Funding Liquidity Risk and the Cross-section of MBS Returns*

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July 6, 2016

Abstract

This paper shows that funding liquidity risk is priced in the cross-section of excess returns on agency mortgage-backed securities (MBS). We derive a measure of funding liquidity risk from dollar-roll implied financing rates (IFRs), which reflect security-level costs of financing MBS positions. We show that factors representing higher net MBS supply are associated with higher funding costs. We also find that funding liquidity risk is compensated in the cross-section of expected returns—securities that are better hedges against market-wide funding liquidity shocks on average deliver lower excess returns—and that this premium is separate from compensation for prepayment risk.

JEL Codes: G1, G12, G19, E43, E58.

Keywords: Agency mortgage-backed securities; Dollar rolls; Implied financing rates; Liquidity; Expected returns; Large Scale Asset Purchase programs.

*First draft: August 13, 2014. We would like to thank Jeff Huther, John Kandrac, Don Kim, Linsey Molloy, and Min Wei for helpful comments on a preliminary version of this paper circulated as "What drives implied financing rates?," and to our discussant David Lucca at the 2016 ASSA-IBEFA meeting for helpful suggestions. We are specially grateful to Katherine Femia for many valuable discussions. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors. All errors are our own.

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1 Introduction

Events of the 2007-2008 financial crisis made the links between funding liquidity, or ability of financial market participants to obtain capital or borrow funds, and asset prices particularly evident. Prompted by tightening of balance sheet constraints, investors reportedly had to liquidate their asset holdings amid falling prices, potentially amplifying initial downward price moves, as well as contributing to higher price volatility and deterioration of market functioning. Furthermore, poor funding liquidity and scarcity of capital hindered arbitrageurs' ability to exploit and eliminate arbitrage opportunities, or "mispricings", in multiple financial markets.

A fledging literature has focused on a question of how funding liquidity is related to expected asset returns, usually proxying funding liquidity with measures based on deviations of asset prices from their "no-arbitrage" counterparts.[1] In this paper, we examine a relationship between asset returns and funding liquidity from a different angle. In particular, we focus on how expensive it is to fund or finance security positions using data from the market for agency mortgage-backed securities (MBS), in which financing rates are available at the individual-security level, and investigate whether exposure of individual securities to systematic funding liquidity shocks embedded in financing rates is priced in the cross-section of expected excess returns. The advantage of using this approach is that it relies on direct security-level measures of funding costs rather than on indirect aggregate proxies of funding liquidity that, in addition, are sometimes constructed from prices of instruments different from those whose returns are examined.[2]

[1] See Gârleanu and Pedersen (2011), Fontaine and Garcia (2012), Fontaine, Garcia, and Gungor (2015), Hu, Pan, and Wang (2013), Golez, Jackwerth, and Slavutskaya (2015) and Junge and Trolle (2015).

[2] An alternative approach for measuring funding liquidity would be to use information on balance sheets of investors and financial intermediaries. However, such information is only available at lower frequencies and may not fully reflect higher-frequency liquidity events. In addition, such approach would rely on making an assumption on whether investors and intermediaries are marginal price-setters in the market under investigation.

We find that MBS that are better hedges against systematic funding liquidity shocks command lower expected returns. These results do not only shed additional light on links between funding liquidity and asset prices, but also contribute to better understanding of how investors value MBS and how the MBS market functions— topics that are of great importance, considering the MBS market's sheer size and the prominent role that MBS spreads play in decision making by MBS investors and mortgage lenders, but that received a fairly limited attention in the literature.

Most agency MBS trading occurs in the to-be-announced (TBA) market, a very active and liquid forward market, in which positions are usually financed through dollar rolls. More specifically, an investor who wishes to establish a long position in a particular MBS, but does not have cash to buy the security, can fund the purchase through a dollar roll transaction, which involves a sale and a purchase of this security through two forward transactions. Prices of these forward transactions can be used to derive the so-called dollar roll implied financing rates (IFRs), reflecting the cost of financing positions of individual securities in the TBA market. As we discuss further, in certain ways dollar rolls are similar to repo transactions, possessing the features of both general and special collateral repos, and the IFRs are akin to repo rates. A decline (increase) in the IFR means more (less) favorable funding conditions for an investor wishing to fund a long position in a particular MBS in the dollar roll market since she now needs to pay a lower (higher) interest rate to do so. As there are no haircuts or margins associated with dollar roll transactions, the IFR represents the only price-based variable reflecting cost of funding through this mechanism.

Previous literature suggests that interest rates associated with collateralized lending through the repo market are a function of how scarce the underlying collateral is.[3] We confirm this intuition in the dollar roll market and find that supply-demand factors are important determinants of IFRs. In particular, we document that a lower private supply of MBS, higher agency CMO production, and higher volume of MBS transactions by primary dealers are associated with lower IFRs or increased dollar roll specialness. Similarly, an increase in the Federal Reserves MBS holdings and outright purchases are associated with dollar roll specialness of some coupons. This effect is not surprising, given the large size of the Federal Reserves purchases and the role that movements in IFRs play in alleviating short-term imbalances between the supply of and demand for collateral by incentivizing holders of MBS to lend securities.

The results above show that dollar roll IFRs, and security financing costs, are lower when corresponding securities are more scarce. This pattern conforms with economic intuition and lends support to using information embedded in dollar roll IFRs to capture funding conditions in the MBS market. Next, we use these rates to construct systematic shocks to funding liquidity and investigate whether funding liquidity is priced in the cross section of MBS returns.

To measure shocks to funding liquidity, we first compute the difference between the MBS GC repo rate and contract-specific dollar roll IFRs. Taking the difference isolates funding liquidity factors specific to the dollar roll market from overall funding liquidity conditions. When the spread between the MBS GC repo and the IFR widens, the cost of financing of long positions in the dollar roll market decreases relative to the financing cost in the GC repo market. We next recover a systematic component of this relative financing cost, which we

[3]For example, see Tuckman and Serrat (2011), Bartolini, Hilton, Sundaresan, and Tonetti (2011) and Bech, Klee, and Stebunovs (2012) for evidence on the effects of changes in supply-demand of Treasury collateral on Treasury GC repo rates, and Duffie (1996), Jordan and Jordan (1997), Krishnamurthy (2002), Moulton (2004), Graveline and McBrady (2011) and D'Amico, Fan, and Kitsul (2014) for such effects on Treasury security-specific repo rates.

model as a latent autoregressive component jointly driving IFRs of multiple MBS, and treat innovations to this common component as funding liquidity shocks. A negative shock drives IFRs closer to the GC repo rate and increases the market-wide cost of financing securities through the dollar roll relative to repo. Our shock series dips most into negative territory in late 2008, after the Lehman collapse.

After recovering funding liquidity shocks, we follow the classic asset pricing procedure summarized in Fama and French (2008) to determine if exposure to these shocks is priced in the cross-section of expected returns. The first step of the procedure entails estimating sensitivities of individual MBS returns to the systematic funding liquidity shocks (funding liquidity betas). As proxies for MBS excess returns, we use securities option-adjusted spreads (OAS), following Gabaix, Krishnamurthy, and Vigneron (2007) who argue that using OAS in place of the actual returns reduces the measurement error at the cost of higher potential of a model misspecification for the prepayment option embedded in the MBS. OAS represent a spread that MBS pay over Treasury securities after adjusting for prepayment option and, as discussed in Boyarchenko, Fuster, and Lucca (2015), are good predictors of future realized MBS returns after hedging for interest rate risk.

The estimated betas suggest that prices of the MBS move in the opposite direction to our funding liquidity shocks, i.e. agency MBS pay more at times when financing terms in the dollar roll market unexpectedly become less favorable. Therefore, these securities can be thought of as hedges against such shocks. A question then arises of whether investors are willing to forego some expected returns to hold those securities that are better hedges against unanticipated changes in systematic funding costs, or whether co-movement with systematic funding liquidity is priced in the cross-section of MBS expected returns. To address the question, we follow two approaches.

First, on a weekly basis we form portfolios based on time-varying funding liquidity betas estimated over three-year rolling windows and compute corresponding portfolio returns over the next 12 months. We find that, on average, the portfolio consisting of the MBS with the highest betas with respect to funding liquidity shocks—that is the MBS that are the best hedges to such shocks—provides lower excess returns than the portfolio formed from the MBS that are the worst hedges against liquidity shocks.

Second, we use the standard two-pass Fama-Macbeth regression procedure in which funding liquidity betas estimated using the entire available history for each security are used as the explanatory variable in cross-sectional regressions of time-averaged contract-specific OAS on the corresponding betas. We find a negative relationship between average excess returns and funding liquidity betas of individual securities. Consistent with our evidence based on portfolio sorts, we find that those MBS contracts that are better hedges against funding liquidity shocks, or those MBS contracts that pay more when position financing conditions deteriorate, provide lower expected excess returns.

Since our measure of funding liquidity shocks is derived using prices of MBS dollar rolls, which in turn depend on forward prices of MBS securities, there is a possibility that it contains information about prepayment risk. We control for this in both asset pricing exercises. First, we perform double sorts and construct portfolios based on funding liquidity betas and conditional prepayment rates. We find that within low and high prepayment rates high-beta (better-hedge) portfolios still provide lower expected returns than their low-beta (worse-hedge) counterparts.

To control for prepayment risk in the Fama-Macbeth exercise, we run second-stage cross-sectional regressions of individual securities average OAS on the exposure to funding liquidity shocks together with compensation for prepayment risk. We measure prepayment risk by regressing returns of individual securities on the prepayment factor, constructed using the spread between the average coupon of the MBS outstanding at a given time and the mortgage rate prevailing at the same time (borrowers are more likely to prepay mortgages underlying MBS with higher coupons). We find that compensation for the funding liquidity exposure remains a significant component of the MBS expected returns even after controlling for prepayment risk.

Our findings suggest that investors are willing to pay a premium to hold assets that help them hedge funding liquidity risks. These results echo findings of the recent literature on the intermediary-based asset pricing, suggesting that exposures to shocks to dealers' capital and leverage are priced in the cross-section of asset returns (e.g. see He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) for theoretical insights and Adrian and Muir (2014) and He, Kelly, and Manela (2015) for empirical investigations). One way to interpret such shocks is as tightening or easing of balance-sheet constraints, with the balance-sheet thresholds being imposed by regulatory guidelines or internal risk management and business practices and, thus, affecting the dealers' risk bearing capacity and willingness to hold securities. Dealers will then be wiling to pay a premium for assets which pay more in the states of the world in which their risk-bearing capacity is lower. Similarly, our funding liquidity shocks can be thought to reflect tightening and easing of investors' balance sheet constraints, as well as affect their willingness to hold securities and bear the associated risks.

In addition to contributing to the literature on funding liquidity and asset prices, our work is related to the literature that focuses on determinants of repo rates and the relationship between repo rates and cash market prices; prominent early examples in this literature include Duffie (1996), Jordan and Jordan (1997) and Buraschi and Menini (2002). From a broader perspective, our findings on determinants of IFRs shed light on the question of whether supply-demand imbalances in collateral markets can have implications for collateral rental rates and broader asset prices, which has become a subject of increased attention in light of recent regulatory developments that could potentially boost demand for high-quality liquid assets (HQLA) and large asset purchases by central banks. For example, the Committee on the Global Financial System report discusses factors influencing supply and demand for HQLA and D'Amico et al. (2014) examines the effects of such factors on Treasury collateral special repo rates.

By extracting information on funding liquidity from MBS dollar rolls, our paper contributes to the branch of literature studying these instruments and started by Duarte, Longstaff, and Yu (2007), one of the early, if not the earliest, studies that brought dollar rolls to the attention of the academic finance literature and that investigated performance of the "mortgage arbitrage" strategy in which long positions in MBS passthroughs are financed through dollar rolls. More recently, Kandrac (2013, 2014) study the impact of Federal Reserve asset purchases on IFRs and Song and Zhu (2014) examine the mechanisms and drivers—including Fed's asset purchases—behind dollar roll specialness, measured by the spreads between dollar roll IFRs and prevailing funding rates. A part of our paper also considers potential drivers of dollar-roll IFRs, including several agency MBS supply-demand factors beyond asset purchases. More importantly, our study differs in being the first, to our knowledge, to derive systematic funding liquidity shocks embedded in the dollar roll IFRs and investigate whether exposure to such shocks is priced in the cross-section of agency MBS returns. Such investigation is novel not only for the dollar roll studies, but also for the broader literature on collateralized funding rates, as this literature tends to focus on how security-specific collateral rents translate into cash prices (e.g. Duffie (1996), Jordan and Jordan (1997) and Song and Zhu (2014)) rather than on expected return premiums associated with funding liquidity risk embedded in those rates. Such a distinction resembles the distinction between studies on the characteristic-based and risk-factor-based return premiums.

Finally, our paper contributes to the literature studying determinants of MBS returns, which is surprisingly uncrowded given the size and importance of the MBS and underlying mortgage markets. Earlier examples include Schwartz and Torous (1989), Stanton (1995), Brown (1999), Levin and Davidson (2005) and Gabaix et al. (2007), which examine importance of prepayment and associated risks for MBS valuation. A more recent related study is Boyarchenko et al. (2015), which finds that cross-section of OAS sorted on moneyness of the underlying MBS passthroughs is explained by pre-payment risk, while time-series variation in OAS is mostly due to non-prepayment risk factor, which could potentially reflect liquidity and supply-demand imbalances. In our work, we employ a market-based proxy of funding liquidity in the MBS market and find that, after controlling for prepayment risk, exposure to innovations in this measure is priced in the cross-section of average OAS.

The rest of the paper proceeds as follows. Section 2 provides background on dollar roll IFRs and funding liquidity shocks. It summarizes mechanics of dollar roll transactions, explains how to interpret the IFRs, explores variation in these rates, emphasing the role of agency MBS supply-demand factors, and finally discusses how we use the IFRs to construct funding liquidity shocks. Section 3 quantifies the compensation for funding liquidity risk in the TBA market. Section 4 concludes.

2 Funding Liquidity in the MBS Market

2.1 A Brief Introduction to Mortgage Dollar Rolls

Agency mortgage-backed securities (MBS) are financial securities that transit to their holders cash flows from specific pools of underlying mortgages and that are guaranteed by three housing finance agencies, Fannie Mae (FNMA), Freddie Mac (FHLMC) and Ginnie Mae (GNMA). Most of agency MBS are traded in a forward market known as the to-be-announced

(TBA) market. In a TBA trade, the buyer and seller agree on general characteristics of the trade, but the buyer does not know the specific securities that will be delivered until the *notification day* (two days before the settlement date), with settlements occurring on a monthly basis. In particular, the buyer and seller agree on the issuing agency, maturity, coupon, and par amount (e.g., $100 million of FNMA 30-year 3.5% pass-through), the price (e.g., $102) and settlement date (e.g., standard next month settlement). Specifying only several security characteristics for trading purposes homogenizes securities backed by distinct pools of underlying mortgages and makes the TBA market active and liquid.[4]

Financing, or funding, of MBS positions in the TBA market occurs through dollar rolls. In general, a dollar roll is similar to a repurchase transaction. In both types of transaction one party agrees to sell securities to another in return for cash (the front leg), and repurchase them at a later point (the back leg). However, there are two important differences between a repo agreement and a dollar roll. First, the ownership of the security sold in the dollar roll transaction is transferred to the purchaser, who receives the intervening cash flows such as (scheduled and unscheduled) principal and coupon payments. Second, the repurchased security can be "substantially similar" to the one sold originally, as opposed to exactly the same, as in the repo transaction.[5]

Dollar rolls can also be viewed as combinations of a simultaneous sale (purchase) of a front-month TBA contract and purchase (sale) of a new TBA contract that settles during the back-month. The value of a dollar roll is determined by the spread between the front- and back-leg prices, which is referred to as the "drop." The drop compensates the roll seller for the lost *carry* (coupon and principal payments) and the risk of being delivered a less desirable security at the back-leg, while also reflecting net funding and collateral demands in

[4]See Vickery and Wright (2013) for a more detailed background on the TBA market.

[5]"Substantially similar" means that the security needs to have the same basic characteristics, including the issuing agency, original maturity, and coupon. For example, FNMA 30-year 3.5%.

the MBS market. For an investor with a long position in a TBA contract financed through the dollar roll, the difference between the dollar roll drop and foregone revenues from projected principal and coupon payments represents the interest rate on the funds obtained to finance the long position, namely, the dollar roll implied financing rate (IFR).

Another way to visualize the concept of the IFR, is to consider an investor who is scheduled to take delivery of an MBS with a particular set of characteristics and a nominal value of L_t dollars in the TBA market. This investor has two options. First, she could postpone the delivery and roll this position from month t to month $t+1$ (and reinvest the proceeds of the sale at the rate r_t). Alternatively, she could hold the MBS over the same period. The IFR is the rate of return under which the investor receives the same expected cash flows under these two choices. That is, given assumptions about the expected prepayment rate, the IFR must satisfy the following equality,

$$\underbrace{(1+f_t)P_tL_t - P_{t+1|t}E(L_{t+1})}_{\text{Cash-flow from dollar roll plus re-investment}} = \underbrace{PR_t + I_t + E(PP_{t+1})}_{\text{Cash-flow from MBS}} \quad (1)$$

where P_t is the front-leg MBS price for month-t settlement, $P_{t+1|t}$ is the agreed repurchase MBS price for month-$t+1$ settlement, $E(L_{t+1})$ is the expected remaining principal after the scheduled principal payments and its prepayments, PR_t is scheduled balance payment, I_t is the interest payment, and $E(PP_{t+1})$ is the expected principal prepayment. The IFR for the month $t/t+1$ dollar roll is denoted f_t.[6]

As dollar rolls are often used for financing long positions in MBS securities, the IFR can be thought of as a rough gauge of expected funding pressures in the TBA market, conceptually similar to how General Collateral (GC) repo rate is used in the repo market. This is in

[6]In practice, investors also compare the exact dates during the month when interest and principal payments are received with the front- and back-leg delivery dates to account for accrued interest when computing the IFRs.

contrast to special collateral (SC) repo in Treasury markets, which is mostly used to obtain securities for the purposes of subsequent short selling rather than to fund long positions. At the same time, dollar rolls possess features similar to those of special collateral (SC) repo, as the dollar rolls underlying collateral includes MBS satisfying specific albeit not exhaustive characteristics, such as coupon, maturity and issuing agency, rather than just belonging to a broad asset class.

2.2 Variation in Dollar Roll IFRs: the Role of Supply and Demand of MBS Collateral

To explore the effect of changes in supply and demand of MBS collateral on dollar roll implied financing rates, we collect data on implied financing rates on Fannie Mae securities with a 30-year maturity from J.P. Morgan, Morgan Markets over the period of January 2013 and December 2015. In particular, we estimate the following model for the IFR of individual dollar roll contracts:

$$f_{i,t} = \alpha_i + \mathbf{z}_{i,t}\gamma_{i,1} + \mathbf{x}_t\gamma_{i,2} + \epsilon_{i.t} \quad (2)$$

where $f_{i,t}$ is the IFR for the month $t/t+1$ dollar roll and security i, and $\mathbf{z}_{i,t}$ and $\mathbf{x}_t$ denote security-level and aggregate explanatory variables, respectively. We define the IFR for the dollar roll with front-month t and back-month $t+1$ as the average of the IFR from the day after the notification day for the month $t-1$ through the notification day for the month t. We omit the first six months for each of the securities because, according to anecdotal reports, trading tends to be scarce over the first few months after the newly-produced security is introduced into the market.

Among the variables included in the vector $\mathbf{z}_{i,t}$ are the total stock of outstanding MBS underlying each of the TBA contracts (net of holdings by the Federal Reserve) and the face value (in US$ billions) of the outright Federal Reserve purchases of each MBS security in the TBA market. Our hypothesis is that a larger private supply makes the security less scarce in the dollar roll market and, therefore, should be associated with a higher IFR.[7] Similarly, the Federal Reserve's agency MBS outright purchases are expected to push up the front-month MBS prices, leading to increases in the "drop" and, consequently, to declines in the IFRs.[8] The vector of security-level controls also includes the expected speed of prepayments as measured by the median expected prepayment speed forecast of the major Wall Street dealers. To differentiate between potentially different impact of prepayment on securities trading above or below their face values, we interact this variable with the spread between a securitys price in the TBA market over its face value of 100 (we refer to this spread as "premium").

The vector $\mathbf{x}_t$ includes issuance of agency Collateralized-Mortgage Obligations (CMO) and the volume of transactions by primary dealers in agency MBS. We expect that higher agency CMO production during the front month would increase demand in the TBA market during that month and, as a result, decrease the IFRs by driving the front-month MBS prices higher relative to their back-month counterparts. Large transactions by dealers (dealer volumes) in agency MBS could be associated with higher IFRs if dealers finance their positions in the dollar roll market (and thus sell dollar rolls) or with lower IFRs if the dealers are purchasing the securities through this market. Finally, we also control for the 1-month MBS repo rate to capture the general level of MBS financing rates.

The results from this regression are presented in Table 1. We report results from time-series regressions for individual contracts, as well as from an unbalanced panel data regression

[7] The availability of securities in the TBA market is determined by the stock of cheapest-to-deliver securities as participants tend to deliver the most economical, or "cheapest-to-deliver," securities. We approximate this stock with the total MBS outstanding, although it is important to keep in mind that this proxy is not perfect.

[8] Although this effect may be offset to the extent Federal Reserve purchases of MBS lower primary mortgage rates and lead to an increase in mortgage origination.

that pools together the data across contracts and allows for contract-level fixed effects. As expected, the coefficient on the total stock of MBS outstanding is positive and highly significant in most regressions. Similarly, the estimated impact of outright SOMA purchases is negative and statistically significant for the 3.0% and 3.5% coupons, implying that Federal Reserves agency MBS purchases had some impact on those securities IFRs. The coefficient on these terms imply that a $1 billion increase in SOMA monthly purchases lowers IFRs by around 1 to 3 basis points. In our pooled regression model and in some contract-level specifications, we also find that an increase in agency CMO production and an increase in inter-dealer MBS transactions are associated with a decline in IFRs. The coefficient on prepayment is statistically different from zero for most coupons. This result is somewhat surprising, given that in an efficient market the drop would be expected to adjust to reflect the new information about anticipated prepayment speeds, and highlights the importance of controlling for prepayment when studying the informational content of the IFRs.

All told, our results suggest that IFRs tend to decline when the underlying MBS collateral becomes more scarce and tend to rise when the collateral is more readily available. From the perspective of an MBS investor long in a TBA contract, scarcity of collateral translates into attractive financing rates. This pattern conforms with economic intuition and lends support to using information embedded in dollar roll IFRs to capture funding conditions in the MBS market.

2.3 Measuring Funding Liquidity in the MBS Market

We next construct a measure of funding liquidity using information from fluctuations in IFRs. In particular, we extract the common factor driving the financing rate on the funds obtained through dollar rolls ($f_{i,t}$) relative to the repo market (r_t). Specifically, we estimate the following unobserved-components model,

$$r_t - f_{i,t} = c + \kappa_i F_t + w_{i,t}$$
$$F_t = \rho F_{t-1} + l_t \tag{3}$$

where r_t is the 1-month MBS GC repo rate, $f_{i,t}$ is the IFR on security i, and F_t is a latent variable driving aggregate funding liquidity in the MBS market. We assume that idiosyncratic shocks $w_{i,t}$ to contract-level funding conditions and market-wide shocks to funding liquidity l_t are jointly normally distributed, and estimate the model using a standard Kalman filter adjusting for the fact that we have an unbalanced panel. We estimate the model using weekly data on IFRs for 30-year Fannie Mae and Freddie Mac securities across coupons ranging from 3.0% through 7.5%. Our sample is from January of 1998 through December of 2015. Estimated model parameters are presented in table 2.[9]

With κ_i being positive for all the securities, the basic interpretation of our measure of funding liquidity, F_t, is that an increase in F_t captures more advantageous funding conditions in the MBS dollar roll market. Figure 1 displays a plot of our measure of aggregate funding liquidity, F_t, along with funding liquidity shocks, l_t obtained from the estimation of (3). For example, our measure shows the largest negative funding liquidity shock in late 2008, after the Lehman collapse and around the beginning of the Federal Reserve's asset purchase programs, which was a period associated with a drop in market liquidity.[10] We also compute the correlation between our measure of funding liquidity shocks and the growth rate of total trading volume in 30-year Fannie Mae and Freddie Mac securities, which

[9] The results presented in the paper are robust to using the 1-month LIBOR instead of the GC repo rate.

[10] Several anecdotal explanations offered by market participants for the sharp rise in the spread between dollar roll IFRs and MBS GC repo rate during this period could help explain why our recovered shocks take large negative values. First, some financial firms, faced with funding pressures, sold MBS holdings. Second, rumors of a government-sponsored refinancing program created risks of faster-than-expected prepayment speeds. Lastly, the reduction of balance sheet capacity of primary dealers likely prevented them from arbitrating the spread away by buying dollar rolls and funding these purchases in the MBS repo market.

is a popular measure of liquidity in the MBS market and is available since May of 2011.[11] We find that funding liquidity shocks are positively correlated with trading volume (0.30, $p-$value$=$ 0.00), consistent with a link between funding conditions and market liquidity highlighted in Brunnermeier and Pedersen (2009).

3 The premium for funding liquidity exposure in the MBS market

This section explores the impact of MBS market-wide funding liquidity shocks on expected returns on agency MBS. As in Gabaix et al. (2007), we proxy the risk premium on an MBS using the security's option-adjusted spread (OAS). The OAS on an MBS is a measure of the expected return over a portfolio of Treasury securities with the same cash flow, after taking into account for the option of prepayment.[12] Even though the OAS is a noisy measure of MBS expected returns because its computation depends on the specific prepayment model used in its computation, Boyarchenko et al. (2015) show that the OAS is a good predictor of interest-rate-hedged returns.

As suggested in Fama and French (2008), we use two related approaches to explore how OAS across securities varies with the exposure to funding liquidity. First, we compute expected returns on portfolios formed based on exposure of individual MBS to innovations in funding liquidity. Second, we use the two-stage cross-sectional regression method of Fama and Macbeth (1973) and test if fluctuations in funding liquidity are a risk factor. For both exercises, we evaluate if the results are robust to controlling for the risk of prepayment,

[11] The data on trading volume is based on the Trade Reporting and Compliance Engine (TRACE) data reported by the Financial Industry Regulatory Authority (FINRA). The data collection started in May of 2011.

[12] See Boyarchenko et al. (2015) for a detailed discussion about the computation and interpretation of the OAS.

which has been highlighted as an important risk faced by MBS investors[13].

3.1 Data

We obtain the OAS on 30-year MBS issued by Fannie Mae and Freddie Mac from J.P. Morgan, Morgan Markets. The data are daily and the sample covers the period between January of 1998 to December of 2015, however, availability of data for each security depends on the coupon of the security. We also collect data on the characteristics of the underlying mortgages at a monthly frequency, including the prepayment rates as measured by the conditional prepayment rate (CPR), the weighted-average coupon (WAC), the weighted average loan age (WALA) measuring the time in months since the origination of the loans, the pool factor computed as the proportion of the original balance outstanding, and the stock of outstanding securities in dollars. In our empirical exercises we use the weekly average of the OAS for each security and drop quotes when the outstanding amount of the security is below 0.5% of total outstanding for the 30-year securities issued by the respective agency. Table 3 presents the average OAS for each security in our data set expressed in basis points along with the average characteristics of the underlying pools.

3.2 Funding Liquidity Portfolio Sorts

In the spirit of Fama and French (1992), we form portfolios sorted on funding liquidity betas, β^l, which we define as the OLS coefficients of a time-series regressions of the OAS on a constant and funding liquidity shocks l_t. In particular, at the beginning of year t, we estimate the ranking β^ls using data for three years before year t and we assign securities to

[13] See, for example, Gabaix et al. (2007)

two β^l-sorted portfolios.[14] After assigning securities to the β^l-sorted portfolios, we compute the OAS on the portfolios for the next 12 months, from January to December of year t. We compute the equally weighted OAS (OAS_{ew})as well as OAS weighted by the outstanding value of each security (OAS_{ow}). As a result, we have weekly OAS on three β^l-sorted portfolios from January 2001 to December 2015.

The top panel of Table 4 reports the average pre-ranking funding liquidity beta, β^l, the average OAS outstanding-weighted (OAS_{ow}) and equally-weighted (OAS_{ow}) for the two β^l-sorted portfolios. Table 4 shows that the funding liquidity beta is positive for all portfolios and that there is a positive and statistically significant spread in pre-ranking β^ls between the most and least exposed portfolios. Therefore, when funding conditions get tighter, the OAS (value) of the portfolios with highest β^l will experience a more pronounced decline (increase) than those with the lowest β^l. The table also shows that there is a negative relation between the average OAS and the funding liquidity beta β^l. In other words, investors are willing to pay a premium to hold the portfolio whose value (OAS) increases (decrease) more in response to negative funding liquidity shocks relative to the least exposed portfolio. In particular, the spread in OAS_{ow} between the most and least exposed portfolio is -11.6 basis points. Intuitively, investors are willing to accept a lower return to hold a portfolio that has underlying securities that are more scarce and as such, a portfolio more valuable in the spot and funding market, in times when funding liquidity deteriorates in the MBS market.

The spread in portfolios may be potentially related to characteristics of the securities underlying our sample. For example, Gabaix et al. (2007) show that the risk of borrowers prepaying their mortgages is one important factor driving the cross-section of MBS returns. The lower panel of Table 4 reports selected characteristics of the two portfolios. We find that

[14]The cut-off points are computed each year and correspond to the 30th and 70th percentile. The least exposed portfolio comprises those securities with a β^l below the 30th percentile and the most exposed portfolio contains securities with a β^l above the 70th percentile.

the average coupon (WAC) is very similar across portfolios. On the other hand, prepayment of the portfolios as measured by the CPR over 1-, 12-months and since its issuance is positively related to the funding liquidity β^l. Consistent with this, we also find that the age of the loans in the portfolio increases with β^l, which is reflected in a higher WALA and lower pool factor. One can argue that our sorting on funding liquidity beta β^l might be reflecting the lower prepayment risk of the portfolio with the highest β^l, because the underlying securities have more seasoned loans which are less likely to prepay.

To control for the prepayment behavior of the underlying securities, we form portfolios sorted on prepayment and the funding liquidity beta. We use two proxy variables to capture prepayment risk, the average 1-month CPR of a security and the spread between the MBS average coupon and the current mortgage rate on a 30-year loan as in Boyarchenko et al. (2015), which captures the incentive to prepay or the securities *moneyness*. Similar to our previous exercise, at the beginning of year t, we compute the ranking β^ls and the average prepayment using data for three years before year t. We assign securities into four portfolios as follows: two β^l-sorted portfolios for securities above the median CPR or incentive to prepay, and two β^l-sorted portfolios for securities below the median CPR or incentive to prepay.[15] Then, we compute the OAS on the portfolios for the next 12 months, from January to December of year t.

Tables 5 and 6 present the average pre-ranking funding liquidity beta, β^l, the average OAS outstanding-weighted (OAS_{ow}) and equally-weighted (OAS_{ow}) for the four prepayment-β^l sorted portfolios. Similar to our results in Table 4, we find that for portfolios with high and low prepayment, there is a negative relationship between the funding liquidity beta β^l and the return on MBS as captured by the OAS. The spread in OAS, both equally- and outstanding-weighted, between the portfolios with the highest and lowest funding β^l is

[15] The cut-off points for the funding liquidly beta are computed each year and correspond to the 50th percentile.

negative and statistically different to zero. We find similar results for portfolios sorted on the funding liquidity β^l and the incentive to prepay (see Table 6).

In sum, MBS investors seem to be willing to accept lower returns on securities that rise in value in times when funding liquidity deteriorates, because these securities allow investors to obtain funding at better terms in the dollar roll market in times when funding costs in the MBS are tighter. These results highlight the importance of funding conditions in the MBS market for the valuation of agency MBS.

3.3 Funding Liquidity and the Cross-Section of MBS Returns

The results presented in Section 3.2 support an asset pricing model for mortgage-backed securities that includes a factor capturing funding liquidity in the MBS market. Here, we compute the market price of funding liquidity using a linear factor model that includes a funding liquidity factor. To estimate the asset pricing model, we consider the OAS on individual agency securities for which we have at least 10 years of data, and the OAS on the two β^l-sorted portfolios constructed in Section 3.2.

3.3.1 Econometric Strategy

We estimate a linear factor model, which explains the variation of returns across MBS through cross-sectional variation in the beta with respect to funding liquidity shocks,

$$E[OAS_i] = \lambda_0 + \lambda_l \beta_i^l \tag{4}$$

where $E[OAS_i]$ is the expected option-adjusted spread on security i, β_i^l is the exposure of security i to funding liquidity shocks, and λ_l is the market price of funding liquidity risk.

Following Fama and Macbeth (1973), we estimate the linear factor model (4) using the two-stage cross-sectional regression method. First, we estimate the β_i^l by performing an OLS regression of the option-adjusted spread on security i on a constant and MBS funding liquidity shocks,

$$OAS_{i,t} = a_i + \beta_i^l l_t + \epsilon_{i,t} \tag{5}$$

where l_t is the funding liquidity shock at time $t = 1, \ldots, T$. Then, we estimate the funding liquidity premium λ^l from a regression of the average OAS on our test assets on a constant and the estimated β^ls,

$$E_T(OAS_i) = \lambda_0 + \lambda^l \beta_i^f + \alpha_i \tag{6}$$

where α_i is the pricing error of security $i = 1, \ldots, N$, and $E_T(OAS_i)$ is the average OAS over the sample period. We report the standard errors for the estimated market price of funding liquidity risk λ^l adjusted for sampling error in the estimation of β^ls as suggested in Shanken (1992). To evaluate our pricing model, we also report the cross-sectional R^2 and the square root of the squared sum of pricing errors (RMSE) $\sqrt{\sum_i \hat{\alpha}_i^2/N}$ along with the statistic of whether all pricing errors are statistically different from zero.[16] Finally, as an additional measure of model fit, we also report the GSL R^2 as suggested in Shanken and Zhou (2007).

3.3.2 Empirical Results

Panel A of Table 7 reports the estimated funding liquidity betas β^l along with standard errors robust to serial correlation and heteroskedasticity (i.e., model (5)). The results show that all securities have a positive significant funding liquidity beta β^l and most estimates are statistically different from zero. Moreover, as shown in Figure 2, the estimated β^ls for each security are negatively related to the expected return on the securities as measured by

[16] We report the statistic $\hat{\alpha}' \text{cov}(\hat{\alpha})^{-1} \hat{\alpha} \sim \chi^2_{N-2}$, where $\hat{\alpha}$ is the vector of pricing errors and $\text{cov}(\hat{\alpha})$ is the estimated covariance matrix, and N is the number of test assets.

the option-adjusted spread, which is consistent with the portfolio evidence we reported in Section 3.2.

Panel B of Table 7 reports the cross-sectional estimates of the market price of liquidity risk. The estimates show that the market price of funding liquidity risk is negative and statistically different from zero. Our model has an adjusted-R^2 of 80%, a GLS R^2 of 56%, and a RMSE of 2.8 basis points. The null hypothesis that all pricing errors are equal to zero cannot be rejected at a standard confidence level. The good performance of our funding liquidity factor model can be seen in Figure 3 that displays the predicted versus the realized OAS from our benchmark model. The OAS on the securities used in our empirical exercise line up very close to the 45-degree line, and the pricing errors are small. In sum, our results suggest that exposure to funding liquidity explains well the cross-sectional variation in option-adjusted spreads in MBS, highlighting the importance of fluctuations in funding conditions in the MBS market.

3.3.3 Robustness to Prepayment Risk

Gabaix et al. (2007) and more recently Boyarchenko et al. (2015) have shown that the risk of homeowners prepaying their loans is an important risk faced by MBS investors, and that it explains the cross-sectional difference in the OAS across securities. To check that our estimates of the risk premium on funding liquidity are not driven by prepayment risk, we estimate a factor model that includes both funding liquidity and prepayment risk,

$$E[OAS_i] = \lambda_0 + \lambda_l \beta_i^l + \lambda_p \beta_i^p (c_i - r^m) \tag{7}$$

where β_i^l is the exposure of security i to funding liquidity shocks and β_i^p is the exposure to prepayment shocks, while λ_l and λ_p are the market price of funding liquidity and prepayment risks, respectively. Following Gabaix et al. (2007), we assume that the compensation for prepayment risk depends on on whether the security's coupon c_i is above or below the mortgage rate r^m. Therefore, the expected OAS of securities with a coupon above the market mortgage rate increases if the mortgage prepays faster than expected.[17]

To evaluate if the funding liquidity factor is still priced once we include the prepayment factor, we estimate equation (7) using the two-pass regression approach and simple regression betas (see Jagannathan and Wang (1998) and Cochrane (2009)). Specifically, in the first stage we estimate the funding liquidty betas, β_i^l, using (5), and we estimate β_i^p as the slope coefficient of an OLS regression of the the option-adjusted spread on security i on a constant and the MBS prepayment factor. We use the change in the spread between the average coupon of outstanding agency securities and the 30-year primary mortgage rate as the prepayment factor. This is consistent with the MBS valuation model in Gabaix et al. (2007), in which the market price of prepayment risk is proportional to the difference between the average market coupon and the primary mortgage rate. In the second stage, for each period t, we run a cross-sectional regression of the option-adjusted spread on a constant, the funding liquidity beta (β_i^l), and the prepayment beta interacted with the spread between the security's average coupon and the current mortgage rate ($\beta_i^p(c_i - r^m)$) to obtain an estimator of the market price of funding liquidity and prepayment risk.

Table 8 reports the estimates of $\hat{\lambda} = (\hat{\lambda}_0, \hat{\lambda}_l, \hat{\lambda}_p)$ along with standard errors that account for cross-sectional heteroskedasticity and autocorrelation. As in our previous exercise, to assess the model fit, we report the cross-sectional R^2 and the RMSE along with the statistic of the test of whether the average pricing error equals to zero. The first row of Table 8 shows that the price of funding liquidity remains statistically significant even after controlling for prepayment risk. While the market price of prepayment risk is positive and statistically

[17]See Gabaix et al. (2007) and Boyarchenko et al. (2015) for a more detailed exposition of the relationship between prepayment and MBS risk.

different from zero, the pricing errors of the augmented model are only slightly below of those obtained in our baseline specification with funding liquidity as the only risk factor.

Taken together, our results suggest that funding liquidity is an important risk faced by investors in the market of agency MBS. Consequently, investors are willing to pay a premium to hold those assets that increase in value in times when funding liquidity conditions tighten.

4 Conclusion

In this paper we investigate whether funding liquidity risk is compensated in the mortgage-backed securities market. Using the implied financing rates (IFRs) as indicators of cost of financing positions in agency MBS passthroughs, we construct systematic funding liquidity shocks and show that exposure to such shocks is priced: Investors are willing to accept lower excess returns to hold individual MBS passthroughs that are better hedges against market-wide funding liquidity shocks, as well as portfolios that are dynamically formed from individual MBS passthroughs with better hedging performance. These results are robust even after we control for prepayment risk. Our results contribute to understanding of the links between funding and cash markets, as well as between liquidity and expected returns.

Our approach of deriving measures of funding liquidity risk using security-specific financing rates is novel and has not been employed in the literature on collateralized funding rates. A question arises whether security financing rates in other markets contain similar information on funding liquidity risk that is relevant for explaining expected returns of the corresponding securities, as well as whether indicators of funding liquidity risk in different markets comove and can cross-price assets in different markets. Ultimately, this question is related to the question of whether all assets are priced by the same marginal investor, be it a representative consumer or a representative financial intermediary, or whether prices in different markets are set by their own marginal investors. Using financing rates in different markets can potentially help address this question without having to identify marginal investors, as well as having to procure information on balance sheets of individual financial agents. Another related question is whether some of the relevant funding liquidity events are sufficiently short-lived so that market-based rather than lower-frequency balance sheet measures are needed to capture them. We leave these questions for future research.

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A Unobserved-Component Model

In this section we briefly outline the algorithm we employ to estimate the unobserved-components model (3),

$$r_t - f_{i,t} = c_i + \kappa_i F_t + w_{i,t}$$

$$F_t = \rho F_{t-1} + l_t$$

where r_t is the 1-month MBS GC repo rate, $f_{i,t}$ is the IFR on security i, and F_t is a latent variable driving aggregate funding liquidity in the MBS market. For our estimation we consider the IFRs on n securities, ($f_{i,t}$ for $i = 1, \ldots, n$). One quality of our dataset is that at time t, we only observe $n_t \leq n$ IFRs. Consequently, we need to modify the standard Kalman Filter to take into account the missing observations.

Let S_t be a matrix of size $n_t \times n$ which is obtained from an identity matrix that omits the rows of the missing observations, and let $\mathbf{y}_t = r_t - \mathbf{f}_t$. Model (3) with an unobserved common component can be written as,

$$\mathbf{y}_t = S_t c + S_t \kappa L_t + S_t \mathbf{w}_t \qquad \text{(observation equation)}$$

$$F_t = \rho F_{t-1} + l_t \qquad \text{(state equation)}$$

with v_t and w_t are iid with variance-covariance matrices $\mathbb{E}\left(v_t^2\right) = Q$ and $\mathbb{E}\left(w_t w_t'\right) = R$, and $\mathbf{y}_t$ is a size n vector. As noted in Kim and Nelson (1999), c cannot be identified by observing $y_{i,t}$. Consequently, we estimate the model in deviations from long-run means. The Kalman filter algorithm under this specification is the following:

Step 0: Set $\hat{L}_{1|0} = 0$ and

$$P_{1|0} = \Gamma = \frac{Q}{1 - F^2}$$

For $t = 1, \dots, T$:

Step 1: Prediction Compute the conditional forecast of the n_t observed values of y_t based on all available information up to time $t-1$,

$$\hat{y}_{t|t-1} = \mathbb{E}\left(y_t|\psi_{t-1}\right) = S_t \kappa L_{t|t-1}$$

with forecast error and corresponding variance are,

$$\begin{aligned} \eta_{t|t-1} =& y_t - \hat{y}_{t|t-1} = y_t - S_t \kappa L_{t|t-1} \\ \mathbb{E}\left(\eta_{t|t-1}\eta'_{t|t-1}\right) =& S_t \kappa \kappa' S'_t P_{t|t-1} + S_t R S'_t \end{aligned}$$

Step 2: Update The updated forecast of the state variable is,

$$\hat{L}_{t|t} = \mathbb{E}\left(L_{t+1}|\psi_{t-1}, y_t\right) = \hat{L}_{t|t-1} + K_t \eta_{t|t-1}$$

where K_t is the weight assigned to new information, namely, the Kalman gain matrix given by,

$$K_t = P_{t|t-1}\kappa' S'_t (S_t \kappa \kappa' S_t P_{t|t-1} + S'_t R S_t)^{-1}$$

The variance of the error associated with this projection is equal to,

$$P_{t|t} = P_{t|t-1} - K_t S_t \kappa P_{t|t-1}$$

Step 3: Forecast The updated value of the state variable can be used to produce a one-step forecast,

$$\hat{L}_{t+1|t} = F\hat{L}_{t|t}$$
$$P_{t+1|t} = F^2 P_{t|t} + Q$$

Maximum Likelihood Estimation

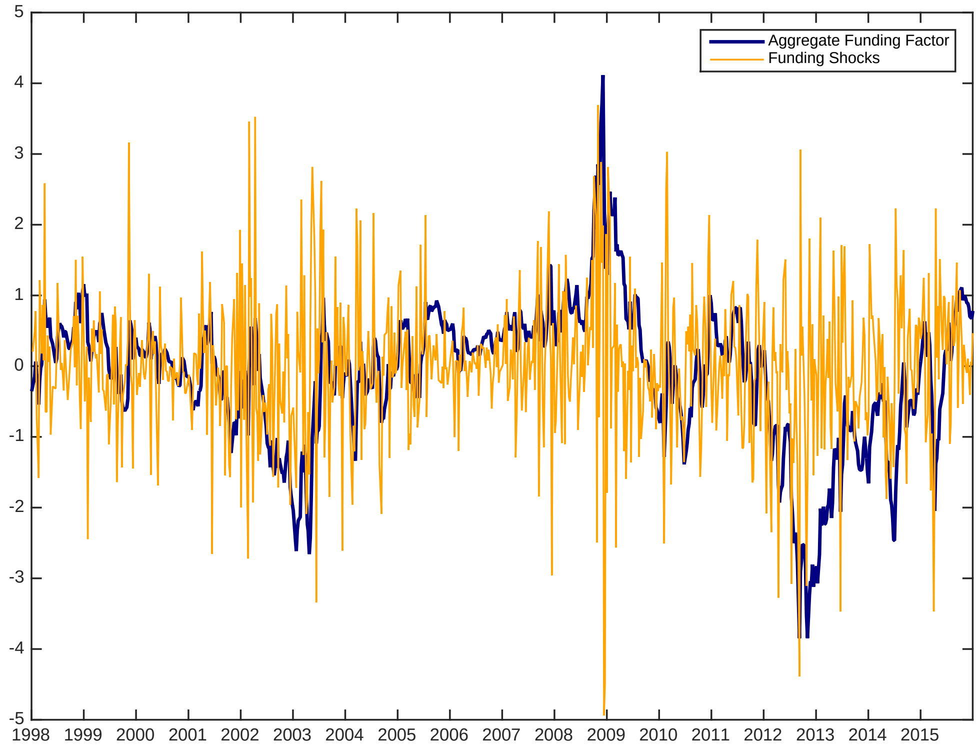
Under the assumptions above, we have,

$$y_t|\psi_{t-1} \sim N(\hat{y}_{t|t-1}, \mathbb{E}\left(\eta_{t|t-1}\eta'_{t|t-1}\right)),$$

The maximum likelihood estimates are obtained by maximizing the sample log likelihood,

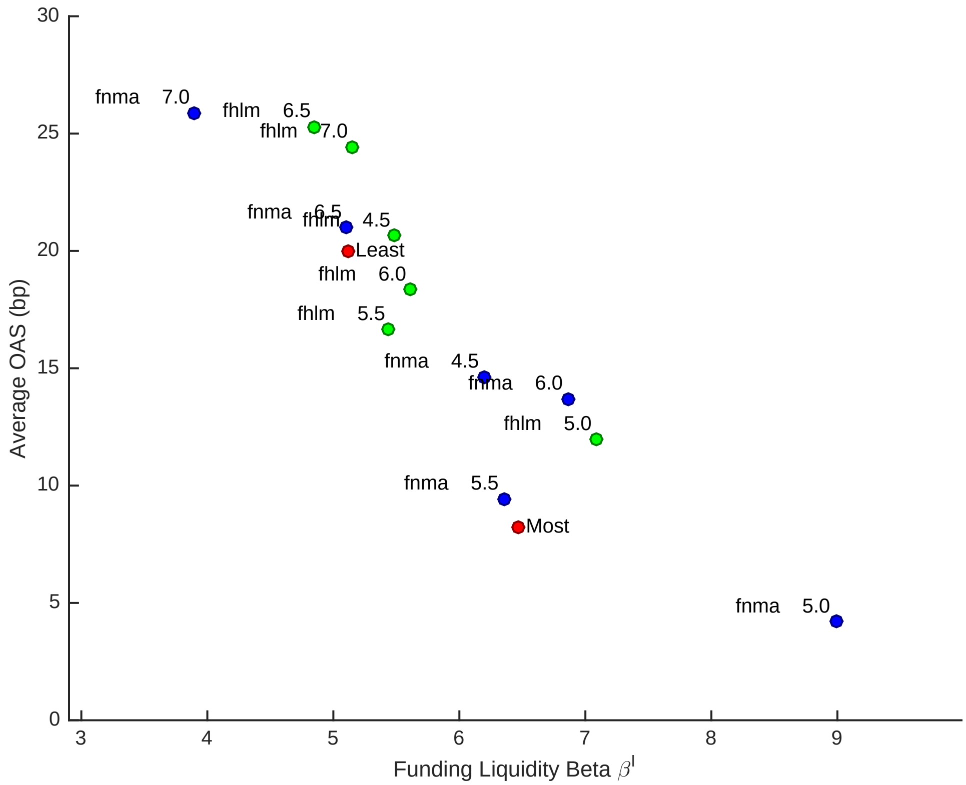
$$\ln \mathcal{L} = -\frac{1}{2}\sum_{t=1}^{T} \ln((2\pi)^n||\mathbb{E}\left(\eta_{t|t-1}\eta'_{t|t-1}\right)||) - \frac{1}{2}\sum_{t=1}^{T} \eta'_{t|t-1}\mathbb{E}\left(\eta_{t|t-1}\eta'_{t|t-1}\right)^{-1}\eta_{t|t-1} \qquad (8)$$

Figure 1: Funding liquidity: Aggregate measure and shocks



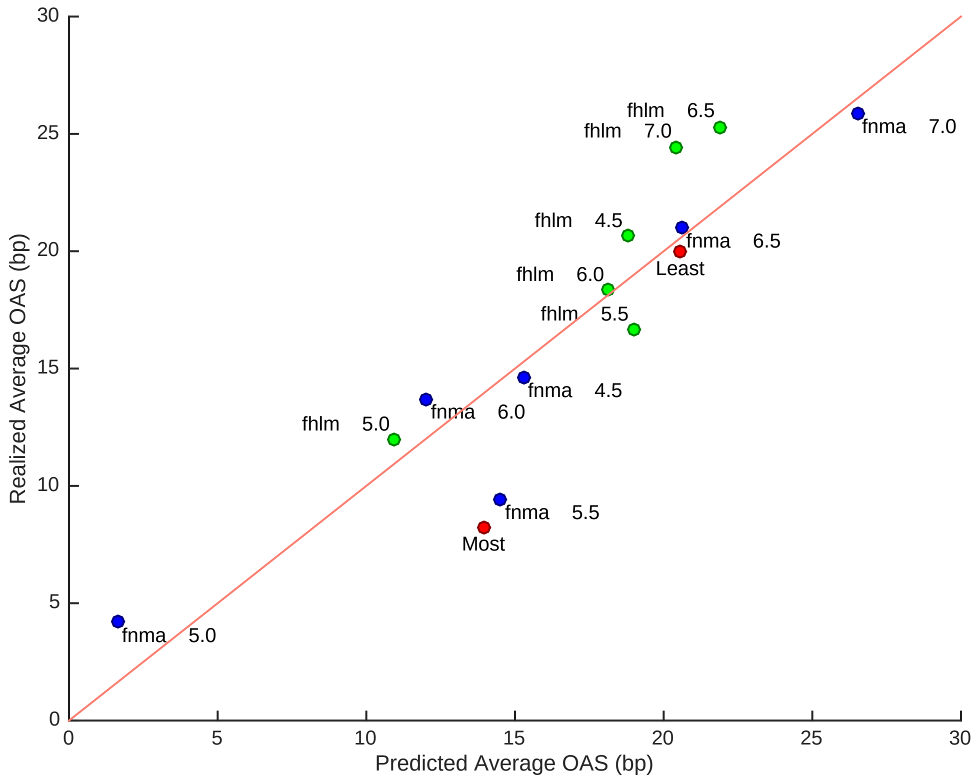
This figure displays our measure of aggregate funding liquidity, F_t, along with shocks to funding liquidity between January 1998 and December 2015. The data is weekly and is standardized to have a standard deviation equal to one for convenience. The aggregate cost of funding in the MBS market is obtained as the common component driving the spread between the 1-month MBS repo rate and dollar roll implied financing rates based on the unobserved-components model (3).

Figure 2: Estimated Funding Liquidity Beta and Average Option-Adjusted Spreads



This scatter plot reports the full sample average OAS against the estimated funding liquidity betas β^l. The test assets include Fannie Mae (FNMA) and Freddie Mac (FHLM) agency MBS with at least 10 years of observations, and the two funding liquidity sorted portfolios constructed in Section 3.2. The estimated β_i^ls come from an OLS regression of the option-adjusted spread on security i on a constant and funding liquidity shocks in the MBS market. The estimates are obtained using weekly data. The OAS sample varies by security and covers the period between January 1998 to December 2015.

Figure 3: Realized versus Fitted Average OAS



This scatter plot reports the full sample average OAS against the fitted OAS from our funding liquidity factor model. The test assets include Fannie Mae (FNMA) and Freddie Mac (FHLM) agency MBS with at least 10 years of observations, and the two funding liquidity sorted portfolios constructed in Section 3.2. The fitted OAS come from the cross-sectional regression of the average OAS associated with our test assets on a constant and the estimated funding liquidity betas, β^l, namely, $E_T(OAS_i) = \lambda_0 + \lambda^l \beta_i^f + \alpha_i$. The straight line is the 45-degree line through the origin. The OAS is expressed in basis points. The OAS sample varies by security and covers the period between January 1998 to December 2015.

Table 1: Drivers of Dollar Roll Implied Financing Rate

	(1) 3.0%	(2) 3.5%	(3) 4.0%	(4) 4.5%	(5) 5.0%	(6) 5.5%	(7) 6.0%	(8) 6.5%	(9) All
Security specific variables									
ln MBS Outstanding	0.186***	0.287***	0.0697	0.322	0.715**	0.561***	0.710***	-0.0704	0.175**
	(7.05)	(4.46)	(1.56)	(1.52)	(2.57)	(4.14)	(4.95)	(-0.30)	(2.42)
SOMA MBS purchases	-0.00887**	-0.0340*	-0.00690	-0.00426					-0.00729
	(-2.61)	(-1.81)	(-0.89)	(-0.67)					(-0.86)
Prepayment forecast x Premium	-0.0586	-0.437***	-0.106***	-0.215***	-0.167***	-0.0703***	-0.00971	-0.0522	-0.111***
	(-1.02)	(-8.47)	(-3.02)	(-3.82)	(-4.84)	(-2.80)	(-0.19)	(-1.57)	(-3.73)
Aggregate market variables									
MBS repor rate 1m	1.294**	3.494***	1.194*	1.046***	0.943***	0.961***	0.987***	1.055***	1.002***
	(2.45)	(4.74)	(1.82)	(18.56)	(26.00)	(28.82)	(15.02)	(22.94)	(58.75)
ln CMO FNMA coll.	-0.0591	0.0475	-0.0469	-0.223*	-0.287***	-0.347***	-0.220*	-0.369**	-0.199***
	(-0.86)	(0.50)	(-0.81)	(-1.95)	(-3.29)	(-4.70)	(-1.68)	(-2.57)	(-4.04)
Growth of dealers MBS volume	-0.222	0.356*	-0.357***	-0.254	-0.209	-0.312	-0.625**	-0.572**	-0.335***
	(-1.45)	(1.80)	(-2.85)	(-1.39)	(-1.01)	(-1.65)	(-2.34)	(-2.00)	(-4.23)
Constant	-2.376***	-4.042***	-0.906*	-3.453	-8.493**	-6.528***	-8.367***	1.473	-1.765*
	(-6.61)	(-4.72)	(-1.73)	(-1.40)	(-2.46)	(-3.99)	(-4.93)	(0.56)	(-2.02)
T	52	72	75	140	148	150	150	150	937
Adj. R-squared	0.612	0.605	0.197	0.957	0.956	0.955	0.923	0.829	0.905

This table presents the estimated coefficients of a regression of the IFR of individual dollar roll contracts on several supply-demand factors. The sample covers January 2003 to December 2015. The last column presents the results of a pooled regression using all coupons and allowing for contract level fixed-effects. The table reports in parenthesis Newey-West t-statistics for the time series regressions and t-statistics using clustered standard errors by coupon for the panel regression. ***, **, and * denote significant at the 1%, 5% and 10%, respectively

Table 2: Maximum Likelihood Estimates of the Unoberved-Components Model for the IFRs

Panel A: Observation Equation

Security	$\hat{\kappa}_i$
FNMA 7.5	0.7029
FNMA 7.0	0.2103
FNMA 6.5	0.2515
FNMA 6.0	0.3816
FNMA 5.5	0.2783
FNMA 5.0	0.3854
FNMA 4.5	0.2588
FNMA 4.0	0.0618
FNMA 3.5	0.1448
FNMA 3.0	0.0323
FHLM 7.5	0.8211
FHLM 7.0	0.2325
FHLM 6.5	0.2276
FHLM 6.0	0.3424
FHLM 5.5	0.2612
FHLM 5.0	0.2161
FHLM 4.5	0.1458
FHLM 4.0	0.0245
FHLM 3.5	0.1230
FHLM 3.0	0.0271

Panel B: State Equation

	Estimate
$\hat{\rho}$	0.9659

This table presents estimated coefficients characterizing the unobserved-components model for the spread between the MBS GC repo rate (r_t) and the contract-specific dollar roll IFRs ($f_{i,t}$),

$$r_t - f_{i,t} = c_i + \kappa_i F_t + w_{i,t} \quad \text{(Observation equation)}$$
$$F_t = \rho F_{t-1} + l_t \quad \text{(State equation)}$$

The data is weekly and covers the period between January 1998 and December 2015.

Table 3: Option-adjusted Spreads and Selected Characteristic of Agency MBS Securities

Fannie Mae MBS

	Coupon									
	3.0	3.5	4.0	4.5	5.0	5.5	6.0	6.5	7.0	7.5
OAS	14.73	14.46	13.65	14.32	3.96	9.25	13.64	20.93	25.87	2.82
CPR 1-month	5.24	8.76	12.69	12.53	16.15	19.69	20.87	23.37	26.05	35.75
CPR 12-months	6.69	10.30	13.30	13.04	16.81	20.94	21.85	24.13	26.69	35.22
CPR since issuance	4.33	8.46	10.28	10.30	12.60	17.20	19.39	23.43	25.74	26.85
WAC	3.60	4.06	4.54	5.02	5.52	6.01	6.57	7.04	7.58	8.06
WALA	14.55	13.80	18.98	29.72	44.05	49.67	43.70	53.09	52.48	49.56
Pool factor	0.92	0.86	0.77	0.71	0.57	0.49	0.46	0.32	0.28	0.33
No. Obs.	183	266	357	649	666	735	940	926.00	748	391

Freddie Mac MBS

	Coupon									
	3.0	3.5	4.0	4.5	5.0	5.5	6.0	6.5	7.0	7.5
OAS	14.73	14.46	13.65	14.32	3.96	9.25	13.64	20.93	25.87	2.82
CPR 1-month	4.89	9.53	13.70	12.86	16.39	19.88	20.97	23.25	26.16	35.15
CPR 12-months	7.55	11.15	14.26	13.57	17.04	21.03	21.85	23.81	26.12	34.78
CPR since issuance	3.98	9.60	11.18	10.60	12.66	17.06	19.18	23.46	25.20	26.68
WAC	3.60	4.04	4.54	5.03	5.52	6.00	6.55	7.01	7.54	8.05
WALA	14.25	13.88	19.74	29.56	42.03	48.02	43.67	56.67	55.93	52.07
Pool factor	0.92	0.86	0.75	0.70	0.58	0.50	0.45	0.30	0.30	0.32
No. of obs.	183	266	357	649	666	735	940	926	748	391

This table presents the option-adjusted spread (OAS) and selected characteristics of the underlying mortgages of 30-year MBS issued by Fannie Mae and Freddie Mac. Among the characteristics we report the prepayment rates as measured by the conditional prepayment rate (CPR), the weighted-average coupon (WAC), the weighted average loan age (WALA) measuring the time in months since the origination of the loans, and the pool factor computed as the proportion of the original balance outstanding.

Table 4: Average OAS on and Characteristics of Funding Liquidity Beta Sorted Portfolios

	Least (1)	Most (2)	Most minus Least (2)−(1)
Funding beta β^l	1.33	7.72	6.39
			(8.97)
OAS_{ow}	19.74	8.12	-11.62
			(-4.15)
OAS_{ew}	21.57	12.06	-9.51
			(-3.14)

Portfolio Characteristics

	Least	Most	Most minus Least
WAC	6.06	6.79	0.72
CPR 1-month	21.52	26.67	5.15
CPR 12-months	21.07	27.35	6.28
CPR since issuance	18.28	25.10	6.82
WALA	39.54	59.26	19.72
Pool factor	0.51	0.28	-0.23

This table presents the option-adjusted spread on portfolios formed on the exposure to funding liquidity shocks along with average characteristics of the underlying pools. Portfolios are formed yearly. Each portfolio is formed using pre-ranking funding liquidity betas, β^l, estimated using three years of weekly OAS before year t. The cut-off points are computed each year and correspond to the 30th and 70th percentile of the estimated funding liquidity betas. After assigning securities to the β^l-sorted portfolios, we compute the OAS on the portfolios for the next 12 months, from January to December of year t. The table reports equally weighted OAS (OAS_{ew})as well as OAS weighted by the outstanding value of each security (OAS_{ow}). The characteristics are simple averages of characteristics of the underlying securities. The data covers January 1998 through December 2015.

Table 5: Average OAS on Portfolios Sorted on Funding Liquidity Beta and Past Prepayment

	High Prepayment			Low Prepayment		
	Least	Most	Most minus Least	Least	Most	Most minus Least
	(1)	(2)	(2) − (1)	(3)	(4)	(4) − (3)
Funding beta β^l	4.42	7.20	2.78	1.85	4.24	2.38
			(0.17)			(0.26)
OAS_{ow}	20.37	12.95	-7.42	14.70	10.88	-3.82
			(1.76)			(1.95)
OAS_{ow}	23.91	16.30	-7.61	15.71	11.36	-4.34
			(1.97)			(1.94)
CPR 1-month	28.51	29.60		18.18	19.72	

This table presents the option-adjusted spread on portfolios formed on past prepayment and the exposure to funding liquidity shocks along with average characteristics of the underlying pools. Portfolios are formed yearly. Each portfolio is formed using pre-ranking funding liquidity betas, β^l, estimated using three years of weekly OAS before year t and the average prepayment as captured by the average 1-month CPR over three years before year t. We assign securities into four portfolios as follows: two β^l-sorted portfolios for securities above the median CPR, and two β^l-sorted portfolios for securities below the median CPR. The cut-off points for the funding liquidly beta are computed each year and correspond to the 50th percentile. After assigning securities to the double-sorted portfolios, we compute the OAS on the portfolios for the next 12 months, from January to December of year t. The table reports equally weighted OAS (OAS_{ew})as well as OAS weighted by the outstanding value of each security (OAS_{ow}). The characteristics are simple averages of characteristics of the underlying securities. The data covers January 1998 through December 2015.

Table 6: Average OAS on Portfolios Sorted on Funding Liquidity Beta and the Incentive to Prepay

	High Prepay Incentive			Low Prepay Incentive		
	Least (1)	Most (2)	Most minus Least (2) − (1)	Least (3)	Most (4)	Most minus Least (4) − (3)
Funding beta β^l	4.00	7.37	3.37	1.98	4.52	2.54
			(0.30)			(0.30)
OAS_{ow}	19.77	14.26	-5.51	14.70	11.39	-3.31
			(2.42)			(1.93)
OAS_{ow}	23.56	17.83	-5.73	15.75	12.01	-3.73
			(2.65)			(1.93)
Coupon minus mortgage rate	1.81	1.90		0.18	0.43	

This table presents the option-adjusted spread on portfolios formed on the incentive to prepay and the exposure to funding liquidity shocks along with average characteristics of the underlying pools. Portfolios are formed yearly. Each portfolio is formed using pre-ranking funding liquidity betas, β^l, estimated using three years of weekly OAS before year t and the average incentive to prepay as captured by the gap between the MBS average coupon and the current mortgage rate on a 20-year loan over three years before year t. We assign securities into four portfolios as follows: two β^l-sorted portfolios for securities above the median CPR, and two β^l-sorted portfolios for securities below the median CPR. The cut-off points for the funding liquidly beta are computed each year and correspond to the 50th percentile. After assigning securities to the double-sorted portfolios, we compute the OAS on the portfolios for the next 12 months, from January to December of year t. The table reports equally weighted OAS (OAS_{ew})as well as OAS weighted by the outstanding value of each security (OAS_{ow}). The characteristics are simple averages of characteristics of the underlying securities. The data covers January 1998 through December 2015.

Table 7: Cross-sectional Regression Results

Panel A: Funding Liquidity Beta		
Security	$\hat{\beta}^l$	$sd(\hat{\beta}^l)$
fnma 4.5	6.20	(2.66)
fnma 5.0	8.98	(3.72)
fnma 5.5	6.35	(3.23)
fnma 6.0	6.86	(2.96)
fnma 6.5	5.11	(2.71)
fnma 7.0	3.90	(4.06)
fhlm 4.5	5.48	(3.02)
fhlm 5.0	7.08	(2.77)
fhlm 5.5	5.44	(2.59)
fhlm 6.0	5.61	(2.31)
fhlm 6.5	4.85	(2.43)
fhlm 7.0	5.15	(3.63)
Most	6.47	(2.40)
Least	5.12	(2.14)

Panel B: Funding Liquidity Risk Premium				
	λ_0	λ_l	$R^2_{ols/gls}$	RMSE
Estimate ($\hat{\lambda}$)	45.64	-4.90	0.80	2.77
	(27.37)	(2.73)	0.56	[19.98]

This table presents the estimates of our benchmark linear factor model for mortgage-backed securities that includes funding liquidity $E[OAS_i] = \lambda_0 + \lambda_l \beta_i^l$. Panel A reports the estimated funding liquidity betas β^l along with Newey-West standard errors. The estimated β_i^ls come from an OLS regression of the option-adjusted spread on security i on a constant and funding liquidity shocks in the MBS market. Panel B reports the cross-sectional estimates of the market price of liquidity risk from a regression of the average OAS on our test assets on a constant and the estimated β^ls. The table reports in parenthesis standard errors adjusted for sampling error in the estimation of β^ls as suggested in Shanken (1992). Panel B also reports the cross-sectional R^2, the GLS R^2, the square root of the squared sum of pricing errors (RMSE) $\sqrt{\sum_i \hat{\alpha}_i^2/N}$ along with the statistic of whether all pricing errors are statistically different from zero in brackets. The data is weekly, the OAS sample varies by security and covers the period between January 1998 to December 2015.

Table 8: Funding Liquidity and Prepayment Risk

	λ_0	λ_l	λ_p	R^2_{ols}	RMSE
Two Factor Model	37.38	-3.72	0.43	0.75	2.65
	(6.86)	(0.81)	(0.18)		[3.43]

This table presents the estimates of the two-factor model for mortgage-backed securities that includes a funding liquidity and a prepayment risk factor $E[OAS_i] = \lambda_0 + \lambda_l \beta_i^l + \lambda_p \beta_i^p (c_i - r^m)$. The estimated β_i^ls come from an OLS regression of the option-adjusted spread on security i on a constant and funding liquidity shocks in the MBS market. The estimated β_i^p comes from an OLS regression of the the option-adjusted spread on security i on a constant and the MBS prepayment factor, namely, the change in the spread between the average coupon of outstanding agency securities and the 30-year primary mortgage rate. The table reports in parenthesis standard errors adjusted for sampling error in the estimation of the betas as suggested in Shanken (1992). It also reports the cross-sectional R^2, the square root of the squared sum of pricing errors (RMSE) $\sqrt{\sum_i \hat{\alpha}_i^2/N}$ along with the statistic of whether all pricing errors are statistically different from zero in brackets. The data is weekly, the OAS sample varies by security and covers the period between January 2001 to December 2015.