0.014	0.858	-0.029
se	0.001	0.018	0.110	0.481	0.056	0.043	0.029
nse (%)	0.001	0.028	0.174	0.760	0.088	0.067	0.046
CD	0.134	0.461	0.127	0.166	0.193	0.650	0.836
AG	0.000	0.004	-0.059	-0.484	0.078	0.229	0.893
se	0.001	0.019	0.121	0.532	0.061	0.047	0.032
nse (%)	0.002	0.031	0.191	0.842	0.097	0.075	0.051
CD	1.382	0.352	1.017	0.594	1.453	1.038	0.268

This table presents the posterior mean, the standard deviation (se), the numerical standard error (nse), and the absolute value of the convergence diagnostic (CD), as in Geweke (1992), for the $K^{\mathbb{P}}$ parameters. These estimates result from the Bayesian estimation, described in Section 4, based on quarterly data from 1972-Q1 to 2012-Q2.

Table III: $K^{\mathbb{Q}}$ Convergence Statistics

	$K_0^{\mathbb{Q}}$		$K_1^{\mathbb{Q}}$	
	const	PC1	PC2	PC3
PC1	0.0002	0.997	0.006	0.005
se	0	0.000	0.002	0.029
nse (%)	0	0.001	0.004	0.045
CD	1.2693	0.579	1.039	1.065
PC2	0.0001	0.0064	0.8365	-0.9061
se	0	0.0004	0.002	0.0237
nse (%)	0	0.0006	0.0031	0.0374
CD	0.984	0.5487	1.0389	1.0649
PC3	0.0001	0.0051	-0.0013	0.6745
se	0	0.0002	0.0011	0.0122
nse (%)	0	0.0003	0.0017	0.0192
CD	0.5793	0.0983	1.044	1.0667

This table presents the posterior mean, the standard deviation (se), the numerical standard error (nse), and the absolute value of the convergence diagnostic (CD), as in Geweke (1992), for the $K^{\mathbb{Q}}$ parameters. These estimates result from the Bayesian estimation, described in Section 4, based on quarterly data from 1972-Q1 to 2012-Q2.