Essays on market liquidity and monetary policy

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Essays on market liquidity and monetary policy

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The first essay examines the ability of financial market illiquidity to predict key Australian and U.S. macroeconomic variables. I analyse whether illiquidity's predictive ability is state-contingent, drawing on recent theoretical work on the potential for a state-contingent relationship. Using a Markov regime switching model, I uncover strong evidence that the predictive power of illiquidity is state-contingent, with much higher predictability in states associated with historical periods of economic and financial stress. Furthermore, economic growth forecasts from Markov regime switching models that include market liquidity in the set of predictor variables are statistically better than forecasts from Markov switching models that exclude market liquidity.

Gorton and Metrick (2010, 2011) argue that a run on the repo market played a key role in the collapse of shadow banks, while Krishnamurthy, Nagel and Orlov (2011) argue the collapse was chiefly due to a run on asset-backed commercial paper (ABCP). In order to assess the validity of these arguments, the second essay empirically examines the link between market liquidity and funding liquidity in various U.S corporate bond markets. Over the entire 2005-09 sample period, I find weak evidence of predictive ability among these variables. Where significant, repos are found to have higher predictive ability than ABCP. In addition, unsecured funding liquidity is found to have as much predictive ability as repos. These findings partially support Gorton and Metrick (2010, 2011), but do not support Krishnamurthy et al. (2011). I also find that the relationship between market liquidity and funding liquidity is state-contingent, a finding which supports the theoretical literature on the existence of nonlinear, regime-switching behaviour.

The final essay assesses the impact, on credit market spreads, of the various "unconventional" policies introduced by the U.S. Federal Reserve, between mid-2007 and early 2009. I also examine the impact of fiscal policies announced during this period, as well as the stance of "conventional" monetary policy. I find that fiscal policy announcements exerted a significant and destabilising influence on market spreads. Furthermore, while the multitude of "unconventional" monetary policy initiatives were effective in reducing market spreads, the efficacy of these policies was undermined by the Federal Reserve's inability to achieve its macroeconomic objectives.

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Abstract

The first essay examines the ability of financial market illiquidity to predict key Australian and U.S. macroeconomic variables. In contrast to prior studies, I find no evidence that financial market illiquidity has predictive power over future economic growth, with liquidity's information content largely subsumed by asset prices. Furthermore, where there is evidence of significant predictive content, it is equity market illiquidity that is typically more important than bond market illiquidity.

A key innovation of this essay is that I analyse whether illiquidity's predictive ability is state-contingent, drawing on recent theoretical work on the potential for a state-contingent relationship. Using a Markov regime switching model, I uncover strong evidence that the predictive power of illiquidity is state-contingent, with much higher predictability in states associated with historical periods of economic and financial stress. Furthermore, economic growth forecasts from Markov regime switching models that include market liquidity in the set of predictor variables are statistically better than forecasts from Markov switching models that exclude market liquidity. The differences between the results from the regime-switching models and the single-state models reflects the fact that, as the non-stressed states have been much more prevalent, parameter estimates from a single-state model averages over both stressed and non-stressed states thus lowering the statistical and economic significance of the estimates.

Gorton and Metrick (2010, 2011) argue that a run on the repo market played a key role in the collapse of shadow banks, while Krishnamurthy, Nagel and Orlov (2011) argue the collapse was chiefly due to a run on ABCP. In order to assess the validity of these arguments, the second essay empirically examines the link between market liquidity and funding liquidity in various U.S corporate bond markets. Over the entire 2005-09 sample period, I find weak evidence of predictive ability among these financial market variables. Where significant, repos are found to have higher predictive ability than ABCP. In addition, unsecured funding liquidity is found to have as much predictive ability as repos. These findings partially support Gorton and Metrick (2010, 2011), but do not support Krishnamurthy et al. (2011). I also find that the relationship between market liquidity and funding liquidity is state-

contingent, a finding which supports the theoretical literature on the existence of nonlinear behaviour, induced by regime change.

The final essay assesses the impact of the various “unconventional” policies introduced by the U.S. Federal Reserve, and key fiscal policies introduced by the U.S. Federal Government, during the 2007-09 period, on credit market spreads. I also examine the impact of fiscal policies announced during this period, as well as the stance of “conventional” monetary policy. Examining policies initiated between July 2007 and early 2009, I find that fiscal policy announcements exerted a significant and destabilising influence on market spreads. Furthermore, while the multitude of “unconventional” monetary policy initiatives were effective in reducing market spreads, the efficacy of these policies was undermined by the Federal Reserve’s inability (or, more provocatively, its failure) to achieve its macroeconomic objectives.

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Contents

List of Figures

List of Tables

Executive summary

The first essay, “Re-assessing the link between financial market liquidity and economic growth”, examines the ability of financial market illiquidity to predict key Australian and U.S. macroeconomic variables, between 1973 and 2010. While the link between financial market illiquidity and economic growth appears intuitive and seems to be confirmed by prior empirical studies, I find contrasting evidence that financial market illiquidity does not have much information content over future economic growth. The information content of market illiquidity appears to be largely subsumed by asset prices. Furthermore, when liquidity does appear to possess incremental information about economic growth, equity market illiquidity is found to be more important than government bond market illiquidity. The general lack of predictability is also implied by the fact that economic growth forecasts from models that exclude market illiquidity from the set of financial explanatory variables are statistically no worse than forecasts from models that include market illiquidity measures.

Finally, I uncover strong evidence that the predictive power of market illiquidity is state-contingent, with much higher predictability in states where liquidity shocks are large and negative, which implies a non-linear, state-contingent relationship between market liquidity and future economic growth. I discuss the practical and policy implications implied by this non-linearity. In particular that central banks should stabilise equity market liquidity, in addition to their current practice of stabilising short-term debt markets, as a key element of their macroeconomic stabilisation objectives.

Gorton and Metrick (2010, 2011) argue that a run on the repo market played a key role in the collapse of the shadow banking system, which precipitated the onset of the financial crisis, while Krishnamurthy, Nagel and Orlov (2011) argue that the collapse was chiefly due to a run on ABCP. In order to assess the validity of these arguments, the second essay, “The interaction between short-term funding and bond market liquidity” empirically examines the link between market liquidity, funding liquidity, volatility and pricing, in the U.S corporate bond markets, between 2005 and 2009. I find modest evidence of a connection between market liquidity, short-term funding liquidity, volatility and pricing, over the 2005-09 period. The strength of the links depend on the type of corporate bond market and the measure used to proxy for funding liquidity. These findings partially support Gorton and Metrick (2010, 2011)'s arguments, and do not support Krishnamurthy et al. (2011)'s argument.

I also provide evidence that the relationship between market liquidity and funding liquidity is state-contingent, which generates a nonlinear relationship between liquidity, volatility and spreads. This finding holds regardless of whether regime changes are specified to occur deterministically or stochastically. In states where shocks to the endogenous variables are sufficiently large (such as during periods of market stress), the responses of the other variables are much more significant, both statistically and economically, than states where the shocks are smaller in magnitude. These findings support the theoretical literature on the existence of nonlinear behaviour, induced by regime change.

The 2007-09 financial crisis moved U.S. monetary policy from a well-established routine of interest-rate targeting to a multi-pronged triage that wedded traditional policy tools with new initiatives aimed at reviving an ailing financial system. The triage was controversial on two grounds: firstly, these initiatives required discretion over targeting particular markets and firms; and secondly, a fear that the liquidity provided may stoke higher inflation, undermining the central bank's macroeconomic objectives. The timing, size, appropriateness and effectiveness of the measures taken by the Federal Reserve during the 2007-09 crisis are the subject of much discussion, analysis, and controversy.

The third and final essay, "The impact of policy initiatives on credit spreads during the 2007-09 financial crisis" assesses the impact of the various "unconventional" policies introduced by the U.S. Federal Reserve, and key fiscal policies introduced by the U.S. Federal Government, during the 2007-09 financial crisis period, on credit market spreads. I also examine the impact of fiscal policies announced during this period, as well as the stance of "conventional" monetary policy, measuring the stance of monetary policy by the difference between the effective Federal Funds interest rate and the interest rate implied by various Taylor rules. Examining policies initiated between July 2007 and early 2009, I find that fiscal policy announcements exerted a significant and destabilising influence on market spreads. I also find that while the multitude of "unconventional" monetary policy initiatives were effective in reducing market spreads, the efficacy of these policies was undermined by the Federal Reserve's inability (or, more provocatively, its failure) to achieve its macroeconomic objectives.

Chapter 1

Re-assessing the Link between Financial Market Illiquidity and Economic Growth

1.1 Introduction

This paper examines the ability of financial market illiquidity to predict key macroeconomic variables, between 1973 and 2010, for Australia and the U.S. In discussions of the current financial crisis, much is made of the apparent correlation between a decline in the liquidity of financial assets and the financial crisis. The vast array of lender- and buyer-of-last resort facilities initiated by policymakers globally have been motivated, to a large extent, by a desire to reduced illiquidity premia in financial markets, and thus improve the effectiveness of the monetary policy transmission mechanism. There are several intuitive reasons for a possible link between financial market liquidity and economic growth. Firstly, Bencivenga, Smith and Starr (1995) construct a model in which lower transaction costs (an increase in market liquidity) boosts investment in projects of all maturities, particularly longer-term projects, which are more productive, but costlier to trade. Lower transaction costs also encourages greater saving, by raising its net return. Higher investment and a higher capital stock raises the economy's equilibrium growth rate. Relatedly, Eisfeldt (2004) argues that expectations of higher productivity and returns result in a larger number of projects initiated, higher issuance of claims, and higher liquidity.

Secondly, changes in people's expectations of consumption and/or investment behaviour can generate trading demands and influence liquidity (Grossman, 1995). To the extent that these expectations are realised, this endows market liquidity with a degree of forecastability over the real economy. Thirdly, liquidity has been found to be a key “state variable” influencing equity returns (Pastor and Stambaugh, 2003), corporate bonds (Acharya, Amihud and Bharath, 2011), and government bonds (Longstaff, 2004). Combining these results with the theoretical work on consumption-based and production-based asset pricing models, which, respectively, link consumption and production with returns, generates another connection between liquidity and the macroeconomy.

Finally, Næs, Skjeltorp, and Ødegaard (2011) document a statistically and economically significant link between U.S. stock market illiquidity and the U.S. macroeconomy, in the post-World War II period. In this paper, I replicate Næs et al. (2011)'s analysis for Australia, extend their U.S. analysis by considering whether bond market liquidity also has predictive ability, and examining whether the relationship between market illiquidity and the real economy is state-contingent.

The main results of this paper are as follows. First, in contrast to other studies, I find that, over the broad sweep of history, financial market illiquidity has no predictive ability over GDP or investment growth. Market illiquidity has only an indirect effect on GDP growth via its predictive ability over consumption growth. In contrast, asset returns have direct predictive power over all economic growth variables. Second, in instances of predictive ability, it is typically equity market illiquidity, rather than government bond illiquidity, which is more important. Third, economic growth forecasts from models that exclude market liquidity from the set of financial explanatory variables are statistically no worse than forecasts from models that include market liquidity. Finally, I uncover strong evidence that the predictive power of market illiquidity is state-contingent (and thus non-linear), with much higher predictability in states associated with economic and financial stress. The statistical significance of these correlations are obscured by the non-state contingent evidence. I discuss the key practical and policy implications of this regime-switching behaviour.

The rest of the paper is organised as follows. Section 1.2 reviews the relevant theoretical and empirical literature, while Section 1.3 motivates the choice of Australia and U.S financial markets. Section 1.4 outlines the data used, and defines my proxies for stock and bond market liquidity. Section 1.5 discusses the empirical methodology employed to deal with the fact that the economic growth data has a publication lag of one quarter. Section 1.6 outlines and discusses the results from the non-state dependent models. Section 1.7 contains the estimation of the state-dependent models, which allow for stochastic regime changes in the VAR relations, providing some discussion of the economic foundations of the different regimes. Section 1.8 offers concluding remarks, including suggestions for future research.

1.2 Related literature

1.2.1 Theoretical literature

The bulk of the theoretical literature links liquidity to the real economy via its effect on investment.[1] Bencivenga, Smith and Starr (1995) consider a deterministic two-period overlapping generations (OLG) model with intermediate and final goods production, and endogenous growth. Each 'young' agent in the economy produces a unique intermediate good, and all the intermediate goods are used to produce one final good, that can either be consumed or converted into future capital by all agents in the economy. There are multiple (linear) technologies for converting the final good into future capital, and these technologies vary by maturity and gross return.[2] Crucially, the OLG specification, together with the assumption that capital investments are unproductive prior to maturity, creates a need for a secondary financial market: when the technology's duration is at least two periods long (authors define this to be 'longer-term'), the only way for an agent to realise some of the "immature" project's cashflows is by issuing claims in the secondary financial market. Transacting in the financial market is costly, with the transaction costs exogenously-determined.[3]

Bencivenga et al. show that a rise in market liquidity (a decline in transaction costs) raises the net return on all (longer-term) projects and raises the net return on savings (when agents are less risk averse than log utility[4]). Both these effects are conducive to a higher rate of economic growth, and imply that changes in market liquidity predict changes in investment and economic growth. Furthermore, as a reduction in transaction costs has the largest effect on longer-term projects' returns, this implies that changes in the liquidity of longer-term assets (e.g. equities) have a larger impact on economic growth than shorter-term assets (e.g. bonds).[5] One of the aims of this paper is to empirically assess the validity of this argument.

Eisfeldt (2004) considers a production economy in which there exist high quality (successful) and low quality (unsuccessful) risky projects, where liquidity changes affect, and are affected by, productivity. 'Liquidity' is defined as the proportion of

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[1] It is worth noting that liquidity can affect the real economy through other channels, such as consumption. Market liquidity has been found to be an important component of assets' returns, and changes in liquidity premia can impact household consumption through the 'wealth' effect (Altissimo et al., 2005).

[2] As the technologies are linear, productivity is the same as the technology's gross return.

[3] As the authors assume that trade in the intermediate and final goods markets, and rental markets for capital, are costless, the financial market transaction costs do not reflect costs in the goods/rental markets.

[4] Here, substitution effects outweigh income effects, so that agents increase their savings rate.

[5] The authors' arguments in support of their assumption invokes Keynesian liquidity preference theory: longer-term assets have higher returns to compensate for their lower liquidity.

claims sold on higher return/higher risk projects relative to low return projects. Risky projects pay off only after two periods, but each investor receives a signal in the interim period about whether their project will succeed or fail. At this point, investors might want to trade away a share of their long-term projects either due to private information (the signal received) or for other reasons (e.g. consumption, investment, or portfolio rebalancing).

Eisfeldt (2004) shows that, when productivity is expected to be high, investment increases and investors initiate larger scale risky projects at all income levels. Consequently, the outcome of risky projects has a larger impact on investors' incomes and, as investors are more risk-averse than log utility, more claims to high-quality projects are sold in order to supplement current income for use in consumption.[6] Eisfeldt does not allow investors access to debt markets (one of the key sources of market incompleteness in her paper), so equity issuance is the only way investors can supplement their current income.

The relatively higher proportion of claims on high-quality projects raises the claims price, which is a weighted average of the prices of high and low risk projects, and market liquidity. Higher market liquidity further boosts the claims price, generating a feedback loop between liquidity and prices. In Eisfeldt's model, higher liquidity is an indicator of high future productivity. Moreover, liquidity follows the cyclical pattern of expected productivity and returns, with more sales of high-quality claims and a higher claims price when productivity is expected to be high.

Finally, Kiyotaki and Moore (2008) consider a dynamic, stochastic production economy with two types of infinitely-lived agents (entrepreneurs and workers) and four traded assets: a non-durable general output, labour, equity and fiat money. In each period a fraction of the entrepreneurs (but none of the workers) can invest in producing new capital using the general output, with the arrival of investment opportunities randomly distributed across entrepreneurs through time. In order to finance the cost of investing, there is a need for a financial market to facilitate transfers from savers to entrepreneurs (investment can't be financed out of labour, as the labour endowment is set to zero). In order to acquire general output as input to production, entrepreneurs sell equity claims to the future returns from the newly produced capital.

The crucial feature of the model – and the source of market incompleteness that generates the interaction between liquidity and the real economy – is as follows. Since the entrepreneur is required to run the project to produce output and, as they cannot commit *ex ante* to work throughout its life, they are only able to pledge a fraction (θ) of future returns from the new capital. Consequently, they

[6] Eisfeldt fixes the relative risk aversion parameter at 2, so income effects outweigh substitution effects, and thus the consumption rate rises. Risk-averse consumers issue more claims to both finance and smooth the higher consumption path.

face a borrowing constraint, and so finance a part of the investment by selling holdings of money and equity of the other agents (acquired in the past). The authors assume that investors' equity holdings are not as liquid as fiat money, with only a fraction (ϕ) able to be sold in any given period.[7] The authors dub θ a borrowing constraint, ϕ a "resaleability constraint", and $\theta + \phi$ as "liquidity constraints". A persistent negative shock to ϕ lowers the amount investing entrepreneurs can use as a down-payment for investment, making their borrowing constraint binding and reducing their ability to finance investment.

1.2.2 Empirical literature

Liquidity may contain less, the same, or more information about the real economy than returns. Liquidity may contain less information if a substantial portion of the price formation process is due to new information being incorporated into prices without a need for trade (akin to Milgrom and Stokey (1982)'s no-trade theorem). Furthermore, if market liquidity reflects the trading of noise traders, non-strategic liquidity providers (e.g. market makers balancing inventory levels; or passive investment funds rebalancing portfolios), and others trading without information, this may dampen or mask the transfer of a signal from liquidity to prices and the real economy. Alternatively, market liquidity might simply pass through information to asset prices so that the information contained in liquidity and returns is identical, and hence liquidity has no marginal information content. Finally, market liquidity may contain more or unique information relative to returns, if variations in returns reflect changes in expected growth rates and discount rates. Investors' changing perceptions about the riskiness of cash flows may confound information about expected growth (Harvey, 1989).

Ultimately, it is an empirical question - which this paper addresses – whether liquidity contains less, the same, or more information about the macroeconomy than asset returns.

Næs, Skjeltorp, and Ødegaard (2011) find that U.S. stock market liquidity is an important predictor of U.S. real GDP and investment growth, even after controlling for returns (such as the spread between long- and short-term U.S. Treasury bonds, and the volatility and level of equity risk premia). Moreover, these findings are robust to the choice of three alternative liquidity measures. These findings suggest the information provided by equity market liquidity about the real economy is not fully subsumed by stock returns.

Furthermore, the incorporation of liquidity measures translates into higher predictability of economic growth, relative to forecasts from univariate models, and

[7] As the authors note, this implies a peculiar transaction cost structure in each period: zero for the first fraction ϕ of equity sold, and then infinite.

multivariate models that include only the other financial variables.

Other recent papers closely related to this literature are Beber and Kavajecz (2011), and Kaul and Kayacetin (2009), who investigate the relationship between equity order flow and macro fundamentals. Beber and Kavajecz (2011) find that an order flow portfolio based on sectoral order flow movements predicts economic growth up to three months ahead, as well as predicting future stock and bond returns, over the period 1993 to 2005. Kaul and Kayacetin (2009) study two measures of aggregate stock market order flow between 1988 and 2004 and find that both measures predict future growth rates for industrial production and real GDP. The common theme of these papers is that the trading process in stock markets contains leading information about the real economy.

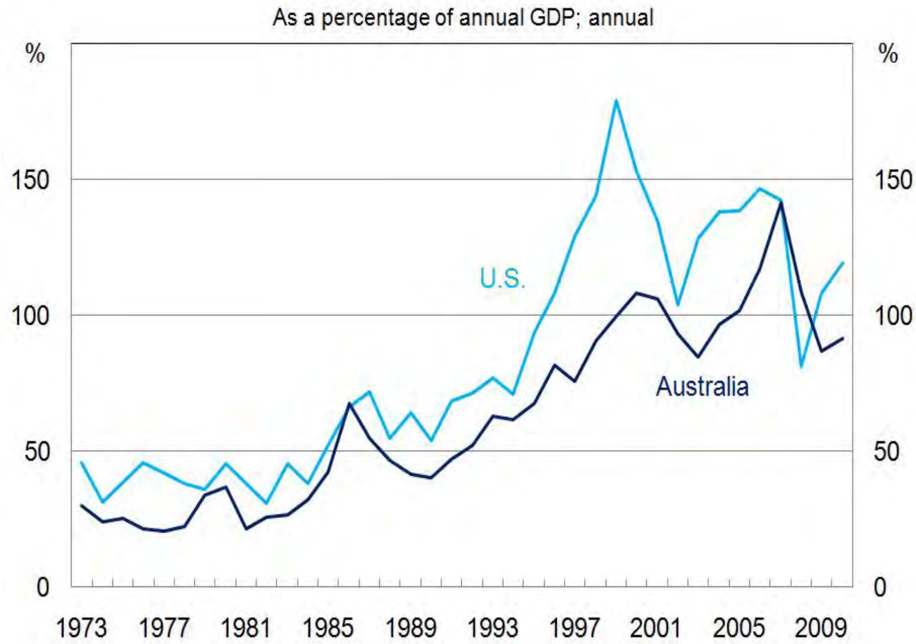
1.3 Choice of countries

My analysis is based on Australia and the U.S. The latter choice reflects the replication of the U.S. evidence in Næs, Skjeltorp, and Ødegaard (2011), while the former reflects my desire to assess the generalisability of the U.S. evidence. Furthermore, while Australia's equity market has typically been a a smaller share of its economy, relative to the U.S., households' stock market participation in Australia is typically been the same (or higher) than for the U.S. Consequently, it is not obvious, *ex ante*, whether Næs et al.'s findings of a link between liquidity and consumption growth would be weaker, the same, or stronger for Australia than the U.S.

Over the past four decades, both the U.S. and Australian equity markets have almost tripled in size (as a percentage of their respective GDP) with Australia's equity market rising from 30 per cent of GDP in 1973 to 91 per cent of GDP in 2010 (Figure 1.1). Over the same period, the U.S. equity market increased from 46 per cent of GDP to 119 per cent of GDP. The largest gap in the relative sizes of these two markets occurred during the dot-com bubble in 1999, when the U.S. financial market's relative size was 79 percentage points larger than Australia's. Reflecting the larger impact of the global financial crisis on U.S. equity markets, in 2008 the relative size of the Australian market was larger than that of the U.S., though this subsequently reversed as financial market strains eased.

A smaller equity market in Australia (relative to the U.S.) could imply a lower degree of risk sharing and thus a smaller impact of equity market shocks on consumption, investment and output. On the other hand, Australian households' equity market participation has historically been higher than for the U.S. For example, in 2007 (the latest date for which U.S data are available), 51 per cent of U.S. households held shares, either directly or indirectly via a managed or superannuation fund (Bucks, Kennickell, Mach and Moore, 2009). I estimate that

Figure 1.1: **Exchange-listed equity market capitalisation**



Sources: Australian Bureau of Statistics; Foster (1997); U.S Bureau of Economic Analysis; World Development Indicators and Global Development Finance (World Bank); World Federation of Exchanges.

around the same (or higher) share of Australian households held shares (directly or indirectly).[8] A potentially higher participation rate for Australia suggests that changes in equity prices and liquidity can have a larger impact on household consumption and income.

A final point is that U.S. corporates are, collectively, more reliant on capital markets for funding than Australian corporates, who rely more on internal funding and intermediated (largely bank) credit. This could mean that changes in market prices and liquidity have a relatively larger impact on U.S. investment. Ultimately, addressing the question of which country has the stronger relationship between market liquidity and the real economy can only be answered empirically, which is the focus of this paper.

[8]In 2007, 46 per cent of Australian households held shares, excluding holdings through superannuation (Australian Securities Exchange, 2008), and 45 per cent of households held shares via superannuation. Data on the exact degree of overlap between these two household samples is not available. The overlap is likely to be high, though not 100 per cent.

1.4 Liquidity Measures and Data

1.4.1 Liquidity Measures

Liquidity is a multi-dimensional concept, and the theoretical literature distinguishes between three sub-forms of market liquidity (Kyle, 1985): (i) the bid-ask spread; (ii) market depth and the 'price impact' of trades; and (iii) market resiliency. Given these various theoretical forms, it is not surprising that there are also many different empirical measures used to capture liquidity. Since my focus is on the link between liquidity and the real economy, I am relatively agnostic about the choice of measure, and consequently I use two widely-used measures. My choices are driven by the desire for sufficiently long time series. While many liquidity measures require intraday information on trades and orders, such information is not available for the long time period considered in this paper, and hence I employ measures that can be calculated using daily data.[9] It is worth noting that both my liquidity measures are inversely related to liquidity: an increase signifies a fall in liquidity.

For the equity market, I consider the following two liquidity measures: the Amihud (2002) illiquidity ratio (*ILR*), and the Roll (1984) estimator of the effective bid-ask spread (*Roll*). Goyenko, Holden and Trzcika (2009) show that "low-frequency" versions of these liquidity proxies do well in capturing the spread cost and price impact estimated using intraday data.[10] In general, the link between equity market illiquidity and economic growth is robust to the choice of liquidity measure.

Roll (1984) develops an estimator of the daily effective spread based on the autocovariance of price changes, as follows. Let V_t be the unobservable, fundamental value of the asset (bond or equity) on day t, evolving as a pure random walk process (i.e. the market is informationally efficient):

$$V_t = V_{t-1} + e_t \tag{1.1}$$

[9] For the U.S., the most widely used intraday equity data comes from the NYSE's Trade and Quote (TAQ) dataset, which commences in 1993. Intraday data prior to 1993 is available from The Institute for the Study of Security Markets (ISSM), which covers stocks listed on the NYSE and AMEX between 1983 and 1992, and listed on the NASDAQ between 1987 and 1992. For Australia, the most comprehensive intraday database is Australian Equities Tick History, constructed by the Securities Industry Research Centre of Asia-Pacific (SIRCA). Equity data histories are available back to 1991.

[10] For example, for equity portfolios sorted by size, monthly correlations between the actual and Roll (1984) estimates of the effective bid-ask spread are between 0.4 and 0.92, with higher correlations at an annual frequency.

Let P_t be the last observed trade price on day t. Assume that it is determined by

$$P_t = V_t + \frac{1}{2} S \cdot Q_t \tag{1.2}$$

where S is the effective spread and Q_t is a buy/sell indicator for the last trade, equalling +1 if the security is bought from the market-maker, and -1 if sold to the market-maker. In an informationally efficient market with no new information about the asset, Q_t is equally likely to be +1 or -1, and so has zero mean. Q_t is also serially uncorrelated, which follows from the following assumptions: (i) there is no new information about an asset between time t-1 and t; and (ii) the market is informationally efficient.

Equation (1.2) implies that the fundamental value is the midpoint of the bid-ask spread, with bid-price $V_t - \frac{1}{2}S$ and ask price $V_t + \frac{1}{2}S$. Combining equation (1.1) and (1.2) yields:

$$\Delta P_t = \frac{1}{2} S \Delta Q_t + e_t$$

Using the properties of Q_t and e_t, and the properties of covariance, gives:

$$Cov\left(\Delta P_t, \Delta P_{t-1}\right) = -\frac{1}{4} S^2$$

or equivalently:

$$S = 2 \cdot \sqrt{-Cov\left(\Delta P_t, \Delta P_{t-1}\right)} \tag{1.3}$$

Equation (1.3) is undefined when the sample serial covariance is positive. Harris (1990) suggests defining $S = -2 \cdot \sqrt{Cov\left(\Delta P_t, \Delta P_{t-1}\right)}$ if $Cov\left(\Delta P_t, \Delta P_{t-1}\right) > 0$, but this would lead to an assumed negative effective spread, which is inconsistent with a profit-maximising market-maker. Thus, when the sample covariance is positive, I follow Næs et al. (2011) and Goyenko, Holden and Trzcinka (2009) in substituting a value of zero.[11]

The second liquidity measure, Amihud (2002)'s illiquidity ratio (ILR), is a measure of the elasticity dimension of liquidity. Elasticity measures of liquidity shows how many units traders can sell (buy) at the current bid (ask) price without moving the price. Kyle (1985) defines the price impact as the response of price to order flow. Amihud (2002) proposes a price impact measure that is closely related to Kyle's measure. The daily Amihud measure is calculated as:

[11] This specification for the sample covariance is also empirically superior: the correlations between market liquidity and the macroeconomic variables are higher using this specification than the correlations using Harris (1990)'s suggestion.

$$ILR_{i,T} = \frac{1}{D_T} \sum_{t=1}^{T} \frac{|r_{i,t}|}{VOL_{i,t}} \tag{1.4}$$

where D_T is the number of trading days within a time window T, $|r_{i,t}|$ is the absolute percentage return on day t for security i, and $VOL_{i,t}$ is the trading volume (in units) on day t. The Amihud measure is called an illiquidity measure since a high estimate indicates low liquidity (i.e. high price impact of trades). Thus, ILR captures how much the price moves for each unit traded. To suppress the reporting of zeros, I multiply the above estimate by 10^6 for practical purposes.

As noted in Section 1.1, this paper examines whether liquidity and pricing in the government bond market is also important for predicting growth in the real economy. Næs et al. (2011) finds that corporate bond returns have predictive power over the real economy, while Acharya, Amihud and Bharath, (2011) finds that government bond market liquidity is an important determinant of corporate bond returns. Taken together, this suggests that government bond liquidity may have predictive power over the real economy. Moreover, Goyenko and Ukhov (2009) document that negative shocks to stock market liquidity increases government bond market liquidity, which is attributed to investors' "flight-to-quality". Goyenko and Ukhov also find a strong lead-lag relationship and bidirectional Granger causality between the illiquidity of the two markets, implying that liquidity innovations in one market are unlikely to subsume liquidity shocks in the other market.

I base my analysis on 10-year government bonds as this is the most liquid and widely traded segment in both the Australian and U.S. markets. I use the Roll (1984) estimator of the effective bid-ask spread, to measure market liquidity. This choice is made for pragmatic reasons: there are no quarterly data on actual bid-ask spreads, or trading volumes, for either the Australian or U.S. 10-year bond market over the entire sample period.[12] Furthermore, there are no data on corporate bond market liquidity, over the full sample.

1.4.2 Data

Liquidity data

For the U.S. stock market, the *Roll* and *ILR* measures are kindly provided by Randi Næs, and used in Næs et al. (2011). These measures are based on individual stocks listed on the New York Stock Exchange (NYSE), between 1947 and

[12] There are bid-ask spread data for 1- and 3-month U.S. Treasury notes over the entire sample period, which I also used to check the robustness of the results. The results using this liquidity measure are qualitatively the same as those based on estimated bid-ask spreads from 10-year Treasury bonds.

2008. In order to extend the sample to the end of 2010, I supplement this data with prices and trading volumes on the S&P 500 index, obtained from Thomson Reuters Datastream.[13]

For the U.S. bond market, I obtain daily yields on 10-year U.S. Treasuries from The Center for Research in Security Prices (CRSP), and use these yields to estimate bond prices. Since the economic growth variables are measured at a quarterly frequency, I estimate equation (1.3) using daily data.

For the Australian equity market, I use data on stock prices and trading volume for each stock listed on the All Ordinaries Index (AOI) as at March 31, 2011. As individual stock price and trading volume data are unavailable prior to 1976, my *ILR* series commences in January 1976. However, since data for an overall market index (calculated by Thomson Reuters Datastream) are available from the start of 1973, I can estimate equation (1.3) over the entire sample period.[14] The use of index-based data also allows me to obtain liquidity measures that control for changes in the AOI's constituents that have occurred over the past three decades; for example, of the 479 stocks comprising the AOI as of March 2011, only $7\frac{1}{2}$ per cent (36 in total) were in the AOI in March 1980.

While the individual stock price data does contain bid and ask prices, there are no data prior to June 2001. As I am interested in the interaction between financial market liquidity and the real economy over entire business cycles, using actual spreads would prevent analysing the recessions during the mid 1970s, and the early 1980s and early 1990s (and the corresponding upswings). Uncovering the connection depends on a sample period long enough to subsume a variety of economic events.[15] As Shiller and Perron (1985) show, increasing the number of observations in studies of economic and financial data by sampling more frequently while leaving the span in years of data unchanged may not greatly increase the statistical power of the test statistics. Moreover, even when the actual spread data are available, the correlation with the Roll estimator is high (0.9), implying that my empirical results are not sensitive to whether actual or estimated bid-ask

[13]Though Næs et al. (2011) construct an equally-weighted market liquidity measure based on individual stocks, which differs from my value-weighted measure based on an overall index, the correlation between the two series (between 1973 and 2008) is around 0.9 (for the *ILR* measure) and 0.6 (for the *Roll* measure).

[14]As the AOI was established in January 1980, Datastream's market index prior to this date is an average of the individual city exchanges.

[15]As Shiller and Perron (1985) emphasise, if two time series, y_t and x_t make long, relatively slow movements through time (a common feature for economic and financial data), then one will need a long time series (spanning many years) before the true joint tendencies of the two variables can be accurately measured. Getting many observations by sampling frequently (say, through weekly or even daily observations) will not give me much power to measure the joint relationship between the two time series if the total time span in which the data are contained is only a few years long.

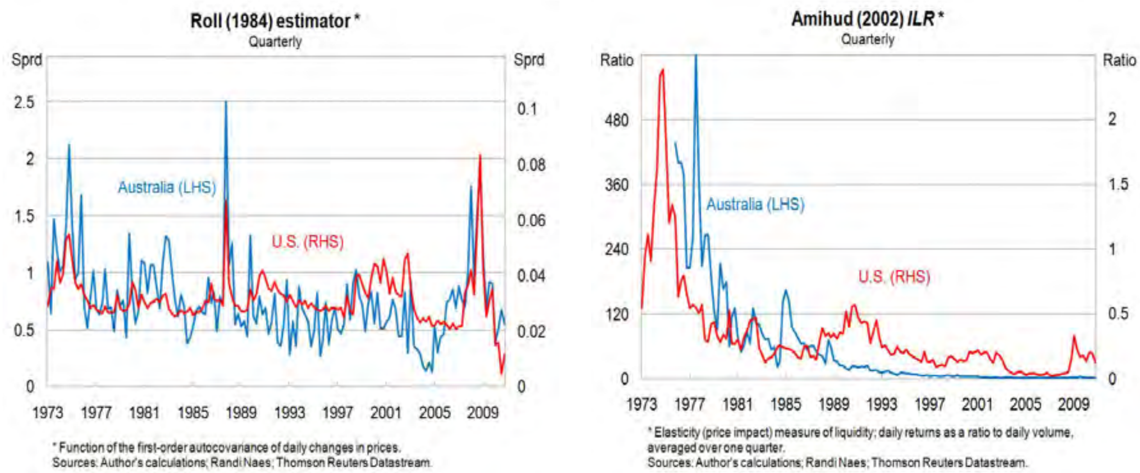
spreads are used as a liquidity measure.

Finally, for the bond market, I obtain daily yields on an index of 10-year Commonwealth government bonds from Bloomberg L.P. and Thomson Reuters Datastream. Using these yields, I construct an index of bond prices, and then apply equation (1.3) to this series. I use the same sample period (March 1973 to December 2010) for both the U.S. and Australia, as data for the latter country are only available from 1973, in order to facilitate a time-consistent comparative analysis (U.S. data are available from 1948).

Figure 1.2 shows the *Roll* and *ILR* measures for Australia and the U.S. Both measures reveal that liquidity is relatively greater in the U.S. equity market, with the Australian equity market between 25 times (*Roll* measure) and 175 times (*ILR* measure) less liquid than the U.S. market.

Over the past four decades, both markets have become more liquid and,

Figure 1.2: **Equity market liquidity**



though both liquidity measures decline over the sample period, the *ILR* measure shows a more pronounced rise in liquidity.

For each country, the correlation between the two equity market liquidity measures, though positive and statistically significant, is not economically large; for Australia, the correlation is 0.17, while for the U.S. it is 0.36 (Table 1.1). The lack of correlation between these two measures is indicative of liquidity's multidimensionality, as no one measure captures all of liquidity's characteristics. The correlations between equity and bond market liquidity are generally statistically insignificant, except for the correlation between Australia's *ILR* and *Bond Roll*, which is statistically significant (at the 5% level), though small in magnitude (-0.21).

Table 1.1: Correlation between liquidity measures

This table reports the pairwise contemporaneous correlations between the various liquidity measures. *Roll* is the Roll (1984) estimator of the effective bid-ask spread in the equity (*Equity Roll*) and bond (*Bond Roll*) markets. *ILR* is the Amihud (2002) illiquidity ratio applied to the equity market. The sample covers the period March 1973 to December 2010, and all data are quarterly.

Panel A: U.S. financial market liquidity		
	Equity Roll	*ILR*
ILR	0.36	
Bond Roll	0.13	-0.14

Panel B: Australian financial market liquidity		
	Equity Roll	*ILR*
ILR	0.17	
Bond Roll	0.12	-0.21

Macro data

To proxy for the state of the real economy, I follow Næs et al. (2011) in using the quarterly growth in GDP (*GDP*), personal consumption expenditure (*CONS*), and private fixed investment (*INV*). In addition, I include growth in durable goods' consumption (*DCONS*). As durable goods provide utility over time, while non-durable goods and services tend to be consumed immediately, the utility received from existing holdings of durable goods tend to be maintained even in the absence of any new purchases, so that spending on durables can be more easily deferred. Many durable goods can also be considered discretionary. Consequently, durable goods' expenditure has been found to more volatile and procyclical than non-durable goods' expenditure.[16]

All these variables are measured in chain volumes, and are seasonally adjusted. For the U.S., all the data are sourced from the Federal Reserve Bank of St Louis. I also use a number of financial variables shown in the literature to contain leading information about economic growth. From the equity market, I use the quarterly real return on the S&P500 index in excess of the three-month T-bill rate (er_m) and the standard deviation of daily excess returns over the quarter (*Vol*). In addition, I use the 'term spread' (*Term*), calculated as the difference between the yield on

[16] For the Australian evidence, see Fisher, Otto and Voss (1996); for the U.S., see Stock and Watson (1999).

a 10-year Treasury bond and the yield on the three-month T-bill, and the 'credit spread' (*Cred*), measured as the yield difference between 30-year Moodys Baa-rated and Aaa-rated non-financial corporate bonds. All these data are sourced from CRSP.

For Australia, the economic data are obtained from the Australian Bureau of Statistics (ABS). As the ABS does not provide direct estimates of durable consumption, I follow Fisher, Otto and Voss (1996) in defining durables' consumption as the consumption of: clothing and footwear; home furnishings and household equipment; and vehicle purchases. The term spread data are obtained from the Reserve Bank of Australia, the equity market returns data are obtained from Thomson Reuters Datastream, and the credit spread data are obtained from the Global Financial Database and UBS Australia AG.[17]

Statistical adjustment of liquidity and economic growth variables

Næs et al. (2011) notes the U.S. *ILR* series displays evidence of $I(1)$ behaviour; the ADF test does not reject the null of a unit root, while the KPSS test rejects the null of (trend) stationarity. This leads them to use first differences for the *ILR* series (along with that for the *Cred* series). However, there are some important issues with this statistical treatment.

Firstly, Næs et al. (2011) use a Hodrick-Prescott filter to detrend the *ILR* series and their detrended series (see their Figure 1) is stationary. Hence, the *ILR* series is actually trend-stationary, not difference-stationary. While differencing a trend-stationary series also removes the deterministic trend, the simple linear trend assumed by the ADF and KPSS tests is misspecified relative to the more sophisticated Hodrick-Prescott filter. More importantly, I found no evidence of unit root behaviour in the *Cred* series, in contrast to Næs et al. (2011). For both the Australian and U.S. *ILR* series, I use the Hodrick-Prescott detrended component for my regressions, and use the *Cred* series in levels.

Secondly, even if evidence of unit-root behaviour were valid, Næs et al. (2011) did not discuss whether these variables are cointegrated, nor do they estimate a vector error correction model (VECM) when estimating a multivariate model. Campbell and Perron (1991) note that even if only one variable in a multivariate model is a unit root process, a cointegrating vector can still exist. Since Næs et al. (2011) claim that some of the variables are $I(1)$ variables, and some others are $I(0)$, a VECM would be more appropriate than first differencing. Campbell and Perron (1991) note that when cointegration is present, an unrestricted VAR

[17] Since none of the major credit ratings agencies (i.e. Standard & Poor's, Moody's, or Fitch Ratings) rated Australian corporate bonds before the early 1990s, I define the Australian credit spread over the entire 1973-2010 period as the yield differential between 10-year Australian Commonwealth government bonds and an index of investment-grade Australian corporates' bonds.

which has $I(1)$ variables as first-differences has omitted variable bias as the lagged equilibrium errors are omitted as regressors.

Finally, Næs et al.'s quarter-t forecast of quarter $t+1$ economic growth includes quarter-t realised economic growth in the set of predictive variables. However, quarter t realised economic growth is *not* available to a forecaster until the end of quarter $t+1$, since economic data are released with a publication lag of one quarter. In this paper, my forecasts are constructured to ensure that a forecaster's quarter-t information set excludes data published after this time.

Table 1.2 shows the contemporaneous correlations between the different variables for the United States (Panel A) and Australia (Panel B). The main finding from this table is that the correlations between the market variables and the economic variables are generally more significant (statistically and economically) for the U.S., than for Australia. The term spread is positively correlated with investment growth, and credit spreads and equity market illiquidity are both negatively correlated with durable consumption growth. Equity market illiquidity is weakly negatively correlated with GDP growth, with a p-value of 0.09.

For Australia, personal consumption growth is uncorrelated with the other three economic growth variables, while durable consumption growth is signficantly correlated with GDP growth and investment growth, with correlations around 0.2. The higher correlation between durables' growth and the other economic variables, relative to personal consumption growth, reflects its discretionary and procyclical nature.

For the U.S., all the financial market variables are correlated with the economic variables, with some exceptions (such as bond market illiquidity and stock return volatility), a finding consistent with that of Næs et al. (2011).

The lack of contemporaneous correlation for Australia provides preliminary evidence that extending Næs et al.'s analysis to Australia is likely to give less statistically significant results. A more formal analysis of the relationship between financial market liquidity and economic growth is provided in the next section.

1.5 Forecasting methodology

I examine the following predictive regression:

$$y_{t+1} = \alpha + \beta SILLIQ_t + \delta BILLIQ_t + \rho y_{t-1} + \gamma' \mathbf{W}_t + \epsilon_{t+1} \tag{1.5}$$

where y_{t+1} is the realised growth in the macroeconomic variable of interest over quarter $t+1$, $SILLIQ_t$ and $BILLIQ_t$ is stock market illiquidity, and bond market illiquidity, measured over quarter t, respectively, $\mathbf{W}_t$ is a vector of market-based control variables (*Term*, *Cred*, *Vol*, er_m) as at the end of quarter t, and y_{t-1} is the realised growth in the macroeconomic variable of interest over quarter t-1. γ'

Table 1.2: Correlations between economic and financial variables

This table reports the pairwise contemporaneous correlations between the economic and financial variables. p-values for two-sided alternate hypotheses are in brackets. The data are quarterly, from March 1973 to December 2010 (152 quarters).

Panel A: U.S. variables

	Market variables							*Macro variables*		
	Eq. Roll	*B. Roll*	*dILR*	*Term*	*Cred*	er_m	*Vol*	*GDP*	*CONS*	*INV*
Term	-0.06	0.22	0.03							
	(0.47)	(0.01)	(0.76)							
Cred	0.31	0.41	0.26	0.17						
	(0.00)	(0.00)	(0.00)	(0.04)						
er_m	-0.40	-0.06	-0.06	0.14	-0.02					
	(0.00)	(0.45)	(0.45)	(0.09)	(0.82)					
Vol	-0.05	-0.06	0.01	0.18	-0.14	0.02				
	(0.56)	(0.44)	(0.9)	(0.03)	(0.08)	(0.82)				
GDP	-0.36	-0.06	-0.24	0.19	-0.21	0.30	0.10			
	(0.00)	(0.49)	(0.00)	(0.02)	(0.01)	(0.00)	(0.21)			
CONS	-0.22	-0.03	-0.04	0.30	-0.08	0.37	0.08	0.64		
	(0.01)	(0.69)	(0.66)	(0.00)	(0.31)	(0.00)	(0.33)	(0.00)		
INV	-0.41	-0.04	-0.32	0.17	-0.24	0.23	0.11	0.80	0.26	
	(0.00)	(0.60)	(0.00)	(0.04)	(0.00)	(0.00)	(0.16)	(0.00)	(0.00)	
DCONS	-0.19	0.08	-0.04	0.30	-0.01	0.30	0.05	0.51	0.86	0.17
	(0.02)	(0.31)	(0.64)	(0.00)	(0.88)	(0.00)	(0.56)	(0.00)	(0.00)	(0.04)

Panel B: Australian variables

	Market variables							*Macro variables*		
	Eq. Roll	*B. Roll*	*dILR*	*Term*	*Cred*	er_m	*Vol*	*GDP*	*CONS*	*INV*
Term	0.03	-0.02	0.09							
	(0.86)	(0.61)	(0.29)							
Cred	0.27	-0.03	0.02	0.19						
	(0.03)	(0.61)	(0.80)	(0.02)						
er_m	-0.34	-0.20	-0.04	0.06	0.03					
	(0.00)	(0.17)	(0.65)	(0.72)	(0.85)					
Vol	0.83	0.21	0.13	-0.01	0.25	-0.48				
	(0.00)	(0.01)	(0.13)	(0.86)	(0.02)	(0.00)				
GDP	-0.13	-0.12	0.06	0.14	-0.02	0.08	-0.08			
	(0.09)	(0.47)	(0.48)	(0.23)	(0.95)	(0.35)	(0.28)			
CONS	0.08	-0.08	0.10	0.05	0.01	-0.02	0.05	0.01		
	(0.29)	(0.17)	(0.22)	(0.46)	(0.89)	(0.91)	(0.49)	(0.87)		
INV	-0.08	-0.03	0.12	0.28	-0.06	0.03	-0.08	0.48	0.01	
	(0.94)	(0.78)	(0.16)	(0.00)	(0.98)	(0.98)	(0.86)	(0.00)	(0.85)	
DCONS	-0.18	0.01	-0.12	-0.11	-0.42	-0.11	-0.15	0.19	0.05	0.21
	(0.03)	(0.95)	(0.14)	(0.18)	(0.00)	(0.18)	(0.07)	(0.02)	(0.54)	(0.01)

is a vector of coefficient estimates on the market-based control variables, α, β, δ and ρ are coefficients corresponding to the intercept, stock market illiquidty, bond market illiquidty, and the two-quarter lagged dependent variable, respectively, and ϵ_{t+1} is the residual term. I use *ILR* and *Roll* to proxy for equity market illiquidity, and consider all four economic growth variables for the dependent variable (y_{t+1}). The specification of equation (1.5) ensures that only data available at quarter t is used in forecasting quarter $t+1$ economic growth.

Equation (1.5) is a restricted, publication-lag-adjusted version of the regression model in Næs, Skjeltorp, and Ødegaard (2011). Adjusted for the publication lag, Næs et al. (2011)'s model is:

$$y_{t+1} = \alpha + \lambda \hat{y}_t + \mu' \mathbf{M}_t + \epsilon_{t+1} \tag{1.6}$$

where $\hat{y}_t$ is the *predicted* growth in the macroeconomic variable of interest over quarter t, with the expectation formed at the end of quarter t, and $\mathbf{M}_t$ is a concatenation of $\mathbf{W}_t$, $SILLIQ_t$ and $BILLIQ_t$. A model-consistent expectation for y_t is:

$$\hat{y}_t = \alpha + \lambda y_{t-1} + \mu' \mathbf{M}_{t-1} \tag{1.7}$$

where $E_t \epsilon_t = 0$ since y_t and ϵ_t are not observed at quarter t. Substituting equation (1.7) into equation (1.6) gives (redefining the intercept and AR coefficients):

$$y_{t+1} = \alpha + \rho y_{t-1} + \mu' \mathbf{M}_t + \lambda \cdot \mu' \mathbf{M}_{t-1} + \epsilon_{t+1} \tag{1.8}$$

I estimated equation (1.8) and found that, for each U.S. and Australian economic growth variable, I could not reject the hypothesis (at conventional significance levels) that $\lambda \cdot \mu = 0$. Dropping this term from the model, partioning $\mathbf{M}_t$ into $\mathbf{W}_t$, $SILLIQ_t$ and $BILLIQ_t$, and partioning μ accordingly, gives equation (1.5).[18]

For the U.S., the Bureau of Economic Analysis (BEA) releases the "final" estimate of GDP for quarter t in the last month of quarter $t+1$. However, they also release an "advance" estimate in the first month of quarter $t+1$, and a "preliminary" release in the second month. For Australia, the Australian Bureau of Statistics (ABS) releases a "final" estimate of GDP for quarter t in the last month of quarter $t+1$, with no advance or preliminary estimate.

y_{t+1} in equation (1.5) relates to the final estimates (as at June 2011) available for each quarter, for the following reason. Since U.S.-based revisions between initial

[18] In this paper, I focus on the specification used in Næs et al. (2011). However, since asset returns can be measured at a higher frequency (daily) than economic growth, cumulating daily returns over a quarter involves an aggregation scheme that may be potentially biased. An extension to this work is considering Mixed Data Sampling (MIDAS) models, which directly estimate the individual daily return coefficients and so may be more efficient than the OLS estimator used in equation 1.5. For details on the MIDAS regression methodology, see Ghysels, Sinko and Valkanov (2007).

and final estimates of quarter-t economic growth are mainly due to measurement errors in the earlier vintage series, I assume that agents have rational expectations about underlying economic growth, and thus these expectations are assumed to be uncorrelated with measurement errors in the earlier vintages. That is, I assume that agents "see through" the early estimates to the final estimates.[19]

An additional complication is that, for both Australia and the U.S., the final estimates are often revised in subsequent quarters, so the researcher has to decide whether to use the 'initial' final estimates for each quarter, available at the end of the proceeding quarter, or revisions made in subsequent periods.[20] I use the final estimates for each quarter between March 1973 and December 2010, as at May 2011, ignoring any subsequent revisions to the final estimates. My reasoning here is that subsequent revisions to final estimates for, say, the 2^{nd} quarter of 2010 are typically either small, or, when sizeable, largely unexpected by market participants, and hence not reflected in market prices or liquidity at the end of the 1^{st} quarter of 2010.[21] However, the issue of large revisions to final estimates made prior to May 2011 is an insurmountable problem, as the ABS does not provide data on final estimates by vintage, while the BEA only provides vintages from February 1991 and only for real GDP.

1.6 Non state-dependent model

1.6.1 In-sample evidence: univariate models

Table 1.3 shows the OLS estimates of the parameters in equation (1.5) for the four U.S. (Panels A and B) and Australian (Panels C and D) economic growth variables. Panels A and C contain the results using the detrended component of Amihud (2002)'s illiquidity ratio (*dILR*), while Panels B and D contain the results relating to Roll (1984)'s estimator of the bid-ask spread (*Roll*).

The connection between market liquidity (both stock and bond markets) and economic growth are broadly the same for the U.S. and Australia. At the 5% level, stock market illiquidity only has predictive power over durables' and personal consumption growth. In these instances, the sign of $\hat{\beta}$ is consistent with *a priori*

[19]The rational expectations assumption does not need to be invoked for the Australian data, as the ABS does not release an advance or preliminary estimate.

[20]A recent example of this was the July 29, 2011 BEA release which revealed significant downward revisions to final estimates of both the level and growth of U.S. GDP dating back to the fourth quarter of 2008.

[21]For example, the large downward revisions to U.S. GDP between 2008 and 2010 in the July 2011 BEA release led to a sharp decline in equity prices as the revisions revealed that the downturn was larger, and the subsequent recovery shallower, than market participants had expected. I exclude these revisions to my series of final estimates of 2008-2010 U.S. GDP growth.

expectations. The *dILR* measure is more important than the *Roll* measure for the U.S., while the opposite is true for Australia. $\hat{\delta}$ is only statistically significant for U.S. consumption growth, with higher bond market illiquidity predicting higher consumption growth, *ceteris paribus*.

Collectively, the estimates of $\hat{\beta}$ and $\hat{\delta}$ provide weak evidence that market illiquidity is an important predictor of economic growth. Financial market liquidity has no predictive power over investment growth, which goes against the theoretical literature's emphasis on investment as the key channel between market liquidity and the real economy (see Section 1.2). The general lack of statistical significance is highlighted by the fact that excluding both illiquidity indicators from the investment and GDP growth equations results in the model's explanatory power increasing (cf $\bar{R}^2$ vs. "ex. liq. $\bar{R}^2$"). Bond market liquidity has no predictive ability for Australian economic growth. Moreover, the lack of statistical significance of $\hat{\beta}$ and $\hat{\delta}$ holds even when equation (1.5) is estimated excluding all the other financial variables.

The term spread and equity returns are, in general, the only financial market variables with direct predictive power over both U.S. and Australian economic growth. The sign and statistical significance of $\hat{\gamma}^{Term}$ is consistent with the large literature documenting a positive correlation between future economic growth and the term spread (among others, see Harvey (1989) and Hamilton and Kim (2002)). However, the correlation is generally more statistically significant for the U.S. than Australia. The sign and statistical significance of $\hat{\gamma}^{er_m}$ is consistent with the finding of Næs et al. (2011).

The overall model has the highest explanatory power for Australian durables' consumption growth ($\bar{R}^2$ value around 0.45). The relatively higher $\bar{R}^2$ for Australian durables consumption growth may reflect Australian households' relatively higher participation in financial markets, which means that bond and equity returns have a larger impact on the consumption of discretionary and durable goods. The stronger evidence for Australia suggests that the 'wealth effect' is more important for Australian households than for the U.S., and that there may be a significant improvement in the precision of forecasts relative to univariate models.

Excluding durables consumption, the model has greater explanatory power for the U.S. (average $\bar{R}^2$ of 0.21) than for Australia (0.06). Australian GDP growth is largely unpredictable, while the $\bar{R}^2$ for investment growth is only 0.05. The lower explanatory power for Australia may reflect its relatively smaller financial market and the lower reliance of Australian corporates on capital markets for funding, which implies a lower degree of risk sharing and a smaller impact of equity market shocks on GDP and investment growth (see Section 1.3).

Table 1.3: **Parameter estimates of predictive regressions**

The table shows the results from estimating equation (1.5) between March 1973 and December 2010 (152 quarters). Stock market illiquidity is proxied by one of two measures: the Hodrick-Prescott detrended component of *ILR*; and *Roll*. Newey-West corrected t-statistics (with four lags) are shown in brackets. $\bar{R}^2$ is the adjusted R^2, and "ex. liq. $\bar{R}^2$" gives the adjusted R^2 excluding stock and bond market illiquidity from the regressors in equation (1.5).

y_{t+1}	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}$	$\hat{\rho}$	$\hat{\gamma}^{Term}$	$\hat{\gamma}^{Cred}$	$\hat{\gamma}^{er_m}$	$\hat{\gamma}^{Vol}$	$\bar{R}^2$	ex. liq. $\bar{R}^2$
				Panel A: *ILR* measure for the U.S.						
GDP	0.215	0.039	-0.338	0.213	0.188	0.020	0.024	0.032	0.22	0.23
	(0.79)	(0.10)	(-0.76)	(1.77)	(4.06)	(0.13)	(3.29)	(0.16)		
CONS	0.481	-0.789	1.007	0.268	0.127	0.037	0.015	-0.076	0.24	0.17
	(2.31)	(-3.39)	(2.92)	(2.71)	(3.23)	(0.37)	(3.15)	(-0.44)		
DCONS	0.009	-2.589	3.615	0.160	0.544	0.350	0.079	-0.072	0.14	0.11
	(0.01)	(-2.24)	(2.28)	(1.58)	(3.11)	(0.74)	(2.96)	(-0.13)		
INV	-0.945	-3.125	3.651	0.067	1.033	-0.454	0.149	-0.212	0.22	0.21
	(-0.98)	(-1.34)	(1.35)	(0.75)	(5.45)	(-0.52)	(3.05)	(-0.27)		
				Panel B: *Roll* measure for the U.S.						
GDP	0.229	-0.457	-0.343	0.208	0.189	0.024	0.024	0.033	0.22	0.23
	(0.65)	(-0.07)	(-0.75)	(1.94)	(4.08)	(0.14)	(3.05)	(0.17)		
CONS	0.366	0.582	1.055	0.228	0.129	0.087	0.015	-0.053	0.20	0.17
	(1.49)	(0.47)	(2.86)	(2.30)	(3.03)	(0.75)	(3.03)	(-0.31)		
DCONS	-0.807	-1.86	3.703	0.155	0.544	0.473	0.082	-0.018	0.13	0.11
	(-0.63)	(-0.81)	(2.34)	(1.52)	(2.97)	(1.07)	(2.99)	(-0.02)		
INV	0.076	-3.01	3.892	0.090	1.020	-0.521	0.144	-0.251	0.21	0.21
	(0.05)	(-0.62)	(1.39)	(1.11)	(5.46)	(-0.56)	(2.88)	(-0.33)		
				Panel C: *ILR* measure for Australia						
GDP	0.765	-0.004	-0.268	0.031	0.082	0.108	0.012	-0.102	0.02	0.00
	(3.67)	(-0.11)	(-0.94)	(0.36)	(1.57)	(1.02)	(1.28)	(-0.53)		
CONS	2.894	-0.592	1.277	0.068	-0.029	-0.211	-0.003	-0.182	0.05	0.01
	(3.06)	(-2.73)	(0.92)	(1.64)	(-0.12)	(-0.47)	(-0.06)	(-0.36)		
DCONS	0.263	-0.019	-0.048	0.582	0.113	-0.204	0.017	0.063	0.40	0.45
	(1.37)	(-0.96)	(-0.22)	(7.64)	(2.24)	(-2.36)	(2.59)	(0.42)		
INV	0.812	0.047	0.979	0.154	0.442	0.221	0.005	-0.426	0.02	0.05
	(0.92)	(0.33)	(0.81)	(1.66)	(2.25)	(0.45)	(0.12)	(-0.46)		
				Panel D: *Roll* measure for Australia						
GDP	0.891	0.119	0.281	-0.097	0.064	0.031	0.005	-0.271	-0.01	0.00
	(4.54)	(0.27)	(0.73)	(-0.93)	(1.39)	(0.25)	(0.54)	(-1.07)		
CONS	3.681	-4.185	1.192	0.095	-0.084	0.061	-0.029	0.169	0.03	0.12
	(4.02)	(-2.28)	(0.97)	(2.12)	(-0.53)	(0.59)	(-0.63)	(0.92)		
DCONS	0.318	-0.582	0.079	0.612	0.116	-0.229	0.018	0.423	0.46	0.45
	(1.89)	(-2.35)	(0.41)	(8.35)	(2.55)	(-3.17)	(3.35)	(2.18)		
INV	0.852	-0.833	1.458	0.152	0.501	0.034	0.018	-0.006	0.05	0.05
	(1.02)	(-0.58)	(1.54)	(1.78)	(2.83)	(0.07)	(0.53)	(-0.05)		

In terms of market liquidity, the U.S.-based results are inconsistent with Næs et al. (2011), who documents a statistically significant relationship between equity market illiquidity and investment and GDP growth. My findings are not sensitive to the choice of sample period; even with Næs et al.'s choice of sample period (March 1947 to December 2008), I do not find much evidence of a role for market liquidity in predicting future economic growth. For the *ILR* measure, Næs et al.'s findings are likely to be a statistical artefact: they use first-differencing, rather than detrending, to render the series stationary. When I fully replicate Næs et al.'s analysis (i.e. using their sample period and first-differencing *ILR*), the results reveal a stronger link between stock market illiquidity, and growth in real GDP and investment.

In summary, the empirical evidence suggests that market illiquidity is not, in general, an important predictor of U.S. or Australian economic growth, controlling for the influence of other predictors. Over the entire 38-year period, market illiquidity has, in general, no information content over future economic growth. Financial market illiquidity impacts on the real economy indirectly via its effect on consumption growth.

I also considered the 2-step predictive ability of VAR models, following Næs, Skjeltorp, and Ødegaard (2011). For the sake of brevity, the formulation and estimation of the VAR models is discussed in Appendix A.1, with only the predictive ability of the models shown in the main body of the paper.

1.6.2 Out-of-sample evidence

An assessment of the merits of the models developed in this paper should include analysing their predictive abilities, which has an important practical dimension. Central banks use expectations of future economic growth to inform their monetary policies, with a focus on the future reflecting both the time lags between policy implementation and effect, and the need to ensure expectations of future economic growth are consistent with their macroeconomic stability objectives. For example, the Reserve Bank of Australia's inflation and economic growth forecasts – set out in their quarterly *Statement on Monetary Policy* reports – are partly generated from reduced-form AR and VAR models.[22] Governments use economic growth forecasts to inform decisions on fiscal policies, while other economic agents use economic growth forecasts when making consumption and investment decisions, and in determining asset prices.

[22] Over the past few years, the RBA has developed various structural VAR models for policy analysis, though the reliance placed on these models' forecasts is less than for reduced-form models. The RBA places greater reliance on policymakers' judgements over model-based forecasts, whereas other central banks – in particular, the Bank of England – places a much higher reliance on model-based forecasts, while still allowing for judgmental adjustments (Debelle, 2009).

One-quarter ahead forecasts

For both Australia and the U.S., I compare one-quarter ahead forecasts of real GDP growth and durables' consumption growth, using the following four models: equation (1.5), which I dub the 'benchmark' model; equation (1.5) excluding the two market illiquidity measures ('No-illiq' model); equation (1.5) excluding all financial market variables ("AR(2)-only" model); and finally, an 'unconditional' model which has only the intercept term in equation (1.5). In choosing a sample period, I use an expanding-window starting with a 40-quarter (10 years) sample from March 1973 to December 1982, adding one quarter to each subsequent sample, ending with the entire 152-quarter sample.

An expanding-window scheme allows me to control for parameter estimation uncertainty, which arises when a rolling-window scheme is used, but does lead to the potential for parameter non-stationarity, as incrementally more data is used for model estimation. As a robustness check of the results outlined below, I also used a rolling-window scheme. I found that the magnitude of the forecast errors differs between an expanding-window and rolling-window scheme, as would be expected given parameter estimation uncertainty. However, the general findings were broadly unchanged: models that exclude liquidity from the set of explanatory variables generate economic growth forecasts that are statistically no worse than the 'benchmark' model.[23]

The equity market illiquidity measure for the U.S. is again *dILR*, and *Roll* for Australia. The root mean squared forecast errors (RMSFEs) for these three models are reported in Table 1.4, along with non-parametric Kruskall-Wallis χ^2 tests of whether the medians of the squared forecast errors across the four models are equal.

The out-of-sample evidence confirms the evidence from Table 1.3: the 'benchmark' model is statistically no better in forecasting 1-quarter ahead economic growth than the 'No-illiq' model.[24] In fact, in most cases, the benchmark model does no better than an 'AR(2)-only' model. For example, for predicting U.S. real GDP growth, the benchmark model does a worse job than the AR(2)-only model, with the latter model about 5 per cent more precise, a statistically significant (at the 10% level) difference (Table 1.4).

However, for both Australia and the U.S., the three conditional models have greater forecast accuracy than a naive forecast based on the sample average, though this greater accuracy is not always statistically significant. Naive forecasts do considerably worse than the conditional models when forecasting growth in Australian

[23]These results are available upon request.

[24]These findings are not sensitive to the measure of equity market illiquidity. In fact, the results are even less supportive of the illiquidity-augmented model when the alternative illiquidity measures are used.

durables' consumption, with 25-35 per cent higher forecast errors than the errors from the conditional models' forecasts.

Table 1.4: **One-quarter ahead forecast errors**

The table shows the root mean squared forecast errors (RMSFEs), for 1-quarter ahead forecasts, for each of the following four models: the 'benchmark' (equation (1.5)); 'No-illiq' (equation (1.5) excluding bond and stock market illiquidity); an AR(2); and an 'unconditional' model (equation (1.5) excluding all terms except the intercept). $RMSFE_{bench}$ and $RMSFE_{alt}$ are the RMSFEs for the benchmark model, and one of the three alternative models, respectively. The table also reports the p-value of Kruskall-Wallis test statistics, which test the null hypothesis that the median squared forecast error of the row model is the same as the column model. *, ** and *** denote rejection of the null at the 10%, 5% and 1% significance levels, respectively. Panels A and B reports the results for the U.S., and Panels C and D report the results for Australia.

Panel A: Forecast errors for U.S. real GDP growth

Statistic	Benchmark	No-illiq	AR(2)	Unconditional
RMSFE	0.304	0.306	0.289	0.317
$\frac{RMSFE_{alt}}{RMSFE_{bench}}$	–	1.01	0.95	1.04

p-value of test of equality of median squared forecast errors

	No-illiq	AR(2)	Unconditional
Benchmark	0.95	0.06*	0.07*
No-illiq	–	0.08*	0.13
AR(2)	–	–	0.03**

Panel B: Forecast errors for U.S. real durables'consumption growth

Statistic	Benchmark	No-illiq	AR(2)	Unconditional
RMSFE	1.272	1.313	1.332	1.355
$\frac{RMSFE_{alt}}{RMSFE_{bench}}$	–	1.03	1.05	1.07

p-value of test of equality of median squared forecast errors

	No-illiq	AR(2)	Unconditional
Benchmark	0.89	0.78	0.56
No-illiq	–	0.89	0.67
AR(2)	–	–	0.79

Panel C: Forecast errors for Australian real GDP growth

Statistic	Benchmark	No-illiq	AR(2)	Unconditional
RMSFE	0.359	0.353	0.371	0.361
$\frac{RMSFE_{alt}}{RMSFE_{bench}}$	–	0.98	1.03	1.01

p-value of test of equality of median squared forecast errors

	No-illiq	AR(2)	Unconditional
Benchmark	0.66	0.85	0.78
No-illiq	–	0.78	0.82
AR(2)	–	–	0.92

Panel D: Forecast errors for Australian real durables'consumption growth

Statistic	Benchmark	No-illiq	AR(2)	Unconditional
RMSFE	0.306	0.314	0.340	0.415
$\frac{RMSFE_{alt}}{RMSFE_{bench}}$	–	1.03	1.11	1.36

p-value of test of equality of median squared forecast errors

	No-illiq	AR(2)	Unconditional
Benchmark	0.82	0.63	0.004***
No-illiq	–	0.81	0.01***
AR(2)	–	–	0.02**

For the U.S., all four models do a better job at forecasting GDP growth, than durables' consumption growth. The forecast errors are around four times larger when forecasting U.S. durables' consumption growth compared to U.S. GDP growth. To put the size of the errors in perspective, quarterly GDP growth and durables consumption growth over the 152-quarter sample was, on average, 0.67 and 0.86 per cent, respectively. Hence, the forecast errors represent between one-half (GDP) and double (durables consumption) of average growth rates, highlighting the models' weak predictive power.

For Australia, the models forecast durables consumption growth better than GDP growth, consistent with the relatively higher predictive power for the former macroeconomic variable (see Table 1.3). The forecast errors are large relative to average growth rates, as was the case for the U.S., though to a lesser extent; for the entire sample, Australian GDP (durables consumption) growth averaged 0.79 per cent (0.71 per cent).

In summary, there is not much incremental gain in predictive accuracy when financial market liquidity is included in the set of explanatory variables. On balance, it is hard not to conclude that the costs incurred in constructing the financial liquidity variables are likely to exceed the benefits of greater forecasting accuracy. Furthermore, while including asset returns does improve the predictive power of the model, these gains are not always statistically significant. To examine whether these findings are sensitive to the forecast horizon, and to consider the predictive ability of the VAR model discussed in Appendix A.1, I examine two-quarter ahead forecasts below.

Two-quarter ahead forecasts

For both Australia and the U.S., I compare two-quarter ahead forecasts of real GDP growth and durables' consumption growth, using four models: a VAR model with the illiquidity measures in each of the AR equations ('Benchmark'); a VAR model with the illiquidity measures appearing only for the financial variable equations ('Illiq-not-in-growth'); no cross-variable AR terms in each equation (i.e. AR(2)); and naive forecasts for each of the variables based on the sample average ('Unconditional'). The formulation of the second model reflects the Granger causality tests (see Table A.1), which showed that illiquidity has a greater predictive ability over asset returns, than economic growth. The third and fourth models are the same as for the analysis of 1-quarter ahead forecasts.

Given the large number of parameters in the full VAR, I use an initial sample period of 60 quarters (15 years), from March 1973 to December 1987, adding one quarter to each subsequent sample, ending with the entire 152-quarter sample.

The RMSFEs of the four models are shown in Table 1.5.[25]

An analysis of the 2-step ahead forecast errors confirms the earlier evidence: the benchmark model is statistically no better in forecasting economic growth than the more parsimonious AR(2) and unconditional models. For the U.S., the best model is an AR(2), with forecast errors significantly (both economically and statistically) lower than the other three models. For Australia, the benchmark, AR(2) and unconditional models have broadly the same RMSFEs, and, for GDP growth forecasts, outperform the model which excludes market illiquidity.

Similar to the 1-quarter forecasts, all four models generally do a better job at forecasting GDP growth than durables' consumption growth. Furthermore, the two-quarter RMSFEs are, in general, higher than the 1-quarter ahead RMSFEs, with the exception of the AR(2) model.

While these results suggest little improvement in predictive power from adding illiquidity to the set of explanatory variables, these results are averaged over entire sample periods and so are not state-dependent. This does not preclude the possibility that the relationship between illiquidity and the real economy may be state contingent, for reasons outlined below.

1.7 State-dependent model

1.7.1 Economic foundations for regime changes

There are at least two theoretical reasons why the relationship between market liquidity and economic growth may be state contingent. Firstly, the state contingency may reflect the increase in (Knightian) uncertainty about the economic environment. Caballero and Krishnamurthy (2008) construct a general equilibrium endowment-economy model with two key features: liquidity shortages and Knightian uncertainty. An initial increase in Knightian uncertainty (i.e. a rise in immeasurable risk) leads agents to question their pricing models and economic assumptions, with investors' rationally responding by limiting risky (productive) activities until the uncertainty is resolved. The declines in risk taking behaviour and market liquidity are even greater when the aggregate quantity of liquidity is limited, as the Knightian agent is concerned that they may end up in a situation where liquidity is required, but not provided. Limited capital and Knightian uncertainty interact and feed upon each other, exacerbating flights to quality, liquidity hoarding, and a decline in risky investment.

The presence of asymmetric information can also generate a state-contingent link between liquidity and the real economy. Brunnermeier and Pedersen (2009)

[25] For robustness, I also used a rolling-window to compute forecasts, but found that the findings under this sample selection method were broadly the same as for the expanding-window method.

Table 1.5: **Two-quarter ahead forecast errors**

The table shows the root mean squared forecast errors (RMSFEs), for 2-quarter ahead forecasts, for each of the following four models: the 'benchmark' VAR (equation (A.1)); 'Illiq-not-in-growth' VAR (equation (A.1) excluding illiquidity from the economic growth equation); an AR(2); and an 'unconditional' model (equation (1.5) excluding all terms except the intercept). $RMSFE_{bench}$ and $RMSFE_{alt}$ are the RMSFEs for the benchmark model, and one of the three alternative models, respectively. The table also reports the p-value of Kruskall-Wallis test statistics, which test the null hypothesis that the median squared forecast error of the row model is the same as the column model. *, ** and *** denote rejection of the null at the 10%, 5% and 1% significance levels, respectively. Panels A and B reports the results for the U.S., and Panels C and D report the results for Australia.

Panel A: Forecast errors for U.S. real GDP growth

Statistic	Benchmark	Illiq-not-in-growth	AR(2)	Unconditional
RMSFE	0.647	1.502	0.331	0.634
$\frac{RMSFE_{alt}}{RMSFE_{bench}}$	–	2.32	0.51	0.98

p-value of test of equality of median squared forecast errors

	Illiq-not-in-growth	AR(2)	Unconditional
Benchmark	0.00***	0.00***	0.15
Illiq-not-in-growth	–	0.00***	0.00***
AR(2)	–	–	0.00***

Panel B: Forecast errors for U.S. real durables'consumption growth

Statistic	Benchmark	Illiq-not-in-growth	AR(2)	Unconditional
RMSFE	2.575	3.632	0.478	2.492
$\frac{RMSFE_{alt}}{RMSFE_{bench}}$	–	1.41	0.18	0.97

p-value of test of equality of median squared forecast errors

	Illiq-not-in-growth	AR(2)	Unconditional
Benchmark	0.02**	0.00***	0.60
Illiq-not-in-growth	–	0.00***	0.001***
AR(2)	–	–	0.00***

Panel C: Forecast errors for Australian real GDP growth

Statistic	Benchmark	Illiq-not-in-growth	AR(2)	Unconditional
RMSFE	0.640	0.829	0.645	0.648
$\frac{RMSFE_{alt}}{RMSFE_{bench}}$	–	1.29	1.00	1.01

p-value of test of equality of median squared forecast errors

	Illiq-not-in-growth	AR(2)	Unconditional
Benchmark	0.00***	0.97	0.80
Illiq-not-in-growth	–	0.00***	0.00***
AR(2)	–	–	0.79

Panel D: Forecast errors for Australian real durables'consumption growth

Statistic	'Benchmark'	Illiq-not-in-growth	AR(2)	Unconditional
RMSFE	0.829	0.848	0.831	0.800
$\frac{RMSFE_{alt}}{RMSFE_{bench}}$	–	1.02	1.00	0.96

p-value of test of equality of median squared forecast errors

	Illiq-not-in-growth	AR(2)	Unconditional
Benchmark	0.16	0.28	0.66
Illiq-not-in-growth	–	0.13	0.07*
AR(2)	–	–	0.10*

construct a general equilibrium exchange-economy model which relates the liquidity of an asset ("market liquidity") to the amount and cost of an investor's capital required to trade the asset ("funding liquidity"). There are three groups of market participants: risk-averse "customers", leveraged risk-neutral "speculators" – who absorb customers' trades – and "financiers", who provide margin finance to speculators. Financiers can be either 'informed' – they can differentiate between customers' liquidity shocks and fundamental value shocks – or 'uninformed'. As the aggregate endowment shock and aggregate supply of risky assets both equal zero, the only inhibitor of perfect risk sharing is the informational asymmetry when financiers are uninformed. Uninformed financiers generate procyclical margins and two equilibria: a high market and funding liquidity equilibrium; and a low market and funding liquidity equilibrium. In the high liquidity equilibrium, declines in speculators' capital have small effects on market liquidity and pricing when capital constraints are slack, but large effects when constraints (almost) bind.

In terms of empirical studies, Næs et al. (2011) conduct an event study of equity market illiquidity around the ten NBER-dated recessions between 1947 and 2008, finding that the deterioration in market liquidity is much larger than that implied by the coefficients from a model estimated over the entire sample period. However, their examination is deterministic: they do not allow for stochastic changes in the link between market liquidity and economic growth, and hence assume that such changes can be predicted by agents, which is inconsistent with rational expectations, efficient markets, and the theoretical work of Caballero and Krishnamurthy (2008) and Brunnermeier and Pedersen (2009).

1.7.2 Markov-switching model

The empirical literature on stochastic regime changes in economic growth is well-established, dating back to the seminal work of Hamilton (1989), which documented a non-linear AR relationship in U.S. real GNP growth, with the non-linearity arising from discrete shifts in the parameters of a linear AR model. In this paper, I extend this literature by allowing for discrete shifts in both the AR and liquidity coefficients in the linear model.

I estimate a Markov-switching (MS) version of equation (1.5), with two possible regimes.[26] A Markov process is one where the probability of being in a particular state is only dependent upon what the state was in the previous period, and transitions between differing regimes are governed by fixed probabilities.[27] Incorporating

[26] The estimation is done using Marcelo Perlin's 'MS Regress' MATLAB package. For details of this package, see Perlin (2011).

[27] Technical details regarding Markov switching models can be found in Hamilton (1994).

regime shifts leads to the following state-contingent version of equation (1.5):

$$y_{t+1} = \alpha(s_t) + \beta(s_t) SILLIQ_t + \delta(s_t) BILLIQ_t + \rho(s_t) y_{t-1} + \gamma'(s_t) \mathbf{W}_t + \epsilon_{t+1} \tag{1.9}$$

where $\epsilon(s_t) \sim NIID(0, \sigma^2(s_t))$, and $\alpha(s_t)$, $\beta(s_t)$, $\delta(s_t)$, $\rho(s_t)$, $\gamma(s_t)$, and $\sigma(s_t)$ are parameter shift functions describing the dependence of the parameters α, β, ρ, γ, and Σ on the existing regime, s_t. s_t denotes a latent state variable, which follows a continuous time Markov-chain with two different regimes ($s_t \in \{0, 1\}$) and transition probabilities:

$$P = \begin{bmatrix} p_{00} & 1 - p_{00} \\ 1 - p_{11} & p_{11} \end{bmatrix}.$$

The choice of an MS model over other popular regime switching models is somewhat arbitrary, since a proper examination and comparison of various regime switching models is outside the scope of this paper. However, one advantage of the MS-AR model is that it requires neither the existence of a weakly exogenous variable, nor lagged values of the dependent variable to identify regime changes. Furthermore, it allows for a latent variable to determine the regimes, while other switching models require this variable to be observable, typically a nontrivial requirement.

While equation (1.9) allows for all coefficients to change with the regime, this requires estimation of 27 distinct parameters, which, given the sample size of 152, constitutes a significant loss of degrees of freedom. In the interests of parsimony and to focus on the variables of interest, I analyse the case where only the AR and illiquidity coefficients in equation (1.9) change, which requires estimating 17 distinct parameters, for each of the four economic growth variables.[28] Table 1.6 contains the results for Australia and the U.S., with the *dILR* measure used for the U.S. and the *Roll* measure for Australia. The results for the alternative liquidity measures are reported in Appendix A.2.

The main findings are that the predictive power of equity market illiquidity over economic growth is much larger in one regime (which I dub the "illiquid" regime) than the other, and this holds for each of the four economic growth variables, for both countries. For both the U.S. and Australia, $\hat{\beta}$ is statistically insignificant in the equations for GDP growth, durables' consumption growth, and investment growth, in the first regime, while it is statistically significant (typically at the 5% level) in the second regime. The statistical significance of $\hat{\delta}$ also increases for the U.S. economic growth variables, across the first and second regimes, though $\hat{\delta}$ is generally statistically insignificant for Australia, in both regimes.

[28] In the interests of parsimony, I do not estimate an MSVAR since this involves estimating a total of 119-189 parameters, with the latter leading to parameters being under-identified.

Table 1.6: **Parameter estimates of regime-switching regression model**

The table shows the results from estimating equation (1.9) between March 1973 and December 2010 (152 quarters), with two regimes and fixed transition probabilities. U.S. equity market illiquidity is proxied by *dILR* (the H-P detrended component of *ILR*), and Australian equity market illiquidity is proxied by *Roll*. t-statistics are shown in brackets. Only the parameters relating to market illiquidity and lagged economic growth are allowed to change across regimes.

y_{t+1}	$\hat{\alpha}^a$	$\hat{\beta}$	$\hat{\delta}$	$\hat{\rho}$	$\hat{\gamma}^{Term,a}$	$\hat{\gamma}^{Cred,a}$	$\hat{\gamma}^{er_m,a}$	$\hat{\gamma}^{Vol,a}$
Panel A: U.S.; 'Liquid' regime								
GDP	-0.210	-0.061	0.327	0.260	0.226	0.445	0.027	-0.342
	(-1.40)	(-0.18)	(0.73)	(2.17)	(7.31)	(2.81)	(3.71)	(-2.35)
CONS	0.612	-0.521	0.461	0.397	0.123	-0.101	-0.003	0.004
	(2.94)	(-2.24)	(1.34)	(1.99)	(3.11)	(-1.01)	(-0.53)	(0.02)
DCONS	1.140	1.144	-1.468	0.168	0.198	0.558	0.050	-0.633
	(1.42)	(0.93)	(-1.25)	(1.61)	(1.15)	(1.38)	(2.21)	(-1.04)
INV	-0.684	1.029	1.769	-0.195	1.267	-0.811	0.152	-0.706
	(-0.61)	(0.87)	(1.76)	(-1.49)	(4.59)	(-0.93)	(3.14)	(-0.67)
Panel B: U.S.; 'Illiquid' regime								
GDP	-0.210	-0.978	-0.174	0.325	0.226	0.445	0.027	-0.342
	(-1.40)	(-2.15)	(-0.11)	(2.43)	(7.31)	(2.81)	(3.71)	(-2.35)
CONS	0.612	-1.066	0.697	-0.425	0.123	-0.101	-0.003	0.004
	(2.94)	(-4.58)	(2.02)	(-2.14)	(3.11)	(-1.01)	(-0.53)	(0.02)
DCONS	1.140	-1.659	4.147	0.149	0.198	0.558	0.050	-0.633
	(1.42)	(-2.35)	(2.15)	(1.76)	(1.15)	(1.38)	(2.21)	(-1.04)
INV	-0.684	-3.955	4.663	0.860	1.267	-0.811	0.152	-0.706
	(-0.61)	(-2.36)	(1.95)	(2.26)	(4.59)	(-0.93)	(3.14)	(-0.67)
Adjusted R-squared of U.S. regime-switching model								
	GDP	*CONS*	*DUR*	*INV*				
	0.28	0.29	0.25	0.31				
Panel C: Australia; 'Liquid' regime								
GDP	0.873	0.395	-0.212	-0.320	0.138	0.207	-0.001	-0.244
	(3.53)	(1.23)	(1.59)	(-2.26)	(2.37)	(1.77)	(-0.16)	(-0.84)
CONS	-2.730	1.120	-0.436	0.911	0.083	0.068	0.004	0.938
	(-4.04)	(1.08)	(-0.53)	(5.74)	(2.15)	(0.32)	(0.24)	(1.48)
DCONS	0.270	-1.086	0.808	0.492	0.075	-0.273	0.036	0.942
	(0.88)	(-2.57)	(1.86)	(5.93)	(1.15)	(-2.82)	(2.85)	(2.56)
INV	1.915	0.449	-0.353	0.058	0.411	-0.093	0.010	-1.990
	(2.47)	(0.31)	(-0.29)	(0.53)	(2.01)	(-0.21)	(0.30)	(-1.64)
Panel D: Australia; 'Illiquid' regime								
GDP	0.873	-0.384	-0.344	-0.072	0.138	0.207	-0.001	-0.244
	(3.53)	(-2.01)	(1.98)	(-0.61)	(2.37)	(1.77)	(-0.16)	(-0.84)
CONS	-2.730	-1.584	0.850	-0.780	0.083	0.068	0.004	0.938
	(-4.04)	(-4.97)	(0.93)	(-3.06)	(2.15)	(0.32)	(0.24)	(1.48)
DCONS	0.270	-2.061	-0.318	0.504	0.075	-0.273	0.036	0.942
	(0.88)	(-3.67)	(-0.39)	(1.24)	(1.15)	(-2.82)	(2.85)	(2.56)
INV	1.915	-1.730	1.521	0.166	0.411	-0.093	0.010	-1.990
	(2.47)	(-2.36)	(1.96)	(1.65)	(2.01)	(-0.21)	(0.30)	(-1.64)
Adjusted R-squared of Australian regime-switching model								
	GDP	*CONS*	*DUR*	*INV*				
	0.15	0.59	0.45	0.05				

Notes: (a) These coefficients are fixed across the two regimes, for each country.

The added flexibility of the MS model translates into greater explanatory power for both Australia and the U.S. For Australia, the largest absolute and proportionate gain in $\bar{R}^2$ is observed for the consumption growth equation, which equals 0.59 for the regime-switching model, compared to 0.15 for the non-state dependent model. For the U.S., the largest gain in $\bar{R}^2$ occurs for durables' consumption growth. Collectively, the gain in explanatory power is highest for Australia.

The statistical significance of $\hat{\beta}$ in the second regime implies that returns do *not* subsume the information content of liquidity. The state-contingent nature of this incremental information may reflect the important role of capital constraints: in states where capital constraints are slack, liquidity shocks do not affect economic growth, and thus uncorrelated with liquidity shocks. However, in states where constraints (are expected to) bind, liqudity shocks impact economic growth.

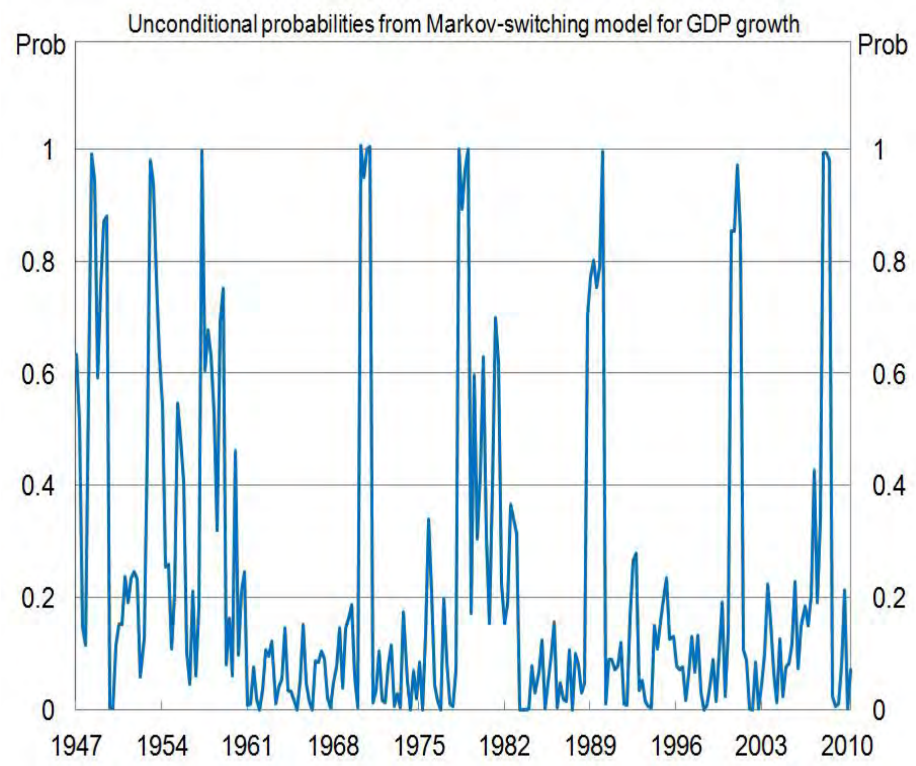
Examining the unconditional probabilities of being in the 'illiquid' regime, for each of Australia and the U.S. shows that the state-contingent nature of the relationship does have economic foundations. For both Australia and the U.S., the probability of being in the illiquid regime has been the largest during time periods associated with macroeconomic downturns: late 1970s (the second oil price shock, and resultant stagflation); the economic recessions of the early and late 1980s, and early 1990s; the U.S. dot-com bust of 2001; and the global financial crisis of late 2008. During these time periods, the probability of being in the 'illiquid' regime, p^{illiq}, was, on average, around 0.7 (Figure 1.3).

In contrast, p^{illiq} has, in general, been significantly lower during periods associated with economic upturns, such as the 'Great Moderation' period from the mid 1990s to 2007. The correlation between p^{illiq} and GDP growth is, unsurprisingly, not perfect: -0.25 for the U.S. and -0.53 for Australia. Furthermore, it is estimated that the 'illiquid' regime (regime 2) existed around 25 per cent (38 quarters) of the time for both Australia and the U.S., over the 38-year sample, while U.S. and Australian economic downturns actually occurred only about 15 per cent of the time.[29]

One reason for the imperfect correlation between p^{illiq} and economic growth is the response of policymakers, in particular central banks. A key rationale for investor-of-last-resort facilities is minimising the spillover of financial market strains onto the real economy, by augmenting (and in some instances entirely replacing) private liquidity provision. For example, during the most virulent phase of the global financial crisis, in late 2008, the Reserve Bank of Australia and the U.S. Federal Reserve implemented several lender-of-last resort policies, which were either a permanent change to their open-market operations (e.g. the widening of

[29] I define a U.S. economic 'downturn' using the NBER's Business Cycle Dating Committee's definition of an economic contraction; the list of NBER-dated economic contractions is obtained from: http://www.nber.org/cycles.html. For Australia, I define a 'downturn' as three consecutive quarters of below-average quarterly real GDP growth.

Figure 1.3: **Probability of being in the "illiquid" regime**
The graph shows the unconditional probability of being in the 'illiquid' regime, estimated from equation (1.9) applied to each of U.S. and Australian GDP growth. The 'illiquid' regime is defined as the regime in which there is a statistically significant relationship between market illiquidity and funding liquidity, as shown by the output in Panels B and D of Table 1.6.



collateral that could be pledged when borrowing from the central bank) or a temporary measure that would cease once market conditions stabilised (e.g. the Federal Reserve's Commercial Paper Funding Facility). To the extent that policymakers can use these facilities to offset negative shocks to private liquidity, a decline in equity market liquidity need not lower economic growth.

Secondly, markets can overshoot, with bouts of irrational exuberance and pessimism increasing the noise of asset prices and liquidity, relative to the information they reveal about the economy.[30] This informational inefficiency affects prices and trading volumes.

The main findings from the predictive regression estimations can be sum-

[30]These arguments are perhaps best summarised by Paul Samuelson's famous quip: "the stock market has predicted nine of the last five recessions."

marised as follows. When the relationship between market illiqidity and economic growth is examined over sufficiently long time periods, illiquidity does not provide any information about future GDP and investment growth. However, in states where liquidity shocks are sufficiently large, market illiquidity (particularly equity market illiquidity) does contain information about future economic growth, even after controlling for the information content in asset returns. That is, in 'illiquid' economic states, illiquidity's information content is not subsumed by returns.

1.7.3 Implications of the regime-switching evidence

One important implication of the above findings is that forecasts that condition on the economic state are likely to be more precise than the non state-contingent forecasts in Section 1.5. For example, Acharya, Amihud and Bharath (2011) find that state-contingent forecasts of corporate bond returns are less biased and more correlated with realised returns during the crisis period of 2008-2009, than non-state contingent forecasts. A proper examination of state-contingent forecasts is outside the scope of this paper, and is left for future research.

The second implication relates to central bank policy. As my liquidity measures can generally be measured in real-time (particularly those based on broad-based market indices, which do not require onerous collection of individual stock data), shocks to liquidity can also be measured in real time. The regime switching evidence in this paper suggests that the occurrence of large, negative liquidity shocks signals lower future economic growth, which means central banks – the most effective investors-of-last-resort – ought to act strenously to offset these shocks. While central banks do this for bond markets, the evidence in this paper is that central banks should also stabilise *equity* market liquidity, in order to stabilise current and future economic growth. These arguments are similar to those of Farmer (2009), who argues that central banks should target broad-based stock market indices by creating investment funds, and as part of their policy announcements, prescribe a price path for this fund, whereby they will guarantee the repurchase of shares in this fund at the set prices.[31] Farmer's idea is to boost stock prices, by making them a lower-risk investment, thereby facilitating greater investment and higher consumption and, ultimately, higher economic growth and employment.

Finally, these arguments are relevant for both Australia and the U.S, but appear to apply more for the U.S. While a one-standard deviation positive illiquidity shock leads to a similar 13 basis point decline in both Australian and U.S. GDP growth, the standard deviation of Australian equity market illiquidity shocks (0.34)

[31] Investing in broad-based indices, rather than individual stocks or sub-indices, may partly insulate central banks from claims of picking 'winners' and 'losers', thereby allowing central banks to maintain their credibility and political independence.

are around three times larger than for the U.S. (0.12). This implies that, were Australian and U.S. illiquidity shocks to be of the same size, the impact on the U.S. would be around three times larger than for Australia.

1.8 Conclusion

This paper has examined the link between financial market illiquidity and economic growth, for Australia and the U.S., between 1973 and 2010. In contrast to other studies, I find that, when averaged over time and thus 'unconditional', financial market illiquidity does not have much information content over future economic growth, with higher predictability observed for U.S., rather than Australian, economic growth. In contrast, asset returns do have predictive power over economic growth, implying that the information content of market illiquidity is largely subsumed by asset prices. Furthermore, equity market liquidity is a more important predictor of economic growth than government bond market liquidity. Liquidity's small incremental information translates into a lack of predictive power: growth forecasts from models that exclude market liquidity from the set of financial explanatory variables are statistically the same as forecasts from models that include market liquidity.

However, these findings are 'unconditional' in the sense that the effects are averaged over time. When I allow the relationship between market illiquidity and future economic growth to be state-contingent, I find strong evidence that the predictive power of market illiquidity is significantly greater during "bad times": time periods historically associated with low economic growth rates, high financial market illiquidity, and lower asset prices.

The non-linear, state-contingent relationship between market liquidity and future economic growth has important practical and policy implications. The practical implications relate primarily to forecasting: economic growth forecasts which condition on the economic and financial state are likely to be more precise than non state-contingent forecasts. The implications for policy relate to central banks' investor-of-last-resort facilities and imply that central banks should offset negative equity market liquidity shocks (in addition to their current practice of stabilising short-term debt markets) as a key element of their macroeconomic stabilisation objectives. These arguments are equally relevant for both Australia and the U.S.

In addition to analysising the forecasting and policy implications, there are two other extensions to this paper. Firstly, a greater exploration of why the liquidity-growth relationship is state-contingent is warranted, by examining the role of funding liquidity. The theoretical and empirical literature on market and funding liquidity argues that in states where funding liquidity shocks are large enough to force agents towards their capital constraints, a positive relationship between market liquidity, funding liquidity, and economic conditions may arise. Secondly, as my analysis has focused on the country-specific relationship between market illiquidity and economic growth, it is worth examining liquidity spillovers across markets and assessing whether, and how, shocks in, say, U.S. financial markets affect Australian economic growth. This would be similar in spirit to the large literature examining the spillover of monetary policy shocks across national borders, and the impact of one country's monetary policy shocks on other nations' economic growth.

Chapter 2

The interaction between short-term funding and bond market liquidity

2.1 Introduction

This chapter examines the empirical link between market liquidity, funding liquidity, volatility and pricing, in the U.S. corporate bond and structured credit markets, over the 2005-09 period, using a reduced form VAR.[1] Most analyses of the financial crisis highlight the rapid expansion of the *shadow banking sector* in the period from 2000 to 2007 and the sector's subsequent collapse (Adrian and Shin (2010), Brunnermeier (2009), Gorton and Metrick (2011)).[2] These papers claim that the global financial crisis was precipitated by difficulties faced by these institutions in obtaining short-term debt on reasonable terms. As with traditional banks, the funding structure employed by shadow banks was short-term. However, unlike traditional banks there was no regulatory structure that offered safety to the shadow-bank depositors. Gorton and Metrick (2010, 2011) argue that a run on the *sale and repurchase agreement* (repo) market was a key factor in the collapse of the shadow banking system, while Krishnamurthy, Nagel and Orlov (2011), and Covitz, Liang, and Suarez (2009) argue that the collapse was chiefly due to a run on *asset-backed commercial paper* (ABCP). A 'liquidity squeeze' in short-term funding markets created a spiral of losses for the shadow banks, in

[1] For the purposes of this chapter, I define a bond as 'corporate' if it is issued by a private company, or if it is an asset-backed security not issued by a U.S. government agency (such as the Federal National Mortgage Association ("Fannie Mae"), or Federal Home Loan Mortgage Corporation ("Freddie Mac")).

[2] Terms in italics may be unfamiliar to some readers and are defined in Appendix B.1. I provide a brief discussion of the mechanics of repo and ABCP in Section 2.2.

which a forced deleveraging by shadow banks and liquidation of assets lowered the liquidity and prices of these assets, leading to the imposition of tighter funding constraints, which prompted further fire sales, leading to even higher losses and illiquidity.

If either of these arguments are valid, we should expect to see a connection between the liquidity and availability of short-term funding, and the pricing, volatility and liquidity of those assets financed using this funding. This chapter examines whether such a link exists, and how this link differs across the various types of U.S. corporate bond markets.

Intuitively, the link between funding liquidity and market liquidity is straightforward: in financial markets, trading typically requires capital. When a trader buys a security she can fund the purchase entirely out of her own capital, or she can use the security as collateral and borrow a fraction of its value against it. The difference between the security price and the amount borrowed (a *haircut*) must be financed by a trader's own capital. Similarly, short-selling requires capital in the form of a margin; it does not free up capital. The ease with which traders obtain funding can therefore affect their demand for an asset which, in turn, can affect traders' ability to provide liquidity in financial markets. While intuitive, there has been little empirical investigation of the link between market liquidity and funding liquidity, a gap in the literature which this chapter addresses using the U.S. corporate bond market.

In repo markets, the run on short-term funding corresponded to an increase in repo haircuts and repo spreads. To see how this can impact market liquidity, consider a bond, formerly fully financed via borrowing through a repo, is subsequently only 90 percent financed. This is a 10 percent increase in the haircut, which is a withdrawal of 10 percent of funding, which the borrower now has to fund in some other way. If there is no new funding forthcoming, the borrower must sell assets. Similarly, a rise in repo yields means a borrower has to repay a larger amount, and obtain the additional funds in another way, for a given amount borrowed, or scale back the amount borrowed for a given amount 'repoed'.

In the ABCP market, the run reflected a combination of rising ABCP yields and a higher degree of overcollateralisation which, in economic terms, is equivalent to an increase in repo haircuts.[3] In order to satisfy the requirements for higher haircuts/collateralisation, the borrower either needs to provide more capital or sell assets. When many firms are forced to delever in this way, sales can occur at fire sale prices and can lead to a drop in market liquidity and prices, and a rise in volatility.

[3]Overcollateralisation describes the situation where the value of collateral exceeds the amount borrowed. Hence, higher overcollateralisation represents the need to provide extra collateral for a given amount borrowed, or to lower the amount borrowed for a given collateral value.

The key results of this chapter can be summarised as follows. Firstly, using a reduced-form VAR, I find modest evidence of a connection between funding liquidity, and market liquidity and pricing, over the entire sample period. Moreover, the strength of the VAR relations depend on the type of corporate bond market and the measure used to proxy for funding liquidity. The link is greatest when repos spreads are used, rather than ABCP or repo haircuts, to proxy for secured funding. These findings support the "run on repo" argument made by Gorton and Metrick (2010, 2011), and do not support the arguments of Krishnamurthy, Nagel and Orlov (2011).

Secondly, unsecured funding is found to be as important as secured funding, in influencing the liquidity and pricing of U.S. corporate bonds. This finding suggests that the theoretical literature's emphasis on secured funding does not fully describe the interaction between market liquidity and funding liquidity.

Finally, I find strong evidence of a state-contingent, and hence non-linear, relationship between market liquidity, funding liquidity, return volatility and spreads. In particular, in states where shocks to the system's variables are small, there is no significant correlation between market liquidity and funding liquidity. When shocks to funding liquidity are large enough to force agents towards their capital constraints, a positive relationship between market and funding liquidity arises. While the existence of nonlinearities in this context is not a theoretical novelty, I document this empirically.

The rest of the chapter is organised as follows. Section 2.2 describes the main features of repurchase agreements and ABCP, and Section 2.3 reviews the relevant theoretical and empirical literature. Section 2.4 outlines the data used, defines my proxies for market liquidity and funding liquidity, and the empirical methodology employed. Section 2.5 outlines and discusses the results from the non time- or state-dependent VAR models. Section 2.6 contains the estimation of the time- and state-dependent models, which allow for deterministic and stochastic regime changes in the VAR relations. Section 2.7 concludes with some suggestions for extending this research.

2.2 Repurchase agreements and ABCP

2.2.1 Mechanics of repos

A repo is an agreement between two parties under which one party sells a security to the other, with a commitment to buy back the security at a later date for a specified price (see Figure 2.1).[4] The difference between the sale and repurchase

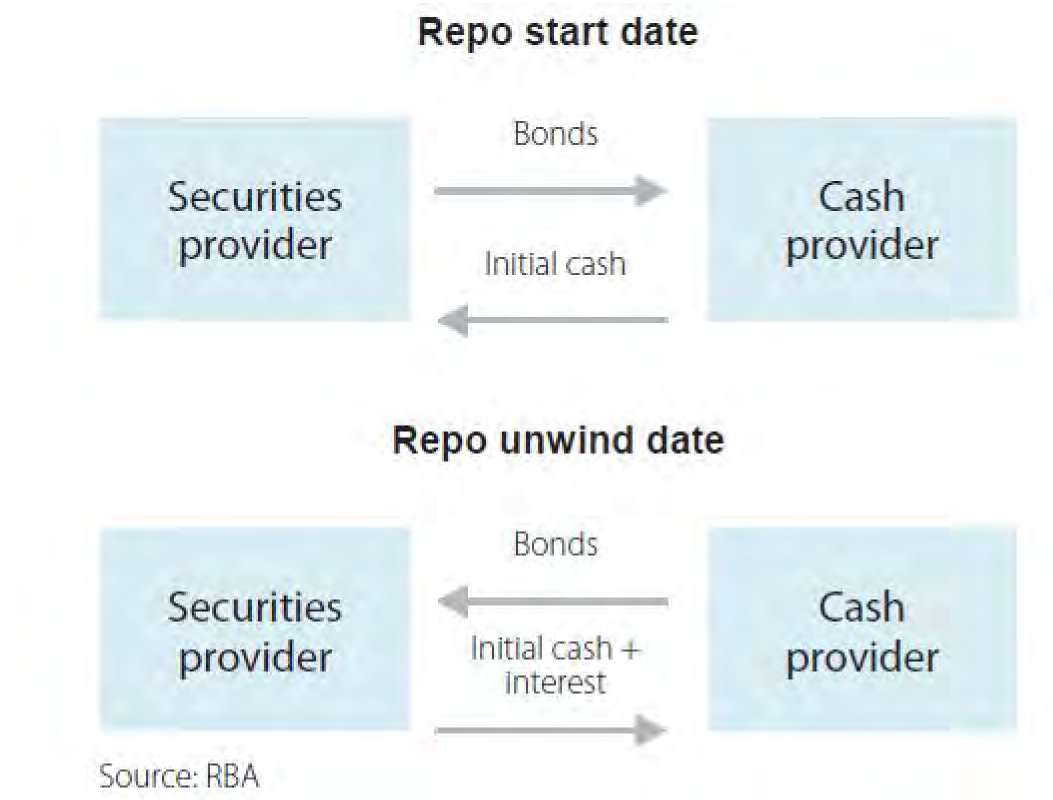
[4]The party that sells a security with an undertaking to repurchase it in the future is said to have contracted a repo. The counterparty (the purchaser of the security) is said to have

price reflects the rate of interest to be earned by the cash provider. While repos are similar to secured loans in an economic sense, a fundamental distinction is that title to the security passes to the cash provider for the duration of the repo.

Repos can be contracted for various maturities, from overnight to longer terms. Parties to these 'term' repos will agree on the maturity date at the inception of the transaction. In contrast, 'open' repos have no defined maturity date, with the interest rate and term being renegotiated each day until the parties to the trade agree to let it mature. Within the Australian and U.S. markets, most repos are contracted on an open basis (Gorton and Metrick (2010); Wakeling and Wilson (2010)).

The borrower typically has to post collateral in excess of the notional amount

Figure 2.1: **Structure of a Repo**



Source: Wakeling and Wilson (2010)

of the loan, with the difference reflecting the haircut. The haircut is defined as $1 - \frac{C}{F}$ with collateral value C and notional amount F. For example, a repo in

contracted a 'reverse repo'.

which the borrower receives a loan of \$95m might require collateral worth \$100m, implying a haircut of 5%.[5]

Repos constitute an important funding source for investment banks (and other shadow banks), money-market and other investment funds, and a variety of market-makers (Krishnamurthy et al., 2011). Repos are typically used to finance securities held on-balance-sheet, or to finance loans provided to other investors. In the latter case, the collateral is *re-hypothecated* in order to serve as collateral in other repos. In terms of their importance as funding instruments, King (2008) estimates that about half of the financial instruments held by dealer banks, as at the end of 2007, were financed through repos.

The type of repo examined in this chapter is known as a bilateral repo, which is a direct repo between the lender and borrower.[6] The risks for a cash lender in a repo stem from the interaction of: (a) the borrower's credit risk, and (b) the illiquidity of the underlying collateral, which might prevent the lender from recovering the amount lent. The lender can protect against these risks by raising the haircut (i.e. reducing the amount of money lent) and/or raising the repo rate, for a given amount of funds loaned through the repo.

2.2.2 Mechanics of ABCP

ABCP is issued by so-called *ABCP conduits* and *structured purpose vehicles* (SPVs) in order to finance the purchase of financial securities like *residential mortgage-backed securities* (RMBS) and other *asset-backed securities* (ABS). It typically has a term to maturity of less than one year. Because short-term paper is issued to fund investments in longer-term assets, this type of funding strategy relies on the ability to roll over the ABCP when it matures. The use of ABCP is consistent with an incentive for banks to structure transactions in such a way as to minimise their regulatory capital requirements. In particular, under the Basel I capital rules, the undrawn back-up liquidity lines provided by banks to conduits are recorded as off-balance sheet (OBS) exposures and generally did not attract a regulatory capital

[5] A key development in the 1980s that spurred the growth of repo was that repos received an exemption from the automatic stay provisions of bankruptcy legislation (Garbade, 2006). This exemption allows the cash lender in a repo to sell the collateral immediately in the event of borrower default without having to await the outcome of bankruptcy proceedings, thereby reducing their counterparty risk exposure.

[6] The other type of repo is a tri-party repo, in which a clearing bank stands as an agent between the borrower and lender. The clearing bank ensures that the repo is properly collateralised within the terms of the repo agreement (relating to the size of the haircut, the marking-to-market process, and the type of securities eligible to serve as collateral). The motivation for this arrangement is to enable those cash lenders lacking the capability to handle collateral flows and assess collateral valuations to participate in the repo market without running the risk of the counterparty not providing the required collateral.

charge whenever the original term to maturity was less than one year (Black and Fisher, 2008).

It is important to note that ABCP can be both a source of funding for investing in ABS, and a type of (short-term) ABS itself. For example, it is common for an SPV to issue both ABCP and longer-term ABS in a particular securitisation, with the servicing of the medium term notes subordinated to the servicing of ABCP.[7]

In this essay, I use the term 'ABCP' to refer to the funding it provides for investing in ABS. Analogously, I exclude non-asset backed commercial paper (CP) from my definition of funding liquidity, since CP is used by companies for working capital and other short-term liquidity needs, not as a source of funding for investing in corporate bonds. My treatment of ABCP accords with Krishnamurthy et al. (2011) who define ABCP in terms of its ability to finance investments in ABS.

Of the two broad types of vehicles that issue ABCP (i.e. conduits and SPVs), conduits are far more common. Conduits are usually set up, or 'sponsored', by a bank, though they are a legally separate, 'bankruptcy remote', entity (Figure 2.2).[8] Unlike vehicles that issue term securitisations (such as RMBS) that typically wind down after a few years, conduits are ongoing entities that have a revolving structure, with assets going in and out of the pool of collateral that backs the ABCP.

Figure 2.3 shows data on the size of U.S. commercial paper and repo markets and provides prima-facie that the repo market was a much larger proportion of short-term funding than the ABCP market. The repo market has consistently been between four and six times larger than the ABCP market. Both markets contracted sharply during the financial crisis period, with the repo market declining from 28 per cent of GDP in mid-2007 to 18 per cent of GDP at end-2010, while the ABCP market contracted from 8 per cent of GDP to 3 per cent of GDP over the same period.[9] As a percentage of GDP, both these short-term funding markets are at levels not seen since 2004.

The evidence is prima facie because the repo data includes repos on U.S. government bonds and agency-issued ABS, as the data are not disaggregated by collateral type. Consequently, the importance of the repo market, relative to the ABCP market, may not be as large as that indicated in Figure 2.3.

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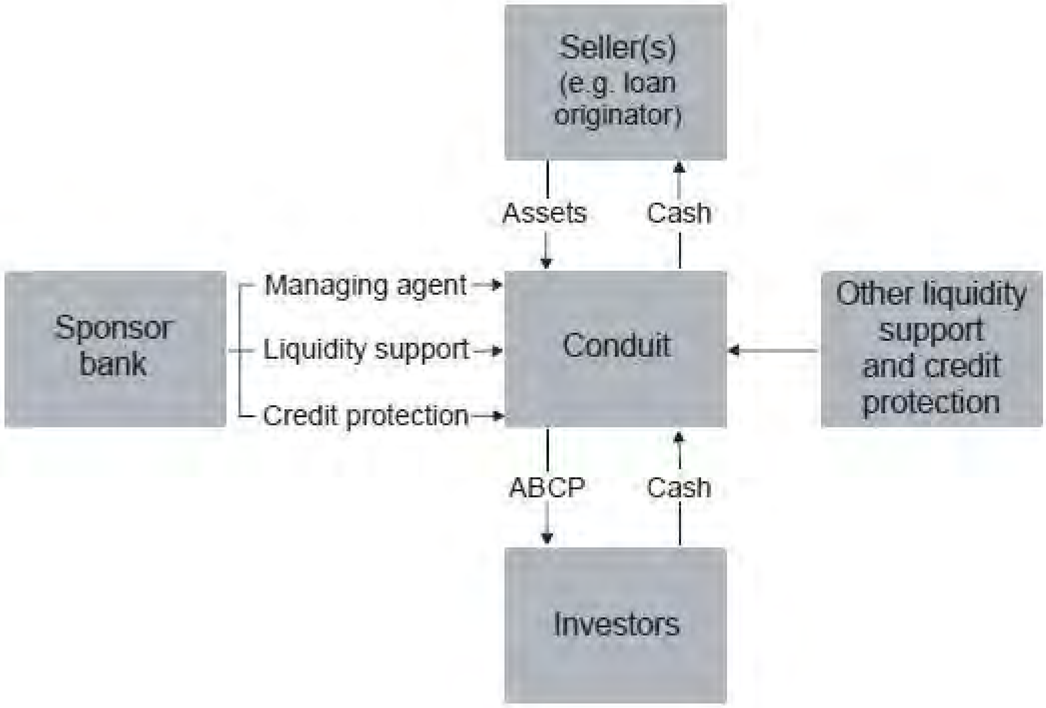
[7]This is often done to lower the credit and liquidity risk of an ABCP. Other forms of credit enhancement include over-collateralisation of the asset pool (commonly 10 per cent) and enhancement of the individual assets in the pool through various forms of insurance (e.g. lender's mortgage insurance).

[8]In a bankruptcy remote structure, the solvency of the conduit is independent of the sponsoring bank.

[9]The data are available from http://www.newyorkfed.org/xml/gsds_finance.html. For more information on primary dealers, see http://www.newyorkfed.org/markets/primarydealers.html.

Figure 2.2: **Stylised Conduit Structure**



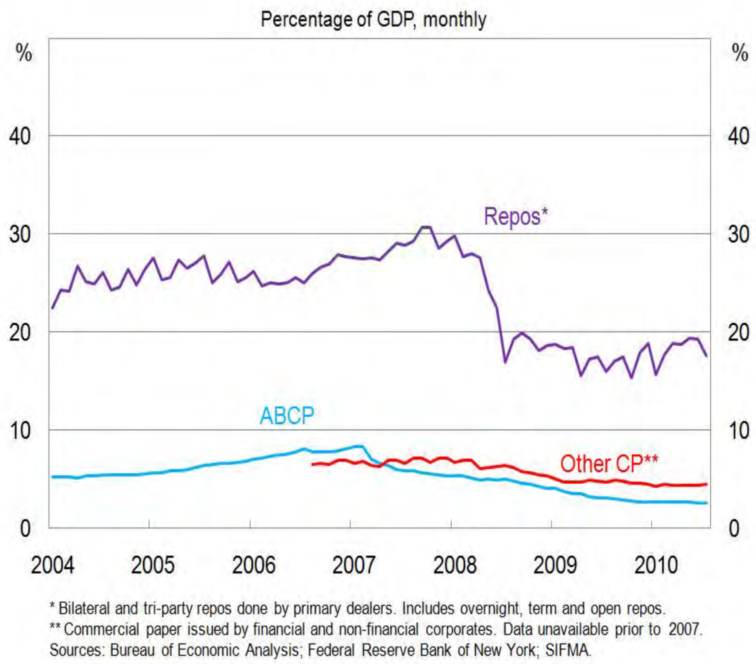
Source: Black and Fisher (2008)

2.3 Related literature

2.3.1 Market liquidity and funding liquidity

Brunnermeier and Pedersen (2009) construct a general equilibrium model of an exchange economy populated by three groups of market participants: risk-averse "customers", risk-neutral "speculators" – who provide market liquidity by absorbing customers' trades – and "financiers", who finance speculators positions. These financiers can be either informed – they know the fundamental value of the risky assets and can differentiate between shocks to customers' liquidity needs and shocks to fundamental values – or uninformed, who only observe prices and can't differentiate between the two sources of shocks. Perfect risk sharing is limited (in part) by the informational asymmetry created when financiers are uninformed about customers' liquidity needs, and so confuse liquidity shocks with shocks to fundamental values. The paper derives a fundamental equation linking market

Figure 2.3: **U.S. short-term debt markets**



liquidity and funding liquidity:

$$|\Lambda_1^j| = m_1^j\,(\phi_1 - 1) \tag{2.1}$$

where $|\Lambda_1^j|$ is a measure of asset j's market illiquidity at time t=1 (defined as the absolute value of the deviation of asset j's price, p_1^j from its fundamental value, v_1^j), m_1^j is its haircut/margin on short-term funding, and ϕ_1 is a speculator's shadow cost of capital at t=1.

Since liquidity risk tends to increase price volatility (as the model prevents customers' liquidity demands from being predicted by the other agents), and since uninformed financiers interpret price volatility as fundamental volatility, margins on speculators' borrowings increases. This limits speculators' ability to provide market liquidity, increasing the price impact of customers' liquidity demands, which raises price volatility. This further rise in volatility is again interpreted by (uninformed) financiers as higher fundamental volatility, which leads to even higher margins, further worsening speculator funding problems, and so on, leading to a "margin spiral". In this sense, when financiers are uninformed, margins can be 'destabilising', as it induces a procyclicality that amplifies funding shocks. An adverse feedback loop between haircuts and asset prices can also be triggered via a "loss spiral", which links the level of haircuts/margins to the strength of speculator deleveraging in response to asset price falls, which is endogenous to the level of the initial haircut. Each liquidity spiral reinforces the other, such that the total effect of the two liquidity spirals exceed the sum of their separate effects.

The model's assumption of leveraged speculators, combined with uninformed financiers, limits the ability of speculators to arbitrage the deviation of prices from fundamental values ($|\Lambda_1^j|$), and implies an upward-sloping demand curve. However, the assumption that all marginal investors are leveraged may be highly restrictive. Brunnermeier (2009) responds to this by arguing that other types of marginal investors may also face funding constraints at the same time (or the fear that funding constraints might bind at some future time) as speculators. Furthermore, potential buyers may find it more profitable to wait out the loss spirals before re-entering the market and might even engage in predatory trading, deliberately forcing others to liquidate their positions at fire-sale prices (Brunnermeier and Pedersen, 2005).

If leverage-induced participation constraints were a major factor behind the decline in market liquidity and prices, we should expect to see a strong empirical relationship between market liquidity and changes in haircuts/margins. Hence, my empirical analysis attempts to address the question: were leveraged investors the major marginal investors in the U.S. corporate bond market during the financial crisis period?

Furthermore, Brunnermeier and Pedersen's argue that uninformed financiers are more representative of real-world funding constraints. However, this assumption is critical to generating pro-cyclical ('destabilising') margins. While Gorton and Metrick (2010) provide data that strongly suggests repo haircuts are procyclical, whether this procyclicality impacts on market liquidity and pricing, and whether this impact is greater than that of other funding sources (such as ABCP, and unsecured funding) is an empirical question which this essay addresses.

To the best of my knowledge, there has not been to date any empirical analysis of the relationship between market and funding liquidity in the corporate bond market. The few papers existing in this research area focus exclusively on the U.S. equity market, likely because of the greater data availability.

Valente (2010) documents a strong link between equity market liquidity and funding liquidity, where market liquidity is defined as the Roll (1984) estimator of the bid-ask spread and funding liquidity is proxied as the difference between short-term *LIBOR* and Treasury bill yields (maturities of three and six months are considered). Valente allows for this relationship to be state-contingent, and finds significant nonlinearities in the link between market liquidity and funding liquidity, consistent with theories of market trading with financially-constrained agents. He estimates a regime-switching model with two regimes: a lower regime characterised by the absence of correlation between market liquidity and funding liquidity, and an upper regime where the two variables are significantly positively correlated. Over the sample period (January 1971 to December 2005) the two variables are uncorrelated most of the time, since shocks to funding liquidity are found to be economically small. This situation persists until agents are forced towards their capital constraints and shocks to funding liquidity becomes economically important.

One criticism of Valente (2010) is that his single-equation model is inconsistent with equation (2.1), in which funding liquidity is the dependent variable. Since the terms in equation (2.1) can be rearranged so that either market or funding liquidity can be the "dependent" variable, this suggests a multivariate-equation model may be more appropriate at capturing this potential bi-directionality. A second criticism is the choice of funding liquidity measure, which may be more useful at capturing the cost of unsecured, interbank funding, rather than the cost of funding equity investments. Nonetheless, the results in Valente (2010) are consistent with the empirical predictions of Brunnermeier and Pedersen (2009).

Chordia, Sarkar and Subrahmanyam (2005) explores liquidity movements in stock and Treasury bond markets, with cross-market dynamics in liquidity documented via estimation of a vector autoregression (VAR) model consisting of a measure of liquidity (bid-ask spreads and market depth), returns, volatility, and order flow in the stock and bond markets. The authors find that a shock to quoted spreads in one market affects the spreads in both markets, and that return volatility is an important driver of liquidity. Innovations to stock and bond market liquidity and volatility prove to be significantly correlated, suggesting that common factors drive liquidity and volatility in both markets. This commonality of liquidity is consistent with one of the theoretical predictions of Brunnermeier and Pedersen (2009).

2.3.2 Run on shadow banks

Brunnermeier (2009) provides a chronology of the main events during the liquidity and credit crunch of 2007-08, identifying and discussing the key trends in the banking industry that laid the foundations for the crisis. In particular, the growth of the shadow banking system provided a way for banks to minimise their prudential capital requirements, by transferring assets off their balance sheet onto shadow banks, who were not depositary institutions and hence were outside the regulatory system. Thus, moving a pool of loans into off-balance-sheet (OBS) vehicles, and then granting a credit line to that pool to ensure a AAA-rating, allowed banks to reduce the amount of capital they needed to hold while the risk for the bank remained essentially unchanged.

Furthermore, banks increasingly financed their asset holdings with shorter maturity instruments, leaving them particularly exposed to a dry-up in funding liquidity, as a result of a move towards greater financing of longer-term assets with short-term repos.

Gorton and Metrick (2010, 2011) argue that the repo market was the focal point for the run on shadow banks: as defaults rose on subprime mortgages during 2006 and 2007, securitised bonds linked to these mortgages experienced heavy losses, which led to a rise in repo haircuts and a dry up of repo funding for these securities. Since repos were the key funding source for these bonds (as claimed by the authors), this dry-up of funding led to further price declines of these securities, setting off a "margin" and "loss" spiral in the spirit of Brunnermeier and Pedersen (2009).

A key criticism of the arguments of Gorton and Metrick (2010, 2011) is that their claims about the importance of repo are based on the primary dealer repo market, the data for which is criticised as being subject to severe multiple counting problems (Singh and Aitken, 2010). Gorton and Metrick (2010)'s estimate of the size of the U.S. repo market – at between US$19 trillion and US$28 trillion as at March 2008 – is grossly inflated, since Gorton (2010) estimates that, as at mid-2008, the total stock of assets in the U.S. banking system was only $10 trillion.[10]

Krishnamurthy, Nagel and Orlov (2011) obtain data on repos of money market funds (MMFs) and security lenders, and estimate that, as at June 2007, ABCP financed 22 per cent of oustanding U.S. private-label ABS, seven times the share financed through repo (3 per cent). These estimates lead them to argue that the ABCP market played a more significant role than the repo market in supporting both the expansion and contraction of the shadow banking sector.

However, their data is a downwards biased estimate of the overall size of the repo market, since it excludes bilateral repos, and tri-party repos between banks. Copeland, Martin and Walker (2011) estimate that MMFs represent between a quarter and a third of the cash invested in the tri-party repo market, while securities lenders represent another quarter. Hence, Krishnamurthy et al.'s data excludes about one-half of the tri-party repo market. Finally, their MMF sample covers only the largest ten MMFs (ranked by value of net assets), representing 60 per cent (by value of net assets) of all MMFs.

The conflicting evidence of Gorton and Metrick (2010, 2011) and Krishnamurthy et al. (2011) provides a cautionary tale about how discussion of the financial crisis has tended to outstrip measurement of the key markets for short-term funding. This essay aims to determine whether ABCP or repo was more relevant in precipitating the financial crisis, on the presumption that the more relevant market would have had a larger impact on bond pricing and liquidity.

[10]Other reasons for suspecting these estimates to be upwardly biased are: (i) repos are not the only form of short-term funding; and (ii) assets are also financed with longer-term debt.

2.4 Data and empirical methodology

2.4.1 Data

Data for the prices and spreads of six separate U.S. corporate bond indices are sourced from Thomson Reuters Datastream (and are constructed by Bank of America Merrill Lynch). These six bond markets are: AAA- and AA-rated MBS tranches; A- and BBB-rated MBS tranches; two AAA-rated ABS tranches, one backed by automotive loans ('Auto ABS'), the other backed by credit card loans ('C/Card ABS'); AAA- and AA-rated corporate bonds; and A- and BBB-rated corporate bonds.[11] Figure 2.4 shows the evolution of the spreads on these six bond types between January 2006 and December 2009, with spreads on all bonds spiking noticeably during late 2008, in the period following the failure of Lehman Brothers and AIG in September 2008, and runs on money market mutual funds. Spreads remained elevated till March 2009, and then began offsetting much of their earlier rise as financial markets stabilised somewhat during 2009. However, at end-2009, spreads were around levels observed during mid-to-late 2008.

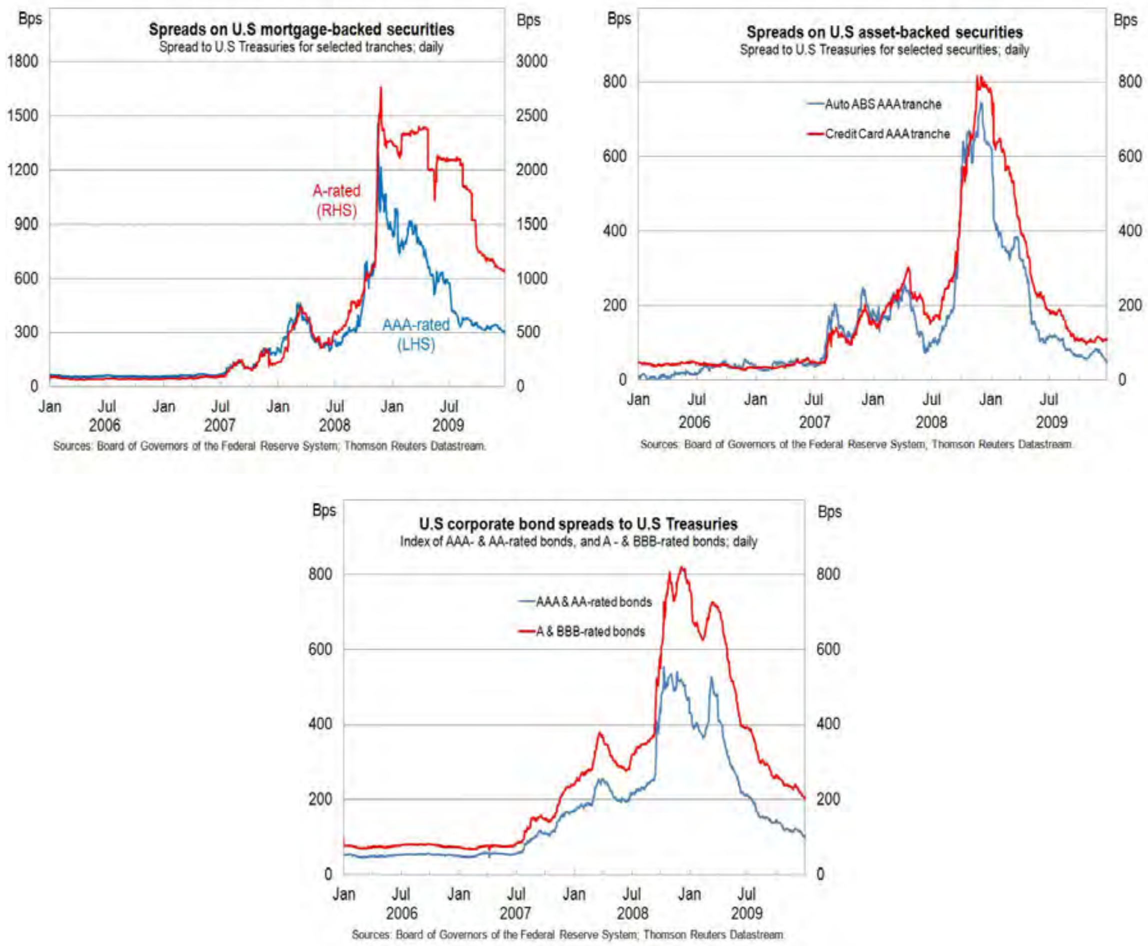
1-month repo yields and repo haircuts are provided by Andrew Metrick, and used in Gorton (2010) and Gorton and Metrick (2011). These data are daily, and from October 3 2005 to February 2 2009 (844 trading days). The data relates to repos between dealer banks. Figure 2.5 shows the evolution of repo spreads between October 2005 and February 2009, for seven U.S. corporate bonds.[12]

Prior to August 2007, spreads across all seven types of repo collateral were generally stable and low, with the lowest spreads (average of -2 basis points) observed for repos collateralised by AAA-rated corporate bonds. Repos backed by AAA-rated subprime RMBS (i.e. the *ABX Index*) and A-rated MBS had the highest spreads, at 12 and 14 basis points respectively, with all spreads fairly stable. However, from August 2007, repo spreads rose steadily across all collateral types; between August 2007 and February 2009 (when the sample ends), repo spreads were, on average, between 80 and 140 basis points higher than in the preceding period. The largest increases were observed for A-rated MBS and AAA-rated CLO collateral (143 basis point increase), a 13- and 19-fold increase respectively, with the smallest spread increases for repos collateralised by AAA-rated and A-rated corporate bonds (80 and 87 basis points, respectively). However, as repos backed by subprime RMBS ceased trading on September 15, 2008, redoing the above analysis for the August 2007-September 15 2008 period reveals that the largest spread

[11] These markets are chosen to ensure consistency with the collateral underlying the repo data from Gorton and Metrick (2011).

[12] AAA-rated and A-rated private-label (i.e. non agency) MBS; AAA-rated and A-rated (vanilla) corporate bonds; AAA-rated ABS backed by automotive loans, credit card loans and student loans; and AAA-rated subprime RMBS (the *ABX Index*).

Figure 2.4: **Spreads on U.S. corporate bonds**



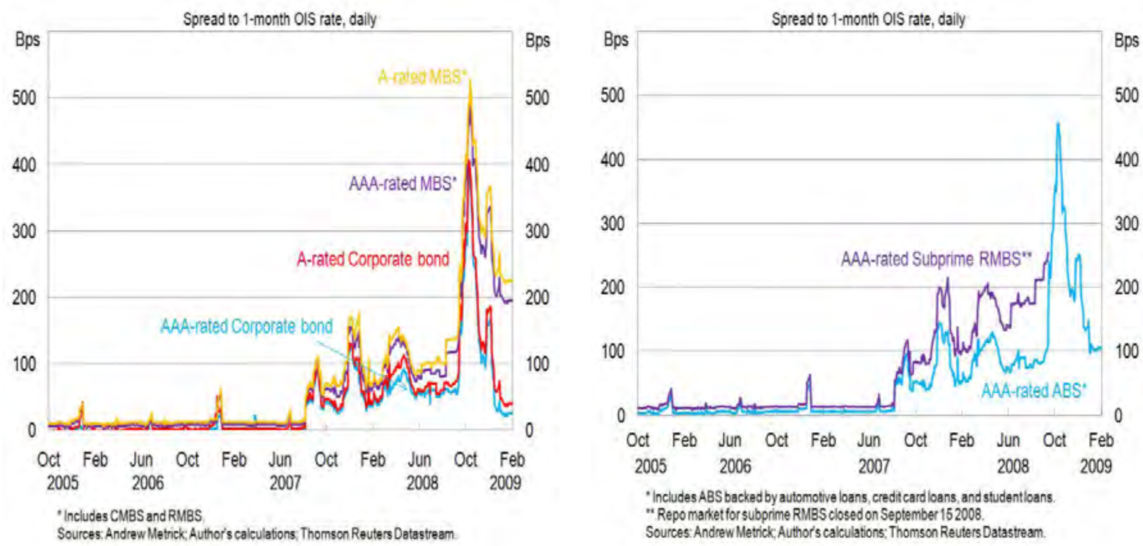
increases were for repos backed by subprime RMBS, which rose 126 basis points.[13]

Mirroring the behaviour in bond spread volatility, the volatility of repo spreads rose sharply during the August 2007-February 2009 period relative to the preceding period; the annualised standard deviation across all seven collateral types was around 4 basis points prior to August 2007, but then jumped to 60 basis points (for AAA- and A-rated corporate bonds) and 89 basis points (for A-rated MBS).

The fall in repo prices (i.e. rise in repo spreads) together with the large decline in repo quantities (Figure 2.3), between August 2007 and February 2009, suggests

[13]In contrast, spreads on repos backed by the other six collateral rose by 60-90 basis points, with repos on A-rated MBSs and AAA-rated CLOs rising the most.

Figure 2.5: **Spreads on 1-month inter-bank repos**



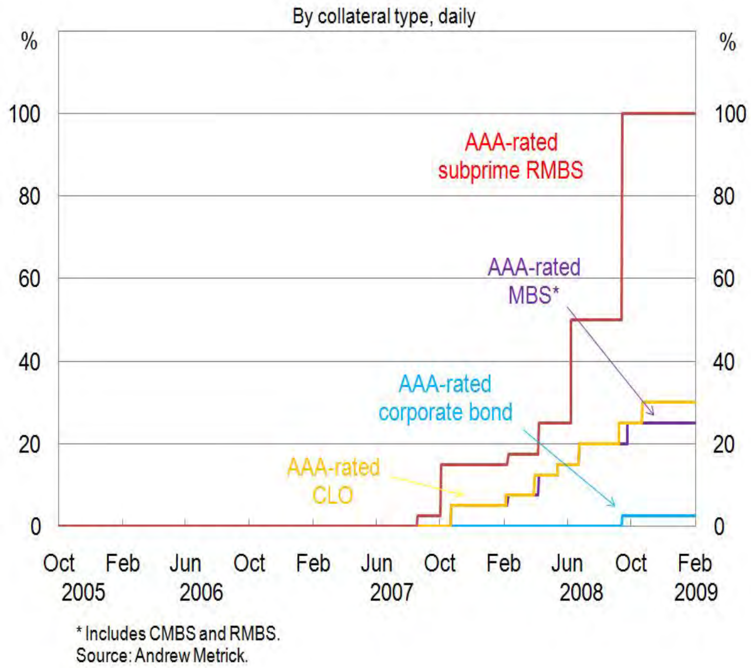
the occurrence of a large, negative demand shock, which offset negative supply shocks. This is also the conclusion of Krishnamurthy et al. (2011), who analyse the tri-party repo market.[14]

Finally, repo haircuts rose sharply during the crisis, from 0 per cent during the pre-crisis period. Haircuts on repos collateralised by subprime RMBS increased the most (and also started to rise the earliest), reaching 100 per cent on September 15 2008, with this repo market ceasing to exist (Figure 2.6). Haircuts on repos collateralised by AAA-rated MBS and AAA-rated CLO rose in unison, with the increase commencing from October 2007, leveling off at 25 and 30 per cent, respectively, from October 2008. Haircuts on repos collateralised by AAA-rated corporate bonds rose the least, with a one-time rise of 2.5 per cent in September 2008.

The repo haircuts and spreads data reveal significant heterogeneity across the seven types of collateral: repos collateralised by mortgage- and asset-backed securities experienced the largest 'repo runs', while repos collateralised by vanilla corporate bonds experienced relatively lower stress. This heterogeneity suggests that the relationship between funding liquidity and market liquidity may not be

[14]He, Khang and Krishnamurthy (2010) show that while dealer banks and hedge funds – sectors that, prior to the financial crisis, largely relied on repo funding – did reduce their holdings of ABS and MBS between August 2007 and February 2009, which reduced the supply of securities available for repo, the reduction was much smaller than the decline in the stock of repos.

Figure 2.6: **Inter-bank repo haircuts**



uniform across all segments of the U.S. corporate bond market, which I analyse more formally in section 2.5.

2.4.2 Empirical methodology

To examine the dynamic relationship between market liquidity, funding liquidity, bond spreads and volatility, I use a Vector Autoregression (VAR) model:

$$\mathbf{X}_t = \alpha + \beta \mathbf{X}_{t-1} + \epsilon_t \tag{2.2}$$

where $\mathbf{X}_t$ is a 5x1 vector containing market liquidity, liquidity of secured funding, bond spreads, LIB-OIS spreads (the cost of unsecured funding) and the weekly standard deviation of daily returns, all observed in week t. The construction of the market liquidity measure is discussed later. The *LIB-OIS* spread is the difference between the 1-month *London Interbank Offer Rate* (LIBOR) and the 1-month *Overnight Indexed Swap* (OIS) rate, with the choice of one month tenor ensuring consistency with the use of 1-month repo spreads. I use weekly observations for all variables, due to my choice of market liquidity measure, discussed below. Finally, ϵ_t is a week-t 5x1 vector of residuals.

The LIB-OIS spread is a commonly used measure of counterparty risk in the interbank market since interbank lending is more risky than lending through an OIS since, in an OIS, counterparties only swap the interest payments (i.e. the principal is nominal). The LIB-OIS spread proxies for the liquidity of unsecured (interbank) funding, while repo haircuts and spreads proxy for the liquidity of secured funding. All three measures relate to short-term funding. While bonds may be financed by longer-term funding, my focus is on short-term funding markets due to their greatly susceptibility to a run (reflecting more frequent rollovers). Furthermore, focusing on short-term funding is consistent with the literature, both theoretical (for example, Brunnermeier and Pedersen, 2009) and empirical (Valente, 2010).

In this essay, I do not attempt to decompose repo spreads, LIB-OIS spreads, or ABCP spreads, into illiquidity and credit components, for three reasons. Firstly, the methods used to decompose spreads assume that the two components are independent, that the recovery rate is constant (or independent of the default probability), and, most importantly, that the default correlation can be precisely estimated. The assumption that liquidity and credit risk are independent has no theoretical foundation, and is made purely for ease of estimation.

Furthermore, Coval, Jurek and Stafford (2009) note that the default correlation is the key input into the valuation and credit rating of a tranched security. The sharp drop in valuations and credit ratings of tranched securities during the crisis reflected an increase in the estimated default correlations and, to a lesser extent, higher default probabilities and lower recovery rates. As the 2007-09 financial crisis made clear, these key inputs were far from independent or constant. This implies that any decomposition reliant on the above assumptions is subject to a large degree of model risk and parameter uncertainty.

Secondly, the decomposition method used in the literature typically uses the premia on credit default swaps (CDSs) written on the bond to isolate the credit risk component. The difference between the bond's spread and the credit risk component is defined as the illiquidity component. This method is feasible only for those bond markets with related CDS markets. However, my sample includes bonds for which data on CDS premia are not available, such as the markets for asset-backed securities and commercial mortgage-backed securities.

Finally, Ericcson and Renault (2006) find that liquidity risk comprises the vast bulk of short-term bonds' spreads, implying that focussing on the entire spread for short-term instruments, like repos, ABCP and unsecured interbank lending, would not bias my econometric results, especially given the above-mentioned limitations of the decomposition.

It is important to note that while my choice of VAR variables is based on equation (2.1), I do not formally test all the implications of the Brunnermeier and Pedersen (2009) model. As the focus of my essay is examining which of the repo or ABCP market was more important in influencing market liquidity and pricing, I use Brunnermeier and Pedersen's model as theoretical motivation, and do not empirically validate their model. Consequently, while Brunnermeier and Pedersen discuss six testable predictions of their model, only one of these are directly tested in my essay, and another is indirectly tested.

By using both secured and unsecured funding, I directly test their model's prediction on a commonality of liquidity pressures, while the regime switching analysis I present in Section 2.6.2 provides an indirect test of B&P's prediction that the relationship between funding and market liquidity is nonlinear.

An important extension to this chapter is to formally test the various implications of Brunnermeier and Pedersen (2009). To do this, one would need to construct measures more closely related to equation (2.1), including an estimate of speculators' shadow cost of capital, ϕ_1 which is the driving force behind the existence of "margin" and "loss" spirals.

Liquidity measures

The literature on liquidity distinguishes between three sub-forms of market liquidity (Kyle, 1985): (i) the bid-ask spread, which measures how much investors lose if they sell one unit of an asset and immediately repurchase it; (ii) market depth and the 'price impact' of trades, which measures how many units traders can sell (buy) at the current bid (ask) price without affecting the price; and (iii) market resiliency, which measures how long it will take for prices that have temporarily fallen to bounce back. I use the Roll (1984) estimator of the effective bid-ask spread as my proxy for market liquidity.

Roll (1984) develops an estimator of the daily effective spread based on the autocovariance of price changes, as follows. Let V_t be the unobservable, fundamental value of the bond on day t, evolving as a pure random walk process (i.e. the market is informationally efficient):

$$V_t = V_{t-1} + e_t \tag{2.3}$$

Let P_t be the last observed trade price on day t. Assume that it is determined by

$$P_t = V_t + \frac{1}{2} S \cdot Q_t \tag{2.4}$$

where S_t is the effective spread and Q_t is a buy/sell indicator for the last trade, equalling +1 if the security is bought from the market-maker, and -1 if sold to the market-maker. In an informationally efficient market with no new information about the bond, Q_t is equally likely to be +1 or -1, and so has zero mean. Q_t is also serially uncorrelated, which follows from the following assumptions: (i) there is no new information about a bond between time $t-1$ and t; and (ii) the market is informationally efficient.

The above expression for P_t implies that the fundamental value is the midpoint of the bid-ask spread, with bid-price $V_t - \frac{1}{2}S$ and ask price $V_t + \frac{1}{2}S$. Combining equation (2.3) and (2.4) yields:

$$\Delta P_t = \frac{1}{2} S \Delta Q_t + e_t$$

Using the properties of Q_t and e_t, and the properties of covariance, we get:

$$Cov\left(\Delta P_t, \Delta P_{t-1}\right) = -\frac{1}{4} S^2$$

or equivalently:

$$S = 2 \cdot \sqrt{-Cov\left(\Delta P_t, \Delta P_{t-1}\right)} \tag{2.5}$$

Equation (2.5) is undefined when the sample serial covariance is positive. Harris (1990) suggests defining $S = -2 \cdot \sqrt{Cov\left(\Delta P_t, \Delta P_{t-1}\right)}$ if $Cov\left(\Delta P_t, \Delta P_{t-1}\right) > 0$, but this would lead to an assumed negative effective spread, which is inconsistent with a profit-maximising market-maker. Thus, when the sample covariance is positive, I follow Goyenko, Holden and Trzcinka (2009) in substituting a value of zero.[15]

I apply equation (2.5) to daily prices of six types U.S. corporate bonds and construct a weekly effective spread for each bond type. As the resulting estimates are dollar values, I scale them by the bond's price (at time $t-1$) in order to allow a comparison of spreads across the different corporate bond market segments. Figure 2.7 shows that, prior to mid-2007, the bid-ask spread was low and fairly stable in all selected U.S. bond markets, but liquidity strains started to occur from the start of 2008. These strains intensified between late 2008 and early 2009, as liquidity declined sharply; during this period, bid-ask spreads were between five and ten times larger than levels observed prior to 2008. The bid-ask spread on mortgage-backed securities reached a high of 5.3 per cent in November 2008, vastly exceeding the 0.3 per cent spread observed prior to November 2008.

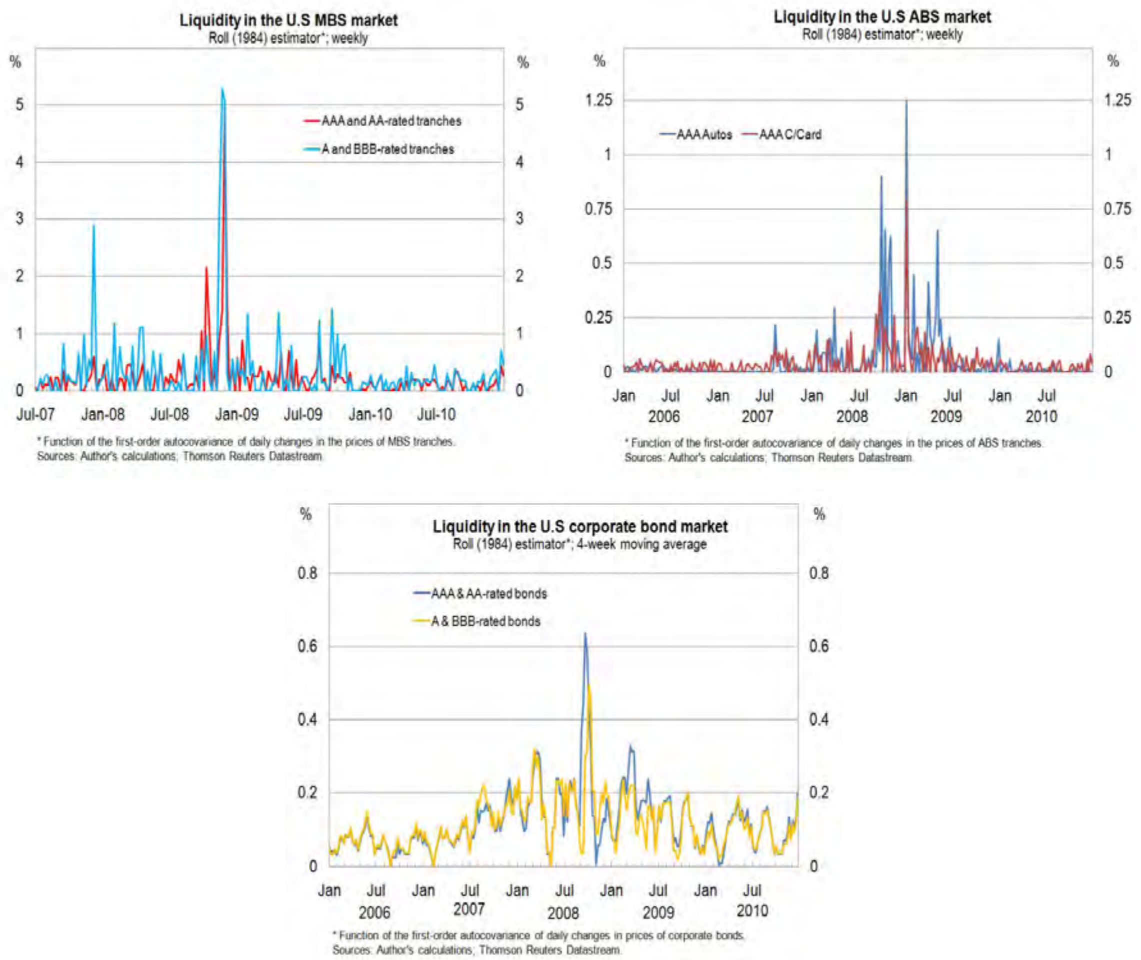
Bid-ask spreads are, on average, positively related to credit risk, a finding consistent with, among others, Ericcson and Renault (2006) who find a positive correlation between credit risk and liquidity risk in the U.S. corporate bond market. For example, the average bid-ask spread on AAA- and AA-rated MBS tranches was 0.2 per cent, while for A- and BBB-rated tranches it was 0.34 per cent). However, there were periods where bid-ask spreads on higher-rated bonds exceeded that of lower-rated bonds (such as during December 2007 for MBS, and October 2008 for

[15] This specification for the sample covariance is also empirically superior: the correlations between market liquidity and the other variables are higher than the correlations using Harris (1990)'s suggestion.

corporate bonds).

Market liquidity subsequently improved – and the bid-ask spread fell – during

Figure 2.7: **Liquidity in the U.S. corporate bond market**



2009 and 2010, as market strains eased, although there were occasional bouts of illiquidity (e.g. March 2009). At end-2010, bid-ask spreads were around levels observed prior to the crisis.

The use of bid-ask spreads as a solitary measure of market liquidity largely reflects data limitations – I have not found any volume or trading measures in order to use price impact or market depth measures of liquidity. Furthermore, the use of the Roll estimator, rather than the actual quoted or effective bid-ask spread, reflects a lack of data on trade prices and bid-ask quotes.

However, where bid-ask spread data are available (which, for the U.S., is in the equity and government bond markets) the Roll estimator has been found to be a consistent estimator of the bid-ask spread, with its estimates highly positively correlated with actual spreads.[16] Furthermore, I find that the standard Roll estimator performs better – in the sense of having the highest correlation with the other variables in the VAR – than two popular variations proposed in the literature: the George, Kaul, and Nimalendran (1991) estimator based on the residual of the regression of a bonds return on a measure of its expected return, and the Gibbs sampler of Hasbrouck (2006).[17] Moreover, I find that the Roll estimator works better than other price-based liquidity measures, such as the percentage of trading days on which zero returns occur, from Lesmond, Ogden and Trzcinka (1999).

Consequently, a caveat is in order: the results outlined below may not be robust to other market liquidity measures. Since liquidity is a multi-dimensional concept, other dimensions of liquidity not considered in this essay (such as market depth) may provide information about market liquidity not captured in the bid-ask spread. Given liquidity's multidimensionality, it is arguably a futile exercise to find 'the' liquidity estimator. Goyenko, Holden and Trzcinka (2009) confirm that estimators of bid-ask spreads correlate highly with actual spread measures, but have a lower correlation with actual measures of price impact or market depth.

An alternative to the bond price indices I use is the National Association of Securities Dealers (NASD) Trade Reporting and Compliance Engine (TRACE) dataset, introduced in 2002 to boost post-trade transparency in the U.S. corporate bond market. The information relates to transaction dates, prices, and quantities traded by NASD members, on all corporate bonds. Consequently, while the TRACE data have the advantages of including both price and quantity data, the collection, screening and analysis of TRACE data is significantly more time consuming. This makes it less appealing from a practical and policy dimension, when decisions often need to be made in real-time. Nonetheless, an interesting extension of this study is to examine whether its findings are robust to the construction of market liquidity measures from the TRACE dataset.

Table 2.1: Granger causality tests

Roll is the Roll (1984) estimator of the effective bid-ask spread. *Haircut* is the size of repo haircuts, and *Repo sprd* is 1-month repo-OIS spreads. *Sprd* is bond spreads to U.S. Treasuries. *Vol* is the standard deviation of daily returns over the preceding week, and *LIB-OIS* is the spread between the 1-month LIBOR and the 1-month OIS rate. The sample period is October 3 2005 to February 2 2009 (175 weeks), and all data are weekly. The null hypothesis tested is that the variable in a particular row does not Granger cause the variable in a particular column ('dependent variable'). *, ** and *** denote rejection of the null at the 10%, 5% and 1% significance levels, respectively. In Panel B, '· · ·' is used when the χ^2 test statistic is the same value as the corresponding entry in Panel A.

Panel A: Repo haircuts as measure of funding liquidity

	Dependent variable				
	Roll	*Haircut*	*Sprd*	*Vol*	*LIB-OIS*
Roll		1.95*	3.92**	6.69***	3.00*
Haircut	16.89***		13.63***	16.19***	9.01***
Sprd	26.54***	16.41***		5.09***	5.28***
Vol	35.98***	2.15*	22.21***		10.23***
LIB-OIS	5.16***	0.17	8.64***	3.92**	

Panel B: Repo spreads as measure of funding liquidity

	Dependent variable				
	Roll	*Repo sprd*	*Sprd*	*Vol*	*LIB-OIS*
Roll		4.17**	· · ·	· · ·	· · ·
Repo sprd	12.02***		15.53***	12.00***	8.72***
Sprd	· · ·	0.04		· · ·	· · ·
Vol	· · ·	8.81***	· · ·	· · ·	
LIB-OIS	· · ·	51.52***	· · ·	· · ·	

Memo item: Do repo spreads and haircuts Granger cause each other?

	Dependent variable	
	Haircut	*Repo sprd*
Haircut		20.01***
Repo sprd	0.77	

Granger causality

Granger causality tests reveal that each of the chosen variables have predictive power over the other variables (Table 2.1). Market liquidity Granger causes bond

[16]Goyenko, Holden and Trzcinka (2009) find that, for size-decile portfolios, the correlations between the effective bid-ask spread and the Roll estimator is between 0.4 and 0.92, at a monthly frequency, with higher correlations at an annual frequency.

[17]For the George *et al.* (1991) estimator, I use a CAPM to obtain the residuals, where the market portfolio's return is an equally-weighted average of the returns on the six corporate bond indices.

spreads and return volatility at the 5% level, and Granger causes repo spreads and haircuts, as well as the LIB-OIS spread, at the 10% level. In turn, funding liquidity Granger cause the other four variables at the 1% level, and this finding is insensitive to the choice of repo spreads or haircuts as the funding liquidity measure. Similarly, bond spreads Granger cause the other variables, at the 1% level, when repo haircuts are used as the measure of funding liquidity, but not when repo spreads are used (the p-value of the χ^2 test statistic is 0.96). Return volatility also has strong predictive power over the other four variables, particularly when repo spreads are used as the proxy for funding liquidity.

The different decision outcomes that result when repo spreads are used compared to haircuts suggests that the correspondence between these funding liquidity measures is not one-to-one. This is confirmed by Granger causality tests between these two variables; while there is strong evidence that repo haircuts Granger cause repo spreads (the associated χ^2 test statistic is statistically significant at the 1% level), repo spreads do not Granger cause haircuts. The endogeneity of repo spreads (relative to repo haircuts) implies that some of the information contained in spreads is incorporated in haircuts, but not in lagged repo spreads. Dang, Gorton and Holmström (2011) argue that a haircut reflects compensation sought by the cash provider to cover potential losses from trading the collateral with more informed traders, in the event that the collateral provider defaults. To the extent that this contingent adverse selection problem is information that can not be inferred from just observing the past history of repo spreads, this may explain the findings in Table 2.1.

In addition, these variables are also strongly contemporaneously correlated,

Table 2.2: Correlation matrix

This table reports the pairwise correlations between the five chosen variables. *Roll* is the Roll (1984) estimator of the effective bid-ask spread. *Haircut* is the size of repo haircuts, and *Repo sprd* is 1-month repo-OIS spreads. *Sprd* is bond spreads to U.S. Treasuries. *Vol* is the standard deviation of daily returns over the preceding week, and *LIB-OIS* is the spread between 1-month LIBOR and 1-month OIS rate. The sample period is October 3 2005 to February 2 2009 (175 weeks), and all data are weekly.

	Roll	*Haircut*	*Sprd*	*Vol*	*Repo sprd*	*LIB-OIS*
Roll	1					
Haircut	0.32	1				
Sprd	0.33	0.62	1			
Vol	0.67	0.50	0.33	1		
Repo sprd	0.37	0.72	0.67	0.55	1	
LIB-OIS	0.28	0.43	0.38	0.38	0.88	1

with pairwise correlations of 0.3 and higher (Table 2.2). In particular, repo spreads and LIB-OIS spreads have a correlation of 0.9, while repo spreads and haircuts, return volatility and market illiquidity, and repo spreads and bond spreads, have pairwise correlations of around 0.7. All the correlations in Table 2.2 are statistically significant at the 1% level. Due to the high collinearity among the five variables, in Section 2.5 I present the (orthogonalised) impulse responses from equation (2.2), with estimates of the model's parameters provided in Table B.1, Appendix B.2.

2.5 Non state-contingent VAR

2.5.1 All bond types

Repo haircuts and repo spreads

I estimate a VAR(1) with choice of lag length based on the Schwartz and Akaike information criterion. Since the sample consists of fairly heterogeneous bonds, I allow for the possibility of heterogeneity by initially including bond-specific dummy variables, so that the model resembles a cross-sectional fixed-effects VAR.

Since the residuals' covariance matrix is not diagonal, using an ordering-sensitive procedure, such as a Cholesky decomposition, to orthogonalise impulse responses uses implicit identification assumptions that should have some theoretical foundation. Brunnermeier and Pedersen (2009)'s "loss spiral" implies that spreads and volatility should be ranked above market liquidity and funding liquidity, while their "margin spiral" implies that liquidity be ranked above spreads and volatility.

As the focus of this paper is assessing the relative importance of repo vs. ABCP funding in influencing market liquidity and pricing, I do not impose a structure on the VAR. Since my focus is not empirically testing or validating the theoretical literature, like Brunnermeier and Pedersen (2009), I use the Pesaran-Shin (1998) procedure, in which the orthogonal set of innovations do not depend on the ordering. Empirically testing the various predictions of Brunnermeier and Pedersen (2009) using the U.S. corporate bond market, which is a useful extension of this essay, would require me to take a firmer stand on identification.[18] The Brunnermeier-Pedersen model also makes some predictions about the signs of the impulse responses, so sign restrictions can augment Cholesky decompositions in the identification scheme.

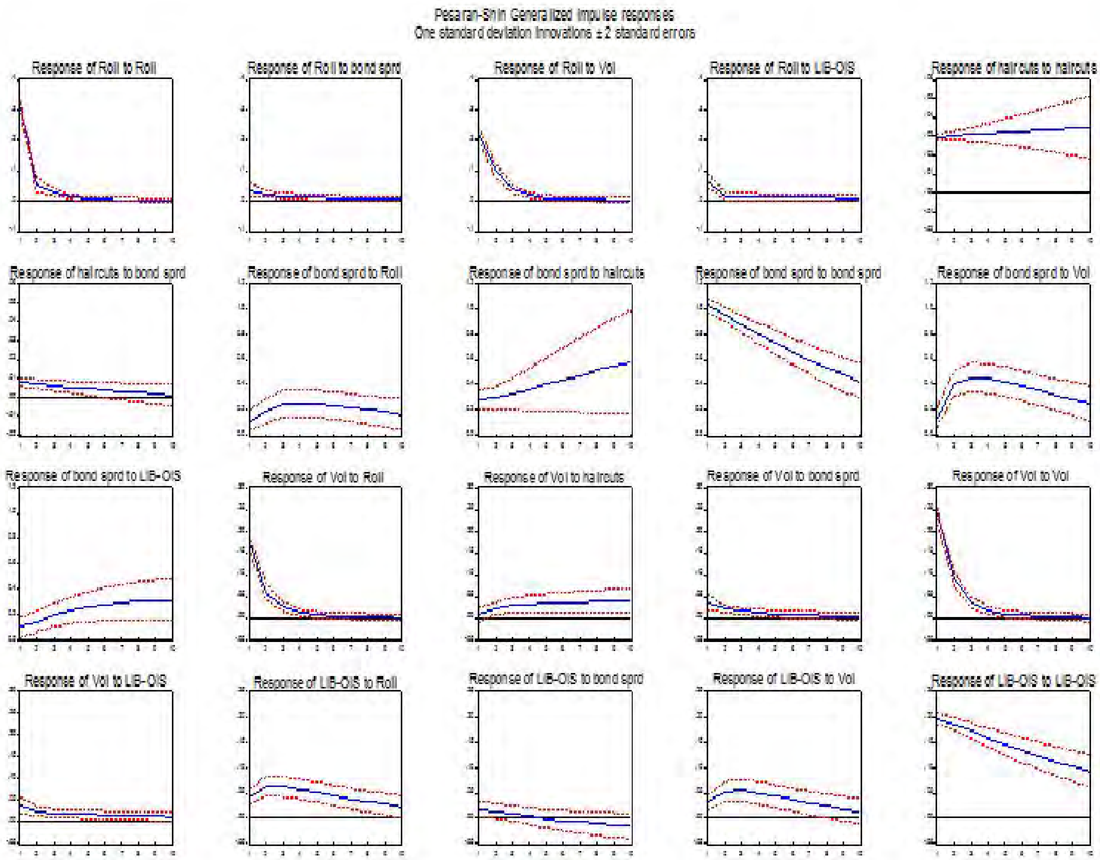
For ease of illustration, I show only those impulse responses that are statistically significant at the 5% level (at any lag up to the tenth). The two-standard-error

[18] Of note, I used a Cholesky decomposition based on two sets of ordering, one corresponding to a margin spiral, and the other to a loss spiral. I found that the magnitude and sign of the impulse responses were, broadly speaking, insensitive to which ordering was used. This provides highly preliminary evidence that the spirals are of roughly equal importance, an interesting finding given that Brunnermeier and Pedersen do not indicate which (if any) of the spirals dominate.

bands for the various impulse responses are based on the variance of the respective VAR residuals' empirical distribution. The empirical distribution is constructed from a bootstrap simulation with 10,000 repetitions. That is, using the sample of residuals, 1000 draws from this sample are made (with replacement), generating a probability distribution ("empirical distribution") based on the 1000 draws. The confidence interval ("error band") is constructed using the critical value, from a Gaussian distribution, corresponding to the 95% confidence level.

Figure 2.8 shows that market illiquidity and return volatility are more respon-

Figure 2.8: **Impulse responses: all bond types**
The figure shows Pesaran-Shin (1998) generalised impulse responses from equation (2.2), using repo haircuts. A two-standard-error band for the impulse responses is determined from the residuals' empirical distribution, using a Monte Carlo with 10,000 repetitions.



sive to *unsecured* funding illiquidity shocks, than shocks to repo haircuts; shocks to haircuts and bond bid-ask spreads have no statistically significant impact on the other variable. A shock to LIB-OIS spreads increases market illiquidity by 5 basis points (30 per cent rise). Furthermore, a market illiquidity shock raises LIB-OIS spreads by 4 basis points (11 per cent), while repo haircuts are unchanged. Return volatility is also more response to shocks to LIB-OIS spreads, than repo haircuts, though the opposite is true for bond spreads' impulse responses. Unsurprisingly, each of the variables respond the most to their own shocks.

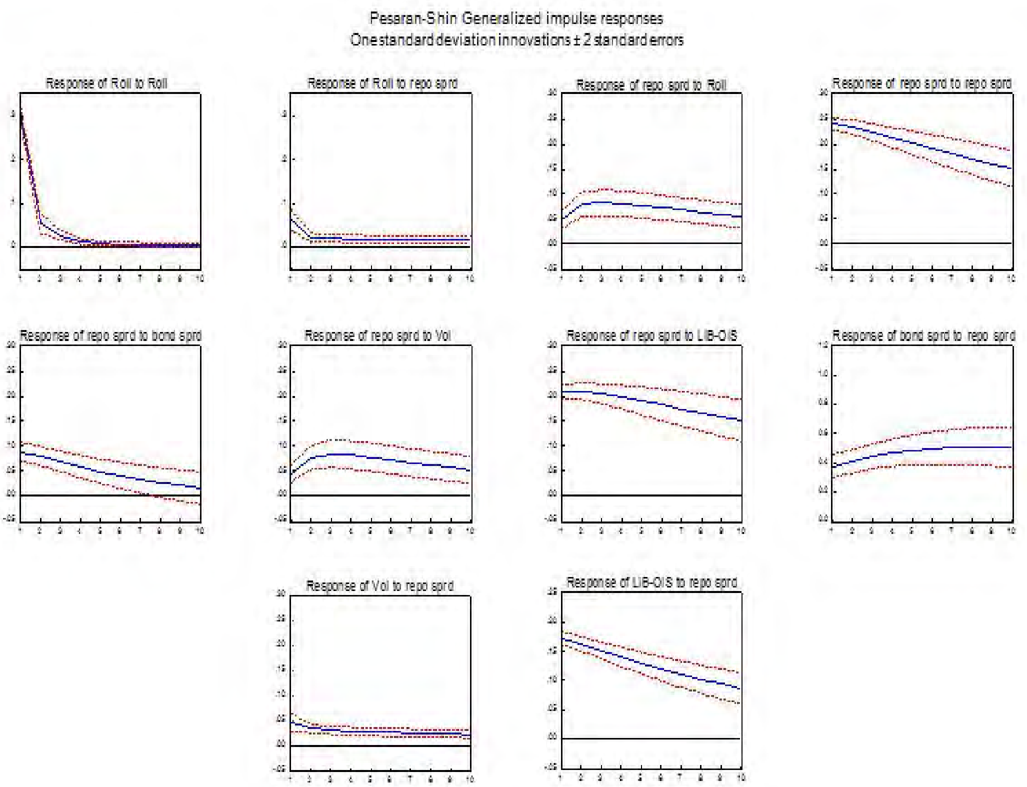
Shocks to repo haircuts impact bond spreads (and repo haircuts) for a surprisingly long period of time, with the response at the tenth lag larger than the impact at the first lag. Return volatility responds strongly to market liquidity shocks, rising by around 20 basis points (a three-quarter increase) in response to a positive, one standard deviation market illiquidity shock. Similarly, market illiquidity increases by 20 basis points (an increase of 120 per cent) in response to a volatility shock. Interestingly, the magnitude of these responses is similar to the responses of these variables to their own shocks. With the exception of the response of haircuts and bond spreads to their own shocks, virtually all the responses die out by the tenth week following a shock. For bond spreads, the half life of their impulse responses is about nine weeks.

The connection between market illiquidity and secured funding illiquidity is stronger when repo spreads are used. Market illiquidity rises by 6 basis points (one-third) in response to a positive shock to repo spreads, a similar response to shocks to unsecured funding illiquidity (Figure 2.9).[19] Furthermore, a positive market illiquidity shock raises repo spreads by around 5 basis points (an increase of 8 per cent), while LIB-OIS spreads rise by 4 basis points (8 per cent rise). The connection between return volatility and secured funding illiquidity is also stronger when repo spreads are used. Finally, the impact of shocks are generally short-lived, with most of the impulse responses decaying to zero by the tenth week following the shock.

In summary, the above evidence suggests that the magnitude of the link between market liquidity and repo funding liquidity is largest for repo spreads, with little connection between market liquidity and repo haircuts. While this provides some evidence for the "run on repo" argument of Gorton and Metrick (2010, 2011), it contradicts their arguments that haircuts were the key signal of distress in repo funding markets. The evidence also suggests that unsecured funding is at least as important as secured funding in influencing the pricing and liquidity of U.S corporate bonds. This implies that the arguments of Brunnermeier and Pedersen (2009) and Dang, Gorton and Holmström (2011), who emphasise the role of secured funding, are an incomplete description of the interaction between market liquidity and funding liquidity. Furthermore, repo spreads and LIB-OIS spreads

[19]Figure 2.9 shows only the impulse responses related to repo spreads, since the impulse responses for the other variables are virtually the same as those shown in Figure 2.8

Figure 2.9: **Impulse responses: all bond types**
The figure shows Pesaran-Shin (1998) generalised impulse responses from equation (2.2), using repo spreads.



are highly responsive to the other's shocks, suggesting a potential commonality of liquidity pressures in secured and unsecured markets. This commonality in funding liquidity is consistent with the empirical findings of Chordia, Roll and Subrahmanyam (2000), who document an interdependence in market liquidity of NYSE-listed stocks, and the theoretical predictions of Brunnermeier and Pedersen (2009).

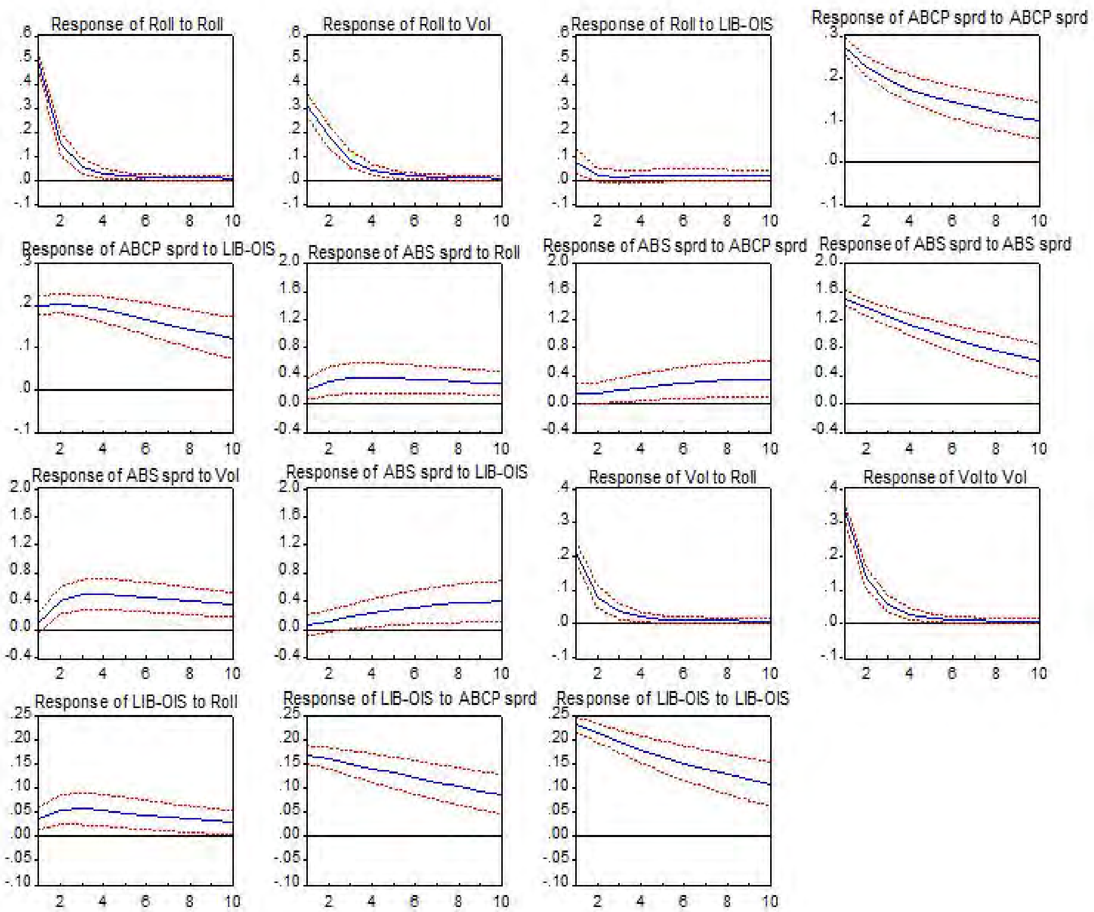
ABCP spreads

In order to assess the importance of the ABCP market, relative to the repo market, in influencing the liquidity and pricing in the ABS market, I estimate equation (2.2) using 1-month ABCP spreads (to OIS) to proxy for funding liquidity (again allowing for bond-specific heterogeneity via a fixed-effects specification). Only those impulse responses statistically significant at the 5% level are shown in Figure 2.10, with the output of the full model presented in Appendix B.3.

In contrast to Figure 2.9, Figure 2.10 shows a relatively weak relationship

Figure 2.10: **Impulse responses: all bond types**

The figure shows Pesaran-Shin (1998) generalised impulse responses from equation (2.2), using ABCP spreads.



between ABCP spreads and market illiquidity. Shock to ABCP spreads have no statistically significant impact on market illiquidity, and vice versa. ABCP spreads and LIB-OIS spreads are highly responsive to each other's shocks, with the impulse responses similar in magnitude to responses to their own shocks. The interaction between ABCP spreads and LIB-OIS spreads supports the above claim of a commonality in liquidity between secured and unsecured short-term funding markets. In terms of the other variables (i.e. bond spreads and return volatility), their impulse responses are similar to that shown in Figure 2.9.

In summary, the evidence suggests that the repo market had a greater influence on U.S. bond market liquidity and pricing than the ABCP market, which is more consistent with the arguments of Gorton and Metrick (2010, 2011), than Krishnamurthy, Nagel and Orlov (2011). However, as noted above, as market liquidity is also highly responsive to unsecured funding shocks, the argument that repos were the chief contributor to the rise in bond spreads and volatility is somewhat incomplete.

Hitherto, I have measured funding liquidity using prices (spreads and haircuts), although it can also be measured using quantities. Hence, I estimate equation (2.2) using data on the outstanding value of ABCP as a proxy for funding liquidity in the ABS market. While the impulse responses – and accompanying discussion – are shown in Appendix B.4, the key finding from this analysis is the lack of a relationship between market liquidity and ABCP funding liquidity. As explained in Appendix B.4, this likely reflects a combination of low data frequency (data are monthly) and a lack of disaggregation between different issuers and different ABCP tenor.

2.5.2 Individual bond types

While a fixed-effects VAR allows for bond-specific heterogeneity in intercepts, I now allow for bond-specific heterogeneity in the slope coefficients by estimating a VAR for each of the six corporate bond segments. The potential for heterogeneity arises from the fact that repo haircuts and spreads on some bond types (e.g. AAA-rated subprime RMBS) rose by much more than others (vanilla corporate bonds), and hence it is possible for there to be differences in the interaction between liquidity, spreads and volatility. Such heterogeneity may, in turn, reflect investor heterogeneity (e.g. differences in investor leverage and the composition of the investor base). Brunnermeier (2009) argues that funding constraints may prevent potential marginal investors from arbitraging away price deviations arising from the "loss" and "margin" spirals of Brunnermeier and Pedersen (2009). These participation constraints may differ across the six bond markets.

Participation constraints include regulatory or portfolio management restrictions (e.g. managed funds' portfolio mandates limiting investments to highly rated bonds), as well as information-based constraints (i.e. investors' incomplete and/or asymmetric information).[20]

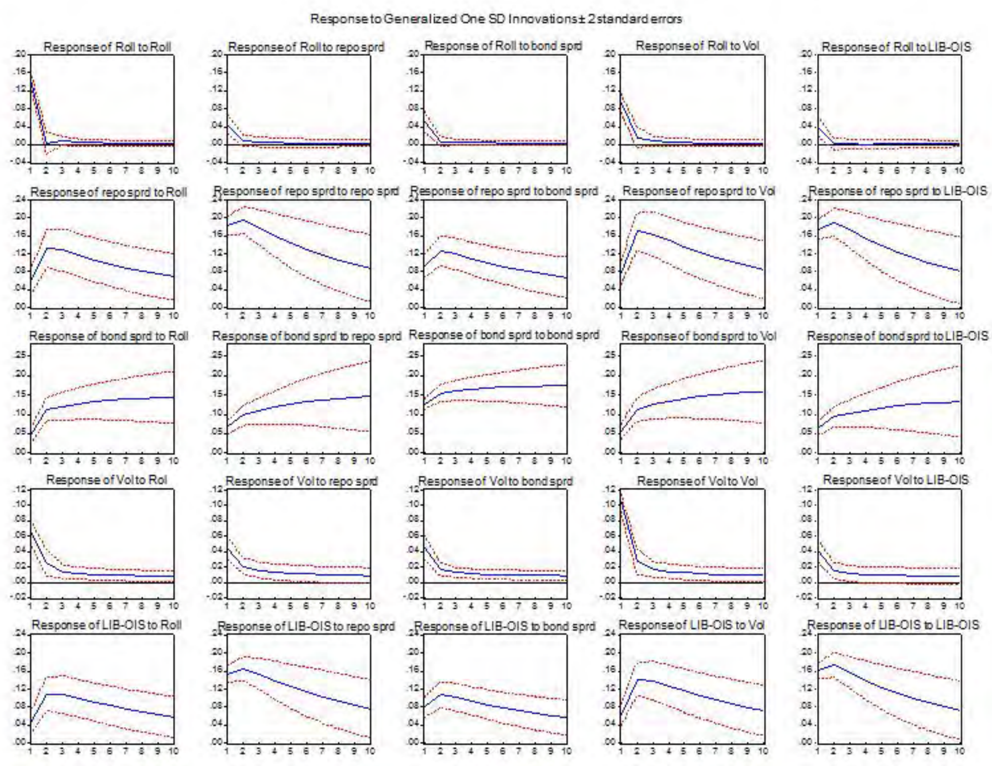
I estimate equation (2.2) for each of the six bond markets, using both repo spreads and haircuts to proxy for funding liquidity. In order to highlight the heterogeneity in the impulse responses, I only show the impulse responses for two selected AAA-rated markets (vanilla bonds and subprime RMBS) in this section,

[20] Allen and Gale (1994) and Brav, Constantinides and Geczy (2002) are two examples of the extensive literature examining the effect of participation constraints on asset pricing.

with the other AAA-rated markets (ABS and MBS) shown in Appendix B.5. For the sake of brevity, I also only show the results where repo spreads proxy for secured funding liquidity, and only those impulse responses that are statistically significant.[21]

The heterogeneity in impulse responses is shown by fact that, for vanilla

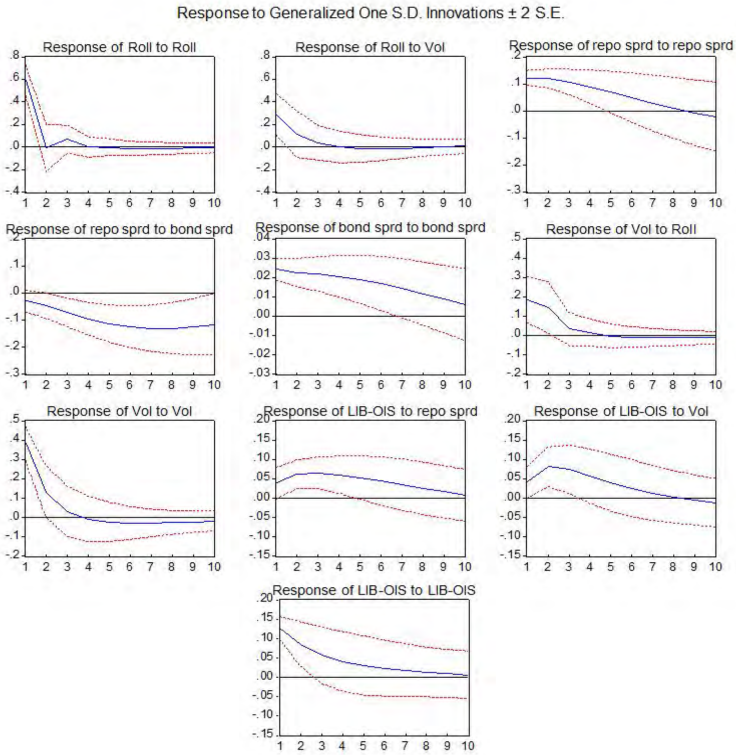
Figure 2.11: Impulse responses: AAA-rated non-asset backed bonds



bonds, all 25 impulse responses are statistically significant, whereas this is not the case for AAA-rated subprime RMBS (Figure 2.11 vs Figure 2.12). For vanilla bonds, a positive shock to repo spreads leads to a one-third rise in both market illiquidity (4 basis points) and return volatility (5 basis points), and a 7 basis point (5 per cent) rise in bond spreads. In contrast, a positive shock to spreads on repos secured by subprime RMBS leads to a 2 basis point (6 per cent) rise in market illiquidity, a 16 basis point (one-fifth) rise in bond spreads, and a 2 basis point (3

[21]The impulse responses for the various corporate bond markets and funding liquidity measures not shown in the essay are available on request.

Figure 2.12: **Impulse responses: AAA-rated subprime RMBS**



per cent) rise in return volatility.

Furthermore, there are differences in the explanatory power of the VAR equations across the six corporate bond markets: the AAA-rated CMBS has the highest explanatory power (the average $\bar{R}^2$ across all five equations is 70 per cent; minimum is 33 per cent), with the lowest explanatory power for AAA-rated subprime RMBS (average $\bar{R}^2$ is 52 per cent; minimum $\bar{R}^2$ is 13 per cent). Finally, likelihood ratio tests strongly reject the hypothesis that the VAR coefficients are the same across the six bond markets.

The above results highlight the significant degree of heterogeneity in the economic and statistical significance of the impulse responses across the individual bond markets. Moreover, while not shown here, the differences in responses also apply in markets with the same bond type (e.g. AAA-rated vs A-rated vanilla bonds), though the differences are relatively smaller.

2.6 Time- and state-dependent VARs

While the results in Section 2.5 reveal a significant relationship between market liquidity and pricing, and secured and unsecured funding liquidity, these results are averaged over time and, hence, unconditional on the prevailing economic state. However, there are sound economic reasons for believing that the relationship between the VAR variables may be state-contingent. As financial institutions are typically the marginal investors in corporate bonds, in normal times these institutions may be far away from their funding or capital constraints. But in times of adverse liquidity shocks, which are likely to occur during periods of economic and financial stress[22], they may need to improve the liquidity of their balance sheets, which means they provide less market liquidity.

In the theoretical model of Brunnermeier and Pedersen (2009), destabilising margins lead to two equilibria: a low haircut, high market liquidity equilibrium; and a high haircut, low market liquidity equilibrium. In their model, a marginal decline in speculators' capital (due to losses on their positions) has a small effect when speculators are far from their funding constraints, but a large effect when speculators are close to their constraints. When speculators are close to their funding constraints, small speculator losses create a "loss spiral" leading to a discontinuous drop in market liquidity, which is reinforced when haircuts rise (the "margin spiral"). This regime-switching behaviour generates the non-linear, discontinuous relationship between market liquidity and funding liquidity, and is the theoretical basis for my empirical analysis of regime switching.

In terms of empirical studies, Acharya, Amihud and Bharath (2011) show that corporate bond returns' sensitivity to market liquidity shocks systematically varies over time, switching between two regimes they call "normal" and "stress". Notably, these two regimes can be predicted by macroeconomic and financial market variables, with the stress regime associated with adverse macroeconomic conditions, such as recessed economic activity, and adverse financial market conditions such as negative stock market returns and heightened volatility. Furthermore, Valente (2010) documents a state-contingent relationship between stock market liquidity and funding liquidity: when funding liquidity shocks are small, market liquidity is unaffected, so that market liquidity shocks are uncorrelated with funding liquidity shocks. However, when funding liquidity shocks are sufficiently large to force agents towards their capital constraints, a positive relationship between equity market and funding liquidity arises. This result is consistent with the testable predictions of the Brunnermeier-Pedersen model.

[22] Acharya and Pedersen (2005) note that significant illiquidity episodes in the stock market between 1964 and 1999 were preceded by large macroeconomic or market-wide shocks (e.g. the 1973 oil price spike and the 1987 stock market crash).

2.6.1 Deterministic regime change

I start the state-dependent analysis by assuming a deterministic, once-and-for-all change in regime. There are two regimes: (i) a 'pre-crisis' period and (ii) a 'crisis' period. The crisis period is chosen to start from one of two dates: August 2007, or September 2008. The choice of August 2007 corresponds to the initial disruption in credit markets, which is typically dated to August 7, 2007, when French bank BNP Paribas suspended redemption of shares held in some of its MMFs (Mishkin, 2011). Following this, the interbank market 'froze up' on August 9, with a sharp rise in counterparty credit risk and a spike in the LIB-OIS spread (Brunnermeier, 2009). The choice of August 2007 also accords with the behaviour of repo spreads and haircuts, which rose sharply from August 2007 onward (Figures 2.5 and 2.6, respectively).

The alternative choice of September 2008 reflects a more turbulent phase of the financial crisis, during which the problems in the U.S. subprime residential mortgage market morphed into a virulent global financial crisis. Key events which occurred during September 2008 included the bankruptcy of Lehman Brothers on September 15, the collapse of American International Group (AIG) and the run on a large money market fund, both on September 16, and the ongoing struggle to get the TARP passed into law (Mishkin, 2011). Other notable developments during this period included the uncertainty about whether the U.S. government had the capability to manage the crisis (Mishkin, 2011).[23]

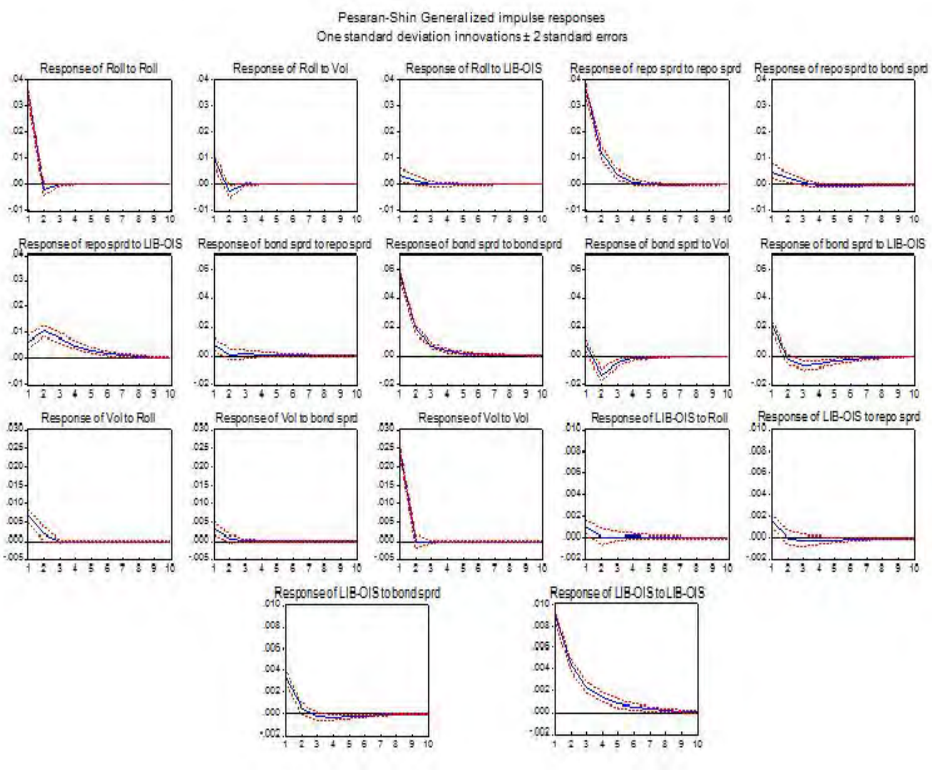
Figure 2.13 shows the Pesaran-Shin (1998) generalised impulse responses for the VAR applied to the pre-August 2007 period, while Figure 2.14 shows the impulse responses for the post-August 2007 period. Repo spreads are used to proxy for funding liquidity. The results (and accompanying discussion) for the pre-September 2008 and post-September 2008 periods are provided in Appendix B.6. Again, I present only the statistically significant impulse responses.

Prior to August 2007, there was little statistical significance in the variables' responses to other variables' shocks. A negative shock to market liquidity generated no significant response in either secured or unsecured funding liquidity, nor bond spreads. Furthermore, where there is evidence of statistical significance, the economic significance is, generally speaking, modest. A shock to repo spreads led to a less than one basis point rise in both bond and LIB-OIS spreads, while return volatility rose only 1 per cent (0.7 basis points) in response to a negative market liquidity shock.

In terms of the off-diagonal entries, the most economically significant result is

[23] Mishkin (2011) notes that the first version of the Troubled Asset Relief Program (TARP) failed on a bipartisan vote, which raised serious doubts about the government's crisis management capabilities. The bill was eventually approved by Congress on October 3, though its passage through parliament required numerous "Christmas-tree" provisions.

Figure 2.13: Impulse response functions: pre-August 2007

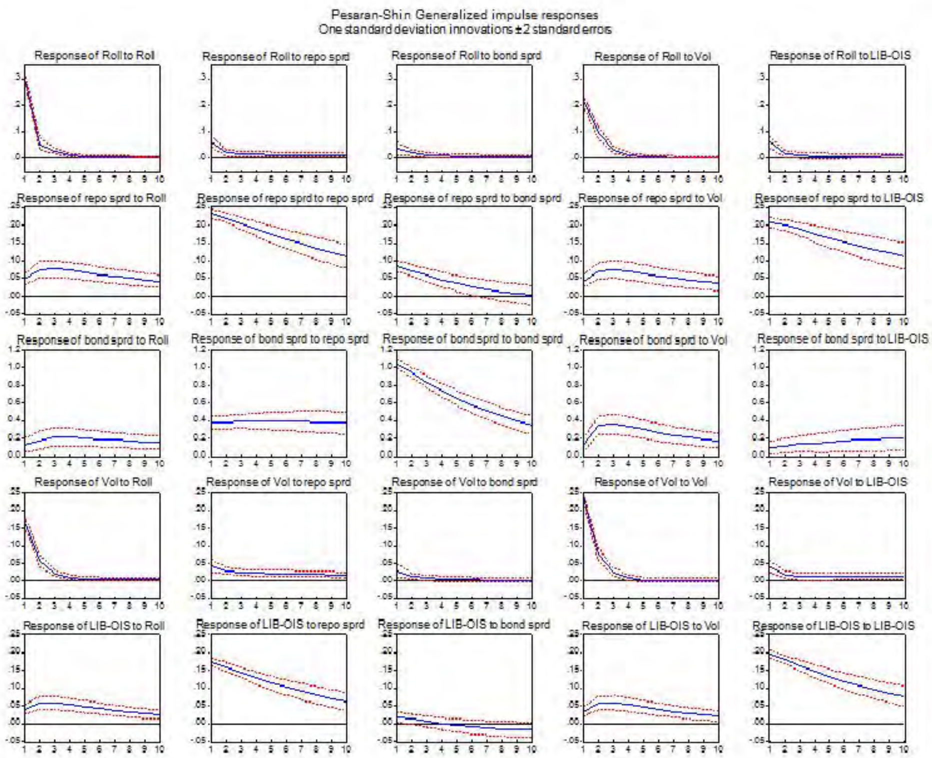


the 45 per cent rise in market illiquidity, following a volatility shock. In addition, not only are the impulse responses small in magnitude; the shocks are also relatively small.

In contrast, there is an economically and statistically significant relationship between all the variables during the financial crisis period (Figure 2.14). A positive shock to market illiquidity led to a 36 per cent and 13 per cent rise in repo spreads and LIB-OIS spreads, respectively, and a 90 per cent rise in volatility. A shock to secured funding liquidity resulted in a 50 per cent decline in market liquidity, a one-sixth and one-quarter rise in the level and volatility of bond spreads, respectively. In terms of off-diagonal entries, market illiquidity responded the most to return volatility shocks, similar to the pre-crisis period, while repo spreads and LIB-OIS spreads responded strongly to each other's shocks. Moreover, higher impulse responses are not the only differentiating feature of the crisis period; the size of the shocks also rose appreciably, compared to the pre-crisis period.

These findings are strengthened when September 2008 is used as the bifurca-

Figure 2.14: Impulse response functions: post-August 2007



tion point – the impulse responses in the crisis period are, generally speaking, even larger than those for the pre-crisis period, compared to using August 2007 as the bifurcation point. Post September 2008, a one-standard deviation funding illiquidity shock led to a 5-7 basis point (90-130 per cent) rise in bid-ask spreads, with the larger response observed for shocks to LIB-OIS spreads. A shock to market illiquidity led to a 15 per cent fall in secured funding liquidity, a 20 per cent fall in unsecured funding liquidity, and a doubling of volatility. The impulse responses of the variables to shocks to repo spreads and LIB-OIS spreads are broadly the same, highlighting the important influence of unsecured funding liquidity on the pricing and liquidity of bonds, a finding similar to that obtained above.

2.6.2 Stochastic regime change

I now conduct a more formal examination of regime change by estimating a Markov Switching VAR (MSVAR) model, with two possible regimes. A Markov process is one where the probability of being in a particular state is only dependent upon what the state was in the previous period, and transitions between differing regimes are governed by fixed probabilities. This differs from models with imposed breaks (which were used in the previous subsection) in that the timing of breaks is endogenous. Indeed, breaks are not explicitly imposed, but inferences are drawn on the basis of probabilistic estimates of the most likely state prevailing at each point in time.[24]

Incorporating regime shifts in the VAR model leads to the state-contingent version of equation (2.2):

$$\mathbf{X}_t = \alpha(s_t) + \beta(s_t)\mathbf{X}_{t-1} + \epsilon(s_t) \tag{2.6}$$

where $\epsilon(s_t) \sim NIID(0, \Sigma(s_t))$, and $\alpha(s_t)$, $\beta(s_t)$ and $\Sigma(s_t)$ are parameter shift functions describing the dependence of the parameters α, β, λ and Σ on the existing regime, s_t. s_t denotes a latent state variable, which follows a continuous time Markov-chain with two different regimes ($s_t \in \{0, 1\}$) and transition probabilities:

$$P = \begin{bmatrix} p_{00} & 1 - p_{00} \\ 1 - p_{11} & p_{11} \end{bmatrix}.$$

The choice of MSVAR model over other popular regime switching models – such as the Threshold VAR (T-VAR) and Self Exciting VAR (SE-VAR) – is somewhat arbitrary, since a proper examination and comparison of various regime switching VAR models is outside the scope of this essay. However, one advantage of the MSVAR model is that it requires neither the existence of a weakly exogenous variable (in the case of a T-VAR), nor lagged values of the VAR variables (SE-VAR), to identify regime changes. Furthermore, an MSVAR allows for a latent variable to determine the regimes, while the other models require this variable to be observable, typically a non-trivial requirement.

While equation (2.6) allows for all VAR coefficients to change with the regime, this requires estimation of 92 distinct parameters (142 parameters if coefficients on bond-specific dummy variables are also allowed to change). Hence, in the interests of parsimony, to guard against model overfitting, and to focus on the variables of interest, I analyse the case where only the slope coefficients in the VAR change, which requires estimating a (still large) total of 82 distinct parameters. The estimation results when repo spreads are used to proxy for funding liquidity are presented in Table 2.3, with the results for haircuts shown in Appendix B.7.

The MSVAR output indicates a strong presence of two regimes – a regime in which the VAR variables are, in general, uncorrelated with each other, and another regime in which the correlations between the variables are typically statistically

[24]For technical details regarding MS models, see Hamilton (1994).

Table 2.3: MSVAR results

The table shows the results from estimating equation (2.6) for all bond markets, with repo spreads the funding liquidity proxy. The MSVAR is estimated with a lag of one week, assuming two regimes, with fixed transition probabilities between regimes, and allowing only the slope coefficients and residual covariances to vary across regimes. Numbers in brackets are t-statistics. The sample period is October 3 2005 to February 2 2009 (175 weeks).

Panel A: Regime 1 ('Liquid Regime')

Dep. var.	*Roll* (-1)	*Repo sprd* (-1)	*Sprd* (-1)	*Vol* (-1)	*LIB-OIS*(-1)	Const.[a]
Roll	0.204	0.066	0.001	0.167	0.011	0.178
	[4.11]	[0.46]	[0.29]	[1.48]	[-0.31]	[1.21]
Repo sprd	-0.180	0.479	0.006	0.187	0.392	0.724
	[-0.63]	[2.13]	[0.16]	[0.43]	[1.27]	[0.8]
Sprd	-0.456	-0.234	0.631	0.184	0.091	2.774
	[-0.28]	[-0.19]	[4.87]	[0.08]	[0.05]	[2.45]
Vol	0.136	0.078	0.010	0.285	-0.130	0.206
	[2.42]	[1.27]	[1.14]	[2.65]	[-1.62]	[0.91]
LIB-OIS	-0.101	0.044	-0.008	0.008	0.838	0.387
	[-0.60]	[0.45]	[-1.59]	[0.04]	[6.88]	[1.39]

Panel B: Regime 2 ('Illiquid Regime')

Dep. var.	*Roll* (-1)	*Repo sprd* (-1)	*Sprd* (-1)	*Vol* (-1)	*LIB-OIS*(-1)	Const.[a]
Roll	-0.134	0.057	0.012	0.164	0.026	0.178
	[-2.11]	[2.20]	[0.22]	[1.69]	[2.85]	[1.21]
Repo sprd	0.167	0.595	0.019	0.227	0.479	0.724
	[2.62]	[8.21]	[4.21]	[1.86]	[1.91]	[0.8]
Sprd	0.432	0.146	0.953	0.212	0.140	2.774
	[3.31]	[1.86]	[11.60]	[2.01]	[1.95]	[2.45]
Vol	-0.043	0.045	0.307	0.808	0.091	0.206
	[-0.01]	[2.64]	[0.72]	[10.41]	[4.56]	[0.91]
LIB-OIS	0.098	0.063	0.023	0.152	0.851	0.387
	[1.33]	[4.17]	[1.99]	[2.51]	[4.65]	[1.39]

Notes: (a) Intercept term is fixed across regimes.

significant. I dub the former regime a 'liquid' regime, and the latter an 'illiquid' regime.

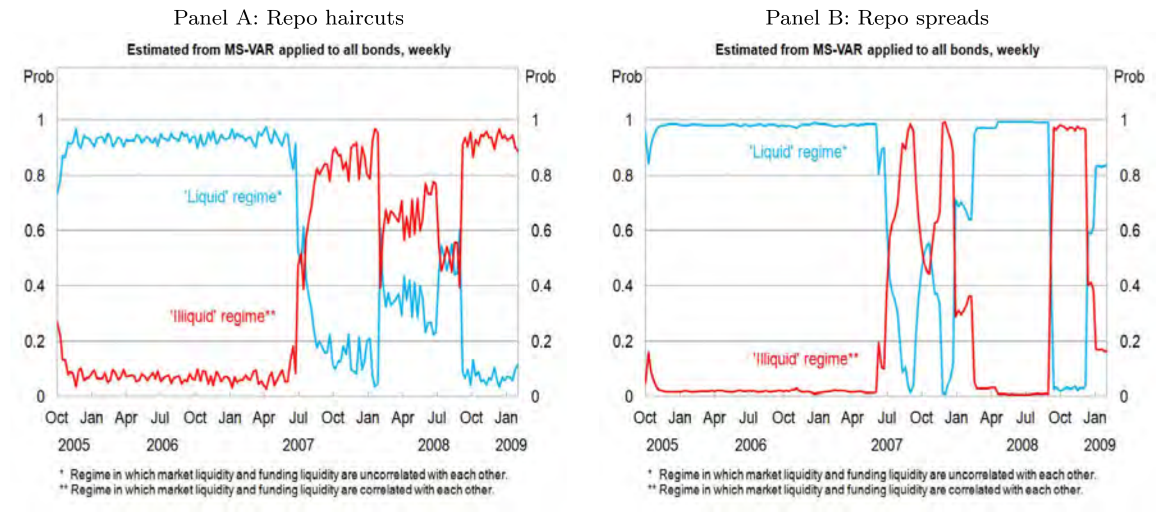
In the illiquid regime, both secured and unsecured funding liquidity, as well as return volatility, have predictive power over market liquidity, while market liquidity and bond spreads have predictive power over repo spreads (at the 5% significance level). These results contrast with the non state-contingent VAR results, where funding liquidity and market liquidity were not significantly correlated (Table B.4, Appendix B.2). In the illiquid regime, both repo spreads and LIB-OIS spreads have predictive power over all VAR variables, but in the liquid regime only have predictive power over themselves. Furthermore, on the basis of the sup-Wald test of Andrews (1993), the differences in VAR parameters across the two regimes are statistically significant.

These findings are similar to the results under a deterministic regime change (Section 2.6.1) in which market liquidity and funding liquidity are found to be correlated during periods of market stress, with little relationship between the variables during other periods. The connection between the deterministic-regime VAR and stochastic-regime VAR is highlighted by examining the unconditional probabilities of the regimes. The probability of being in the illiquid regime, p^{illiq}, is the highest during periods of market stress – such as during late 2007 and late 2008 – and this holds regardless of whether repo spreads or haircuts are used. For the MSVAR with repo haircuts, p^{illiq} rose sharply, from 0.1 to 0.9, during the second half of 2007, though it fell during early 2008 as market conditions stabilised (Panel A, Figure 2.15). After remaining broadly unchanged over most of 2008, p^{illiq} rose again during the market disruptions in September, and remained elevated.

The profile of p^{illiq} is broadly the same when repo spreads are used, though

Figure 2.15: **Probability of being in the illiquid or liquid regimes**

The graphs show the probability of being in a 'liquid' versus 'illiquid' regime, estimated from an MSVAR model. The VAR is estimated with a lag of one week, assuming two possible regimes with fixed transition probabilities. The series in Panel A (Panel B) are the probabilities obtained when repo haircuts (1-month repo spreads) are used to proxy for funding liquidity. The 'illiquid' ('liquid') regime is defined as the regime in which there is a statistically significant (insignificant) relationship between market liquidity and funding liquidity.



there is a smaller rise in July 2007, with sustained rises throughout 2008 (Panel

B). Notably, p^{illiq} falls sharply in January 2009, when repo spreads are used, in contrast to the behaviour when haircuts are used. This difference mirrors the profiles of repo spreads and haircuts; by January 2009, repo spreads were at levels existing between August 2007 and early September 2008, whereas haircuts remain at elevated levels (Figure 2.5 vs. Figure 2.6). This association between p^{illiq} and financial conditions provide preliminary evidence on the economic and financial foundations of the liquid and illiquid regimes. A detailed examination of the economic foundations for these regimes, including the extent to which the regimes can be predicted from economic and financial indicators, is left for future research.

2.7 Conclusion

This essay has found that the link between short-term secured and unsecured funding liquidity, and the volatility and pricing of U.S corporate bonds, is generally significant (though modest) when repo spreads proxy for funding liquidity, and generally insignificant when repo haircuts and ABCP spreads are used. These findings partly support Gorton and Metrick (2010, 2011), who argue that repo runs were the key factor in the collapse of the shadow banking system, and do not support Krishnamurthy, Nagel and Orlov (2011), who attribute the collapse largely to ABCP runs. Moreover, the link between market liquidity and unsecured funding liquidity is at least as important as the link between market liquidity and secured funding liquidity. This suggests that the emphasis placed on secured funding by Brunnermeier and Pedersen (2009) and Dang, Gorton and Holmström (2011) do not fully describe the interaction between market liquidity and funding liquidity. Furthermore, the magnitude of the links between the variables depends on the type of corporate bond market, with the link strongest for AAA-rated ABS and vanilla bonds, and weakest for AAA-rated subprime RMBS.

I also provided evidence that the relationships between market liquidity, funding liquidity, volatility and spreads are state-contingent, for both deterministic and stochastic regime changes. In states where shocks to the system's variables are sufficiently large (such as during periods of market stress), the responses of the other variables are much more significant, both statistically and economically, than states where the shocks are smaller in magnitude. These findings support the theoretical literature on the existence of (non-linear) regime-switching behaviour.

There are several extensions to this research. The first is to examine the importance of investor heterogeneity in influencing the bond-specific relationship between the VAR variables by identifying the types of investors, and their associated capital constraints, within each bond market. Second, it is important to examine whether the observed heterogeneity in the behaviour between the VAR variables reflects the differential impact of various policy initiatives introduced during the financial crisis period. For example, from March 2008, the Federal Reserve initiated a series of programs to offset the reduction in private sector funding of the shadow banking sector. To the extent that the lender-of-last-resort facilities had a greater impact on the ABS and subprime RMBS markets – markets in which repo haircuts and spreads rose the most – than non-asset backed bonds, this may explain the lack of statistical significance between the variables in these markets.

Third, a more rigorous examination of regime-switching behaviour can be undertaken, comparing the performance of different regime-switching models. In this vein, an exploration of the economic foundations of these regimes is worthwhile, assessing the extent to which the regimes identified in this chapter can be predicted by macroeconomic and financial variables.

Fourth, this chapter focused on short-term funding markets (reflecting these markets' greater susceptibility to runs), so a natural extension is to examine longer-term secured and unsecured funding markets. Fifth, it is worth considering whether the results are robust to measures that capture other dimensions of liquidity (like price impact or market depth), which can provide information about market liquidity not captured in the bid-ask spread.

Sixth, the statistically and economically significant VAR relations implies a degree of predictability of returns, volatility and pricing, which is useful for investors and policymakers. The policy dimension reflects the fact that, in order to minimise the economic and financial effects of a 'credit crunch', policymakers often need to lower not only risk-free rates, but also spreads between risky bonds and risk-free assets.

Finally, a formal test of the predictions of Brunnermeier and Pedersen (2009) should be undertaken, using the corporate bond data in this essay. This exercise would involve constructing measures that capture speculators' shadow cost of capital, which is the driving force behind the model's "margin" and "loss" spirals. Furthermore, the impulse response analysis could be extended, by considering various ways to identify the shocks in the VAR. In particular, the "loss" and "margin" spirals imply different orderings of the variables, and so a Cholesky decomposition based on these differing orderings would allow one to examine the relative importance of these spirals. Furthermore, the Brunnermeier-Pedersen model makes predictions about the signs of the impulse responses, so sign restrictions can augment Cholesky decompositions in the identification scheme. Undertaking this analysis would allow one to analyse the structural underpinning of the reduced-form correlations presented in my essay.

Chapter 3

The impact of policy initiatives on credit spreads during the 2007-09 financial crisis

3.1 Introduction

This chapter assesses the impact of the various “unconventional” policies introduced by the U.S. Federal Reserve, and key fiscal policies announced by the U.S. Federal Government, during the 2007-09 financial crisis period, on market spreads. The crisis moved U.S. Federal Reserve policy from a well-established routine of interest-rate targeting to a multi-pronged triage that wedded traditional policy tools with new initiatives aimed at reviving an ailing financial system. The triage was controversial on two grounds: firstly, these initiatives required discretion over targeting particular markets and firms; and secondly, a fear that the liquidity provided may stoke higher inflation, undermining the central bank’s macroeconomic objectives. These changes in the operation of central bank policy have been especially jarring following a quarter-century of generally quiescent macroeconomic activity and policy, a period often characterized as the “Great Moderation”. The timing, size, appropriateness and effectiveness of the measures taken by the Federal Reserve during the 2007-09 crisis are the subject of much discussion, analysis, and controversy.

The number of studies examining the effectiveness of various policies has grown rapidly, with some studies having examined the effectiveness of the Federal Reserves Term Auction Facility (TAF), with conflicting findings (Taylor and Williams (2009) vs. McAndrews, Sarkar and Wang (2008)). Other papers have assessed the effectiveness of the U.S. dollar swap lines between the Federal Reserve and other central banks in alleviating dislocations in foreign currency markets (Baba and

Packer (2009) and McAndrews (2009)). In contrast to these single policy-centric studies, Aït-Sahalia, Andritzky, Jobst, Nowak, and Tamirisa (2010) found that central bank liquidity support and liability guarantees, along with bank recapitalisations by the public sector, led to a reduction in interbank risk premia.

Given the large number of "unconventional" policy initiatives introduced by the Federal Reserve to combat the crisis – between December 2007 and March 2009 the Federal Reserve initiated 16 programs – analysing the efficacy of these programs requires an organising framework. In this essay, I use the framework developed in Kroszner and Melick (2010), who classify the policy initiatives along three dimensions: (i) an expansion of the type of counterparties receiving support; (ii) a broadening of the collateral eligible for support; and (iii) a lengthening of the maturity of the support. This framework reveals that the various "unconventional" policies are effectively supplements of "conventional" central bank policy, for reasons outlined below.

Using this framework, this essay makes six important contributions to the literature. Firstly, I find that all three types of policies were effective in reducing market spreads, with the most effective being policies that broadened the range of collateral eligible for secured funding from the Federal Reserve. Secondly, I find that these policies were more effective in reducing unsecured and secured funding costs than reducing bond spreads. Thirdly, these policies were more effective in reducing the level of spreads than their conditional variances. Fourthly, I find that "implementation effects" and "flow-of-funds" effects – respectively, the effect on spreads at the time policies were implemented, and the effect on spreads from higher amounts loaned from these programs – were an order of magnitude larger than "announcement effects" – the effect on spreads at the time these policies were announced. Fifth, fiscal policy announcements did not have a stabilising influence on market spreads, and in some instances had significant destabilising effects, consistent with Taylor (2011).

Finally, I find that the stance of "conventional" monetary policy had a destabilising influence on spreads, with contractions in monetary policy associated with increases in market spreads. Following Rudebusch (2009) and the macroeconomics literature, I measure the monetary policy stance as the deviation of the actual Federal Funds interest rate from the interest rate implied by a Taylor rule. As a Taylor rule relates the level of the Federal Funds rate to the objectives, as stated in Section 2A of the *Federal Reserve Act*, of price stability and maximum employment, measuring the policy stance as the difference between these two interest rates is more appropriate than using the level of the Federal Funds rate.

While the Federal Reserve's various "unconventional" policies did reduce financial market strains, these policies were not sufficient to ensure that the Federal Reserve met its macroeconomic objectives, as enshrined in the Taylor rule. This, in turn, exacerbated market strains, and reduced the efficacy of the the unconventional policies. These findings are akin to Friedman and Schwartz (1963)'s argument that the Federal Reserve's contractionary policy stance during the 1930s destabilised financial markets and exacerbated the Great Depression, a view subsequently upheld by the U.S. Federal Reserve (Bernanke, 2002).

The rest of the essay is organised as follows. Section 3.2 outlines the key conventional and unconventional Federal Reserve policy responses to the differing crisis events, and Section 3.3 reviews the relevant literature. Section 3.4 outlines the data used and the estimation of Taylor rules, and Section 3.5 discusses the empirical methodology employed. Section 3.6 discusses the estimated announcement effects of the various policy initiatives examined in this chapter. Section 3.7 contains the results from the regime-switching VAR, while Section 3.8 discusses the implementation and flow-of-funds effects of the various Federal Reserve programs on market spreads. Section 3.9 concludes with a discussion of avenues for future research.

3.2 The U.S. Federal Reserve's policy initiatives

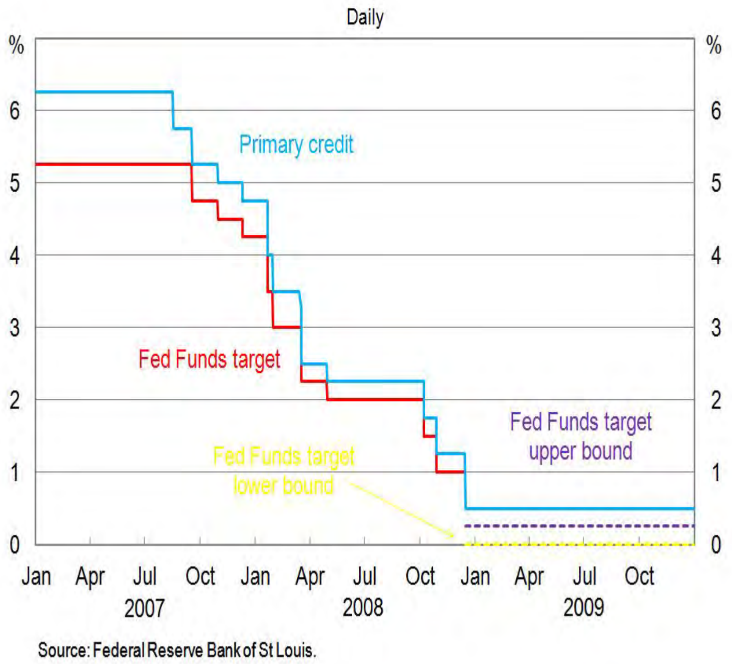
3.2.1 "Conventional" policy responses

One aspect of the Federal Reserve's response to the crisis involved its traditional tools of changing the target Federal Funds rate and primary credit rate.[1] Between the reforms to the discount window program in 2003 and the start of the financial crisis in mid 2007, the term of primary credit loans was always overnight, and its interest rate was set 100 basis points above the target Federal Funds rate (Figure 3.1). However, as the crisis unfolded, lending conditions became less restrictive: on August 17, 2007, the maximum term was lengthened to 30 days (and the spread lowered to 50 basis points) and then, on March 16, 2008, the maximum term was extended to 90 days (and the spread lowered to 25 basis points).

Kroszner and Melick (2010) note that the Federal Open Market Committee (FOMC) followed "standard" procedure – reducing the Federal Funds rate and primary credit rate by 25 basis points at each meeting – in easing monetary policy from September 2007 through to the end of the year. As the market turmoil intensified around year-end, the FOMC reduced rates by a total of 125 basis points. Rates were cut an additional 75 basis points at the March 2008 meeting (along with the fall in the spread between the primary credit rate and the Federal Funds rate). October 2008 saw a further 100 basis point cut in interest rates, as well

[1] The primary credit rate is the interest rate charged by the Federal Reserve for secured, short-term loans to depository institutions. The lending facility offered by the Federal Reserve is termed the 'discount window'.

Figure 3.1: **Target Federal Funds Rate and Primary Credit Rate**



as an unprecedented internationally co-ordinated rate cut of 50 basis points, and another 100 basis point cut in December when the FOMC moved to targeting the Federal Funds rate within a range of 0 to 25 basis points (Figure 3.1).

The third traditional tool, reserve requirements, was not used by the Federal Reserve during the early stages of the crisis. However, on October 6, 2008, the Federal Reserve announced it would begin paying interest on depository institutions' required and excess reserve balances. The interest on reserves (IOR) program has allowed the Federal Reserve to maintain the effective Federal Funds rate within its target range, although some economists have considered it analogous to an increase in reserve requirements, and thus contractionary (Beckworth (2008); Woodward and Hall (2009)). These economists argue that the IOR program negated some of the stimulus provided by the use of conventional and "unconventional" monetary policy.

3.2.2 "Unconventional" policy responses

By December 2007 it was evident that the Federal Reserve's traditional policy tools were not achieving the desired economic and financial market goals. Kroszner and Melick (2010) note that, between December 2007 and March 2009, the Federal Reserve introduced 16 "unconventional" programs to combat the crisis. Since even describing, much less assessing, these initiatives can easily get bogged down in a long list of confusing and easily forgotten acronyms, Kroszner and Melick (2010) organise the various policies into one (or more) of three categories: (i) policies that expand the type of counterparties receiving support; (ii) policies that broaden the collateral required to access the support; and (iii) policies that lengthen the maturity of the support. Kroszner and Melick (2010) sort chronologically the various Federal Reserve policies into these three categories, and their table is reproduced below (Table 3.1).

I adopt Kroszner and Melick (2010)'s categorical scheme to analyse the impact of the "unconventional" policies on market pricing. The authors note that their choice of organising framework reflects the Federal Reserve's modification to their lender-of-last-resort (LOLR) facilities to reflect changes in the financial system over the past few decades. In order for the Federal Reserve to be able to use their LOLR facilities effectively, three changes to pre-existing policies needed to be adopted. First, dealing with new counterparties was critical to extending central bank assistance to important markets and firms in the intermediation chain, thereby acknowledging the interconnectedness of institutions and markets. Second, accepting a wider range of collateral reflected the reality of a financial system that evolved from bank intermediation towards greater reliance upon securitisation and market-based intermediation. Finally, extending the maturity of the support was designed to instill confidence in market participants that institutions and counterparties will have a source of funding for longer periods, reducing the likelihood that negative liquidity shocks force fire-sales and compromise solvency.[2]

In this sense, the various unconventional policies can be seen as extensions of the Federal Reserve's traditional toolkit to deal with the architecture of the modern financial system. The complementary nature of the nontraditional and traditional tools means we can gauge the effectiveness of "unconventional" policies by the extent to which it allowed the Federal Reserve to meet its dual mandate of price stability and full employment. This provides one key justification for why I include the stance of conventional monetary policy in my analysis.

[2]Bernanke (2009) presents an alternative framework that classifies each non-traditional initiative into three descriptive categories: lending to financial institutions; providing liquidity to key credit markets; and purchasing longer-term securities.

Table 3.1: The U.S. Federal Reserve's "unconventional" policy initiatives

As at November 18, 2009

Description						Objectives		
Initiative	**Announced**	**First used**	**Authorised until**	**Max. size**[a]	**Current size**[a]	**Lengthen maturity**	**Broaden collateral**	**Expand c'party**
Term Auction Facility	Dec 12, 2007	Dec 17, 2007	Ongoing	493	109	x		
Central bank swap lines	Dec 12, 2007	Dec 20, 2007	Jan 2, 2010	583	28			x
Term Securities Lending Facility	Mar 11, 2008	Mar 27, 2008	Jan 2, 2010[b]	234	0	x		
Maiden Lane (Bear Stearns)	Mar 14, 2008	June 26, 2008	Ongoing	30	26		x	x
Primary Dealer Credit Facility[c]	Mar 16, 2008	Mar 19, 2008[d]	Jan 2, 2010	148	0			x
Term Securities Lending Facility Options	Jul 30, 2008	Aug 27, 2008	Suspended[e]	50	0	x		
American International Group support								
FRBNY lending to AIG	Sep 16, 2008	Sep 17, 2008[d]	Ongoing	90	45		x	x
Maiden Lane II	Oct 11, 2008	Dec 12, 2008	Ongoing	20	16		x	x
Maiden Lane III	Oct 11, 2008	Nov 25, 2008	Ongoing	28	23		x	x
Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility	Sep 19, 2008	Sep 24, 2008[d]	Jan 2, 2010	152	0		x	
Commercial Paper Funding Facility	Oct 7, 2008	Oct 27, 2008	Jan 2, 2010	351	15		x	x
Money Market Investor Funding Facility	Oct 21, 2008	Unused	Oct 30, 2009	Unused	0			x
Citigroup support	Nov 23, 2008	Unused	Unused	Unused	0			x
Term Asset-Backed Securities Loan Facility	Nov 25, 2008	Mar 25, 2009	Mar 31, 2010 Jun 30, 2010[f]	44	44	x	x	x
Purchase of MBS guaranteed by GSEs	Nov 25, 2008	May 5, 2009	Mar 31, 2010[g]	847	847	x		x
Purchases of direct GSE debt	Nov 25, 2008	Dec 5, 2008	Mar 31, 2009[g]	153	153	x		x
Bank of America support	Jan 16, 2009	Unused	Unused	Unused	0			x
Purchases of longer-term U.S. Treasuries	Mar 18, 2009	Mar 25, 2009	Oct 30, 2009[g]	311	311	x		

Source: Kroszner and Melick (2010).

Notes:

(a) In U.S.$ billions.

(b) Auctions against Schedule 1 collateral suspended on January 7, 2009.

(c) Includes transitional support for Goldman Sachs, Morgan Stanly, and Merrill Lynch announced on September 21, 2008.

(d) Based on first appearance in the Federal Reserve Board's H.4.1 statistical release.

(e) Suspended on June 25, 2009.

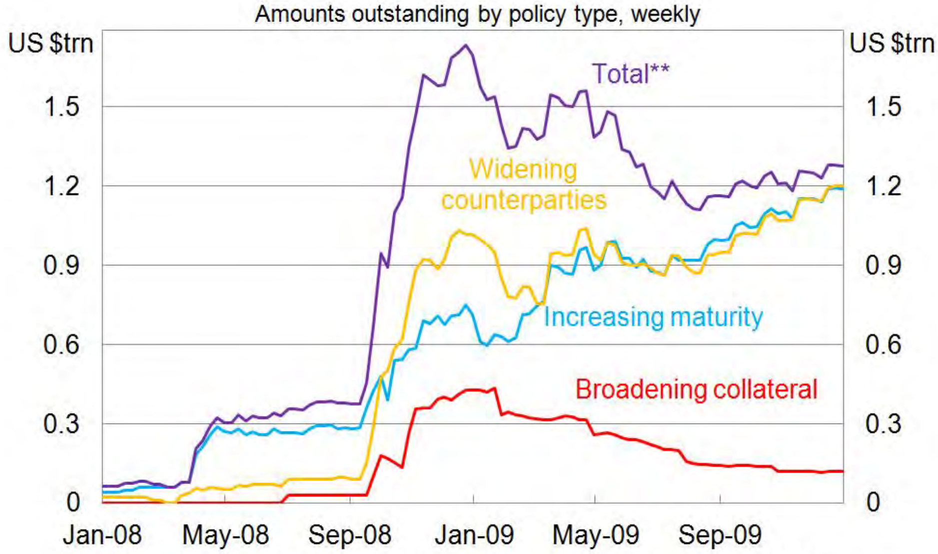
(f) Loans against newly issued ABS and legacy CMBS authorized through March 31, 2010, loans against newly issued CMBS through June 30, 2010.

(g) Based on FOMC statements.

In terms of the size of the "unconventional" monetary policies, the largest were those that widened the counterparties to, and increased the maturity of, Federal Reserve support. The stock of securities acquired by the Federal Reserve under each of these programs was US$1.2 trillion as at the end of 2009 (Figure 3.2). In contrast, the size of programs that broadened the collateral eligible for Federal Reserve support was only US$0.1 trillion as at end-December 2009. The stock of securities acquired under all three types of programs was US$1.3 trillion as at the end of 2009.[3]

Collectively, the size of the Federal Reserve's "unconventional" programs rose

Figure 3.2: **U.S. Federal Reserve "unconventional" programs***



* 'Unconventional' programs and categorisation schemes from Kroszner and Melick (2010).
** Programs appearing under multiple categories in Kroszner and Melick are only counted once.
Sources: Author's calculations; Federal Reserve Bank of New York; Kroszner and Melick (2010).

the most in September 2008, reflecting the collapse of Lehman Brothers and AIG, the failure of large money market funds, and the systemic nature of market runs at this time. The stock of securities held reached a high of US$1.73 trillion as at the end of 2008, before declining throughout 2009, due to declines in the size of programs that broadened the range of eligible collateral, as market conditions stabilised somewhat (Figure 3.2).

I also include policy initiatives that did not directly impact the Federal Reserve's balance sheet, such as the Troubled Asset Relief Program (TARP), which was created through the *Emergency Economic Stabilization Act of 2008*. While

[3]The sum of the stock of securities held under the individual program categories typically exceeds the stock of securities held under all three program categories since the various Federal Reserve policy initiatives were typically classified under more than category (see Table 3.1).

these policies are more fiscal, than monetary, in nature, omitting these policies may bias the estimated impact of the various Federal Reserve policies on market pricing. I consider four policies, grouping them under the title "Fiscal policies":

1. TARP;
2. the Temporary Liquidity Guarantee Program (TLGP), under which the Federal Deposit Insurance Corporation (FDIC) guaranteed the senior debt obligations of FDIC-insured depositories and their holding companies;
3. the Capital Purchase Program (CPP), under which the U.S. Department of the Treasury used TARP funds to purchase preferred stock and warrants of financial institutions; and
4. the use of the Exchange Stabilization Fund by the U.S. Treasury to provide a temporary guarantee of \$1 per share for money-market fund accounts.

3.3 Related literature

The theoretical literature on central banks' LOLR facilities is well-established, dating back to Thornton (1802) and Bagehot (1873), so only a summary of the literature's key elements is provided here. As Freixas, Giannini, Hoggarth and Soussa (1999) note, the key rationale for LOLR facilities is preventing the failure of illiquid-but-solvent institutions, as failure (or the threat of failure) has negative externalities on the broader financial system and the macroeconomy. The failure of a large institution, or a number of smaller ones, could result in system-wide financial instability, potentially threatening the ability of the financial system to perform its primary functions, such as the provision of the payments system, the efficient pricing of risk, and the allocation of resources. For a discussion of the theoretical literature up the late 1990s, see Freixas et al. (1999); recent additions to the literature include Caballero and Krishnamurthy (2008) and Holmström and Tirole (2011).

The empirical literature on LOLR facilities is also well-established, with the financial crisis of 2007-09 having resulted in numerous studies examining the efficacy of policy initiatives. However, there is little consensus on the impact of the various policies. To a large extent, the different findings across the studies reflect: (i) differences in the specification of the dependent variable (levels or first differences); (ii) whether the entire amount of a credit spread should be used or just the liquidity component (the latter generating questions about the methods used to extract this component); (iii) the size of the time window around an event; and (iv) differences in ways of extracting a policy's "announcement effect". These last two points are perhaps the most important.

Limiting the size of the window can prevent a bias in the estimated announcement effects, when other events are erroneously included with a given event. As Frankel (2010) notes, the event study literature has long established that the event window should be less than one day. However, a longer event window allows for any pre- or post-event "drift", where the former reflects the possibility of information leakage, and/or insider trading, prior to the event, and the latter allows for any market under- or over-reaction at the time of the event. While I follow the literature in using public announcement dates to identify policy events, I focus on the 3-day interval around an event to allow for any pre- and post-event drift.

It is worth noting that my econometric estimations also used one 1-day event window, and two 2-day event windows. The 1-day window focused solely on the announcement day; the two 2-day windows used, respectively, the announcement day and the prior day, and the announcement day and the proceeding day. I found that the economic and statistical significance of the estimated announcement effects, across the various conditional mean and conditional variance models, were lower for these alternative windows. These results imply that the alternative time intervals omit the behaviour of market spreads both preceding and proceeding the various policy announcements, and suggest that pre- and post-event drift were important aspects of the overall 'announcement effect'. The results for the alternative event windows are available on request.

To estimate the announcement effect, I use a larger set of conditioning variables than the related literature. The majority of the related literature focus on one market spread (typically, the LIBOR-OIS spread), and use lagged values of this variable to estimate the announcement effect of a particular policy. In contrast, as outlined in Section 3.5, I use three spreads and a larger set of conditioning variables to overcome the possibility of omitted variable bias in the estimates of the announcement effect.

Examining the effects of the Federal Reserve's Term Auction Facility (TAF)[4], Taylor (2011) finds no evidence that the TAF lowered the LIBOR-OIS spread, with only weak evidence that the TAF reduced other short-term debt spreads. In fact, in some instances, the TAF *increased* spreads. In contrast, McAndrews, Sarkar and Wang (2008) and Wu (2009) document that the TAF did ease market strains. Wu (2009) specifies a step function that equals 0 prior to the TAF being announced, and 1 thereafter, whereas Taylor (2011)'s step function equals 1 only at the time the TAF was announced. Wu's specification assumes the TAF has a permanent impact on the LIBOR-OIS spread and allows for post-event drift in

[4]In order to remove the stigma associated with discount window borrowing, the TAF was introduced in December 2007 to allow depository institutions to borrow from the Federal Reserve without needing to disclose this to the market. The TAF was designed to mimic the tenders conducted by the European Central Bank.

spreads. However, as Wu does not control for post-TAF announcements, the estimated coefficient on the TAF event is biased. While the smaller event window (1 day) used by Taylor (2011) reduces this bias, it does not allow for any examination of pre- or post-event drift.

Examining unconventional policy initiatives announced by the American, British, EU, and Japanese authorities, Aït-Sahalia, Andritzky, Jobst, Nowak, and Tamirisa (2010) find that announcements of domestic and foreign currency liquidity support were mostly associated with reductions in interbank lending spreads, while fiscal policy announcements had negligible effects. The authors also find that announcements of ad hoc bank bailouts had by far the largest impact, but not in a positive way; bailouts *aggravated* distress in interbank markets, with the negative response spilling over geographic borders. In contrast, systematic financial restructuring measures were more likely to be associated with a reduction in interbank risk premia. Furthermore, liability guarantee announcements had mixed effects, reducing interbank spreads during the subprime crisis, but widening spreads after the crisis deepened. Announcements of asset purchases (e.g. the TARP) were ineffective throughout the crisis, due to problems faced in implementing these measures.

In terms of other policies introduced during the crisis, Fleming, Hrung and Keane (2009) find that the Term Securities Lending Facility (TSLF)[5] offset some of the spike in short-term funding spreads at the time, partly associated with the failure of Bear Stearns. Adrian, Burke and McAndrews (2009) find that the Primary Dealer Credit Facility (PDCF)[6], introduced shortly after the TSLF, lowered credit default swap premia on dealers' and banks' senior bonds.

My essay's contribution to the literature is to include other Federal Reserve policy initiatives during the crisis using Kroszner and Melick (2010)'s organising framework (see Table 3.1), as well as an assessment of the impact of various fiscal policy initiatives. Focusing on the effect of a broad range of monetary and fiscal policy initiatives, aggregated categorically, rather than one particular policy, has three advantages. Firstly, it facilitates a comparison of the effectiveness of the various policy categories; secondly, it allows for a comparison of different fiscal and monetary policies; and thirdly, it minimises the potential for 'omitted policy bias' in the models' coefficients, which can arise in studies of single events, when

[5]The TSLF, introduced on March 11, 2008, allowed primary dealers to borrow Treasury securities from the Federal Reserve, for 28 days, secured by a range of private securities. The TSLF was designed to limit the runs in the repo markets for private collateral, by allowing dealers to pledge Treasury securities as collateral in repos, making it easier for them to continue obtaining cash through repos.

[6]The PDCF effectively gave primary dealers discount window access, allowing them to borrow from the Federal Reserve at the primary credit rate. The fact that primary dealers could obtain funding at the same terms as depository institutions generated a large amount of controversy among market participants and in the media.

other events are erroneously included with the given event.

This last point is particularly pertinent when undertaking research on the corporate bond market: in contrast to the equity market, corporate bond market price data are typically available at a daily frequency, while the various policies were typically announced close together, or in some instances, in conjunction.[7]

3.4 Data

3.4.1 Financial market data

Data on the pricing of U.S. corporate bonds are from Thomson Reuters Datastream (and constructed by Bank of America Merrill Lynch). The data are available for six types of corporate bonds: (i) AAA- and AA-rated "vanilla" (i.e. non-asset-backed) bonds; (ii) A- and BBB-rated vanilla bonds; (iii) AAA- and AA-rated asset backed securities, backed by automotive loans; (iv) AAA- and AA-rated asset backed securities, backed by credit cards; (v) AAA-rated mortgage backed securities (MBS); and (vi) A-rated MBS.

Figure 3.3 shows the evolution of the spreads on these six bond types between January 2006 and December 2009. Spreads on all bonds spiked noticeably in September 2008, following the failure of Lehman Brothers and AIG, and runs on money market mutual funds. Other notable events during this period included the uncertainty about whether the U.S. government had the capability to manage the crisis (Mishkin, 2011).[8] Spreads remained elevated until March 2009, and then reversed much of their earlier rise as financial markets stabilised during 2009.

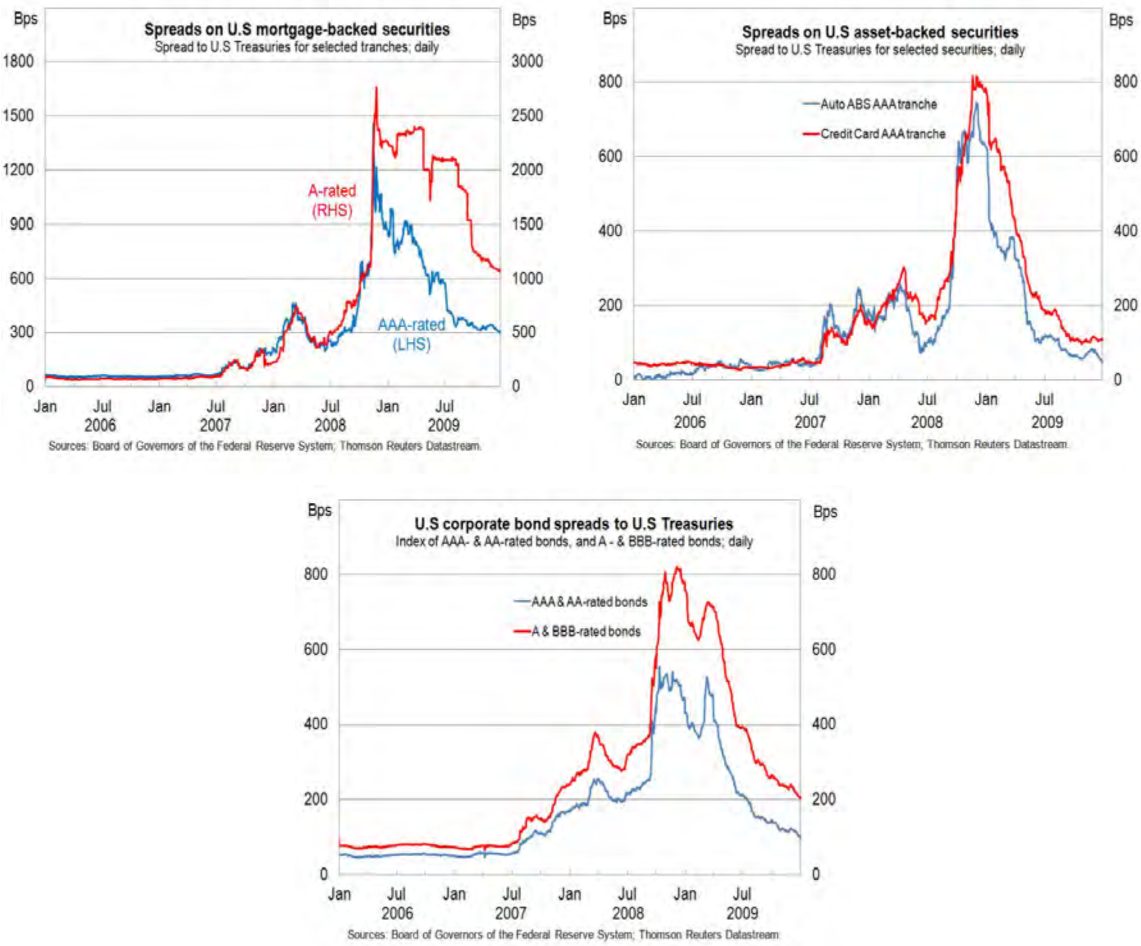
In this essay, I consider one form of secured funding, sale and repurchase agreements ("repos"), and one form of unsecured funding, U.S. interbank loans. I use 1-month repo-OIS spreads to measure the cost of secured funding, and the spread between the 1-month London Interbank Offer Rate (LIBOR) and the 1-month OIS rate to measure the cost of unsecured funding.

Since Bagehot's dictum requires that LOLR facilities be targeted at illiquid-but-solvent institutions, one could argue that the efficacy of LOLR policies should be evaluated on the basis of whether it reduced illiquidity (rather than credit) premia. However, there are five reasons why this essay (as well as the related

[7]For example, the Term Asset-Backed Securities Loan Facility (TALF) was announced on the same day, November 25, 2008, as the decision to start purchasing agency-guaranteed mortgage backed securities, and the decision to purchase agency-issued debt. Kroszner and Melick (2010)'s organisational framework can be used to estimate the separate effects of these policies.

[8]Mishkin (2011) notes that the first version of the Troubled Asset Relief Program (TARP) failed on a bipartisan vote, which raised serious doubts about the government's crisis management capabilities. The bill was eventually approved by Congress on October 3, though its passage through parliament required numerous "Christmas-tree" provisions.

Figure 3.3: **Spreads on U.S. non-government bonds**



literature) does not attempt to decompose spreads into illiquidity and credit components.

Firstly, the methods used to decompose spreads assume that these two components are independent, that the recovery rate is constant (or independent of the default probability), and, most importantly, that the correlation between assets' credit risks can be precisely estimated. The assumption that liquidity and credit risk are independent has no theoretical foundation, and is made purely for ease of estimation. Coval, Jurek and Stafford (2009) note that the default correlation is the key input into the valuation and credit rating of a tranched security. The sharp drop in valuations and credit ratings of tranched securities during the crisis reflected an increase in the presumed loss correlations, higher default probabilities and lower recovery rates. As the financial crisis made clear, these key inputs were far from independent or constant. Hence, any decomposition reliant on the above assumptions is subject to a large degree of model risk and parameter uncertainty.

Secondly, the decomposition methods typically use the premia on credit default swaps (CDSs) written on the bond to isolate the credit risk component. The difference between the bond's spread and the credit risk component is defined as the illiquidity component. This method is feasible only for those bond markets with related CDS markets. However, my sample includes bonds for which data on CDS premia are not available, such as the markets for asset-backed securities (ABS) and commercial mortgage-backed securities (CMBS).

Thirdly, Ericcson and Renault (2006) find that liquidity risk comprises the vast bulk of short-term bonds' spreads. As my funding measures are for one month terms, focusing on the entire spread for these instruments is unlikely to bias my econometric results. The above-mentioned limitations of any spread decomposition provides further justification for this treatment.

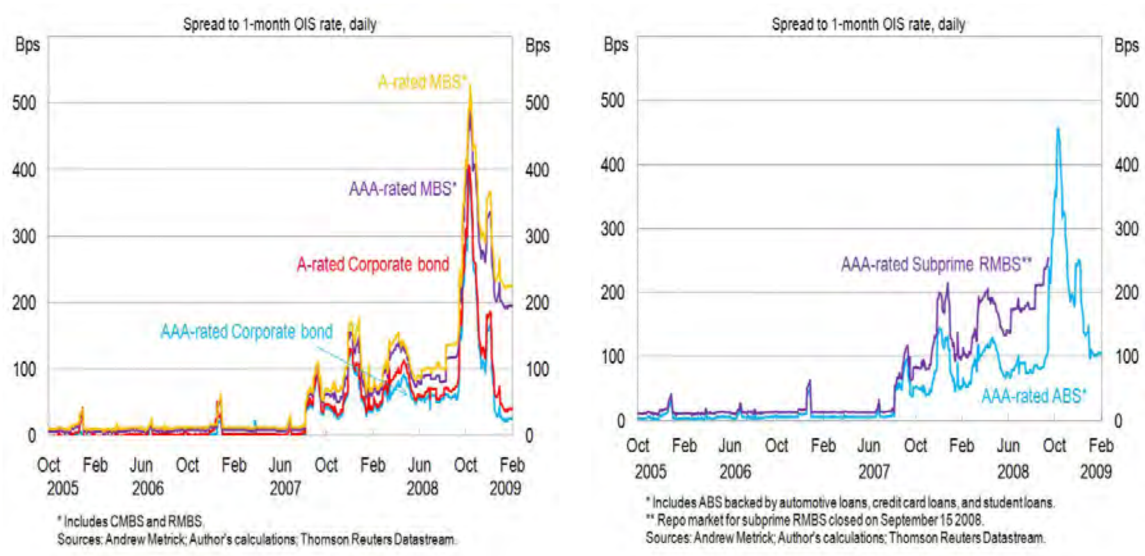
In addition, a key motivation of bank recapitalisation policies, like the TARP, was to prevent defaults on banks' assets from affecting senior creditors. Hence, the intention of these policies was to reduce *credit risk*, along with liquidity risk. Moreover, some of the Federal Reserve's LOLR facilities were aimed at reducing counterparty credit risk, in both secured and unsecured credit markets, by purchasing assets from banks and government-sponsored enterprises.

Finally, and perhaps most importantly, while Bagehot's dictum has theoretical merit, Goodhart and Huang (1999) argue that a central bank is rarely able, in practice, to make the distinction between insolvent and illiquid-but-solvent institutions, especially in the short time-scale in which a lending decision may have to be made. Furthermore, while there are reputational and direct financial costs to a central bank from lending to a bank later revealed to be insolvent, this may be outweighed by the cost to the financial system if support was not provided and the bank subsequently failed.

Data for 1-month LIBOR and 1-month OIS rates are from Thomson Reuters Datastream. Data for 1-month repo yields are kindly provided by Andrew Metrick, and used in Gorton (2010) and Gorton and Metrick (2011). The data relates to repos between dealer banks, and are daily, from October 3 2005 to February 2 2009 (844 trading days). Figure 3.4 shows the evolution of repo spreads between October 2005 and February 2009, for the six chosen U.S. corporate bond markets.

Prior to August 2007, spreads across all six types of repo collateral were generally stable and low, with the lowest spreads (average of -2 basis points) observed for repos collateralised by AAA-rated corporate bonds (Figure 3.4). However, from August 2007, repo spreads rose steadily across all collateral types; between August

Figure 3.4: **Spreads on 1-month inter-bank repos**



2007 and February 2009 (when the sample ends), repo spreads were, on average, between 80 and 140 basis points higher than in the preceding period. The largest increase in repo spreads was observed for A-rated MBS (143 basis point increase), a 13-fold increase over the preceding period, with the smallest increase for repos collateralised by AAA-rated and A-rated corporate bonds (80 and 87 basis points, respectively). However, as repos backed by subprime RMBS ceased trading on September 15, 2008, if the above analysis was performed for the August 2007 – September 15, 2008 period, the largest increase in spreads were for repos backed by subprime RMBS (an increase of 126 basis points).

3.4.2 Measuring the monetary policy stance

As noted in Section 3.1, I also consider the impact of "conventional" monetary policy on market pricing and liquidity. Following the widely-accepted practice in the macroeconomics literature, I define the stance of monetary policy as the difference between the actual effective Federal Funds rate and the effective Federal Funds rate implied by a Taylor rule. Taylor (1993) developed a hypothetical policy rule for the Federal Funds rate, which closely approximated the target Federal Funds rate between the late 1980s and early 1990s. The general version of the rule is:

$$i_t = \pi_t + r_t^* + a_\pi (\pi_t - \pi_t^*) + a_y (y_t - \bar{y}_t) \tag{3.1}$$

where i_t is the target Federal Funds rate, π_t is the inflation rate, π_t^* is the desired inflation rate, r_t^* is the assumed equilibrium (Wicksellian) real interest rate, y_t is the natural logarithm of the level of real Gross Domestic Product (GDP), and $\bar{y}_t$ is the natural logarithm of potential GDP, at time t. The Taylor rule thus specifies that i_t should respond to the divergence of the actual rate of inflation from the target inflation rate, and also to the divergence of actual real GDP from potential GDP.

The main issues associated with estimating equation (3.1) are estimating potential GDP, and specifying a target inflation rate. Over my period of analysis, the Federal Reserve did not have an explicit inflation rate target, unlike central banks like the Bank of England and the European Central Bank, so specifying the value of π_t^* is not clear-cut. More importantly, estimating $\bar{y}_t$ is not straightforward. The most common practice is the use of statistical filters, such as that proposed by Hodrick and Prescott (1980, 1997) (henceforth, HP). However, the use of an HP filter has been strongly criticised by Cogley and Nason (1993) as the filter can generate spurious cycles in non-cyclical data. Furthermore, equation (3.1) embodies a contemporaneous (or backward) Taylor rule, which is inconsistent with the forward looking nature in which the Federal Reserve and other central banks set monetary policy. In addition, the GDP series have historically been subject to more revisions than other series, such as the unemployment rate (Koenig, 2005).

For these reasons, I estimate a forward-looking Taylor rule based on inflation forecasts and an unemployment rate gap. The specification is:

$$i_t = \alpha + \beta \hat{\pi}_t^{t+T} + \delta \left(u_t - n_t \right) \tag{3.2}$$

where $\hat{\pi}_t^{t+T}$ is the expected inflation rate at time $t+T$, with the expectation formed at time t, u_t is the unemployment rate, and n_t is the natural unemployment rate. The unemployment terms appear due to the use of Okun's law in equation (3.1). This version of the Taylor rule more closely embodies the Federal Reserve's dual objectives of low and stable inflation, and maximum employment. It is possible to obtain (3.1) from (3.2) under the assumption that π_t^* and r_t^* are both constant.

Equation (3.2) is partly based on the model used in Rudebusch (2009), as I also use the Congressional Budget Office (CBO)'s estimate of the natural unemployment rate.[9] However, in contrast to Rudebusch (2009), I use inflation expectations not realised inflation. I use two measures of inflation expectations, setting $T = 5$ in equation (3.2): (i) the Federal Reserve Bank of Cleveland's measure of inflation expectations[10]; and (ii) the difference between the yield on a 5-year Treasury bond

[9] The data are obtained from the Federal Reserve Bank of St Louis.

[10] Inflation expectations are derived from an affine model, driven by state variables including the short-term real interest rate, expected inflation, and volatility factors that follow GARCH processes. The parameters are estimated using data on inflation swap rates, nominal yields and

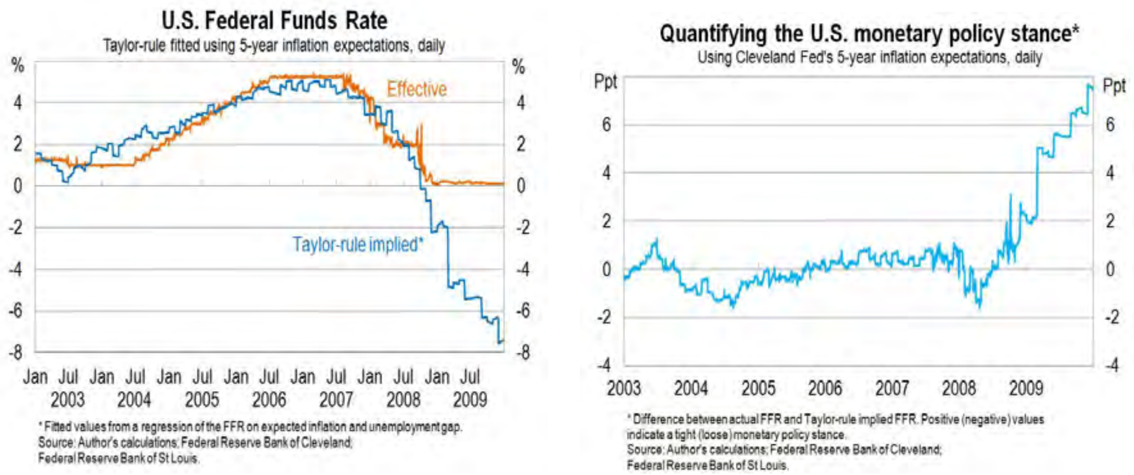
and the yield on a 5-year Treasury Inflation Protected Security (TIPS).[11]

The inclusion of an "unemployment gap" in the Taylor rule reflects the Federal Reserve's dual mandate as embodied in Section 2A of the *Federal Reserve Act*. Using this specification for the Taylor rule for the post-December 2008 period (i.e. the period during which the zero lower bound has been binding), rather than a "pure inflation" targeting framework with $\delta = 0$, is consistent with recent comments by Federal Reserve officials on the importance of the unemployment aspect of the statutory mandate (Kotcherlakota (2012)).

I estimate equation (3.2) between January 2, 2003 and the December 15, 2008, the latter date reflecting the day prior to the commencement of the targeting of the Federal Funds rate within the 0 to 25 basis point range. I use the estimated coefficients to estimate the Taylor-rule implied Federal Funds rate between December 17, 2008 and December 31, 2009. Figure 3.5 reveals the actual and Taylor-rule implied effective Federal Funds rates, based on the Federal Reserve Bank of Cleveland's measure of inflation expectations, while Appendix C.1.1 contains the corresponding graphs using the 5-year Treasury bonds-TIPS spread. The profile of the series are broadly the same under both measures.

The Taylor rule closely approximated the actual effective Federal Funds rate

Figure 3.5: **U.S. Federal Funds rate**



survey forecasts of inflation, in contrast to much of the existing literature which tends to use only the latter two variables. For more details, see Haubrich, Pennacchi, and Ritchken (2011).

[11] In order to test the sensitivity of the results, I set $T = 1$ and $T = 10$ in (3.2), for both measures of inflation expectations. While the coefficient estimates of (3.2) differ between each of the chosen maturities, the Taylor rule estimates of i_t are broadly unchanged.

between January 2003 and November 2008 (the $\bar{R}^2$ is 0.85), but the approximation error became increasingly large once the zero lower bound began to be a binding constraint (left panel, Figure 3.5). The Taylor rule implied rate continued to decline during 2009, reflecting a decrease in inflation expectations and a rise in the gap between the actual and natural unemployment rate, reaching a low of -7.5 per cent during November 2009. The binding zero constraint on the Federal Funds rate meant that monetary policy became increasingly contractionary from July 2008, reaching a high of 7.5 per cent in late 2008 (right panel, Figure 3.5).

The consensus in macroeconomics, summarised in Mishkin (2009), is that monetary policy retains its potency and ability to achieve a central bank's macroeconomic objectives even at the zero bound. I use these arguments as justification for defining the stance of U.S. monetary policy as the difference between the actual and Taylor-rule implied Federal Funds rate.

As negative Federal Funds rates are obviously infeasible, once the Federal Funds rate hit the zero lower bound, the Federal Reserve engaged in various "unconventional" policy measures to try to fulfil its dual mandate. If these policies had been successful in achieving the Federal Reserve's dual mandate, the Taylor-rule implied Federal Funds rate would have been much higher. It is likely that this counterfactual value would have exceeded zero; I estimate that the effective Federal Funds rate consistent with a zero unemployment gap would have been, on average, 3.57 per cent between December 2008 and December 2009, with a corresponding expected average inflation rate of 2.33 per cent.[12] The counterfactual Federal Funds rate would have been consistent with the Federal Reserve's dual mandate.

Hence, Figure 3.5 reveals that the Federal Reserve's unconventional policies failed to achieve their dual mandate. Focusing solely on the level of the effective Federal Funds rate obscures this finding, and may lead to "the fallacy of identifying tight money with high interest rates and easy money with low interest rates" (Friedman, 1998).

3.5 Empirical methodology

To examine the relationship between bond spreads and conventional and "unconventional" monetary policy, I follow Frank and Hesse (2009) and use a Vector Autoregression (VAR):

$$\mathbf{X}_t = \alpha + \beta\mathbf{X}_{t-1} + \Theta D_t^{Fiscal} + \Gamma\mathbf{D}_t^{Unconv} + \eta Stance_t + \epsilon_t \tag{3.3}$$

[12] The counterfactual expected inflation rate is estimated from a regression of the unemployment gap on the expected 5-year inflation rate (from Haubrich et al., 2011), setting the unemployment gap to zero. I use this counterfactual inflation rate in equation (3.2) to estimate the counterfactual Federal Funds rate.

where $\mathbf{X}_t$ is a 3x1 vector containing bond spreads, 1-month repo-OIS spreads, and 1-month LIBOR-OIS spreads, $\mathbf{D}_t^{Unconv}$ is a 1x3 vector of dummy variables for each of the three types of "unconventional" monetary policies. Each element of $\mathbf{D}_t^{Unconv}$ equals 1 if a policy from the respective category was announced on day t, $t-1$, or $t+1$; or zero. D_t^{Fiscal} is a scalar dummy variable equal to 1 if a fiscal policy announcement was made on day t, $t-1$, or $t+1$; or zero. The specifications for $\mathbf{D}_t^{Unconv}$ and D_t^{Fiscal} reflects the use of a 3 day interval around an event, to allow for pre- and post-event drift.

The use of a VAR reflects the fact that the three spread variables Granger cause each other (see Appendix C.2). For the AR terms, a one day lag is chosen on the basis of the Akaike and Schwartz-Bayesian information criterion, as well as a desire for parsimony.

The various LOLR facilities introduced by the Federal Reserve were typically aimed at alleviating strains in short-term funding markets, reflecting these markets' greater susceptibility to investor runs, compared to longer-term funding markets. Hence, I include the cost of short-term funding in the VAR. These policies were also aimed at limiting fire-sales of assets, like corporate bonds, in response to liquidity problems in the secured and unsecured markets. Consequently, the VAR also includes spreads on corporate bonds.

The inclusion of conditioning variables – lagged values of the dependent variables, the monetary policy stance and various policy dummy variables – means that I focus on the surprise component of the separate policy announcements. This treatment is similar to that used by Aït-Sahalia, Andritzky, Jobst, Nowak, and Tamirisa (2010), who focus on the 3-month LIBOR-OIS spread and use a pure random walk model to extract the residual return. In contrast, I use a larger set of conditioning variables, since I focus on three key market spreads, and specify a stationary model, since there is no theoretical basis for a unit root in market spreads.

During the crisis, some unconventional policies involved the Federal Reserve purchasing risky assets. For example, on November 25, 2008, the Federal Reserve announced it would purchase MBS guaranteed by housing-related U.S. government sponsored enterprises (GSEs)[13], and purchase the senior debt of these GSEs. These policies blurred the distinction between monetary and fiscal policy, since traditional monetary policy has revolved around investments in (risk-free) U.S. Treasury securities. In order to control for the effect of fiscal policy on market spreads, I include the dates of key fiscal policy announcements. These dates are identified below.

$Stance_t$ is defined as the difference between the effective and Taylor-rule im-

[13] The Federal National Mortgage Association ('Fannie Mae'), Federal Home Loan Mortgage Corporation ('Freddie Mac'), and the Federal Home Loan Banks.

plied Federal Funds rates (see Figure 3.5), and is measured using 5-year inflation expectations from Haubrich, Pennacchi and Ritchken (2011). α, β, Γ, Θ, and η are parameters to be estimated, while ϵ_t is a 3x1 vector of residuals, on day t.

The inclusion of fiscal and monetary policy in equation (3.3) is made for two reasons, and deserves some discussion. The first reason is statistical: I include fiscal policy as a policy control variable, to ensure that there is no "omitted policy bias" in the estimated monetary policy coefficients (Γ and η). The second reason is economic: Christiano, Eichenbaum and Rebelo (2011), along with several other theoretical papers in the macroeconomic literature, show that government spending has a large multiplier when the zero interest rate bound is binding, and that a complementarity between monetary and fiscal policy exists in a liquidity-trap environment, which is the environment examined in this chapter. This complementarity provides the theoretical rationale for the specification of equation (3.3).

The announcement dates for the various "unconventional" monetary policies are from Kroszner and Melick (2010), (see Table 3.1). To this, I add two dates associated with announcements of extensions to these policies, from Federal Reserve Bank of St. Louis (2011):

- December 2, 2008: extension of three key LOLR facilities (PDCF, AMLF[14], and TSLF) through to April 30, 2009;
- February 3 2009: extension, to October 30, 2009, of those liquidity facilities scheduled to expire on April 30, 2009;

The dates of fiscal policy announcements are from Federal Reserve Bank of St. Louis (2011). The dates are: (i) September 19, 2008; (ii) September 29, 2008; (iii) October 3, 2008; (iv) October 14, 2008; and (v) November 12, 2008. The events relating to these dates are detailed in Appendix C.3.

These dates correspond to events that may have had both stabilising and destabilising effects on spreads. Mishkin (2011) argues that the initial rejection of the Troubled Asset Relief Program (TARP) bill (on September 23, 2008), its subsequent delay in finally being passed, and the various "Christmas-tree" provisions that were included in the bill in order for it to pass through both houses of Congress, were all events that aggravated market spreads. Taylor (2011) argues that the lack of detail in the original TARP bill (a total of $2\frac{1}{2}$ pages, with no mention of oversight and few restrictions on the use of funds) created significant

[14] The Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility was announced on September 19, 2008 under which non-recourse loans were made to banks at the primary credit rate, to finance purchases of ABCP from money market funds (MMFs) at above-market prices. The cash obtained by the MMFs could then be used to meet redemption requests, thereby increasing their willingness to continue providing short-term secured funding, primarily via repos, to banks.

uncertainty about the TARP's stated aims and likely effects, which destabilised market spreads. On the other hand, Aït-Sahalia, Andritzky, Jobst, Nowak, and Tamirisa (2010), find that announcements of systematic bank recapitalisation policies, such as the eventual passage of the TARP bill on October 3, 2008, had a stabilising influence on interbank loan spreads. My inclusion of all dates related to the TARP announcements is designed to estimate the average impact of the TARP on market spreads.

The various fiscal and monetary policies were motivated on the basis of returning markets to "normal" functioning, with a desired reduction in both the level and volatility of spreads. I follow Frank and Hesse (2009) and estimate a multivariate (tri-variate) 1^{st}-order GARCH model of the following form:

$$\mathbf{H}_t = \mathbf{C}\mathbf{C}' + \mathbf{A}\epsilon_{t-1}\epsilon'_{t-1}\mathbf{A}' + \mathbf{B}\mathbf{H}_{t-1}\mathbf{B}' + \mathbf{E}D_t^{Fiscal} + \mathbf{F}\mathbf{D}_t^{Unconv} + \mathbf{G}Stance_t \quad (3.4)$$

where $\mathbf{H}_t$ is the 3x3 covariance matrix of the VAR model's residuals at time t, ϵ_{t-1} is a 3x1 matrix of the VAR residuals (at time $t-1$), and $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, $\mathbf{E}$, $\mathbf{F}$, and $\mathbf{G}$ are parameter matrices to be estimated. $\mathbf{D}_t^{Unconv}$, D_t^{Fiscal}, and $Stance_t$ are the same as in equation (3.3).

Equation (3.4) is the popular BEKK GARCH (1,1) model, developed by Engle and Kroner (1995), augmented with the policy variables as exogenous regressors. Even without including the parameters on the policy variables, a drawback of the BEKK model is the large number of parameters (24) that need to be estimated.[15] However, its advantage, over other multivariate GARCH models, is that it ensures $\mathbf{H}_t$ is positive definite.[16] In over to avoid overfitting, I test whether the full BEKK model can be reduced to a 'diagonal' BEKK model, in which $\mathbf{A}$ and $\mathbf{B}$ are both diagonal, such that $\sigma_{jk,t} := Cov_{t-1}(\epsilon_{j,t}, \epsilon_{k,t})$ depends only on $\sigma_{jk,t-1}$ and $\epsilon_{j,t-1}, \epsilon_{k,t-1}$.

In addition to the guarantee of $\mathbf{H}_t$ being positive definite, I choose the BEKK model in order to compare my results with Frank and Hesse (2009). While the choice of VAR and GARCH models are the same as Frank and Hesse (2009), I consider the contemporaneous impact of the policies on the level and volatility of spreads, while Frank and Hesse allow for 1- and 2-day lagged effects. However, Frank and Hesse (2009) provide no justification for why lagged effects might be more important than contemporaneous effects.

One possible justification might be that, to the extent that these policies were deemed "unconventional" or non-traditional, it might have taken some time for market participants to assess the policies' impact on spreads and volatility. A counterargument is that these policies, when viewed through the framework of

[15]Excluding the policy variables, equation (3.4) requires estimating $(p+q)\,N^2 + N\,(N+1)\,\frac{1}{2}$ parameters, where p and q are the number of lags of $\epsilon\epsilon'$ and $\mathbf{H}$, respectively, and N is the number of dependent variables. Here, $N = 3$ and $p = q = 1$.

[16]Bauwens, Laurent and Rombouts (2006), and Silvennoinen and Teräsvirta (2008) survey the extensive literature on multivariate GARCH models.

Kroszner and Melick (2010), supplemented the Federal Reserve's traditional open market operations (OMOs), and so may not have been deemed unconventional. As OMOs have a contemporaneous effect on market prices, a rational expectation of the impact on the "unconventional" policies would consider only contemporaneous effects. Hence, a lagged effects formulation appears inconsistent with rational expectations. Moreover, it also assumes (implicitly) that markets are informationally inefficient.

In contrast to Frank and Hesse (2009), my construction of $\mathbf{D}^{Unconv}$ and $\mathbf{D}^{Fiscal}$ allows for both lagged and contemporaneous (and leading) effects, as I consider the 3-day window around each type of fiscal and "unconventional" monetary policy announcement. The results of this VAR(1)-GARCH(1,1) model are discussed in Section 3.6.

3.6 Non state-dependent VARs

3.6.1 All corporate bonds

Table 3.2 contains the parameter estimates from equation (3.3), with three important findings. Firstly, Federal Reserve policy announcements had modest impacts on spreads, with statistically significant (at the 5% level) announcement effects observed only for LIBOR-OIS spreads. For LIBOR-OIS spreads, Federal Reserve policies that broadened the eligibility of collateral (D^{Collat}) and the type of counterparties (D^{Cpart}) were more effective in reducing spreads, than policies that increased the maturity of support (D^{Mat}). However, the economic significance was modest, with spreads falling only around one basis point on each of the three days around each announcement (i.e. the cumulative effect is a 3-4 basis point decline in spreads).[17]

Secondly, fiscal policy announcements were found to have an insignificant direct effect on bond spreads, but significant – though *destabilising* – announcement effects on repo and LIBOR-OIS spreads. In response to fiscal policy announcements, repo spreads and LIBOR-OIS spreads rose by around 40 basis points and 7 basis points, respectively, over the 3-day event window. This finding is consistent with Taylor (2011).

Finally, the monetary policy stance is found to have adversely affected credit spreads: a one-standard-deviation rise in *Stance* (a 92 basis point tightening of

[17] In terms of the AR coefficients, I generally can not reject the null hypothesis that spreads contain a unit root. However, I do not allow for non-stationarity in spreads as there is no theoretical justification for a unit root in spreads; one of the implications of an $I(1)$ process is that $Prob(s_t < |R| = 0)$ as $t \to \infty \forall R \leq \infty$, for each of the 3 types of spreads (s). The reliance on theory here reflects the low power of unit root tests: in any finite sample, a "true" trend-stationary process can be arbitrarily well-approximated by a difference-stationary process.

Table 3.2: VAR parameter estimates – all bonds

This table reports the parameter estimates from equation (3.3), with multivariate GARCH(1,1) corrected z-statistics in brackets. The multivariate GARCH model is equation (3.4). *LIB-OIS* is the spread between the 1-month LIBOR and the 1-month OIS rate, *Repo* is the 1-month repo-OIS spread, and *Bond* is the spread between duration-matched U.S. corporate bonds and U.S. Treasuries. D^{Fiscal} is a dummy variable that equals 1 when a fiscal policy announcement is made (or one day preceding or proceeding the announcement), while D^{Mat}, D^{Cpart} and D^{Collat} are dummy variables relating to a 3-day window around Federal Reserve policies to, respectively: lengthen the maturity of open market operations, expand the type of counterparties, and broaden the type of collateral eligible for secured lending. Finally, *Stance* is the monetary policy stance, defined as the difference between the actual effective Federal Funds rate and the effective rate implied by a Taylor rule (equation (3.2)). The estimations are based on daily data from July 1, 2007 to February 2, 2009 (397 trading days).

Dep. var	*LIB-OIS*(-1)	*Repo*(-1)	*Bond*(-1)	D^{Fiscal}	D^{Mat}	D^{Cpart}	D^{Collat}	*Stance*	adj. R^2
LIB-OIS	0.953	0.001	0.001	0.023	-0.005	-0.011	-0.015	0.047	0.98
	[19.1]	[11.1]	[5.32]	[2.19]	[-1.55]	[-2.04]	[-2.19]	[2.21]	
Repo	0.018	0.972	0.004	0.135	-0.003	-0.019	0.008	0.007	0.98
	[4.15]	[8.02]	[4.23]	[7.54]	[-1.13]	[-3.15]	[0.99]	[2.62]	
Sprd	0.051	0.026	0.971	0.006	-0.040	0.069	0.083	0.037	0.98
	[0.52]	[0.11]	[8.21]	[0.14]	[-0.89]	[0.25]	[1.31]	[2.16]	

monetary policy) increased bond and interbank loan spreads by around 3 basis points, and repo spreads by 1 basis point. In contrast, a similar rise in D^{Collat} lowered repo spreads by a total of 1 basis point over the 3-day event window. These results suggest that the efficacy of the Federal Reserve's unconventional policies was reduced by the contractionary stance of conventional policy. Although the Federal Reserve's unconventional policies were seemingly impressive in terms of its breadth, these policies were insufficient to ensure that the central bank satisfied its macroeconomic objectives, and thus exacerbated market strains.

Likelihood ratio tests suggest that the full BEKK model is more appropriate than a diagonal BEKK model. For the sake of brevity, I report only the parameter coefficients and Bollerslev-Wooldridge robust z-statistics corresponding to the policy variables in equation (3.4) with the full output available upon request.[18]

Collectively, the results reveal that the policy announcements had a weak impact on market volatility (Table 3.3). Announcements of policies that extended the counterparties to Federal Reserve support had a statistically significant (at the 1% level) negative effect on the conditional variance of LIB-OIS and repo spreads, but no significant impact on the conditional variances of bond spreads. Fiscal policy announcements had a *destabilising* impact on the conditional variance of repo spreads, similar to the evidence in Table 3.2, but no impact on other conditional variances. Fiscal policy announcements were associated with a 60 per cent (13 basis point) rise in the conditional volatility of repo spreads, an economically and

[18]Bollerslev and Wooldridge (1992) provide an adjustment to the covariance matrix which ensures that QML estimators of the parameters in equation (3.4) remain consistent and asymptotically normally distributed even when the residual conditional distribution is non-Gaussian.

Table 3.3: BEKK multivariate GARCH model estimates – all bonds

This table reports selected parameter estimates from equation (3.4), with Bollerslev-Wooldridge adjusted z-statistics in brackets. $\sigma^2_{LIB-OIS}$, σ^2_{Repo}, and σ^2_{Bond} is the conditional variance of residuals from equation (3.3) for, respectively, *LIB-OIS*, *Repo* and *Bond*. D^{Fiscal} is a dummy variable that equals 1 when a fiscal policy announcement is made (or one day preceding or proceeding the announcement), while D^{Mat}, D^{Cpart} and D^{Collat} are dummy variables relating to a 3-day window around Federal Reserve policies to, respectively: lengthen the maturity of open market operations, expand the type of counterparties, and broaden the type of collateral eligible for secured lending. Finally, *Stance* is the monetary policy stance, defined as the difference between the actual effective Federal Funds rate and the effective rate implied by a Taylor rule (equation (3.2)). The estimations are based on daily data from July 1, 2007 to February 2, 2009 (397 trading days).

Dep. var	D^{Fiscal}	D^{Mat}	D^{Cpart}	D^{Collat}	*Stance*
$\sigma^2_{LIB-OIS}$	-0.002	0.000	-0.006	-0.001	0.001
	[-0.64]	[1.59]	[-4.82]	[-2.20]	[5.54]
σ^2_{Repo}	0.017	-0.019	-0.036	0.000	0.001
	[2.78]	[-0.16]	[-3.72]	[0.38]	[4.05]
σ^2_{Sprd}	0.081	0.034	-0.049	-0.088	-0.12
	[0.05]	[0.10]	[-0.18]	[-0.27]	[-0.05]

statistically significant (at the 1% level) result.

Notably, a tightening in monetary policy (i.e. a rise in the value of *Stance*) led to a rise in both $\sigma^2_{LIB-OIS}$ and σ^2_{Repo}, with these effects statistically significant at the 1% level. A one-standard-deviation positive shock to *Stance* raised the conditional variance of LIBOR-OIS and repo spreads by 3 basis points (7 per cent and 3 per cent, respectively). These findings are similar to those in Table 3.2.

3.6.2 Individual bond segments

The discussion in the previous subsection was based on the impact of policy initiatives on all six bond markets. However, it is possible that the impact of these initiatives differs across the various bond markets, since certain policies (such as the Term Asset-Backed Loan Facility) were targeted at specific bonds (such as asset-backed securities, or ABS), and so these policies may have had a greater impact on alleviating strains in these markets, than in other markets. The targeting of the ABS market reflected the fact that securitisation markets experienced greater stresses than vanilla bond markets, due to investors' loss of confidence in the valuation and ratings methodology of these securities, and the subsequent rise in 'model risk' (Coval, Jurek and Stafford, 2009). The liquidity support provided by the various fiscal and monetary policies could have had a larger impact on restoring investor confidence in the value of asset-backed securities, than for vanilla bonds.

To examine potential bond-specific heterogeneity, I group all ABS into one category (labeled 'All ABS') and all non-ABS into another ('Non-ABS'). The aggregation of all types of ABS reflects the fact that even for those Federal Reserve policies (like the TALF) which targeted securitisation markets, a wide range of ABS were eligible for support. I estimate equation (3.3) for each of these two categories, reporting the results in Table 3.4.

Table 3.4 reveals some evidence of bond-specific heterogeneity. While fis-

Table 3.4: VAR parameter estimates – bond categories

This table reports the parameter estimates from equation (3.3), with multivariate GARCH(1,1) corrected z-statistics in brackets. The multivariate GARCH model is equation (3.4). *LIB-OIS* is the spread between the 1-month LIBOR and the 1-month OIS rate, *Repo* is the 1-month repo-OIS spread, and *Bond* is the spread between duration-matched U.S. corporate bonds and U.S. Treasuries. D^{Fiscal} is a dummy variable that equals 1 when a fiscal policy announcement is made (or one day preceding or proceeding the announcement), while D^{Mat}, D^{Cpart} and D^{Collat} are dummy variables relating to a 3-day window around Federal Reserve policies to, respectively: lengthen the maturity of open market operations, expand the type of counterparties, and broaden the type of collateral eligible for secured lending. Finally, *Stance* is the monetary policy stance, defined as the difference between the actual effective Federal Funds rate and the effective rate implied by a Taylor rule (equation (3.2)). Panels A and B report the results for all asset-backed bonds and non-asset-backed bonds, respectively. The estimations are based on daily data from July 1, 2007 to February 2, 2009 (397 trading days).

Dep. var	*LIB-OIS*(-1)	*Repo*(-1)	*Bond*(-1)	D^{Fiscal}	D^{Mat}	D^{Cpart}	D^{Collat}	*Stance*
			Panel A: All asset-backed bonds					
LIB-OIS	0.991	0.003	0.000	0.015	-0.001	-0.011	-0.002	0.005
	[10.5]	[3.48]	[1.69]	[6.36]	[-1.55]	[-7.40]	[-5.55]	[2.32]
Repo	0.005	0.956	0.002	0.250	-0.004	-0.062	-0.003	0.007
	[0.19]	[51.6]	[4.41]	[15.6]	[-1.12]	[-6.54]	[-0.96]	[1.97]
Sprd	0.028	-0.011	0.994	0.207	0.074	0.138	0.158	0.022
	[1.15]	[-0.97]	[36.9]	[4.39]	[0.83]	[0.53]	[1.07]	[4.67]
			Panel B: All non-asset-backed bonds					
LIB-OIS	0.945	0.008	-0.007	0.137	-0.027	-0.027	0.004	0.009
	[32.7]	[0.34]	[-3.10]	[4.09]	[-3.16]	[-2.85]	[1.09]	[3.54]
Repo	-0.002	0.974	-0.002	0.200	-0.018	-0.022	-0.036	0.008
	[0.57]	[31.1]	[-1.02]	[5.16]	[-1.54]	[-1.81]	[-1.92]	[2.81]
Sprd	-0.041	0.127	0.983	-0.011	-0.016	0.037	0.020	0.008
	[-1.86]	[2.41]	[18.8]	[-0.31]	[-0.81]	[1.29]	[0.33]	[2.10]

cal policy announcements have a destabilising affect on ABS spreads and ABS repo spreads, these policy announcements do not affect vanilla bond spreads. In addition, while all types of unconventional monetary policy announcements are insignificant for bond spreads, there are differences in announcement effects for repo-OIS spreads. Policies that expanded the type of counterparties have highly statistically significant (at the 1% level) announcement effects for spreads on ABS repos, with spreads declining by one-seventh (18 basis points) over the 3-day window (Panel A). These announcement effects are double in size of those for spreads on non-ABS repos, which decline by 7 per cent (6 basis points), and are also less statistically significant (Panel B).

The monetary policy stance remains a statistically significant influence on the spreads of both bond categories, though the economic significance remains modest. A 100 basis point tightening in monetary policy raises spreads on ABS and repos collateralised by ABS by 1-2 basis points, about the same as the increase in non-ABS spreads. In summary, the evidence in Table 3.4 suggests that while there is some evidence of bond-specific heterogeneity, reflecting the fact that some unconventional monetary policies were targeted at idiosyncratic segments of the bond market, these policies' effects were felt across the broader bond market.

It is also worth noting that equation (3.4) was estimated separately for all ABS, and all non-ABS. Similar to Table 3.4, I found little evidence of bond-specific heterogeneity in the significance of the policy variables, with the results omitted for the sake of brevity, though available on request.

3.7 State-dependent VAR

While the categorical analysis used above helps to make the model fairly parsimonious, it assumes that individual policies within each category had the same effect on market spreads. It also assumes that the 3-day event window is appropriate for each policy announcement; that is, it assumes that each policy had, at most, only one day of pre- or post-event 'drift'. These assumptions may not be realistic as some policies may have been anticipated by the market more than one day prior to the announcement, while some other policies may have taken longer to affect spreads. For example, announcements of new programs, as opposed to extensions of existing programs, may have been considered 'untested' by market participants, which may have both reduced the announcement-day effect and increased the post-event drift, as agents considered the pricing implications of these policies. In contrast, announcements of program extensions may not have had a drawn out effect on spreads, as these announcements, while possibly being 'news', were not novel.

There is also a theoretical justification for this regime-switching approach. Christiano, Eichenbaum and Rebelo (2011) develop a general equilibrium model in which fiscal policy has a larger multiplier when the zero interest rate constraint is binding. Outside of this "liquidity trap", the fiscal multiplier is zero, as the central bank can use monetary policy to fully offset any fiscal policy change. The theoretical work of Christiano, Eichenbaum and Rebelo (2011) implies that the fiscal policy coefficient, as well as the various monetary policy coefficients, may depend on whether the economy is in, or expected to move into, a liquidity trap. This can generate a state-dependency in the estimated policy coefficients.

To perform this "policy-specific" analysis, I estimate a Markov Switching VAR (MSVAR) model. For the sake of simplicity, I use a model in which two possible regimes exist, with fixed transition probabilities. The Markov-switching model differs from models with imposed breaks in that the timing of breaks is entirely endogenous. Indeed, breaks are not explicitly imposed, but inferences are drawn on the basis of probabilistic estimates of the most likely state prevailing at each point in time.[19]

Incorporating regime shifts in the VAR model leads to the state-contingent version of equation (3.3):

$$\mathbf{X}_t = \alpha\left(s_t\right) + \beta\left(s_t\right)\mathbf{X}_{t-1} + \eta Stance_t + \epsilon\left(s_t\right) \tag{3.5}$$

where $\epsilon\left(s_t\right) \sim NIID\left(0, \Sigma\left(s_t\right)\right)$, and $\alpha\left(s_t\right)$, $\beta\left(s_t\right)$, and $\Sigma\left(s_t\right)$ are parameter shift functions describing the dependence of the parameters α, β, λ, η, and Σ on the existing regime, s_t. s_t denotes a latent state variable, which follows a continuous time Markov-chain with two different regimes ($s_t \in \{0,1\}$) and transition probabilities:

$$P = \begin{bmatrix} p_{00} & 1-p_{00} \\ 1-p_{11} & p_{11} \end{bmatrix}.$$

To make the model fairly parsimonious, equation (3.5) is estimated allowing for regime shifts only in α (the intercept vector) and the conditional covariance matrix of ϵ ($\mathbf{H}_t$). In the interests of parsimony, I confine my estimations to the MSVAR model, and do not estimate a Markov switching version of equation (3.4).[20] The output is contained in Table 5.[21]

The output reveals a strong presence of two regimes, one in which the intercept terms are statistically insignificant (at the 5% level), and another regime in which the intercept terms are statistically significant (at the 1% level). I dub the former regime a 'lower spread' regime, reflecting the lower unconditional spreads in this regime, relative to the latter, 'higher spread' regime.

In order to assess the effectiveness of the various fiscal and monetary policies, I calculate the unconditional probability of being in the second regime on each day, $p^{highsprd}$, and then examine whether there were any fiscal or monetary policies announcements associated with key turning points in $p^{highsprd}$. The unconditional probability arising from estimating equation (3.5) for all six corporate bond types are shown in Figure 3.6, with the key turning points shaded.

$p^{highsprd}$ rose sharply between July and September 2007, and then fell be-

[19]Technical details regarding Markov switching models can be found in Hamilton (1994). A BDS test of the various VAR models' residuals rejects the null (at the 1% level) that a linear specification is appropriate, providing further justification for examining nonlinear models. In addition, Andrews (1993) test for regime change strongly rejects the null of no structural break in the estimated parameter coefficients.

[20]Allowing for regime shifts in only the intercept terms and the residual covariance matrix reduces the number of parameters to be estimated from 52 to 34. The MSVAR is estimated using Perlin (2011)'s algorithm. I estimate the standard errors using the 'sandwich' estimator (i.e. the outer products of the gradient vectors) which is robust to a failure of the assumption that the residuals are conditionally normally distributed.

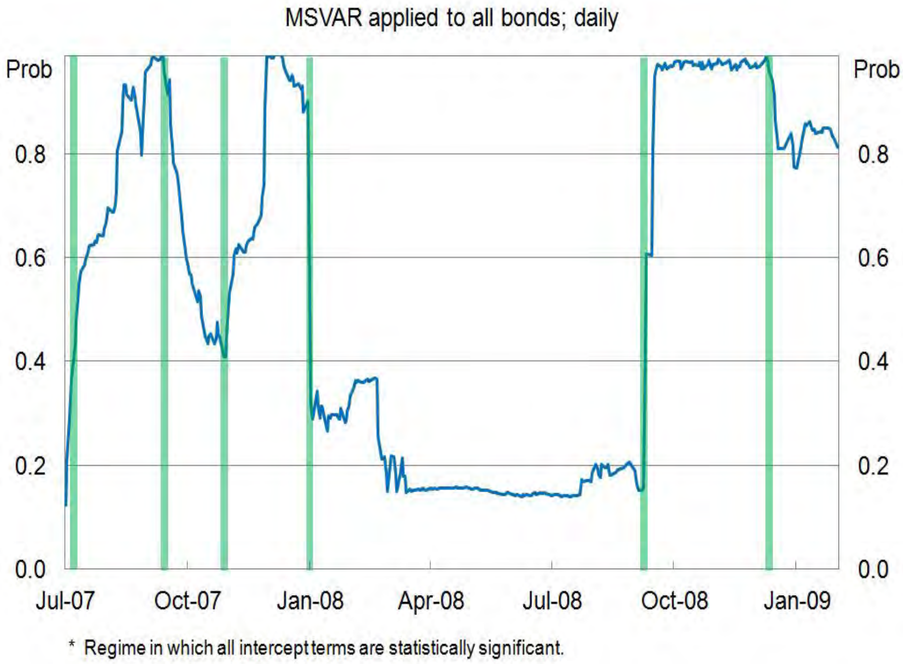
[21]The sup-Wald tests of Andrews (1993) reveal that the differences between the parameters for each regime are statistically significant. Since the regime switching parameters are unidentified under the null hypothesis of no switching, traditional Wald tests can not be used to test the statistical significance of parameter differences.

Table 3.5: MSVAR parameter estimates – all bonds

This table reports the quasi-maximum likelihood parameter estimates of the intercept terms (denoted by α) from equation (3.5), with robust t-statistics in brackets. *LIB-OIS* is the spread between the 1-month LIBOR and the 1-month OIS rate, *Repo* is the 1-month repo-OIS spread, and *Bond* is the spread between duration-matched U.S. corporate bonds and U.S. Treasuries. The estimations are based on daily data from July 1, 2007 to February 2, 2009 (397 trading days).

Parameter	*LIB-OIS*		*Repo*		*Bond*	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
α	-0.143	0.564	-0.197	0.723	-0.242	2.811
	[-1.25]	[2.89]	[-1.69]	[3.57]	[-1.90]	[3.11]

Figure 3.6: **Probability of being in the "higher spread" regime***



tween late September and October 2007, before again rising sharply in November 2007. $p^{highsprd}$ fell significantly in 2008 and stabilised at low levels (around 0.2) during most of 2008, until a dramatic spike in September 2008. Following this, it remained at elevated levels close to 1.0 for the next three months, and then fell slightly during end 2008 and early 2009. The six shaded areas correspond to the following periods: (i) early July 2007; (ii) mid September 2007; (iii) late October 2007; (iv) early January 2007; (v) early September 2008; and (vi) December 2008.

July - September 2007

There were no fiscal or unconventional monetary policy announcements associated with the movements in $p^{highsprd}$ between July and September 2007 (Table 3.1; and Appendix C.3). Instead, the fall in $p^{highsprd}$ between late September and October 2007 likely reflected the use of conventional monetary policy: a reduction in the Federal Funds rate (Figure 3.1). However, during the second half of 2007, U.S. monetary policy was modestly contractionary; the effective Federal Funds rate was, on average, around 60 basis points higher than the Taylor-rule implied rate, over this period. This contractionary stance may have partly contributed to the rise in $p^{highsprd}$ between July and December 2007 (the correlation between *Stance* and $p^{highsprd}$ during this period was 0.17).

November 2007 - January 2008

$p^{highsprd}$ rose sharply between early November and December 2007, reaching a peak of 1.0 on December 4, before falling slightly from December 12, 2007, with an even larger decline observed in early January 2008. The initial drop in $p^{highsprd}$ likely reflected the announcement, on December 12, 2007, of the Term Auction Facility (TAF) and U.S. dollar swap lines between the Federal Reserve and, respectively, the ECB and Swiss National Bank.[22] These policies were implemented on December 17 and December 20 (both in 2007), respectively.

These policies had a modest impact on $p^{highsprd}$, which fell slightly over December 2007. The larger decline in early January 2008 may also have been due to these policies, though this would have required a drawn out response (over ten trading days). McAndrews, Sarkar and Wang (2008) and Wu (2009) document that the bulk of the TAF's impact on market spreads occurred during the TAF's operation, rather than upon its announcement, although, as noted in Section 3.3 these papers do not control for the influence of intervening fiscal and other monetary policies.

September 2008

After stabilising at around 0.2 during most of 2008, $p^{highsprd}$ spiked sharply in September 2008, following the failure of Lehman Brothers and AIG, and runs on large U.S. money market funds. Mishkin (2011) and Taylor (2011) argue that fiscal policy aggravated, rather than stabilised, market strains during this time, an argument consistent with my empirical analysis. Furthermore, the October 3, 2008 announcement that the TARP bill was passed into law did not appear to

[22] Under these swap lines, the Federal Reserve sold U.S. dollars to foreign central banks, and bought Euros and Swiss dollars, respectively, at prevailing market exchange rates, with the transactions reversed at a pre-specified time (between one day and three months) in the future.

lead to a decrease in $p^{highsprd}$, which remained elevated throughout October 2008. In addition, U.S. monetary policy became increasingly contractionary during this period (see Figure 3.5), another contributor to market instability. The elevated value of $p^{highsprd}$ between September 2008 and early December 2008 suggests that fiscal and "unconventional" monetary policies announced during this time[23] were largely ineffective in reducing market strains.

December 2008

$p^{highsprd}$ declined from 1.0 to 0.8 between early and mid December 2008. While there were no new fiscal or monetary policies announced at this time, the decline may have reflected the announcement, on December 2, 2008, that three LOLR facilities were being extended to the end of April 2009. The decline may also have been due to the implementation of those LOLR programs introduced in November 2008. For example, the program of buying GSE-issued debt was implemented from December 5, 2008, and the purchase of RMBS from AIG was implemented from December 12, 2008.

In summary, instances where $p^{highsprd}$ fell were typically not associated with fiscal or monetary policy announcements. In fact, falls in $p^{highsprd}$ typically occurred during periods in which policies were implemented so that, if the various fiscal and monetary policy initiatives were important in reducing market strains, the effect came after these policies were announced. Furthermore, instances where large errors in fiscal and monetary policy occurred – such as the failures to pass the TARP bill in September 2008, and adhere to optimal monetary policy rules during the second half of 2007 and the final quarter of 2008 – were instances in which $p^{highsprd}$ rose sharply.

These findings are consistent with the statistical analysis in Section 3.6, which found that the efficacy of these LOLR policies was partly undermined by the stance of conventional monetary policy.

3.8 Implementation effects

The discussion in Sections 3.6 and 3.7 focused largely on the announcement effects of the various fiscal and monetary policies. The examination of announcement effects assumes a degree of informational efficiency, in that each of the LOLR programs only affect market spreads upon announcement, with no effect upon each program's implementation, which may be a restrictive assumption.

[23] For example, the Federal Reserve announced, in November 2008, plans to purchase RMBS and collateralised debt obligations (CDOs) from AIG; and to purchase RMBS guaranteed by GSEs and GSE-issued debt.

There are two reasons for considering 'implementation effects'. The first concerns the framing of "conventional" monetary policy as the targeting of overnight interbank interest rates on the basis of open market operations in low risk assets. Policies based on longer-term and riskier assets, in an environment of a virtually zero Federal Funds rate, were viewed as "unconventional" since they were outside the traditional paradigm, even though these policies, in essence, augmented the Federal Reserve's traditional toolkit. Thus, there may have been a large degree of uncertainty about the potential effect of these policies on market spreads, at the time of announcement.

Secondly, there may have been doubts about the Federal Reserve's credibility in implementing these policies, which also may have muted their announcement effects. On the one (extreme) hand, if the unconventional policies were deemed completely credible, spreads should have fallen upon announcement of these policies, such that subsequent implementation was not required. Hence, the mere fact that these policies were implemented suggests the announcements lacked complete credibility. On the other hand, as noted above, the perceived "unconventional" nature of these policies may have muted their announcement effects, such that subsequent implementation was required.

To examine the potential for implementation effects, I use the dates given in Kroszner and Melick (2010) (see Table 3.1), and augment equations (3.3) and (3.4) with 3 dummy variables relating to the three types of unconventional monetary policies. These dummy variables equal 1 on the implementation date of the various policies, and zero otherwise. The VAR(1)-GARCH(1,1) model becomes:

$$\mathbf{X}_t = \alpha + \beta \mathbf{X}_{t-1} + \Theta D_t^{Fiscal} + \Gamma \mathbf{D}_t^{Unconv,Ann} + \eta Stance_t + \mu \mathbf{D}_t^{Unconv,Imp} + \epsilon_t \quad (3.6)$$

where $\mathbf{X}_t$, D_t^{Fiscal}, and $Stance_t$ are the same as in equation (3.3). $\mathbf{D}_t^{Unconv,Ann}$ is a 1x3 vector of dummy variables that equal one when an "unconventional" monetary policy announcement occurs at time t, $t-1$, or $t+1$, and zero otherwise. $\mathbf{D}_t^{Unconv,Imp}$ is a 1x3 vector of dummy variables that equal one when one of the three types of unconventional monetary policies are implemented, and zero otherwise. ϵ_t is a 3x1 vector of residuals, with $\epsilon_t|\Sigma_{t-1} \sim N(0, \mathbf{H}_t)$. The conditional covariance matrix $\mathbf{H}_t$ is given by:

$$\begin{aligned} \mathbf{H}_t = \mathbf{CC}' + \mathbf{A}\epsilon_{t-1}\epsilon'_{t-1}\mathbf{A}' + \mathbf{BH}_{t-1}\mathbf{B}' + \mathbf{E}D_t^{Fiscal} + \mathbf{FD}_t^{Unconv,Ann} \\ + \mathbf{GD}_t^{Unconv,Imp} + \mathbf{J}Stance_t \end{aligned} \quad (3.7)$$

For the sake of brevity, I report only the parameter coefficients corresponding to the policy variables. The results for equations (3.6) and (3.7) are given in Tables 3.6 and 3.7, respectively.

All three categories of "unconventional" monetary policy initiatives had sig-

Table 3.6: VAR parameter estimates – all bonds

This table reports the parameter estimates from equation (3.6), with multivariate GARCH(1,1) corrected z-statistics in brackets. The multivariate GARCH model is equation (3.7). *LIB-OIS* is the spread between the 1-month LIBOR and the 1-month OIS rate, *Repo* is the 1-month repo-OIS spread, and *Bond* is the spread between duration-matched U.S. corporate bonds and U.S. Treasuries. D^{Fisc} is a dummy variable that equals 1 when a fiscal policy announcement is made (or one day preceding or proceeding the announcement), while $D^{Mat,Ann}$, $D^{Cpart,Ann}$ and $D^{Coll,Ann}$ are dummy variables relating to a 3-day window around announcements of the three types of Federal Reserve policies. $D^{Mat,Imp}$, $D^{Cpart,Imp}$ and $D^{Coll,Imp}$ are dummy variables equal to one on days when the respective Federal Reserve policy types are implemented. Finally, *Stance* is the monetary policy stance, defined as the difference between the actual effective Federal Funds rate and the effective rate implied by a Taylor rule (equation (3.2)). The estimations are based on daily data from July 1, 2007 to February 2, 2009 (397 trading days).

Dep. var	D^{Fisc}	$D^{Mat,Ann}$	$D^{Cpart,Ann}$	$D^{Coll,Ann}$	*Stance*	$D^{Mat,Imp}$	$D^{Cpart,Imp}$	$D^{Coll,Imp}$
LIB-OIS	0.069	0.003	-0.025	-0.021	0.033	-0.021	-0.037	-0.085
	[4.62]	[0.59]	[-2.78]	[-2.07]	[2.31]	[-4.07]	[-4.93]	[-5.62]
Repo	0.105	0.003	-0.009	0.004	0.020	-0.033	-0.053	-0.117
	[4.25]	[0.25]	[-0.54]	[0.24]	[2.14]	[-2.77]	[-2.33]	[-4.92]
Sprd	0.107	-0.025	0.068	-0.032	0.048	0.013	-0.207	-0.258
	[3.17]	[-0.39]	[0.28]	[-1.53]	[1.96]	[1.32]	[-2.84]	[-2.97]

nificant implementation effects on LIBOR-OIS and repo spreads, with less significant effects for bond spreads (Table 3.6). For all spreads, implementation effects greatly dominated announcement effects, across all three types of monetary policies. This finding is consistent with the graphical analysis of regime probabilities in Section 3.7, which revealed that the periods in which $p^{highsprd}$ declined were typically those periods in which monetary policies were implemented, rather than announced.

The implementation effects were greatest for programs that widened the collateral eligible for Federal Reserve liquidity support, with spreads falling between 10 and 26 basis points, upon the programs' implementation (Table 3.6). Announcement effects are statistically significant only for LIBOR-OIS spreads, and only for two of the three policy categories, which fell by $7\frac{1}{2}$ basis points over the 3-day window. The second largest implementation effects was observed for programs that broadened the range of counterparties to Federal Reserve support, with spreads declining by 5-11 basis points upon the programs' implementation.

Finally, even after controlling for the effects of "unconventional" monetary policies, fiscal policy announcements still had significant and destabilising influences on spreads. In addition, the monetary policy stance remains a significant influence on spreads, as was the case in Table 3.2.

Table 3.7 reveals that significant implementation effects occur only for the conditional variance of LIBOR-OIS and bond spreads, and only for Federal Reserve policies that expanded the range of counterparties and eligible collateral ($D^{Cpart,Imp}$ and $D^{Coll,Imp}$, respectively). In terms of announcements, the only

Table 3.7: BEKK multivariate GARCH model estimates – all bonds

This table reports selected parameter estimates from equation (3.4), with Bollerslev-Wooldridge adjusted z-statistics in brackets. $\sigma^2_{LIB-OIS}$, σ^2_{Repo}, and σ^2_{Bond} is the conditional variance of residuals from equation (3.6) for, respectively, *LIB-OIS*, *Repo* and *Bond*. D^{Fisc} is a dummy variable that equals 1 when a fiscal policy announcement is made (or one day preceding or proceeding the announcement), while $D^{Mat,Ann}$, $D^{Cpart,Ann}$ and $D^{Collat,Ann}$ are dummy variables relating to a 3-day window around announcements of the three types of Federal Reserve policies. $D^{Mat,Imp}$, $D^{Cpart,Imp}$ and $D^{Collat,Imp}$ are dummy variables equal to one on days when the respective Federal Reserve policy types are implemented. Finally, *Stance* is the monetary policy stance, defined as the difference between the actual effective Federal Funds rate and the effective rate implied by a Taylor rule (equation (3.2)). The estimations are based on daily data from July 1, 2007 to February 2, 2009 (397 trading days).

Dep. var	D^{Fisc}	$D^{Mat,Ann}$	$D^{Cpart,Ann}$	$D^{Coll,Ann}$	*Stance*	$D^{Mat,Imp}$	$D^{Cpart,Imp}$	$D^{Coll,Imp}$
$\sigma^2_{LIB-OIS}$	0.008	-0.021	0.001	0.002	0.003	-0.001	-0.013	-0.029
	[0.92]	[-2.72]	[0.93]	[0.62]	[3.91]	[-0.27]	[-3.40]	[-6.85]
σ^2_{Repo}	0.010	-0.004	0.006	0.000	0.017	-0.003	-0.023	0.036
	[0.46]	[-0.20]	[0.37]	[-0.01]	[1.77]	[-0.16]	[-0.87]	[1.27]
σ^2_{Sprd}	-0.089	-0.001	-0.331	-0.007	0.001	-0.201	-0.197	-0.317
	[-0.32]	[-0.16]	[-3.34]	[-0.09]	[0.92]	[-0.61]	[-4.11]	[-2.98]

policies with significant effects were those that increased the maturity of Federal Reserve support (for the LIBOR-OIS spread), and policies that expanded the range of counterparties (for bond spreads). In contrast to Table 3.3, neither $D^{Collat,Ann}$ nor $D^{Fiscal,Ann}$ are statistically significant.

In sum, the evidence in Tables 3.6 and 3.7 suggests that the implementation effects of Federal Reserve policies outweighed the announcement effects, though the statistical significance of these effects is greater for conditional means. All three types of "unconventional" monetary policies were important in reducing market strains, though the most important were policies that expanded the range of eligible collateral in the Federal Reserve's open market operations, followed by policies that broadened the range of counterparties. Notably, fiscal policy announcements continued to exert a destabilising influence on conditional means, while the monetary policy stance continued to have a destabilising influence on both conditional means and conditional variances.

3.8.1 Flow-of-funds effects

The above discussion focused on the effects of the Federal Reserve's "unconventional" policies at the time these policies started (so-called "implementation effects"). However, it is possible that these policies also had "flow-of-funds" effects; market strains may not have eased until the Federal Reserve began lending sufficient amounts of funds to troubled institutions. Significant flow-of-funds effects would suggest that investors were not forward-looking and did not form rational expectations. An alternative possibility, as noted above, is that Federal Reserve policy may have been subject to a time inconsistency issue, so spreads did not fall until these programs were implemented.

In this section, I examine flow-of-funds effects by considering the correlation between market spreads and the outstanding value of the various Federal Reserve LOLR programs. A key empirical limitation with this analysis is that data on the size of the various programs are weekly, which makes it impossible to examine higher-frequency impacts of the Federal Reserve's programs on market spreads. It also precludes examination of announcement and implementation effects, as the weekly dates typically do not coincide with the announcement and implementation dates in Table 3.1.[24] Consequently, the results below should be treated with some caution, since an inability to control for high-frequency announcement and implementation effects may bias the estimated flow-of-funds effects.

One possible way to include flow-of-funds effects into the prior analysis is to include them as exogenous variables in the VAR(1)-GARCH(1,1) model. However, I find strong evidence – on the basis of the test of Hausman (1978) – that $\mathbf{Stock}_t$ is endogenous. Hence, I formulate a multivariate model in which the instrumental variables for $\mathbf{Stock}_t$ are its own 1-period lagged values, such that the model resembles the previous VAR(1)-GARCH(1,1), but with AR terms relating to the stock of Federal Reserve programs (in trillions of U.S. dollars) appearing as exogenous regressors:

$$\mathbf{X}_t = \alpha + \beta \mathbf{Y}_{t-1} + \eta Stance_t + \nu \mathbf{Stock}_{t-1} + \epsilon_t \tag{3.8}$$

where $\mathbf{X}_t$ and $Stance_t$ are the same as in equation (3.3) (though measured at a weekly frequency), while $\mathbf{Stock}_{t-1}$ is a 1x3 vector related to the weekly outstanding value of the three types of "unconventional" monetary policies. ϵ_t is again a 3x1 vector of residuals, with $\epsilon_t|\Sigma_{t-1} \sim N(0, \mathbf{H}_t)$. The conditional covariance matrix $\mathbf{H}_t$ is given by:

$$\mathbf{H}_t = \mathbf{CC}' + \mathbf{A}\epsilon_{t-1}\epsilon'_{t-1}\mathbf{A}' + \mathbf{BH}_{t-1}\mathbf{B}' + \mathbf{J}Stance_t + \mathbf{K}Stock_{t-1} \tag{3.9}$$

The output of equations (3.8) and (3.9) are presented in Tables 3.8 and 3.9, respectively.

Table 3.8 reveals that there are highly statistically significant "flow-of-funds" effects on bond spreads, with less significant effects on LIBOR-OIS and repo spreads. A U.S. \$1 trillion rise in the stock of securities obtained through the Federal Reserve's "unconventional" policies leads to a 62 basis point (12 per cent) fall in bond spreads, an economically significant result, but has no significant effect

[24]Even if announcement or implementation dates coincided with the dates of the weekly lending data, the dummy variable specification would presume the effects last for one week. Using a 1-week event window would bias the estimated effects, since other events occurring during a particular week are erroneously included with the given policy event.

Table 3.8: VAR parameter estimates – all bonds

This table reports the parameter estimates from equation (3.8), with multivariate GARCH(1,1) corrected z-statistics in brackets. The multivariate GARCH model is equation (3.9). *LIB-OIS* is the spread between the 1-month LIBOR and the 1-month OIS rate, *Repo* is the 1-month repo-OIS spread, and *Bond* is the spread between duration-matched U.S. corporate bonds and U.S. Treasuries. *Stance* is the monetary policy stance, defined as the difference between the actual effective Federal Funds rate and the effective rate implied by a Taylor rule (equation (3.2)). $Stock^{All}$ is the outstanding value (as at the end of each Wednesday) of securities held under all the various Federal Reserve LOLR programs. $Stock^{Mat}$, $Stock^{Cpart}$, and $Stock^{Collat}$ is the weekly stock of securities held under Federal Reserve programs that, respectively, increase the maturity of support (*Mat*); widen the counterparties to the support (*Cpart*); and broaden the types of collateral eligible for secured funding (*Collat*). All outstanding values are in trillions of U.S. dollars. The estimations are based on daily data from July 1, 2007 to February 2, 2009 (397 trading days).

Dep. var	*Stance*	$Stock^{All}(-1)$	$Stock^{Mat}(-1)$	$Stock^{Cpart}(-1)$	$Stock^{Collat}(-1)$
Panel A: All "unconventional" Federal Reserve programs					
LIB-OIS	-0.001	-0.012			
	[-0.26]	[-1.32]			
Repo	-0.001	-0.036			
	[-0.03]	[-1.56]			
Sprd	0.181	-0.617			
	[11.7]	[-10.4]			
Panel B: Individual types of "unconventional" Federal Reserve programs					
LIB-OIS	0.044		-0.017	-0.176	-0.108
	[2.35]		[-0.78]	[-1.70]	[-2.44]
Repo	0.022		0.160	-0.256	-0.167
	[-1.37]		[0.96]	[-3.89]	[-3.56]
Sprd	0.191		-1.292	0.109	-0.585
	[1.81]		[-2.11]	[1.36]	[-2.05]

on LIBOR-OIS and repo spreads (Panel A).[25]

While the flow-of-funds effects are, in aggregate, insignificant for LIBOR-OIS and repo spreads, there are significant effects for specific policies. In particular, those Federal Reserve programs that expanded the range of counterparties (*Cpart*) and eligible collateral (*Collat*) led to significant declines in LIBOR-OIS and repo spreads. A U.S.$0.3 trillion rise in the stock of securities acquired under *Cpart* led to a decline in LIBOR-OIS and repo spreads of 5 basis points and 8 basis points, respectively, while a similar rise in the stock of securities acquired under *Collat* led to a decline of 3 and 5 basis points, respectively (Panel B). In terms of bond spreads, policies that increased the maturity of support (*Mat*) had the largest flow-of-funds effects; a $0.3 trillion rise in the stock of assets obtained under *Mat* led to a 38 basis point decline in bond spreads.

The policies with the largest flow-of-funds effects are not necessarily the biggest policies by U.S. dollar value; for example, although *Collat* was the smallest of the three policy types (see Figure 3.2), it had greater flow-of-funds effects on LIBOR-OIS and repo spreads, than the larger *Mat* programs.

[25] The U.S dollar values chosen for the comparative static analysis is based on outstanding values of the collective and individual Federal Reserve programs shown in Figure 3.2

The flow-of-funds effects are weaker for conditional variances than for con-

Table 3.9: BEKK multivariate GARCH model estimates – all bonds

This table reports selected parameter estimates from equation (3.4), with Bollerslev-Wooldridge adjusted z-statistics in brackets. $\sigma^2_{LIB-OIS}$, σ^2_{Repo}, and σ^2_{Bond} is the conditional variance of residuals from equation (3.8) for, respectively, *LIB-OIS*, *Repo* and *Bond*. *Stance* is the monetary policy stance, defined as the difference between the actual effective Federal Funds rate and the effective rate implied by a Taylor rule (equation (3.2)). $Stock^{All}$ is the outstanding value (as at the end of each Wednesday) of securities held under all the various Federal Reserve LOLR programs. $Stock^{Mat}$, $Stock^{Cpart}$, and $Stock^{Collat}$ is the weekly stock of securities held under Federal Reserve programs that, respectively, increase the maturity of support (*Mat*); widen the counterparties to the support (*Cpart*); and broaden the types of collateral eligible for secured funding (*Collat*). All outstanding values are in trillions of U.S. dollars. The estimations are based on daily data from July 1, 2007 to February 2, 2009 (397 trading days).

Dep. var	*Stance*	$Stock^{All}(-1)$	$Stock^{Mat}(-1)$	$Stock^{Cpart}(-1)$	$Stock^{Collat}(-1)$
		Panel A: All "unconventional" Federal Reserve programs			
$\sigma^2_{LIB-OIS}$	0.008	-0.014			
	[7.73]	[-3.48]			
σ^2_{Repo}	0.018	0.022			
	[2.57]	[1.31]			
σ^2_{Sprd}	0.013	-0.001			
	[1.72]	[-0.14]			
		Panel B: Individual types of "unconventional" Federal Reserve programs			
$\sigma^2_{LIB-OIS}$	0.004		-0.008	-0.023	0.006
	[4.89]		[-1.98]	[-1.32]	[0.95]
σ^2_{Repo}	0.018		0.001	-0.013	0.018
	[3.21]		[1.55]	[-0.71]	[0.46]
σ^2_{Sprd}	0.570		-0.081	0.543	-0.048
	[20.4]		[-1.63]	[0.29]	[-0.82]

ditional means. Collectively, the Federal Reserve's LOLR programs only had a significant impact on the conditional variance of LIBOR-OIS spreads (Panel A, Table 3.9). A U.S.$1 trillion dollar rise in the stock of securities held by the Federal Reserve led to a 12 basis point (11 per cent) fall in LIBOR-OIS spreads' conditional volatility. Individually, only programs that increased the maturity of Federal Reserve support had a flow-of-funds effect, with the only dependent variable affected being the conditional variance of LIBOR-OIS spreads (Panel B, Table 3.9). While this effect is statistically significant (at the 5% level), its economic significance is modest; a U.S.$0.3 trillion dollar rise in *Mat* leads to a 8 basis point (7 per cent) fall in conditional volatility. The lack of economic significance in the size of the estimated coefficients is consistent with Frank and Hesse (2009), though they focus on one specific policy (the Term Auction Facility) and one spread (LIBOR-OIS spread).

These findings are consistent with the possibility that the Federal Reserve faced a time-consistency problem when announcing their policies. Moreover, since these programs were viewed as "unconventional", since they were outside the traditional framing of monetary policy as the targeting of overnight interest rates via investments in low-risk government securities, there may been uncertainty about their efficacy in reducing market spreads. It may also suggest that investors' expectation formation evolved in an adaptive, non-rational manner, as well as evidence of informational inefficiency, since any time consistency issues would have been resolved once the Federal Reserve implemented their policies. Consequently, if investors were forming rational expectations and markets were informationally efficient, the policies' effects on spreads should have occurred at the time of implementation; subsequent amounts loaned through these programs should not have constituted new information. Since these alternative views have observationally equivalent implications for market spreads, it is not clear which, if any, of these views were the dominant forces during this period.

Baba and Packer (2009) note that there were large and sustained deviations from covered interest rate parity during the crisis, which suggests a large degree of informational inefficiency in the FX market. Baba and Packer find that U.S. dollar funding from the ECB, supported by U.S. dollar swap lines with the Federal Reserve, lowered the volatility (though not the level) of deviations from CIP. Disentangling the separate effects of policy credibility, non-rational expectations, and informational inefficiency, on the estimated announcement, implementation and flow-of-funds effects, is outside the scope of this chapter, and is an important, though challenging, exercise for future research.

3.9 Conclusion

In this essay I assessed the impact of the various "unconventional" policies, introduced by the U.S. Federal Reserve during the 2007-09 financial crisis period, on market spreads. I also examined the impact of key fiscal policy announcements made by the U.S. Federal Government. This essay has a key differentiating feature from the related literature – rather than focus on one or two policy initiatives, I examined the market impact of all major fiscal and unconventional monetary policies announced between mid-2007 and early 2009. Due to the large number of policies – between December 2007 and March 2009 the Federal Reserve initiated 16 programs – I used Kroszner and Melick (2010)'s categorisation scheme to classify the various policies into three categories: (i) an expansion of the type of counterparties receiving support; (ii) a broadening of the collateral eligible for support; and (iii) a lengthening of the maturity of the support.

Using this framework, this essay presented six key findings. Firstly, all three types of Federal Reserve policies were effective in reducing market spreads, with the most effective being policies that broadened the range of collateral eligible for secured funding from the Federal Reserve. This finding is consistent with Gorton (2010)'s argument that asset markets – especially the markets for bonds securitised by U.S. residential mortgages – rather than specific institutions, precipitated the onset of the global financial crisis. Thus, policies that broadened the range of eligible collateral to include broader segments of securitised bond markets were more effective in alleviating market strains than either of the other two types of policies.

Secondly, I find that these policies were more effective in reducing short-term unsecured and secured funding costs, rather than spreads on longer-term bonds. This finding is consistent with Ericsson and Renault (2006), who find that liquidity risk represents the largest component of short-term debt spreads, with the opposite true for longer-term securities. Hence, the liquidity support offered by the Federal Reserve may have been more effective in reducing liquidity risk premia, rather than credit risk premia. Consequently, these policies had a larger impact on funding costs than bond spreads.

Thirdly, these policies were more effective in reducing the level of spreads rather than their conditional variances. These findings contrast those of Baba and Packer (2009), who, focusing on the effects of one particular policy initiative (U.S. dollar swap lines between central banks), find greater effects on conditional variances than conditional means. One point of difference between my findings and those of Baba and Packer (2009) is that I focus on the effect of all key unconventional policies, as well as fiscal policy announcements, rather than individual policies.

Fourthly, I find that "implementation effects" and "flow-of-funds" effects – respectively, the effect on spreads at the time policies were implemented, and the effect on spreads from higher amounts loaned from these programs – were an order of magnitude larger than "announcement effects" – the effect on spreads at the time these policies were announced. These findings have three key implications.

Firstly, these findings suggest that the Federal Reserve may have faced a time-consistency issue at the time their LOLR policies were announced. Secondly, as these policies were outside the typical framing of monetary policy, these policies were perceived as "unconventional", creating uncertainty about these policies' effects on market spreads. Thirdly, the findings may be evidence of investor irrationality (in the form of myopia) and/or markets' informational inefficiency. Disentangling these separate effects, and identifying which, if any, dominate(s) is an important exercise for future research.

Fifth, fiscal policy announcements had either insignificant, or significant but destabilising, effects on market spreads. Taylor (2011) found that the Troubled Asset Relief Program (TARP) bill created greater market uncertainty and exacerbated market strains. In contrast to Taylor (2011), I examined a broader range of fiscal policies, but reached a similar conclusion.

Following Rudebusch (2009), I measured the monetary policy stance as the deviation of the actual Federal Funds rate from the rate implied by a Taylor rule. This measure of the policy stance implied that policy became increasingly contractionary during the crisis. My final finding in this essay was that the policy stance had a destabilising influence on spreads, offsetting some of the stabilising influence of the various unconventional policies and thereby limiting the effectiveness of the Federal Reserve's overall response to the crisis. In short, the Federal Reserve's success in reducing strains in U.S. credit markets was undermined by their inability (or, more provocatively, their failure) to achieve their macroeconomic objectives.

These findings have two additional research extensions, the first being an examination of the impact of the monetary policy stance on U.S. equity markets and other assets sensitive to growth expectations. Secondly, as this essay focused on U.S. monetary policy and U.S. credit markets, a cross-country analysis should be undertaken, examining the effect of both local central bank and foreign central banks' (like the U.S. Federal Reserve) monetary policy settings on asset prices. Krugman (2008) argues that the 'international finance multiplier' – the process by which changes in asset prices are transmitted internationally through their effects on the balance sheets of leveraged global financial institutions – played a key role in transmitting the U.S. crisis to a systemic run, in addition to international trade linkages. As Krugman notes, an implication of a large international finance multiplier is that monetary and fiscal policy initiatives have positive cross-border externalities. To investigate the importance of these externalities, the analysis undertaken here should be extended to consider the various fiscal and monetary policy initiatives on global credit markets.

Appendix A

Appendix to Chapter 1

A.1 In-sample evidence: multivariate models

A.1.1 Granger causality

In this section, I consider the possibility of economic growth variables having predictive power over market illiquidity, since such a finding would improve the conditional forecasts of a multivariate model vis-a-vis a univariate representation. Söderberg (2008) and Goyenko and Ukhov (2009) find, respectively, that Scandinavian and U.S monetary policy Granger cause stock and bond market illiquidity in these countries. As economic growth has been found to Granger cause the stance of monetary policy, it is likely that economic growth may also Granger cause market liquidity. In testing whether economic growth variables Granger cause the quarter-t financial market variables, I use the economic growth values at the end of quarter t-2, since the economic data are published with a lag of one quarter.

The findings are reported in Table A.1. With the exception of the term spread, there is weak evidence that economic growth Granger causes asset returns or liquidity. For the U.S., term spreads are Granger caused by durables' and overall consumption growth, while Australian term spreads are Granger caused by durables' consumption growth, GDP growth, and investment growth. In conjunction with the predictive power of term spreads for economic growth (see Table 1.3), the strong evidence of bi-directional causality is consistent with the findings of Ang, Piazessi and Wei (2006).

In contrast to the U.S., Australian economic growth variables also Granger cause stock returns, though the level of statistical significance (10%) is not overly strong. These findings may reflect the possibility that Australian economic growth indicators provide information on future growth in earnings and dividends, information not contained in lagged daily returns, which also reflect discount rate innovations.

Table A.1: Granger causality tests

The table shows Granger causality tests between the economic growth and financial variables, for the U.S. (Panel A) and Australia (Panel B), over the entire sample period (March 1973 to December 2010). *dILR* is the Hodrick-Prescott detrended component of *ILR*, and *Eq. Roll* and *Bd. Roll* is the Roll estimator of the effective bid-ask spread in the equity and bond market, respectively. The null hypothesis tested is that the variable in a particular row does not Granger cause the variable in a particular column ('dependent variable'). The choice of lag length for each test is based on the Schwartz criterion. *, ** and *** denote rejection of the null at the 10%, 5% and 1% significance levels, respectively.

	Dependent variable						
	dILR	*Eq. Roll*	*Bd. Roll*	*Term*	*Cred*	er_m	*Vol*
			Panel A: U.S.				
GDP	0.41	0.92	1.09	0.72	1.46	0.22	1.79
CONS	0.95	0.06	1.74	4.20**	2.63	0.01	0.26
DCONS	0.13	0.50	0.08	10.23***	0.08	0.07	0.23
INV	0.02	1.18	0.04	0.03	0.07	0.00	3.25*
dILR		0.02	1.02	7.17***	5.96**	12.96***	0.37
Eq. Roll	7.42***		3.56*	4.08**	6.87***	0.29	0.01
Bd. Roll	2.18	6.85***		0.04	0.02	0.14	0.52
Term	8.40***	3.17*	0.25		2.13	2.73*	2.93*
Cred	1.43	3.93**	10.61***	3.35*		1.10	2.73*
er_m	29.53***	0.01	0.06	1.53	18.25***		1.03
Vol	0.02	0.52	0.25	0.62	1.31	0.14	
			Panel B: Australia				
GDP	1.17	0.06	0.59	6.23**	3.89*	5.64*	0.69
CONS	0.30	1.36	0.73	0.46	0.81	0.08	0.47
DCONS	1.52	0.02	0.01	8.20***	2.12	3.46*	0.75
INV	0.14	1.22	0.63	3.83*	2.12	3.32*	2.04
dILR		0.09	3.35*	0.84	0.16	0.95	0.38
Eq. Roll	0.02		0.01	1.96	0.79	0.01	5.91**
Bd. Roll	0.99	0.98		5.29**	0.09	1.86	0.63
Term	0.23	1.70	0.17		0.71	0.66	1.93
Cred	0.01	0.38	0.20	7.28***		0.01	1.43
er_m	0.53	0.02	1.12	0.10	0.78		1.11
Vol	0.03	0.41	0.33	1.63	1.05	1.39	

In terms of the predictive content among financial market variables, there is evidence of bi-directional Granger causality between U.S. bond and stock market illiquidity, similar to the findings of Goyenko and Ukhov (2009). The predictive content of the other financial variables are also stronger for the U.S. than for Australia: U.S. equity market illiquidity has predictive power over the pricing and illiquidity of government bonds, as well as term spreads and credit spreads, in contrast to Australian equity market illiquidity.

In summary, the Granger causality tests imply that using a VAR to forecast the financial variables would be superior than generating forecasts from univariate AR models.

A.1.2 VAR models

For the financial market variables, I estimate a VAR(1), with the economic growth equation given by equation (1.5). The lag length is chosen on the basis of the Schwartz criterion and a desire for parsimony, to minimise overfitting. In each VAR, there are 8 variables: an economic growth variable (*GDP*, *CONS*, *DCONS*, or *INV*), plus the 7 financial market variables. Furthermore, there are 16 possible VARs: 8 for Australia (4 VARs for each stock market illiquidity measure) and 8 for the U.S. Hence, for the sake of brevity, I report only the VAR results for growth in real GDP and durables' consumption (respectively, *GDP* and *DCONS*). I choose *GDP* to facilitate comparison with Næs et al. (2011), and *DCONS* is chosen as equation (1.5) has the highest $\bar{R}^2$ for this economic growth indicator. I do not present the results for the other two VARs, with the results available upon request.
The model estimated is a VAR of the following form:

$$\mathbf{X}_t = \alpha + \beta' y_{t-2} + \gamma' \mathbf{Z}_{t-1} + \epsilon_t \tag{A.1}$$

where $\mathbf{X}_t$ is a vector consisting of one economic growth variable (quarterly growth in real GDP or real durables' consumption), and the following six financial market variables:

- stock market illiquidity (*dILR* measure for the U.S.; *Roll* measure for Australia);
- *Roll* measure of bond market illiquidity (*Bd. Roll*);
- the slope of the government bond yield curve, defined as the difference between 10-year and 3-month government bond yields (*Term*);
- corporate bond spreads (*Cred*). For the U.S., this is defined as the difference between Moody's 30-year Aaa-rated and Baa-rated corporate bond yields; for Australia, it is the yield differential between 10-year Australian Commonwealth government bonds and an index of investment-grade Australian corporates' bonds;
- quarterly equity market returns in excess of 3-month government bond yields (er_m); and
- the standard deviation of daily excess equity returns over each quarter (*Vol*).

$\mathbf{Z}_{t-1}$ is $\mathbf{X}_{t-1}$ excluding the economic growth variable, and y_{t-2} is the growth in the macroeconomic variable of interest between quarter t-3 and t-2. This specification for the VAR is consistent with the fact that publication of the economic data is subject to a one-quarter lag.

For the U.S., the VAR is based on the (detrended) *ILR* measure of stock market illiquidity, while for Australia I use the *Roll* measure, as these measures have, respectively, the highest $\bar{R}^2$ over U.S. and Australian economic growth. Finally, I also present the impulse responses from the four VARs (two for each country). For ease of illustration, I show only the impulse responses that have statistically significant values (at the 5% level) at some point between the first and tenth period following a shock.

As the impulse responses are based on orthogonalised error terms, differences occassionally arise between the size and statistical significance of the impulse response functions (IRFs), and the statistical significance of the estimated VAR coefficients. This reflects the collinearity between the regressors (see Table 1.2), which reduces the precision of the estimators. Consequently, I focus on the IRFs, which, given the presence of multicollinearity, is more appropriate.[1]

For all impulse response figures, I use Pesaran-Shin (1998) generalised IRFs, which do not depend on the ordering of the variables in the VAR when orthogonalising shocks. I use this method for both practical and theoretical reasons. Firstly, the literature is equivocal on the ordering of the liquidity and economic growth variables. On one hand, one can argue that economic growth is exogenous to financial market prices, and hence should be ranked first in the VAR. However, Næs, Skjeltorp, and Ødegaard (2011) put economic growth last in the ordering since growth data (but not financial market data) are published with a one quarter lag. While the issue of a publication lag is important from a forecasting perspective, it is not obvious why this should matter from a structural or theoretical perspective.

Furthermore, Chordia, Sarkar and Subrahmanyam (2005) argue (verbally; not on the basis of a theoretical model) that information and endowment shocks generally affect prices and liquidity through trading, implying that market illiquidity should appear before the level or volatility of returns. In contrast, in Eisfeldt (2004)'s theoretical model, shocks to agents' expected returns – which affect realised returns – contemporaneously affect market illiquidity, but not vice versa, implying that market illiquidity should rank below returns. Furthermore, it is an open question whether stock or bond market illiquidity should rank above the other; Goyenko and Ukhov (2009) rank stock market illiquidity above bond market illiquidity using Chordia, Sarkar and Subrahmanyam (2005) whose arguments, as noted above, lack rigorous theoretical motivation.

In order to assess the issue of ordering sensitivity, I used a Cholesky decomposition using each of the following seven orderings:[2]

1. *Cred*, *Term*, *BILLIQ*, *Vol*, er_m, *SILLIQ*, and *GDP* (Næs, Skjeltorp, and

[1] The coefficients for the various VAR models are available on request.

[2] Where relevant, the list also shows the corresponding paper (in brackets).

Ødegaard, 2011);

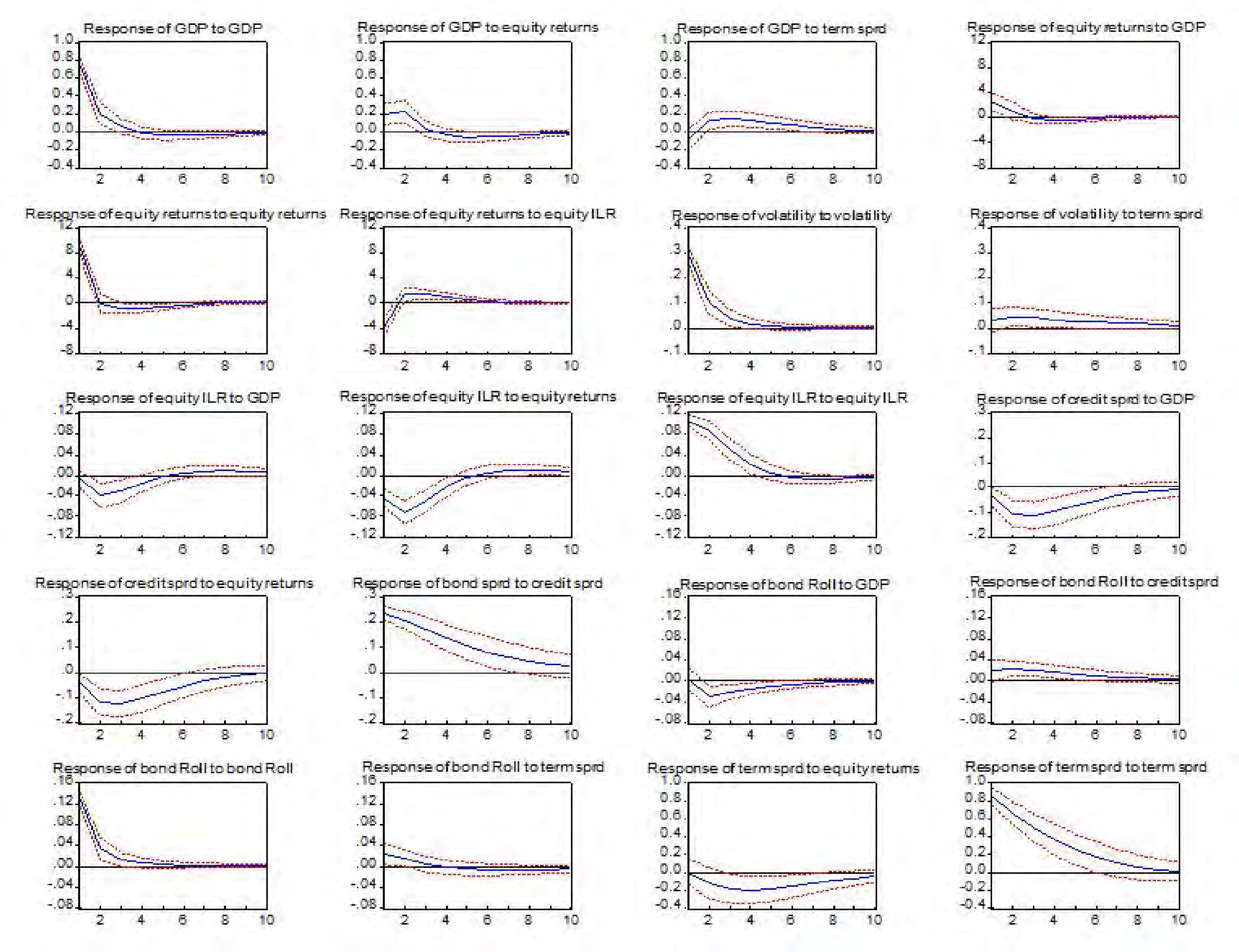
2. *Vol*, er_m, *SILLIQ*, *Cred*, *Term*, *BILLIQ*, and *GDP* (Næs et al., 2011);
3. *SILLIQ*, *BILLIQ*, *Vol*, er_m, *Cred*, *Term*, and *GDP* Chordia, Sarkar and Subrahmanyam, 2005);
4. *BILLIQ*, *SILLIQ*, *Cred*, *Term*, *Vol*, er_m, and *GDP* (Chordia et al., 2005);
5. *Vol*, er_m, *Cred*, *Term*, *SILLIQ*, *BILLIQ*, and *GDP* (Eisfeldt, 2004);
6. *Cred*, *Term*, *Vol*, er_m, *SILLIQ*, *BILLIQ*, and *GDP* (Eisfeldt, 2004); and
7. *GDP*, *Cred*, *Term*, *Vol*, er_m, *SILLIQ*, and *BILLIQ*.

I found that the statistical significance of the IRFs was not invariant to the specific ordering used, a finding also documented by Næs et al. (2011). Hence my second justification for the Pesaran-Shin (1998) methodology is pragmatic: rather than report 7! sets of impulse responses, I use an ordering-insensitive procedure to avoid the possibility that conclusions based on any given ordering may not be robust to a change in ordering.

The two-standard-error bands for the various impulse responses are based on the variance of the respective VAR residuals' empirical distribution. The empirical distribution is constructed from a bootstrap simulation with 10,000 repetitions. That is, using the sample of residuals, 10,000 draws from this sample are made (with replacement), generating a probability distribution ("empirical distribution") based on the 10,000 draws. The confidence interval ("error band") is constructed using the critical value, from a Gaussian distribution, corresponding to the 95% confidence level.

Figure A.1 shows that GDP growth shocks *do* impact financial market illiquidity, in contrast to the univariate-based results in Table A.1. A positive shock to GDP growth lowers equity market illiquidity by around 4 basis points below its trend level, lowers bond market illiquidity by 3 basis points (one-fifth), almost triples average equity returns, and lowers credit spreads by 12 basis points (an 8 per cent fall). Stock market illiquidity shocks lowers equity returns by 1 percentage point (72 per cent), though the response dies out by the fifth quarter following the shock. In contrast, shocks to bond market illiquidity only affect itself. These findings provide further evidence that financial market illiquidity changes (either expected or unexpected) have little direct impact on GDP growth or other financial variables. The impact of these shocks on real GDP growth is indirect; liquidity impacts asset returns, which, in turn, impact real GDP growth. Real GDP growth declines by 20 basis points (30 per cent) in response to a typical negative shock to equity returns, and declines by 10 basis points in response to a positive shock to

Figure A.1: **Impulse responses for U.S. real GDP growth**
The figure shows Pesaran-Shin (1998) generalised impulse responses, and accompanying two-standard error bands, for the VAR containing U.S. real GDP growth and selected financial market variables.



term spreads.[3]

These results imply that market illiquidity shocks affect GDP growth indirectly, via its effect on asset returns: positive illiquidity shocks lower returns, which in

[3]A rough calculation of the indirect effect of illiquidity shocks on real GDP growth can be determined by multiplying the impulse response of equity returns by the proportion that this response represents of its standard deviation. This calculation implies that a positive shock to equity illiquidity lowers real GDP growth by 2 basis points (3 per cent) on average, a fairly modest result.

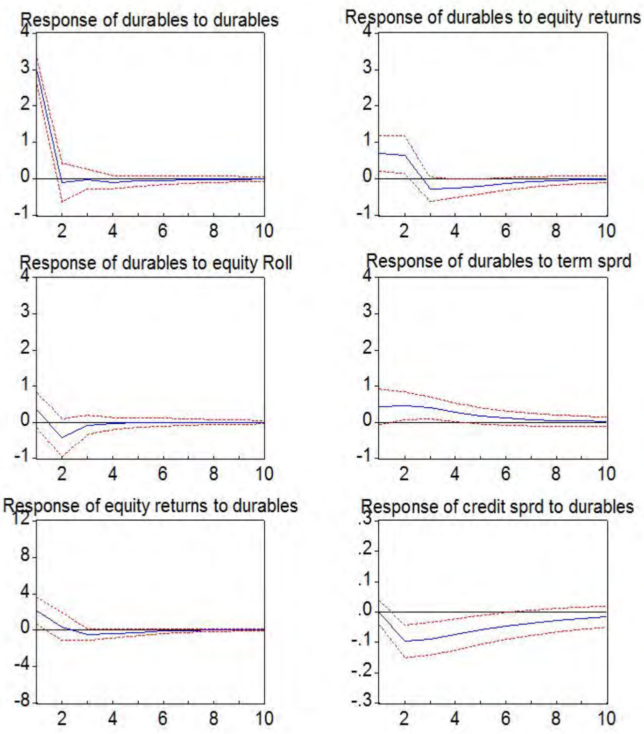
turn lowers economic growth. Furthermore, real GDP growth's response to illiquidity shocks is statistically significant (at the 10% level) when asset returns are excluded from the VAR. This suggests that, to the extent that market illiquidity does impact future economic growth, this impact is largely subsumed by asset returns. For equity market illiquidity, its effect is subsumed by excess equity returns, while for the bond market it is the term spread.

As the impulse responses of financial variables to financial variables' shocks are virtually identical when either GDP growth or durables' consumption growth appears in the VAR, I omit these impulse responses.

In contrast to Figure A.1, the impulse responses for U.S. durables' consump-

Figure A.2: **Impulse responses for U.S. real durables' consumption growth**

The figure shows Pesaran-Shin (1998) generalised impulse responses, and accompanying two-standard error bands, for the VAR containing U.S. real durables' consumption growth and selected financial market variables.



tion growth are more significant, both statistically and economically (Figure A.2). U.S. durables' consumption growth declines by around 50 basis points (one-half) a quarter after a positive equity market illiquidity shock, an economically and statistically significant response. In addition, there is the indirect impact, via equity returns: a positive shock to equity returns raises durables' consumption growth by 75 basis points (87 per cent). As is the case with Figure A.1, asset returns are highly responsive to economic growth shocks; a positive shock to U.S. real GDP (durables consumption) growth raises equity returns by $2\frac{1}{2}$ percentage points, or 180 per cent (2 percentage points) one quarter after the shock, while credit spreads decrease by around 100 basis points, or 65 per cent, two quarters after the shock. A positive bond market illiquidity shock has no impact on durables' growth, while a positive equity market illiquidity shock generates a small rise in durables' growth, though this response is only statistically significant at the 10% level.

In summary, the information content of market illiquidity seems largely to be subsumed by information in prices, for both the equity and bond markets. Moreover, where illiquidity shocks do have significant effects, it is typically the equity market, rather than the bond market, which is more important, which mirrors the findings from Table A.1.

Goyenko and Ukhov (2009) find that bond market liquidity responds faster to monetary policy shocks than equity market liquidity, with the bond market's impulse responses relatively longer-lived. Given the time lags involved in transmitting policy changes to the real economy, Goyenko's and Ukhov's findings may imply that equity market illiquidity is a relatively better predictor of short-term economic growth, while bond market illiquidity is a better predictor of medium-term economic growth. My findings provide support to the first part of this argument (i.e. short-term predictability), although a proper examination of predictability at different horizons is outside the scope of this paper and is left for future research.

For Australia, the results generally reveal that the financial market variables are highly responsive to financial market shocks, but unresponsive to GDP growth shocks (Figure A.3). Also, GDP growth does not respond to financial market shocks. This contrasts with the U.S. evidence above, and is consistent with the view that Australia's relatively smaller financial markets implies a lower degree of risk sharing and thus a smaller impact of market shocks on economic growth.

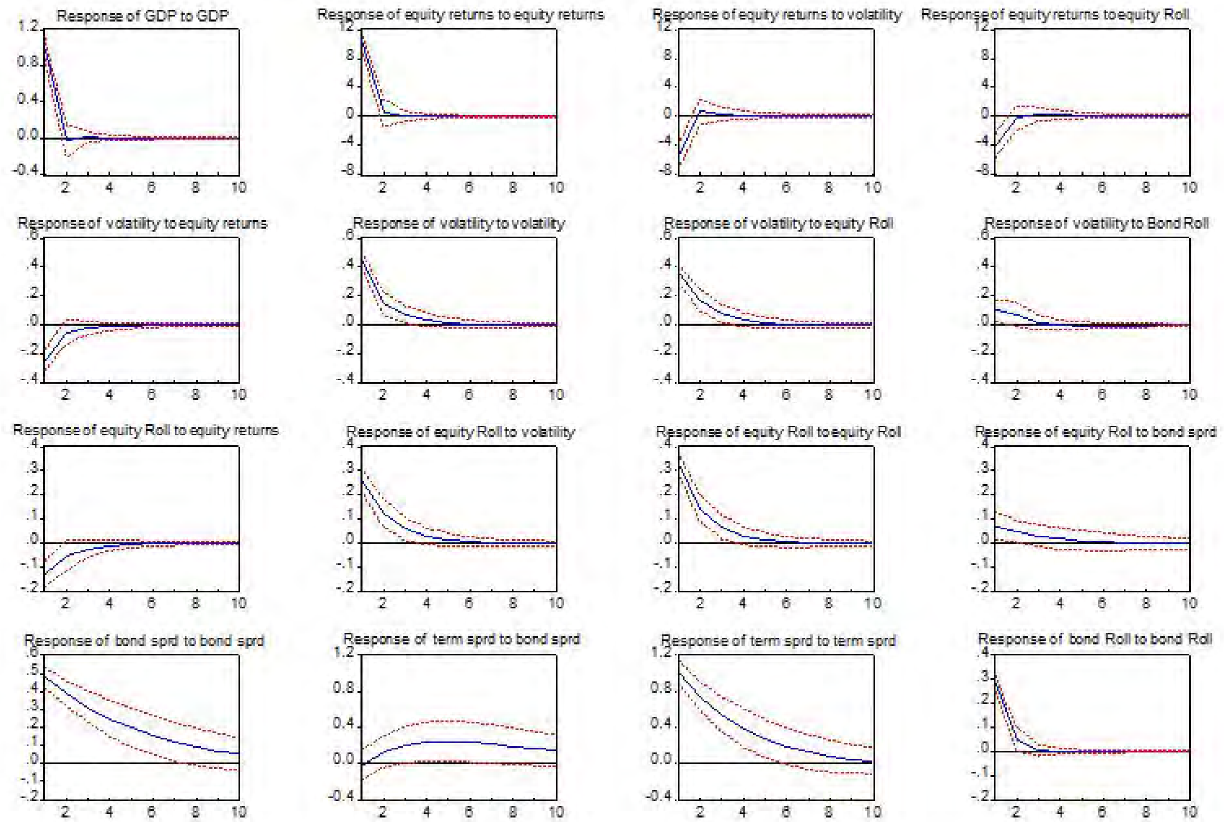
In terms of the financial variables, the level and volatility of equity returns, and equity market illiquidity, are highly responsive to each other's shocks, with equity returns falling two-fold in response to a positive volatility and illiquidity shock.

In turn, equity return volatility rises by 2 and 4 percentage points (a one- and three-fold rise) in response to a one-standard deviation shock to equity returns and illiquidity, respectively. Equity illiquidity and credit spreads are also responsive to each other's shocks; a positive shock to spreads leads to a 1 percentage point (130 per cent) rise in illiquidity (i.e. liquidity falls), while an illiquidity shock leads to a 125 per cent (100 basis point) rise in credit spreads.

Examining the (statistically significant) impulse responses for a VAR that in-

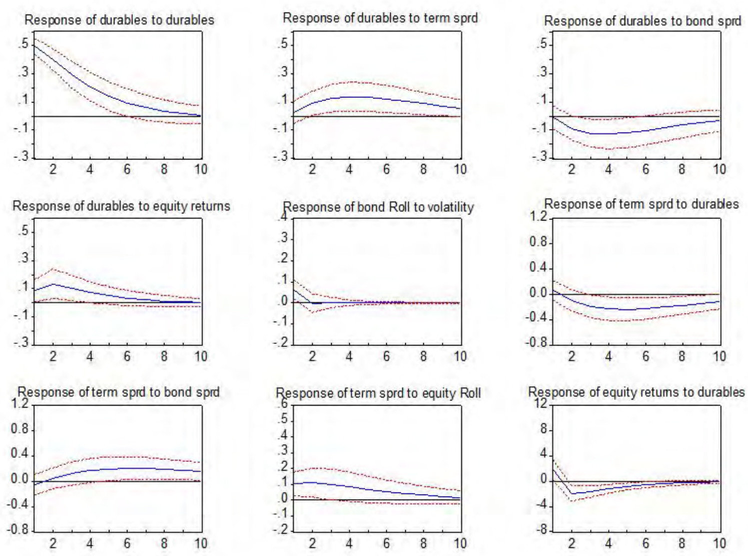
Figure A.3: **Impulse responses for Australian real GDP growth**

The figure shows Pesaran-Shin (1998) generalised impulse responses, and accompanying two-standard error bands, for the VAR containing Australian real GDP growth and selected financial market variables.



cludes durables' consumption growth reveals that durables' consumption is much more responsive to financial market shocks than GDP growth, and vice-versa (Figure A.4). For example, a shock to term spreads (i.e. an unexpected steepening of the yield curve) leads to a $1\frac{1}{2}$ percentage point rise in durables' growth (a one-and-three-quarter rise) about a year after the shock, while a one standard deviation positive shock to bond spreads lowers growth by a similar amount one year after the shock (Figure A.4). This behaviour of durables' consumption growth is intuitive: an unexpected steepening of the yield curve signals higher future growth and incomes, which raises the discretionary component of consumption as agents bring forward consumption. An unexpected rise in bond spreads works in a similar (though opposite) fashion.

Figure A.4: **Impulse responses for Australian durables' consumption growth**
The figure shows Pesaran-Shin (1998) generalised impulse responses, and accompanying two-standard error bands, for the VAR containing Australian real durables' consumption growth and selected financial market variables.



Financial market variables are also more responsive to discretionary consumption shocks, with a positive shock to durables' consumption leading to a 30 basis point (one-third) decline in the term spread a year after the shock, and a $1\frac{1}{2}$ percentage point rise in equity returns in the quarter following the shock. The response of equity returns likely reflects revisions to expected profit growth following the unexpected rise in discretionary expenditure.

A.2 Additional Markov-switching models

Table A.2 reports the results for the Markov-switching model (equation (1.9)) using the *Roll* and *dILR* measures of equity market illiquidity for the U.S. and Australia, respectively.

Table A.2: **Parameter estimates of Markov-switching regression model**

The table shows the results from estimating equation (1.9) between March 1973 and December 2010 (152 quarters), with two regimes and fixed transition probabilities. U.S. equity market illiquidity is proxied by *Roll*, and Australian equity market illiquidity is proxied by *dILR* (the H-P detrended component of *ILR*). t-statistics are shown in brackets. Only the parameters relating to market illiquidity and lagged economic growth are allowed to change across regimes.

y_{t+1}	$\hat{\alpha}^{a}$	$\hat{\beta}$	$\hat{\delta}$	$\hat{\rho}$	$\hat{\gamma}^{Term,a}$	$\hat{\gamma}^{Cred,a}$	$\hat{\gamma}^{er_m,a}$	$\hat{\gamma}^{Vol,a}$
Panel A: U.S.; 'Liquid' regime								
GDP	0.654	-0.181	-0.893	0.076	0.144	0.010	0.013	-0.141
	(2.80)	(-0.33)	(-1.04)	(1.03)	(4.19)	(0.09)	(2.32)	(-1.23)
CONS	0.674	3.893	-1.271	0.137	0.026	0.173	0.009	-0.240
	(3.34)	(1.44)	(-3.85)	(1.74)	(0.62)	(1.66)	(1.94)	(-2.13)
DCONS	-0.164	1.259	-1.817	0.184	0.424	-0.060	0.066	0.115
	(-0.20)	(0.63)	(-1.1)	(2.35)	(2.47)	(-0.15)	(2.89)	(0.19)
INV	0.132	2.127	4.056	-0.136	1.185	-1.989	0.126	-0.397
	(0.09)	(0.66)	(1.82)	(-1.94)	(5.52)	(-2.96)	(3.84)	(-0.47)
Panel B: U.S.; 'Illiquid' regime								
GDP	0.654	-1.869	0.344	0.300	0.144	0.010	0.013	-0.141
	(2.80)	(-2.28)	(0.84)	(2.39)	(4.19)	(0.09)	(2.32)	(-1.23)
CONS	0.674	-2.116	0.272	-0.277	0.026	0.173	0.009	-0.240
	(3.34)	(-2.04)	(0.33)	(-1.58)	(0.62)	(1.66)	(1.94)	(-2.13)
DCONS	-0.164	-2.530	1.773	0.210	0.424	-0.060	0.066	0.115
	(-0.20)	(-2.92)	(0.51)	(2.68)	(2.47)	(-0.15)	(2.89)	(0.19)
INV	0.132	-4.336	-7.757	0.966	1.185	-1.989	0.126	-0.397
	(0.09)	(-2.02)	(-3.62)	(6.34)	(5.52)	(-2.96)	(3.84)	(-0.47)
Adjusted R-squared of U.S. regime-switching model								
	GDP	*CONS*	*DUR*	*INV*				
	0.25	0.20	0.24	0.26				
Panel C: Australia; 'Liquid' regime								
GDP	0.770	0.019	-0.812	0.356	0.089	0.104	0.001	-0.139
	(3.11)	(0.41)	(-1.43)	(1.98)	(1.89)	(0.89)	(0.09)	(-0.48)
CONS	2.286	-2.160	2.583	-0.786	0.316	-0.017	0.008	-1.839
	(2.15)	(-0.36)	(0.54)	(-2.03)	(2.82)	(-0.03)	(1.98)	(-1.87)
DCONS	0.840	0.000	0.275	0.246	0.127	-0.433	-0.007	-0.396
	(4.40)	(-0.02)	(1.03)	(10.63)	(3.89)	(-8.49)	(-1.22)	(-4.24)
INV	1.130	0.050	2.617	0.054	0.423	0.052	0.007	-0.542
	(1.46)	(0.26)	(1.57)	(0.33)	(2.07)	(0.12)	(0.21)	(-0.45)
Panel D: Australia; 'Illiquid' regime								
GDP	0.770	-0.021	0.812	0.480	0.089	0.104	0.001	-0.139
	(3.11)	(-0.40)	(1.89)	(3.46)	(1.89)	(0.89)	(0.09)	(-0.48)
CONS	2.286	-0.426	0.522	0.329	0.316	-0.017	0.008	-1.839
	(3.38)	(-1.57)	(0.33)	(4.28)	(2.82)	(-0.03)	(1.98)	(-1.87)
DCONS	0.840	-0.102	-0.342	0.571	0.127	-0.433	-0.007	-0.396
	(4.40)	(-1.96)	(-0.45)	(4.26)	(3.89)	(-8.49)	(-1.22)	(-4.24)
INV	1.130	-0.076	-2.630	0.341	0.423	0.052	0.007	-0.542
	(1.46)	(-0.16)	(-0.63)	(2.93)	(2.07)	(0.12)	(0.21)	(-0.45)
Adjusted R-squared of Australian regime-switching model								
	GDP	*CONS*	*DUR*	*INV*				
	0.12	0.21	0.39	0.12				

Notes: (a) These coefficients are fixed across the two regimes, for each country.

Appendix B

Appendix to Chapter 2

B.1 Glossary of Key Terms

This glossary provides definitions for all terms given in italics in the body of the paper.

ABCP conduit: A *special purpose vehicle* (SPV) that issues commercial paper in order to finance the purchase of financial assets including mortgages, receivables and long-term securities (including *residential mortgage-backed securities* (RMBS)). Unlike vehicles that issue term securitisations (such as RMBS), which typically wind down after a few years, conduits are ongoing entities with a revolving structure, with assets going in and out of the collateral pool backing the ABCP.

ABX, ABX Index, ABX Index Spread: The ABX Index tracks *credit default swaps* (CDS) on a fixed sample of 20 RMBS, for which the underlying collateral is predominantly U.S. sub-prime mortgages. There are five sub-indices, each corresponding to a different rating *tranche* of the RMBS. Importantly, the tranches referenced by the indices are selected based on their ratings at the time the indices are launched, and are not affected by any subsequent changes to these ratings. This means that over time, the A-rated ABX index, for example, will not necessarily always reference A-rated tranches. The ratings on the five tranches are: AAA, AA, A BBB and BBB-. Every six months the indices are reconstituted and a new vintage of the index and sub-indices are issued.

A new series, or 'roll', of the indices is added every six months based on subprime RMBS issued in the six months prior to the roll date. The first series of the index, the '06-1' series, began trading in January 2006 and referenced 20 RMBS issued in the second half of 2005. The RMBS referenced in each series are selected based on a poll of ABX market-makers and tend to be those that have the most liquid CDS markets. To be considered for inclusion in the index, the RMBS must meet a pre-identified set of criteria, relating to their size, the characteristics of their underlying mortgage pools, and their expected lives.

At their launch, each ABX index contract has a fixed notional amount and the 20 underlying RMBS tranches are equally weighted. As the tranches are paid down or experience write-downs, the notional amount of each index declines proportionately.

Asset-backed securities (ABS): An asset-backed security is a bond which is backed by the cash flows from a pool of specified assets in a *special purpose vehicle* (SPV) rather than the general credit of a corporation. The asset pools may be residential mortgages, in which case it is a residential mortgage-backed security (RMBS), commercial mortgages (a commercial mortgage-backed security, or CMBS), automobile loans, credit card receivables, student loans, aircraft leases, royalty payments, and many other asset classes.

Commercial mortgage-backed security (CMBS): See asset-backed securities.

Credit default swaps (CDS): A credit default swap is a derivative contract in which one party (the 'protection buyer') agrees to pay the other (the 'protection seller') a fixed periodic coupon for the life of the swap. The other party makes no payments unless a specified credit event occurs. Credit events are typically defined to include default, bankruptcy or debt restructuring for a specified reference asset. If such a credit event occurs, the protection seller makes a payment to the buyer, and the swap terminates. Typically, the size of the payment depends inversely on the reference asset's recovery rate following the credit event.

Haircut: The collateral pledged by borrowers towards the repo has a haircut or "initial margin" applied, which means the collateral value exceeds the amount borrowed. This haircut reflects the perceived underlying risk of the collateral and protects the lender against a change in its value. Haircuts are different for different asset classes and ratings.

LIB-OIS: The spread between the *LIBOR* and the *OIS*.

LIBOR: The London Interbank Offered Rate (LIBOR) is a series of interest rates, of different maturities and currencies, at which banks offer to lend unsecured funds to each other. These rates are calculated by the British Bankers Association as the averages of quotes contributed by a panel of banks and announced at 11:00 am local time in London. This is called the rate "fixing". Quotes are ranked and the top and bottom quartiles are discarded. LIBOR is fixed for 15 different maturities, from overnight to one year, and in ten international currencies. For more details, see Gyntelberg and Wooldridge (2008).

Overnight indexed swap (OIS): A fixed-for-floating interest rate swap where the floating leg of the swap is tied to the rate at which depositary institutions lend their reserve balances to each other, typically overnight (in the U.S., this is the effective Fed Funds rate). The term of the swap ranges from one week to, typically, two years. At maturity, the two parties agree to exchange the difference between the interest accrued at the agreed fixed rate and interest accrued through geometric averaging of the floating reference rate on the agreed notional amount. There is no exchange of principal.

Repurchase agreement (repo), *Reverse repurchase agreement* (reverse repo): A sale and repurchase agreement ("repo") is a sale of a security combined with an agreement to repurchase the same security at a specified price at the end of the contract. A repo is economically similar to a secured loan, though a fundamental distinction is that title to the security passes to the cash provider for the duration of the repo. From the perspective of the cash provider, it is a reverse repurchase agreement, or "reverse repo".

Rehypothecation: "Hypothecate" means to pledge collateral. Rehypothecation is the practice of reusing (or repledging) collateral received in one transaction with an unrelated third party in an unrelated transaction.

Residential mortgage-backed security (RMBS): See asset-backed securities.

Securitisation: The process of financing by segregating specified cash flows, from loans originated by a firm (the "sponsor"), and selling claims specifically linked to these cash flows. This is accomplished by setting up another company, called a *special purpose vehicle* (SPV), and then selling the specified cash flows to this company, which purchases the rights to the cash flows by issuing (rated) securities into the capital market.

Shadow banking sector: financial institutions that consist of non-depository banks and other financial entities (e.g., investment banks, hedge funds, money market funds, *special purpose vehicles*, and insurers). Due to their non-depository nature, they are not subject to the same regulations as depositary institutions. Examples of shadow banks included Bear Stearns and Lehman Brothers. The term "shadow banking system" was first used by Paul McCulley at the 2007 Jackson Hole conference (McCulley, 2009). McCulley identified the birth of the shadow banking system with the development of money market funds in the 1970s – money market accounts function largely as bank deposits, but money market funds are not as regulated as banks.

Special purpose vehicle (SPV), *Structured investment vehicle* (SIV): A legal entity established for a specific, limited, purpose by another entity (the "sponsor" firm). An SPV can take the form of a corporation, trust, or partnership. The SPV may be a subsidiary of the sponsoring firm (or it may stand-alone), which is not consolidated with the sponsoring firm for tax, accounting, or legal purposes (or may be consolidated for some purposes but not others). An SPV can only carry out some specific purpose, or circumscribed activity, or a series of such transactions. An essential feature of an SPV is that it be "bankruptcy remote", so that the solvency of the SPV is independent of the solvency of the sponsor. An SPV is not an operating company in the usual sense, but more of a 'robot' company in that it is a set of rules. It has no employees or physical location.

Tranche (French for "cut"): a slice of a portfolio ranked by rating and seniority. e.g. a AAA-rated tranche ranks above a BBB-rated tranche.

B.2 All-bond VARs

Table B.1: Vector Autoregression results: all bond types

The table shows the results from estimating equation (2.2) with the following variables: market liquidity (*Roll*), secured funding liquidity (*Haircuts* in Panel A; *Repo sprd* in Panel B), bond spreads (*Sprd*), return volatility (*Vol*), and unsecured funding liquidity (1-month LIBOR-OIS spread, *LIB-OIS*). All variables are expressed in percentage point terms. The VAR is estimated with a lag of one week and includes six bond-specific dummy variables. Numbers in brackets are t-statistics. The sample period is October 3 2005 to February 2 2009 (175 weeks).

Panel A: Repo haircuts liquidity measure

Dep. var.	*Roll* (-1)	*Haircuts* (-1)	*Sprd* (-1)	*Vol* (-1)	*LIB-OIS* (-1)	adj. R^2
Roll	-0.004	0.930	-0.001	0.001	0.002	0.26
	[-0.73]	[35.0]	[2.62]	[0.19]	[1.00]	
Haircuts	-0.004	0.828	0.001	0.001	0.003	0.88
	[-0.76]	[34.9]	[2.58]	[0.14]	[1.29]	
Sprd	-0.817	0.866	0.888	1.905	0.170	0.94
	[-4.56]	[0.85]	[57.7]	[8.42]	[2.10]	
Vol	-0.032	0.632	0.002	0.384	0.057	0.44
	[-0.77]	[2.66]	[0.57]	[7.28]	[3.02]	
LIB-OIS	0.060	0.335	-0.009	0.049	0.919	0.87
	[1.73]	[1.71]	[-3.05]	[1.13]	[59.4]	

Panel B: Repo spreads liquidity measure

Dep. var.	*Roll* (-1)	*Repo sprd* (-1)	*Sprd* (-1)	*Vol* (-1)	*LIB-OIS* (-1)	adj. R^2
Roll	-0.105	-0.006	0.008	0.499	0.019	0.23
	[-2.02]	[-0.09]	[1.37]	[7.58]	[0.25]	
Repo sprd	0.056	0.893	-0.006	0.096	0.080	0.93
	[1.37]	[18.0]	[-1.33]	[1.85]	[1.33]	
Sprd	-0.687	0.259	0.877	1.707	-0.103	0.94
	[-3.98]	[1.22]	[43.4]	[7.79]	[-0.40]	
Vol	-0.001	0.260	-0.012	0.333	-0.230	0.48
	[-0.01]	[5.27]	[-2.56]	[6.49]	[-3.87]	
LIB-OIS	0.030	0.002	-0.006	0.091	0.921	0.87
	[0.89]	[0.05]	[-1.59]	[2.14]	[18.8]	

B.3 VAR results using ABCP spreads

Table B.2: Vector Autoregression results: all asset-backed bonds

The table shows the results from estimating equation (2.2) on all asset-backed bonds, with ABCP spreads as funding liquidity proxy. The VAR is estimated with a lag of one week and includes four bond-specific dummy variables. Numbers in brackets are t-statistics. The sample period is October 3 2005 to February 2 2009 (175 weeks).

Dep. var.	*Roll* (-1)	*ABCP sprd* (-1)	*Sprd* (-1)	*Vol* (-1)	*LIB-OIS* (-1)	adj. R^2
Roll	0.127	0.120	0.013	0.427	-0.101	0.27
	[2.00]	[1.12]	[2.40]	[4.63]	[-0.84]	
ABCP sprd	0.005	0.621	-0.005	0.086	0.333	0.85
	[0.15]	[10.5]	[-1.50]	[1.68]	[5.07]	
Sprd	-0.232	-0.132	0.903	1.170	0.375	0.93
	[-1.20]	[-0.41]	[54.1]	[4.20]	[1.04]	
Vol	-0.029	0.119	0.005	0.431	-0.044	0.51
	[-0.67]	[1.65]	[1.31]	[6.94]	[-0.54]	
LIB-OIS	0.042	0.043	-0.005	0.019	0.874	0.86
	[1.40]	[0.86]	[-2.04]	[0.45]	[15.7]	

B.4 VAR results using ABCP outstandings

I estimate equation (2.2) for all asset-backed bonds, using the stock of ABCP to proxy for funding liquidity.[1] While the outstanding value of repos could serve as another proxy for funding liquidity, the available data does not separate outstandings by collateral type, and so includes repos collateralised by government bonds. Hence, this data are not used.

As the ABCP series is not disaggregated by the type of underlying ABS, I use the same ABCP outstandings for all types of ABS considered, with all the data in the VAR at a monthly frequency.[2] The output is presented in Table B.3.

The evidence from Table B.3 is that the ABCP stock has predictive power only over itself. Moreover, none of the other variables have predictive power over the stock of ABCP.

The lack of significance when using quantity measures of funding liquidity is

[1] The results are unchanged even when a VAR is estimated for individual asset-backed bonds. For the sake of brevity, these results are not reported but are available upon request.

[2] ABCP outstandings is obtained from the Securities Industry and Financial Markets Association webpage: http://www.sifma.org/research/statistics.aspx. The data are available from June 2004.

Table B.3: Vector Autoregression results: all asset-backed bonds

The table shows the results from estimating equation (2.2) on all ABS, using *ABCP stock* – the stock of ABCP as a percentage of GDP – as the funding liquidity proxy. *LIB-OIS* is the spread between 1-month LIBOR and 1-month OIS. All data are monthly, and the VAR is estimated with a lag of one month. Numbers in brackets are t-statistics. The sample period is September 30 2005 to January 31 2009 (41 months).

Dep. var.	*Roll* (-1)	*ABCP stock* (-1)	*Sprd* (-1)	*Vol* (-1)	*LIB-OIS* (-1)
Roll	-0.229	0.055	0.028	0.230	0.009
	[-2.29]	[1.62]	[3.82]	[3.39]	[0.14]
ABCP stock	-0.082	0.904	-0.008	0.038	-0.057
	[-0.69]	[22.4]	[-0.91]	[0.47]	[-0.77]
Sprd	-0.216	0.112	0.967	-0.810	1.403
	[-0.31]	[0.48]	[21.4]	[-1.74]	[3.26]
Vol	-0.001	-0.019	-0.012	0.488	0.372
	[-0.00]	[-0.41]	[-1.15]	[5.21]	[4.28]
LIB-OIS	-0.008	-0.128	-0.006	-0.245	0.587
	[-0.04]	[-2.24]	[-0.48]	[-2.15]	[5.56]

likely due to the lower data frequency, which makes it impossible to detect intra-month movements between the system's variables, and the fact that the series is not disaggregated by the term of the ABCP. This means that the data does not pickup compositional shifts in the ABCP market, either between issuers or between different ABCP maturities. Krishnamurthy et al. (2011) document a sharp fall in repo maturities during the crisis, and it is possible that a similar phenomenon occurred in the ABCP market, but this can not be discerned from the aggregate data.

B.5 Individual bond VARs

Figure B.1: Impulse responses: Auto & Credit-Card ABS

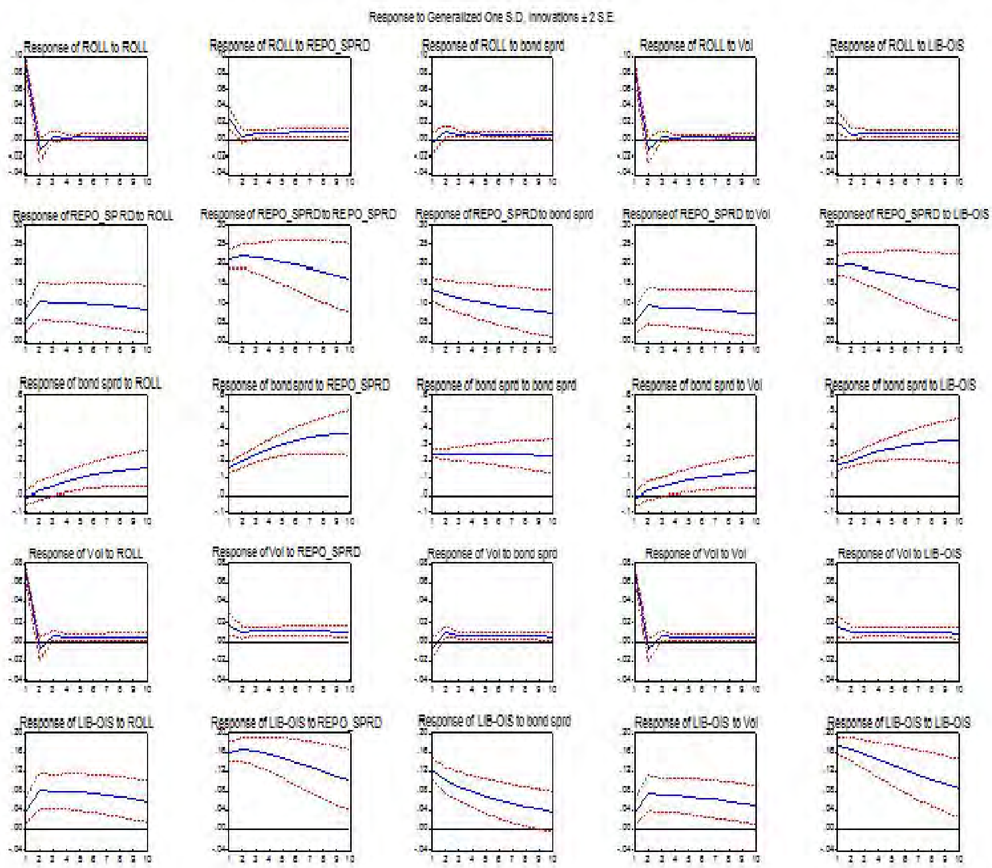
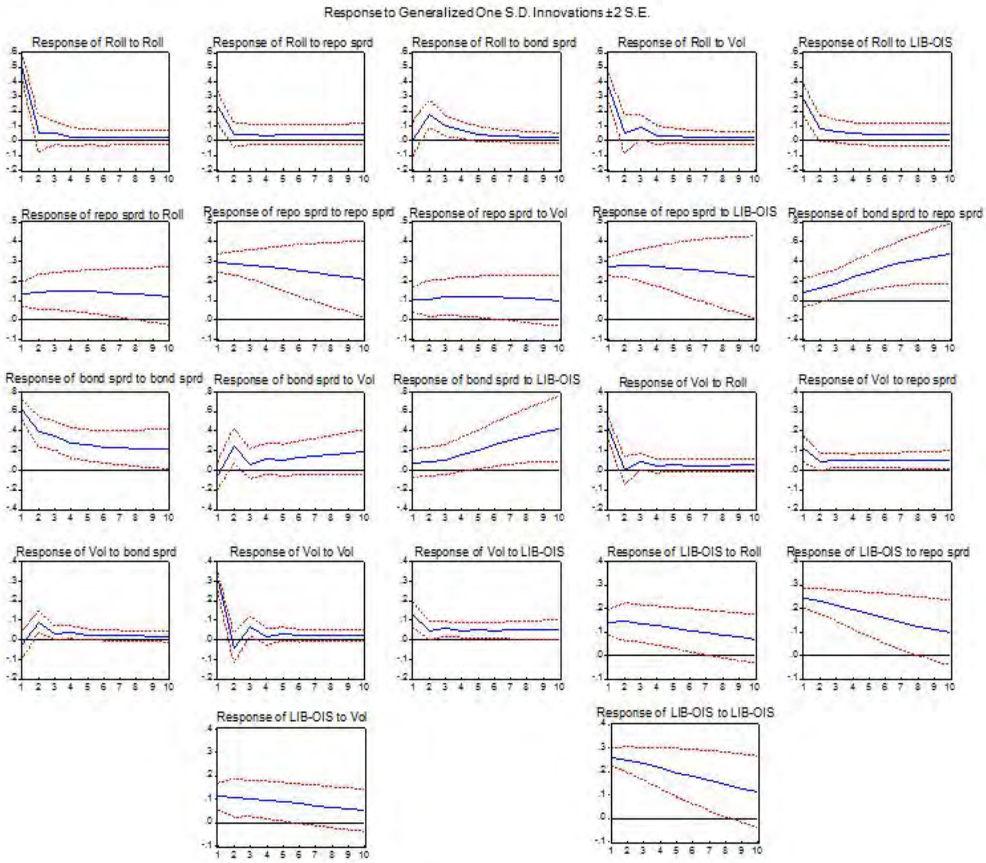


Figure B.2: Impulse responses: Commercial MBS

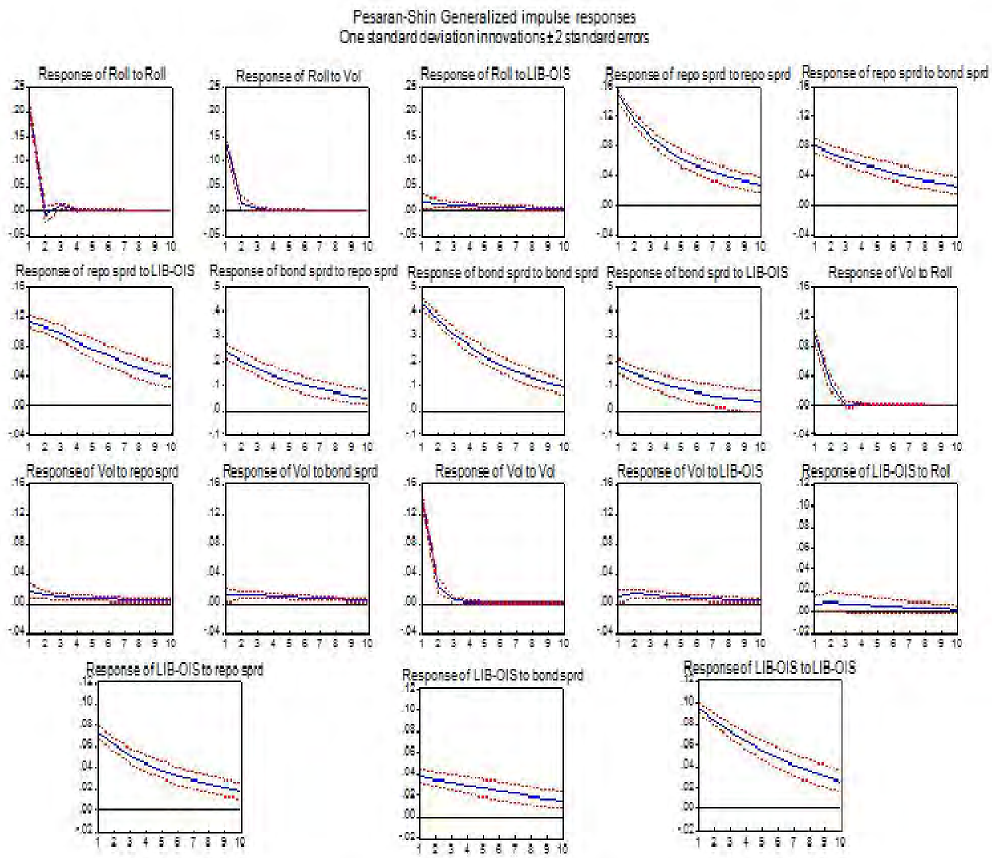


B.6 Additional impulse responses

Similar to the analysis in Section 2.6.1, there was a weak relationship between market liquidity and funding liquidity prior to September 2008. Market liquidity and return volatility were strongly responsive to each other's innovations, while repo spreads and bond spreads were also responsive to the other's shocks. In contrast, there was neither a significant relationship between market liquidity and bond spreads, nor a significant relationship between bond spreads and return volatility.

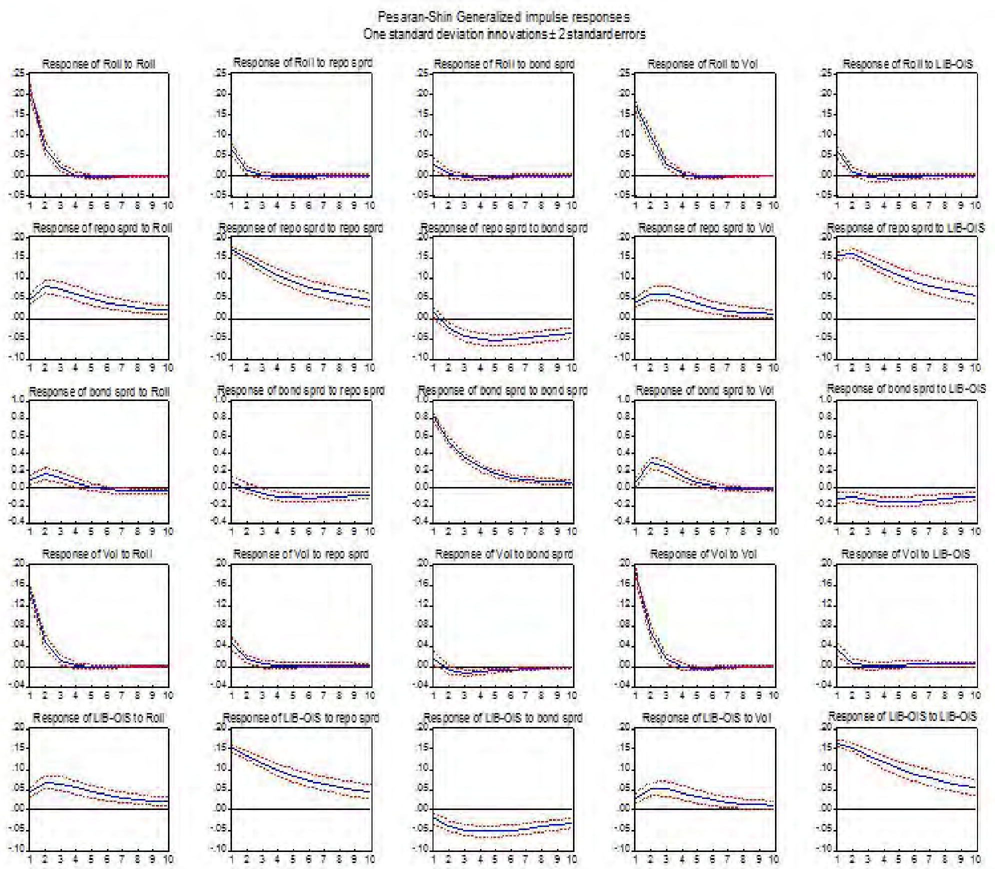
In contrast, during the post-September 2008 period, market liquidity responded strongly to shocks in all the other variables, with a funding illiquidity shock having led to a 5 basis point (one-third) rise in bid-ask spreads. In turn, a positive,

Figure B.3: Impulse response functions: pre-September 2008



one-standard deviation market illiquidity shock led to a 6 basis point (10 per cent) fall in funding liquidity, and an 8 per cent rise in volatility. Market liquidity and volatility were strongly responsive to each other's innovations, while repo spreads and bond spreads remained responsive to each other's shocks, though the magnitude of this relationship was lower than during the pre-crisis period.

Figure B.4: Impulse response functions: post-September 2008



B.7 Additional MSVAR results

Table B.4: MSVAR results

The table shows the MSVAR results with repo haircuts as funding liquidity proxy. The MSVAR is estimated with a lag of one week, assuming two regimes (Regime 1, Panel A; Regime 2, Panel B) with fixed transition probabilities. Only the slope coefficients and residual covariances are allowed to change across regimes. t-statistics are in brackets. The sample period is October 3 2005 to February 2 2009 (175 weeks).

Panel A: Regime 1 ('Liquid Regime')

Dep. var.	*Roll* (-1)	*Haircuts* (-1)	*Sprd* (-1)	*Vol* (-1)	*LIB-OIS*(-1)	Const^a
Roll	0.170	-0.018	0.028	0.233	0.011	0.186
	[1.38]	[-0.03]	[0.88]	[2.13]	[0.2]	[0.05]
Haircuts	0.022	0.913	-0.007	0.042	-0.005	0.026
	[0.52]	[4.47]	[-1.45]	[0.71]	[-0.25]	[0.64]
Sprd	-0.421	0.112	0.642	0.034	-0.075	2.761
	[-0.17]	[0.01]	[1.48]	[0.01]	[-0.07]	[1.53]
Vol	0.273	0.747	-0.009	0.280	0.038	0.144
	[2.85]	[1.69]	[-0.49]	[2.12]	[0.87]	[0.63]
LIB-OIS	-0.034	-0.072	-0.010	0.055	0.826	0.297
	[-0.58]	[-0.09]	[-0.47]	[0.2]	[9.71]	[0.86]

Panel B: Regime 2 ('Illiquid Regime')

Dep. var.	*Roll* (-1)	*Haircuts* (-1)	*Sprd* (-1)	*Vol* (-1)	*LIB-OIS*(-1)	Const.^{a}
Roll	-0.100	0.026	0.135	0.170	0.046	0.186
	[-1.86]	[1.98]	[0.01]	[2.08]	[2.22]	[0.05]
Haircuts	0.043	0.892	0.046	0.035	0.102	0.026
	[2.33]	[2.97]	[3.94]	[0.02]	[0.05]	[0.64]
Sprd	0.395	-0.120	0.980	0.663	0.181	2.761
	[2.56]	[-0.06]	[3.56]	[1.97]	[2.15]	[1.53]
Vol	0.121	0.265	0.199	0.764	0.058	0.144
	[1.22]	[3.38]	[0.03]	[2.05]	[2.01]	[0.63]
LIB-OIS	0.124	0.686	0.019	-0.074	0.881	0.297
	[0.18]	[2.62]	[2.54]	[1.85]	[7.19]	[0.86]

Notes: (a) Intercept term is fixed across regimes.

B.8 Repo haircuts and spreads in the same VAR

In this section, I consider the impulse responses from a reduced-form VAR which has both repo spreads and repo haircuts. As before, we have:

$$\mathbf{X}_t = \alpha + \beta \mathbf{X}_{t-1} + \epsilon_t \tag{B.1}$$

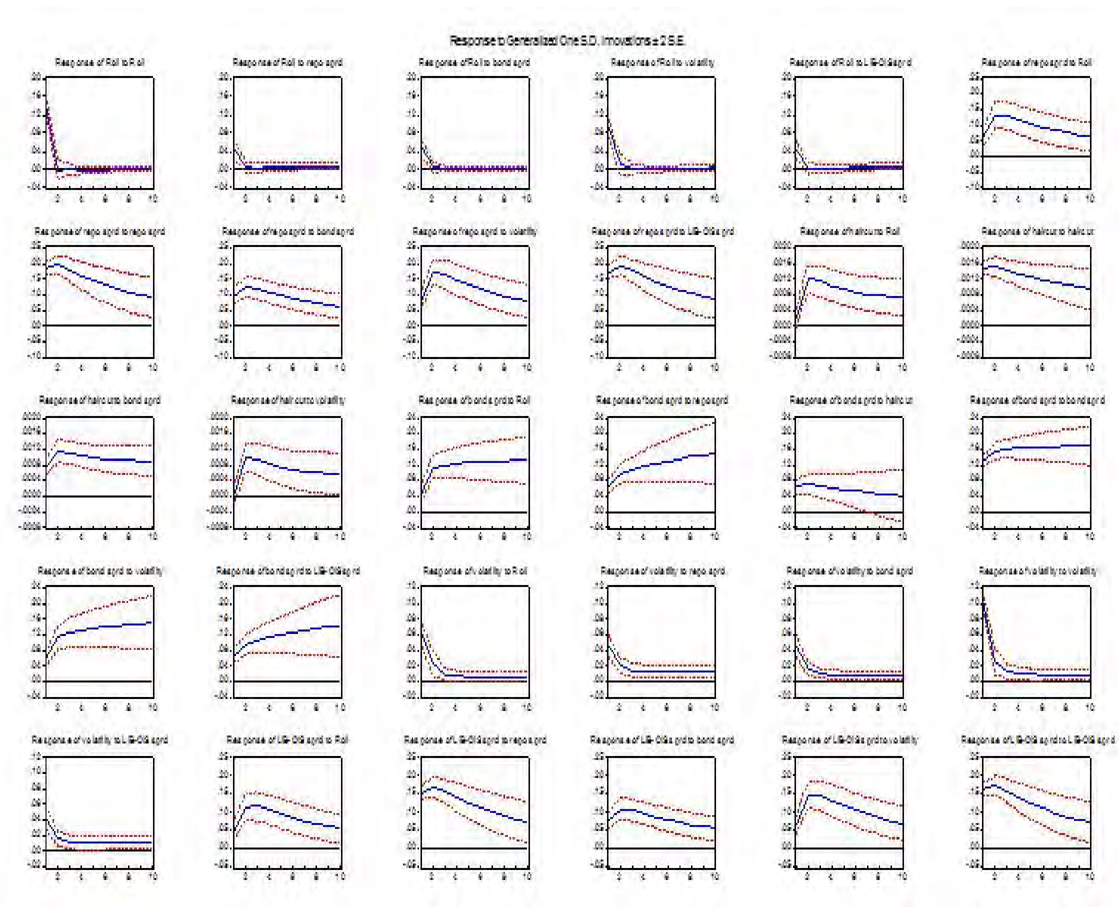
Here, $\mathbf{X}_t$ is a 6x1 vector containing market liquidity, repo spreads, repo haircuts, bond spreads, LIB-OIS spreads, and the weekly standard deviation of daily returns, all observed in week t.

As was the case in Chapter Two, for ease of illustration, the only impulse responses shown are those that are statistically significant (at the 5% level). Figure B.5 shows the impulse responses for the VAR estimated for all bonds. These impulse responses reveal that the key findings from Chapter Two are largely unchanged; that is, the impulse responses of market liquidity to funding liquidity shocks (and the impulse responses of the other VAR variables to funding liquidity shocks) are stronger for repo spread shocks, than shocks to repo haircuts. While repo haircuts' impulse responses, to shocks in the other VAR variables, are typically statistically significant, the converse is not true: only the impulse responses of bond spreads are statistically significant, in response to repo haircut shocks.

These conclusions generally hold at the individual bond level; shocks to repo

Figure B.5: **Impulse responses: all bond types**

The figure shows Pesaran-Shin (1998) generalised impulse responses from equation (2.2), using repo haircuts and repo spreads, for all bond types. A two-standard-error band for the impulse responses is determined from the residuals' empirical distribution, using a Monte Carlo with 10,000 repetitions.



spreads typically lead to larger impulse responses in the other, non-repo-related variables, than shocks to repo haircuts (Figures B.6 – B.9). This was also the finding in Chapter Two.

Figure B.6: **Impulse responses: Non-asset backed bonds**

The figure shows Pesaran-Shin (1998) generalised impulse responses from equation (2.2), using repo haircuts and repo spreads, for AAA-rated non-asset backed bonds. A two-standard-error band for the impulse responses is determined from the residuals' empirical distribution, using a Monte Carlo with 10,000 repetitions.

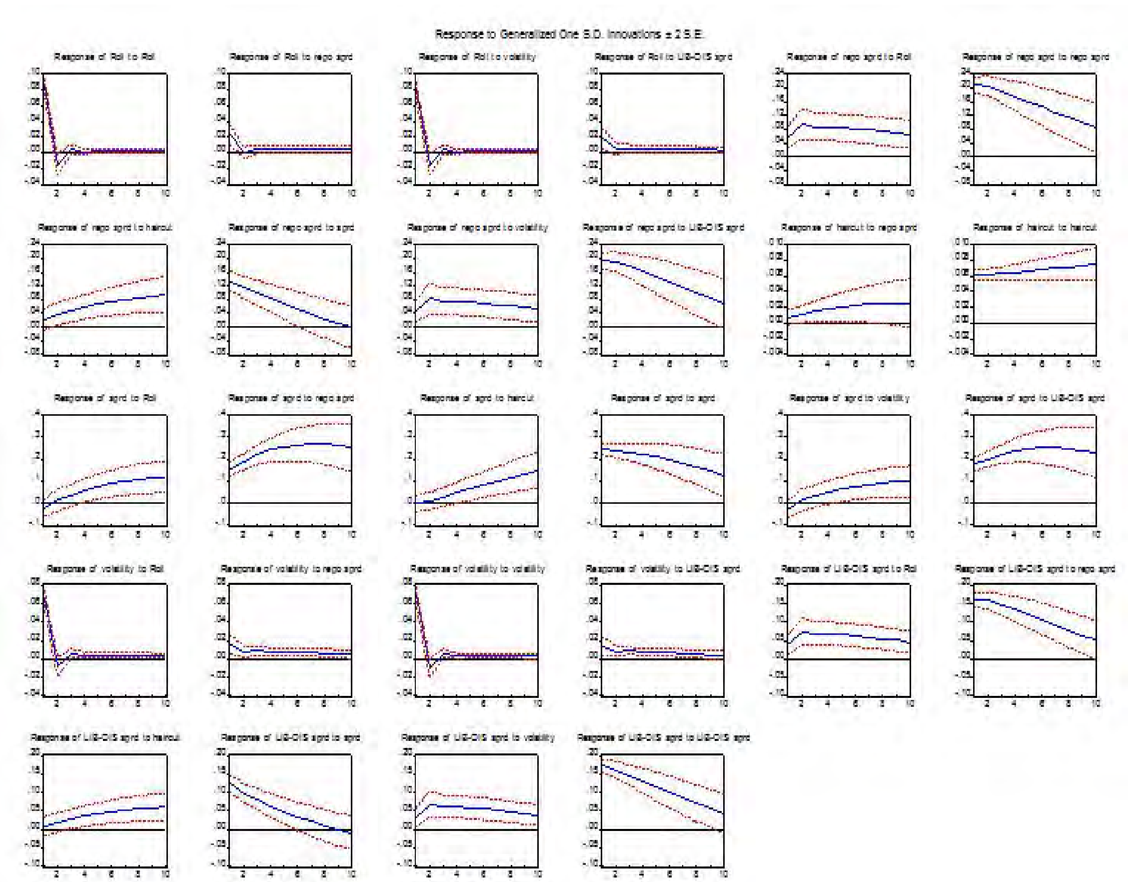


Figure B.7: **Impulse responses: Subprime RMBS**

The figure shows Pesaran-Shin (1998) generalised impulse responses from equation (2.2), using repo haircuts and repo spreads, for AAA-rated subprime RMBS. A two-standard-error band for the impulse responses is determined from the residuals' empirical distribution, using a Monte Carlo with 10,000 repetitions.

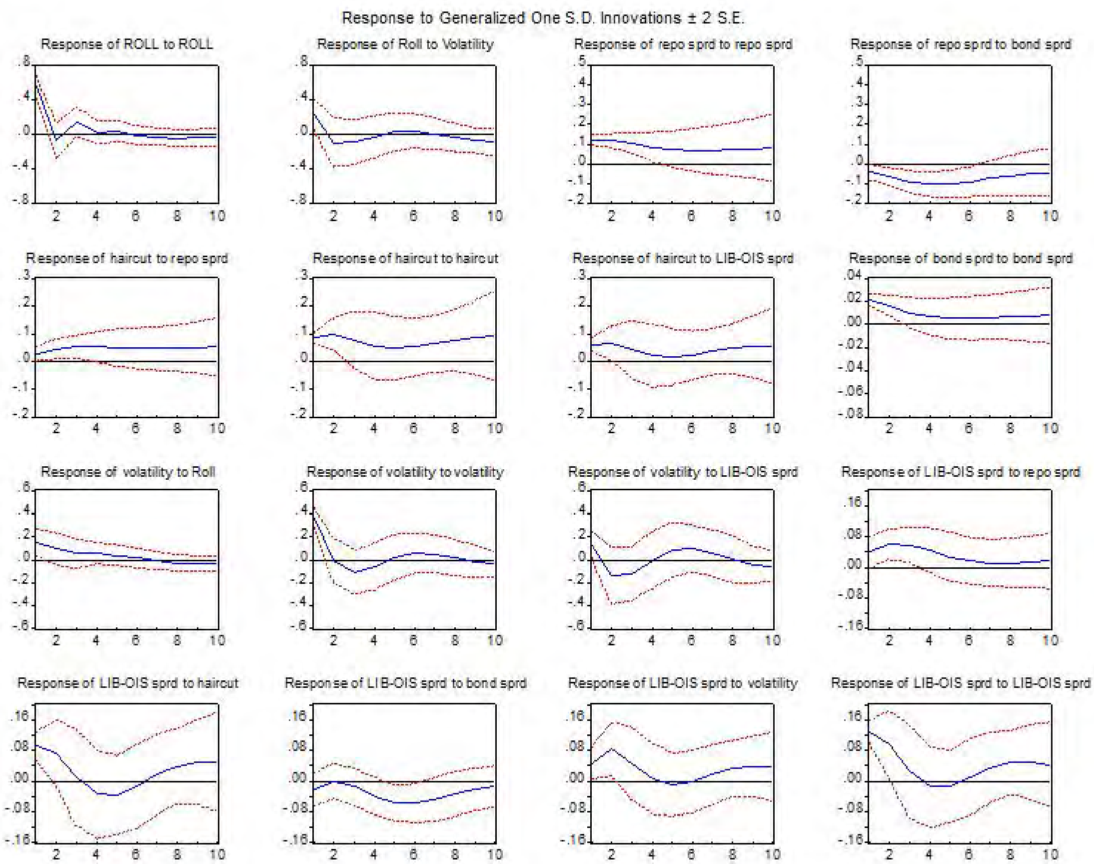


Figure B.8: **Impulse responses: Auto & Credit-Card ABS**

The figure shows Pesaran-Shin (1998) generalised impulse responses from equation (2.2), using repo haircuts and repo spreads, for AAA-rated automotive and credit-card ABS. A two-standard-error band for the impulse responses is determined from the residuals' empirical distribution, using a Monte Carlo with 10,000 repetitions.

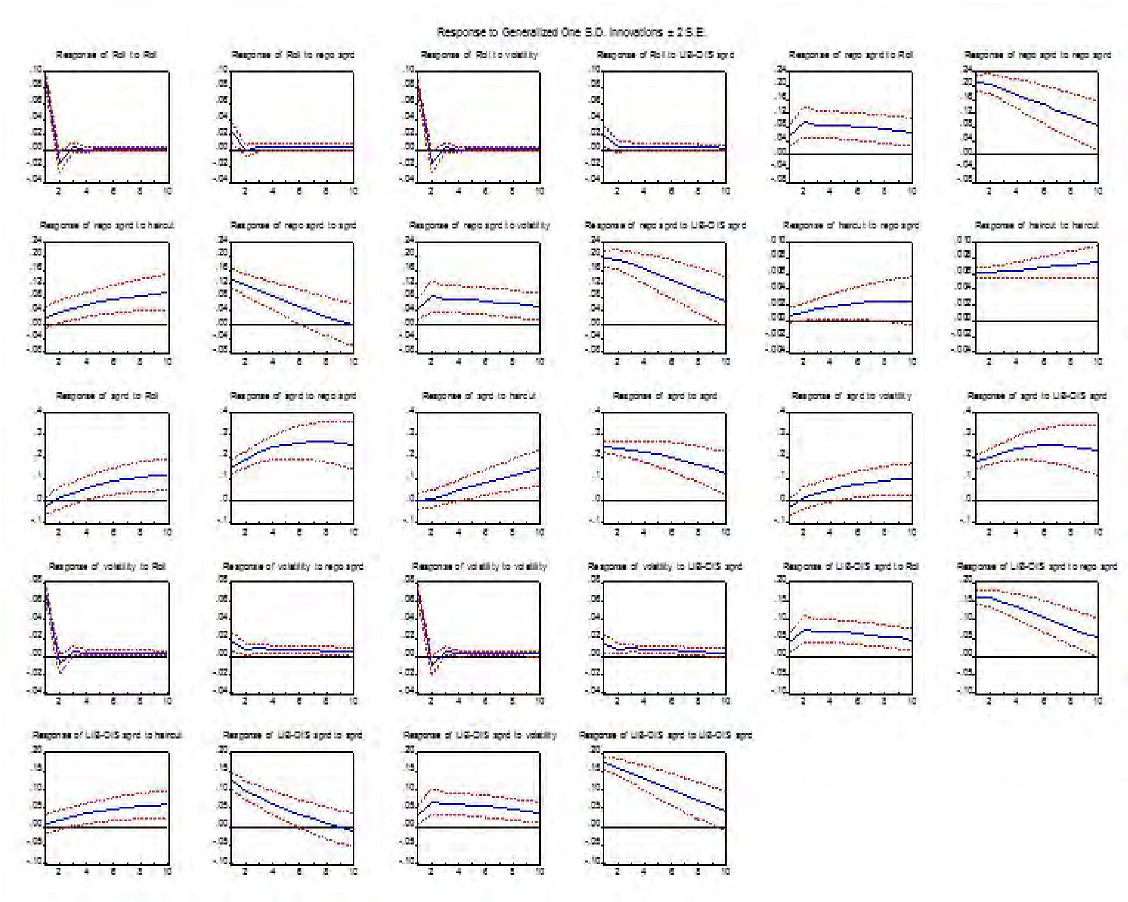
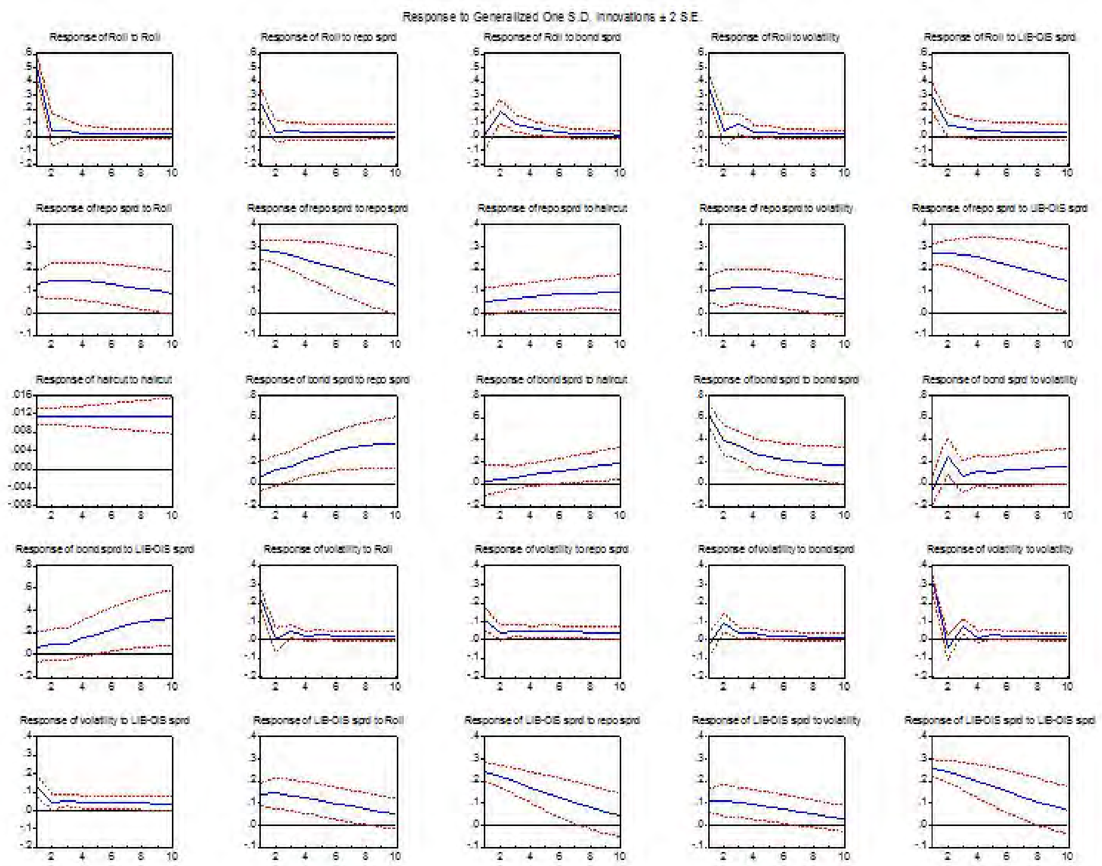


Figure B.9: **Impulse responses: Commercial MBS**

The figure shows Pesaran-Shin (1998) generalised impulse responses from equation (2.2), using repo haircuts and repo spreads, for AAA-rated commercial MBS. A two-standard-error band for the impulse responses is determined from the residuals' empirical distribution, using a Monte Carlo with 10,000 repetitions.



Appendix C

Appendix to Chapter 3

C.1 Alternative Taylor rules

C.1.1 Unemployment-based Taylor-rules

I estimated equation (3.2) using the difference between T-year Treasury bond yields, and T-year TIPS yields. I first set T=5; and then T=10. The implied Taylor rule and associated monetary policy stance are presented below. It is notable that the levels of the two alternative monetary policy stances differ, particularly after December 15, 2008 (when the zero lower bound was reached); between December 15, 2008 and December 31, 2009, the 10-year series was, on average, around two-fifths below the 5-year series (Figures C.1 and C.2, respectively).

However, the correlation is very high (0.98). Similar correlations apply when comparing the 5-year and 10-year TIPS measures against 5-year inflation expectations from Haubrich, Pennacchi and Ritchken (2011).

This implies that although the size of the VAR model's estimated coefficients would differ across the two measures, the statistical significance of these estimates, and the size of impulse response functions (whose values are standardised), would be largely unchanged. Thus, the findings of the paper are insensitive to the choice of TIPS tenor, or the choice of tenor from Haubrich, Pennacchi and Ritchken (2011)'s inflation expectations.

C.1.2 Output-gap-based Taylor rule

Since Taylor (1993)'s original formulation is based on output gaps, in this section I estimate Taylor rules using an output gap defined as the difference between real GDP and the Congressional Budget Office (CBO)'s estimate of real potential GDP. I use Haubrich, Pennacchi, and Ritchken (2011)'s estimate of 5-year inflation expectations, and I also include an AR(1) term in equation (3.1) in order to improve

Figure C.1: **Effective Federal Funds rate based on 5-year TIPS yields**

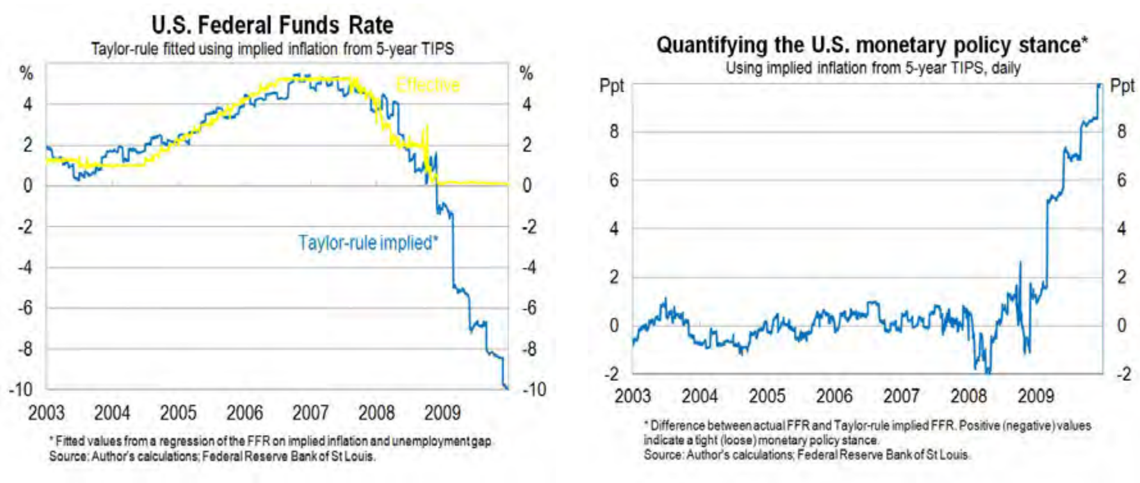
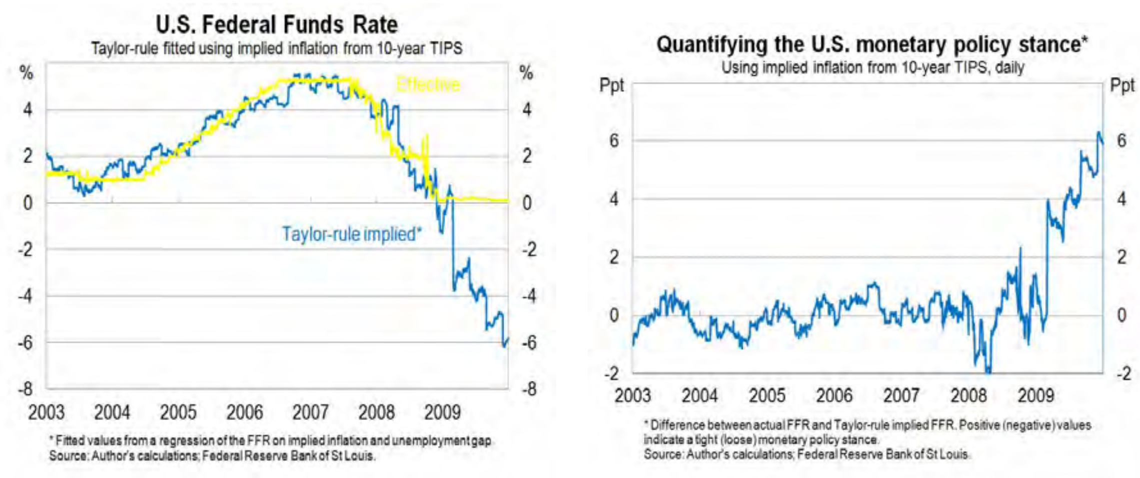


Figure C.2: **Federal Funds rate based on 10-year TIPS yields**



the explanatory power of the Taylor rule.[1] Since estimates of actual and potential real GDP estimates are both subject to larger revisions than estimates of actual or natural unemployment rates, output-gap based Taylor rules (and the associated

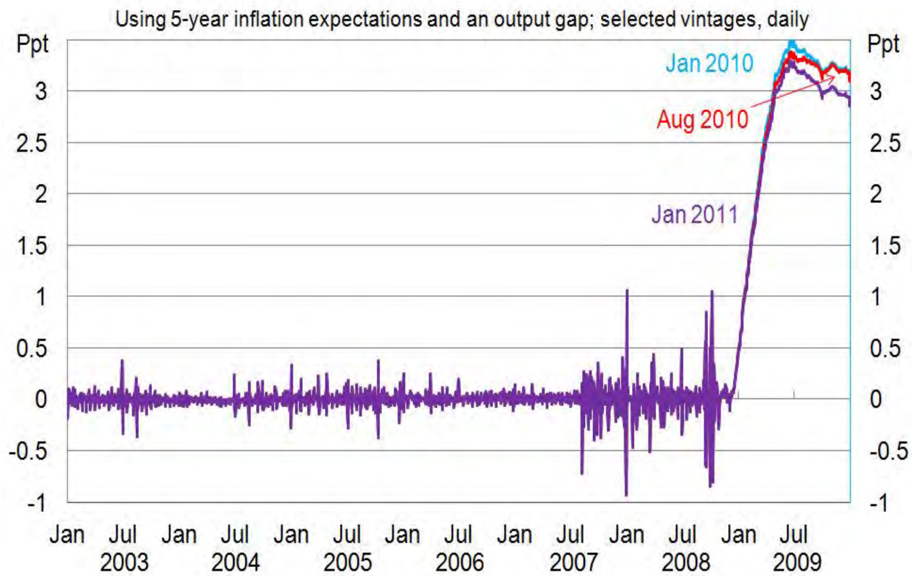
[1]Excluding an AR(1) term, the $\bar{R}^2$ is around 0.5 for each of the three models estimated in this section. With an AR(1) term, the $\bar{R}^2$ rises to 0.99. In contrast, adding an AR(1) term to equation (3.2) does not add much to the model's explanatory power.

monetary policy stance) differ across the different published GDP vintages.

Focusing on three randomly selected data publications – August 2010, January 2011 and January 2012 – all three estimates of the policy stance are highly positively correlated with each other, with pairwise correlations close to 1. However, there are some differences in the levels of the series, particularly from late 2008, reflecting the differences in the output gap estimates between these three publications. Despite these differences, U.S. monetary policy became increasingly contractionary, under all three measures, from late 2008; by June 2009, the actual Federal Funds rate was around $3\frac{1}{2}$ percentage points above the Taylor-rule implied rate (Figure C.3).

Notably, the pairwise correlations between the output-gap and unemployment-

Figure C.3: **The stance of U.S. monetary policy***



* Output gap based on CBO's estimates of potential output, described in their August 2010, January 2011, and January 2012 publications.
Sources: Author's calculations; Congressional Budget Office; Federal Reserve Bank of Cleveland.

gap estimates of the policy stance are around 0.94. This implies that though the magnitude of the VAR model's estimated coefficients may differ between the output-gap and unemployment-gap measures, the statistical significance of these estimates would be unchanged. Combining the results from the previous section, this suggests that this paper's findings are largely insensitive to the choice of inflation expectations measure, as well as the choice of an output-gap or unemployment-gap measure of the policy stance.

C.1.3 Details about the CBO's measure of the natural unemployment rate

The choice of the CBO measure was made following Rudebusch (2009). As CBO (2004) notes, the CBO's estimate is derived from applying Okun's law to the CBO's measure of potential real GDP. In turn, potential real GDP is estimated using the Solow growth model, which attributes the growth of real GDP to the growth of labour, capital, and technological progress. The CBO de-trends each of these components using statistical filters (like the H-P filter) and arrives at a measure of potential real GDP. In short, the CBO method relies on both economic theory and statistical analysis to estimate potential GDP.

As CBO (2004) notes, statistical filters have an advantage over the economic-centric approaches in that they are more flexible in how they estimate the trends in the data series and the values of parameters. Filtering techniques do not require any judgments about when trend growth changes during the sample. Because they follow the data more closely, those methods can identify trend changes more quickly.

However, a key drawback of statistical filtering is that they do not benchmark their trends to any external measure of capacity. Therefore, unlike the results obtained from the use of economic theory (as is the case with the Okun-law and Solow-growth techniques noted above), their results should be interpreted as *trend* GDP, not *potential* GDP. That is, statistical filters are unlikely to yield estimates of output consistent with stable inflation. Moreover, the filtering methods do not produce cyclically adjusted estimates of GDP, meaning that they do not attempt to remove the effects of business-cycle fluctuations from the variable being filtered. For example, CBO (2004) shows that a filtered estimate of real GDP slows considerably during each recession and accelerates afterward. A cyclically-adjusted, structural measure of trend GDP would not display that type of cyclical fluctuation. For these reasons, sole reliance on statistical techniques to estimate potential real GDP is inappropriate.

C.2 Granger causality tests

Bivariate Granger causality tests between the three financial market variables were performed, with the test statistics in Table C.1.

Table C.1: Granger causality tests

Repo is the 1-month repo-OIS spread, *Bond* is bond spreads to U.S. Treasuries, and *LIB-OIS* is the 1-month LIB-OIS spread. The sample period is July 2 2007 to December 31 2009 (626 trading days), and all data are daily. The null hypothesis tested is that the variable in a particular row does not Granger cause the variable in a particular column ('dependent variable'). For each test, the number of lags is equal to one. *, ** and *** denote rejection of the null at the 10%, 5% and 1% significance levels, respectively.

	Dependent variable		
	Repo	*Bond*	*LIB-OIS*
Repo		14.59***	5.30**
Bond	1.23		3.73**
LIB-OIS	1.15	15.56***	

C.3 Fiscal policy announcements

- September 19, 2008: first proposal of the Troubled Asset Relief Program (TARP) by U.S. Treasury Secretary Paulson. The U.S. Treasury Department announces a temporary guarantee program that will make available up to U.S.$50 billion from the Exchange Stabilization Fund to guarantee investments in participating money market funds.
- September 29, 2008: TARP bill rejected by the U.S. House of Representatives.
- October 3, 2008: passage of the TARP bill into law, called the *Emergency Economic Stabilization Act of 2008*.
- October 14, 2008: announcement of the Capital Purchase Program (CPP) under which the U.S. Treasury would use TARP funds to buy preferred stock and warrants of nine financial institutions[2].

[2]Citigroup, Wells Fargo, JP Morgan, Bank of America, Goldman Sachs, Morgan Stanley, State Street, Bank of New York Mellon, and Merrill Lynch.

- October 14, 2008: The Federal Deposit Insurance Corporation (FDIC) guarantees senior debt obligations of depository institutions and their holding companies under the Temporary Liquidity Guarantee Program (TLGP).

- November 12, 2008: U.S. Treasury Secretary Paulson announces that the U.S. Treasury would not use TARP funds to buy mortgage-related assets from financial institutions.

One issue with the above categorisation is whether the TARP should be considered an element of fiscal policy, or (unconventional) monetary policy, to the extent that the TARP involved loans made to stressed financial institutions and markets, which are akin to the open market operations of a central bank. However, there are two reasons why the TARP should be considered an element of fiscal policy. Firstly, the TARP was not a Federal Reserve policy initiative – the TARP was announced by the U.S. Federal Treasury. Furthermore, it operated independently of the Federal Reserve, did not directly impact the Federal Reserve's balance sheet, and did not involve any Federal Reserve oversight (Kroszner and Melick, 2010). Secondly, as Swagel (2009) notes, the vast bulk of TARP funds were used to purchase illiquid assets from, and inject capital into, financial institutions. Swagel (2009) argues that these actions are more fiscal, than monetary, in nature, as the Federal Reserve's programs were typically loans to distressed institutions, rather than outright purchases. In this sense, the TARP was a key element of the Federal Government's spending activities.

Appendix D

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