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

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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.

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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 fledgling 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 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 the links between funding liquidity and asset prices, but also contribute to the 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 the decision making by MBS investors and mortgage lenders, but that has 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 measure of aggregate funding liquidity starts drifting into negative territory and reaches a through in late 2008, after the Lehman collapse. We also find that the onset of Federal Reserve's asset purchase programs is accompanied by an improvement in funding liquidity conditions.

We use a cross-section of hedged returns on generic 30-year MBS issued by Fannie Mae and Freddie Mac traded in the TBA market to determine if fluctuations in funding liquidity are priced in the cross-section of expected returns. First, we estimate the exposure of hedged returns on individual MBS to aggregate funding liquidity shocks (funding liquidity betas) and we find that average returns increase monotonically with the exposure to funding liquidity. In particular, we find that portfolios of securities with a negative liquidity beta command the lowest average returns, while portfolios of securities with a high positive liquidity beta command the highest expected return. In other words, agency MBS perform well when financing terms in the dollar roll market unexpectedly become less favorable have lower expected returns. Therefore, these securities can be thought of as hedges against these shocks. In contrast, those that perform poorly in times of adverse financing conditions in the MBS market tend to have higher expected returns. A question then arises of whether investors are willing to forgo 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.

Using the pricing restriction for the cross-section of MBS securities, we find that the price of funding liquidity is positive, which reflects the positive relationship between average hedged returns and funding liquidity betas of individual portfolios. The market price of risk is economically and statistically significant suggesting that a decline in funding liquidity is a bad state for the MBS investor.

We confirm our findings using portfolios sorted on the exposure to funding liquidity betas. Specifically, we form portfolios based on time-varying funding liquidity betas estimated over two-year rolling-windows and compute corresponding portfolio hedged returns over the next 12 months. We find that, on average, the portfolio consisting of the MBS with the negative 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.

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, Krishnamurthy, and Vigneron (2007), which examine importance of prepayment and associated risks for MBS valuation. A more recent related study is Boyarchenko, Fuster, and Lucca (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 hedged returns.

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, emphasizing 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

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

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 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,

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

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

[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%.

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 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:

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

[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.

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

[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.

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 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,

$$\begin{aligned} r_t - f_{i,t} &= c + \kappa_i\, F_t + w_{i,t} \\ F_t &= \rho\, F_{t-1} + \ell_t \end{aligned} \tag{3}$$

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 November of 2017.

Panel A of Table 2 presents the loadings of each security κ_i on the latent variable driving funding liquidity across securities. Our estimates show that κ_i is positive for all securities suggesting that an increase in F_t captures more advantageous funding conditions in the MBS dollar roll market. Moreover, our measure of aggregate funding liquidity seems to capture well the overall time-series variation of the IFRs for several securities and is not driven by one specific security, as shown in Figure 1. This is also reflected in the R^2s shown in the third column of Panel A of Table 2, which is significant for several securities.

Figure 2 displays our measure of aggregate funding liquidity, F_t, over the sample period of January 1998 and November 2017. Before 2007, F_t is on average positive suggesting that funding conditions in the TBA market were relatively more advantageous than in the repo market. However, starting in 2007 F_t starts drifting into negative territory and turns significantly negative 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.[9] A significantly negative value suggests that the cost of financing an MBS position in the TBA market increased, making it more expensive and difficult to finance MBS securities. The trough in aggregate funding conditions coincides with the onset of Federal Reserve asset purchases programs.

The evolution of our measure of funding liquidity in the MBS market sheds some light on the effect that the Federal Reserve large-scale asset purchases (LSAPs), commonly known as quantitative easing (QE) programs, had on funding liquidity conditions. As shown in Figure 2, the increase in aggregate funding liquidity matches the onset of LSAPs. Particularly, funding liquidity starts moving up from its trough in late 2008 as the Federal Reserve purchased substantial quantities of agency MBS (QE1). Interestingly, during QE2, when the Federal Reserve purchased only Treasury securities, financing conditions do not show further improvement but remain around the levels seen by the end of QE1. There is a further improvement in funding liquidity once the Federal Reserve resumed buying

[9] 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.

agency MBS securities using the principal payments from agency securities in September of 2011 (OT). While liquidity conditions remained favorable during the time the Federal Reserve continued purchasing MBS securities under the QE3 program, liquidity conditions started converging towards levels seen before the crisis as the Federal Reserve announced the reduction in the quantity of MBS securities bought by the end of 2013. This evidence suggests that the Federal Reserve LSAPs had a positive effect on funding conditions in the agency MBS market, which highlights the information content of F_t as a measure of funding liquidity.

Finally, we explore the relationship between F_t and well-known measures of market liquidity for the MBS market, namely, total trading volume and the Amihud measure of price impact for FNMA securities. In particular, using weekly data on both measures of market liquidity for the period covering May of 2011 and October of 2017, we estimate the response of market liquidity to funding liquidity shocks,

$$\Delta L_{t+4} = \alpha + \phi \, \ell_t + \epsilon_{t+4} \tag{4}$$

where L_t is a proxy variable for market liquidity in week t, and ℓ_t is a shock to funding liquidity. The slope coefficient ϕ from this regression captures the response of market liquidity four weeks ahead to a shock to funding liquidity today. Table 3 presents the estimated the response of trading volume and the Amihud measure of price impact for FNMA securities to a funding liquidity shock along with t-statistics robust to serial autocorrelation. To ease the interpretation of the coefficients we standardize the dependent variable.

Our estimates show that negative funding liquidity shocks lead to market illiquidity. In particular, we find that a deterioration in funding liquidity leads to a decline in trading volume and an increase in the Amihud measure of price impact. The response of market liquidity to increased funding liquidity risk is consistent with a link between funding conditions and market liquidity highlighted 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 suggested in Fama and French (2008), we use two related approaches to explore how MBS returns 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, which has been highlighted as an important risk faced by MBS investors[10].

3.1 Data

We obtain returns on generic 30-year MBS issued by Fannie Mae and Freddie Mac from Barclays. In particular, we collect returns hedged to mitigate impact of increasing interest rates using a matched position on interest rate swaps for each generic agency MBS security traded in the TBA market. Our data is monthly and the sample covers the period between January of 1998 to December of 2017; however, availability of data for each security depends on the coupon of the security. Also, we collect each security's option-adjusted spread (OAS),

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

which is a measure of the expected return over a portfolio of Treasury securities with the same cash flow, after taking into account the option of prepayment. Additionally, we 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. Table [X] presents the average return and 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 regression of the MBS return on a constant and funding liquidity shocks ℓ_t. In particular, at the beginning of year t, we estimate the ranking betas, β_ℓ, using data for two years before year t and we assign securities to five $\beta_\ell-$sorted portfolios. The first portfolio comprises those securities with a β_ℓ in the top 20 percent, and fifth portfolio contains securities with a β_ℓ below the 20th percentile. After assigning securities to the β_ℓ-sorted portfolios, we compute the return on the portfolios for the next 12 months, from January to December of year t. For each portfolio, we compute the value-weighted return using as weights the outstanding value of each security. As a result, we have monthly hedged returns on portfolios with varying exposure to funding liquidity shocks from January 2000 to November 2017.

Table 5 reports the average pre-ranking funding liquidity beta, β_ℓ, along with the average value-weighted returns and the Sharpe ratio for each of the five portfolios. We also report the spread in the liquidity betas and the measures of expected return along with standard errors in parenthesis. We use a bootstrap methodology to conduct inference avoiding the need to make assumptions about the asymptotic distribution of the test statistics, which may be unreliable for small samples as in our study. Specifically, we use the stationary bootstrap of Politis and Romano (1994) and take into account the autocorrelation of returns and estimated betas by sampling data in blocks. Our standard errors for inference are computed using 1000 bootstrap replications.

As shown in Table 5, the average funding liquidity beta decreases as we move from the portfolio in the first quintile to the one in the fifth quintile. We find that the first portfolio has a positive and statistically significant β_ℓ, suggesting that this portfolio tends to perform well when funding conditions are easing while it performs poorly when funding liquidity deteriorates. On the other hand, the fifth portfolio has negative and statistically significant funding liquidity beta implying that when funding conditions get tighter the hedged return on this portfolio will increase. The portfolios in the middle three quintiles have positive exposure to funding liquidity shocks that becomes not statistically significant for the lowest values. Therefore, as funding liquidity dries out the portfolio with a negative funding liquidity beta (Low portfolio) tends to perform well, while the portfolio with a positive beta (High portfolio) is prone to experience lower returns. As shown in the last column, the difference in exposure to funding liquidity shocks between the High and Low portfolios is positive and statistically significant.

Table 5 also reports the average monthly returns and the Sharpe ratio for the five portfolios and the spread in average returns between the High-β_ℓ and Low-β_ℓ portfolios. We find that there is a positive relationship between the average hedged return and the funding liquidity beta β_ℓ. In particular, the average monthly return declines monotonically from 3.2 basis points to 0.75 basis points as the funding liquidity beta estimate declines (see Figure 3). Moreover, the return on a portfolio that is long the High-β_ℓ portfolio and short the

Low-β_ℓ portfolio is positive and statistically different from zero. A similar picture emerges when we look at the Sharpe ratio. The Sharpe ratio of the High-β_ℓ portfolio is about 0.15 while that of the Low-β_ℓ portfolio is 0.03, and the Sharpe ratio of the zero cost portfolio is positive and statistically different from zero at 0.13. All in all, investors demand a premium to hold the portfolio that declines in value in times when funding liquidity deteriorates in the MBS market.

Figure 3 shows that there is a positive relationship between the average hedged return and the average funding liquidity beta β^l. However, the monotonic relationship in average returns for the $\beta_\ell-$sorted portfolios may be potentially related to characteristics of the securities underlying our sample other than their exposure to funding liquidity. 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. Table 6 reports selected characteristics of the two portfolios; the incentive to pre-pay as captured by the spread between the underlying loans average coupon rate and the prevailing mortgage rate $c - r$, the prepayment characteristics captured by the WALA, and the CPR, the OAS and the portfolio's duration. We find that there is no monotonic relationship between the estimated β_ℓ and variables capturing prepayment. The Low-β^l portfolio has a higher prepayment rate and more seasoned loans or higher WALA, but the difference is not statistically significant. Consequently, it is difficult to argue that our sorting on funding liquidity beta β^l might be reflecting the past prepayment behavior of the portfolios, but it can still reflect the risk of prepayment risk going forward.

To control for the prepayment behavior of the underlying securities, we form portfolios sorted first on prepayment and then on the funding liquidity beta. We proxy prepayment risk using the average 1-month CPR of a security. Similar to our previous exercise, at the beginning of year t, we compute the ranking $\beta_e ll$s and the average prepayment using data for two 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. As in our previous exercise, within each prepayment category, the first portfolio comprises those securities with a β^ℓ below the 20th percentile and the second portfolio contains securities with a β^l above the 80th percentile. Then, we compute the OAS on the portfolios for the next 12 months, from January to December of year t.

Table 7 presents the average pre-ranking funding liquidity beta, β^l, the average value-weighted return on the four prepayment-β^ℓ sorted portfolios. Consistent with our results in Table 3, we find that for portfolios with high and low prepayment, there is a positive relationship between the funding liquidity beta β^ℓ and the return on the MBS portfolio. The spread in average hedged returns between the portfolios with the High-β^ℓ and Low-β^ℓ is positive and statistically different from zero.

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. In contrast, investors demand a premium on securities that decline in value in times when funding liquidity deteriorates, because investors face the risk of expensive dollar roll financing. 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 risk using a linear factor model that includes a funding liquidity factor. To estimate the asset pricing model, we consider the hedged return on the five 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 hedged returns across MBS portfolios through the cross-sectional variation in the beta with respect to funding liquidity shocks,

$$E[R_i] = \lambda_\ell \beta_{\ell,i} \tag{5}$$

where $E[R_i]$ is the expected hedged return on portfolio i, $\beta_{\ell,i}$ is the exposure of portfolio 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 (5) in two stages. First, we estimate the $\beta_{\ell,i}$ by performing an OLS regression of the hedged return on portfolio i on a constant and MBS funding liquidity shocks,

$$R_{i,t+1} = a_i + \beta_{\ell,i} l_{t+1} + \epsilon_{i,t+1} \tag{6}$$

where ℓ_t is the funding liquidity shock at time t. Then, we estimate the funding liquidity premium λ_ℓ from a regression of the average hedged return on our test assets on the estimated $\beta_{\ell,i}$s,

$$E_T(R_i) = \lambda_{T,\ell} \beta_{i,T-1,\ell} + \alpha_{i,T} \tag{7}$$

where $\alpha_{i,T}$ is the pricing error of portfolio $i = 1, \ldots, 5$, and $E_T(R_i)$ is the average hedged return over the sample period. As in Fama and Macbeth (1973), we proceed recursively to account for the fact that funding liquidity betas might be time-varying. In particular, we use a two-year window to estimate Equation (6) and the subsequent one year period to estimate Equation (7). We report the average value of the year-to-year estimates of the market price of funding liquidity risk $\lambda_\ell = \frac{1}{N}\sum_{T=1}^{N}\lambda_{T,\ell}$.

We use bootstrap to conduct inference to take into account the uncertainty about the firs-stage estimates and avid making assumptions about the asymptotic distribution of the test statistics. As in the previous section, we use the stationary bootstrap of Politis and Romano (1994) and take into account the autocorrelation of returns and estimated betas by sampling data in blocks. Our standard errors for inference are computed using 1000 bootstrap replications.

3.3.2 Empirical Results

Panel A of Table 8 reports the average funding liquidity betas β^l along with their corresponding t-statistics (i.e., the average of the betas from model (6)). The results show that their post-ranking β_ℓs align very well with the pre-sorting β_ℓs and all of the estimates are statistically different from zero, suggesting that funding liquidity shocks are a useful factor predicting risk compensation on agency MBS.

Panel B of Table 8 reports the cross-sectional estimates of the market price of liquidity risk. The estimates show that the market price of funding liquidity risk is positive and statistically different from zero. Our model has an average adjusted-R^2 of 59%. The good performance of our funding liquidity factor model can be seen in Figure **??** that displays the realized expected hedged return versus the predicted expected hedged return from our benchmark model. The hedged returns 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 the expected returns on MBS, highlighting the importance of fluctuations in funding conditions in the MBS market.

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 $i = 1, \dots, n$). 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 $t = 1, \ldots, T$:

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

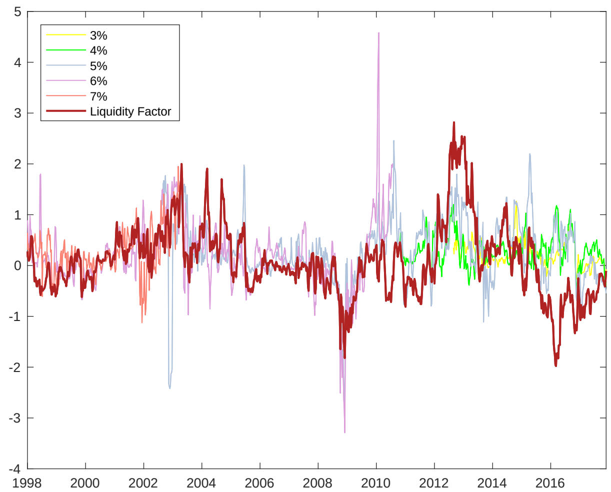
Under the assumptions above, we have,

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

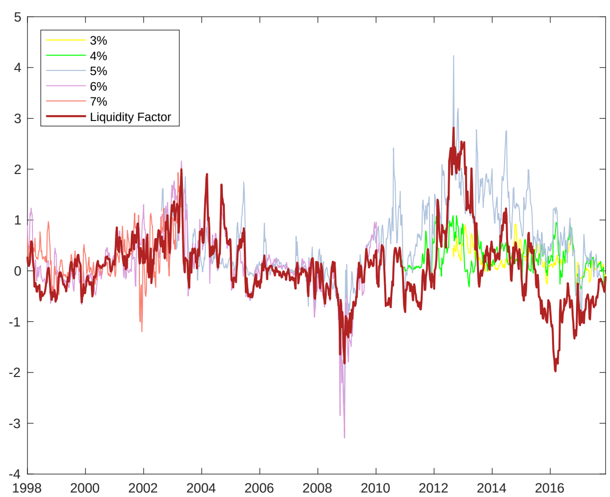
The maximum likelihood estimates are obtained by maximizing the sample log likelihood,

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

Figure 1: Funding Liquidity Factor



(a) Funding Liquidity and IFR For FNMA securities



(b) Funding Liquidity and IFR For FHLM securities

Figure 1 displays our measure of funding liquidity, F_t, derived from the unobserved-components model for the dollar roll specialness of agency MBS securities presented in Section 2.3 along with the dollar roll specialness for FNMA and FHLM securities. The data is weekly and covers the period between 1998 and November 2017.

Figure 2: Funding liquidity in the market of Mortgage Backed Securities

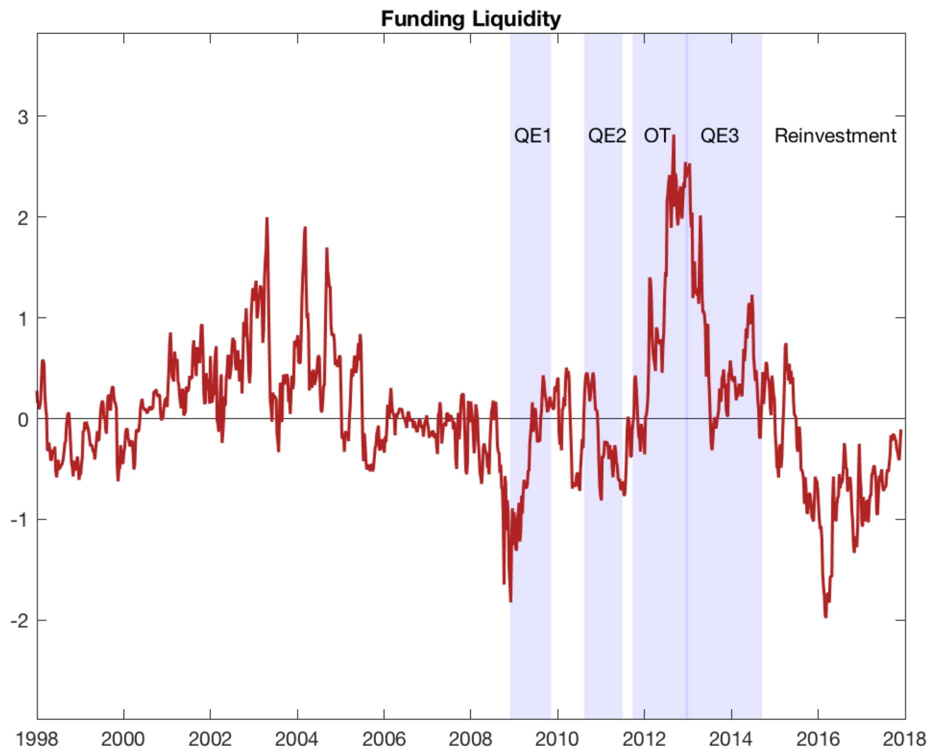
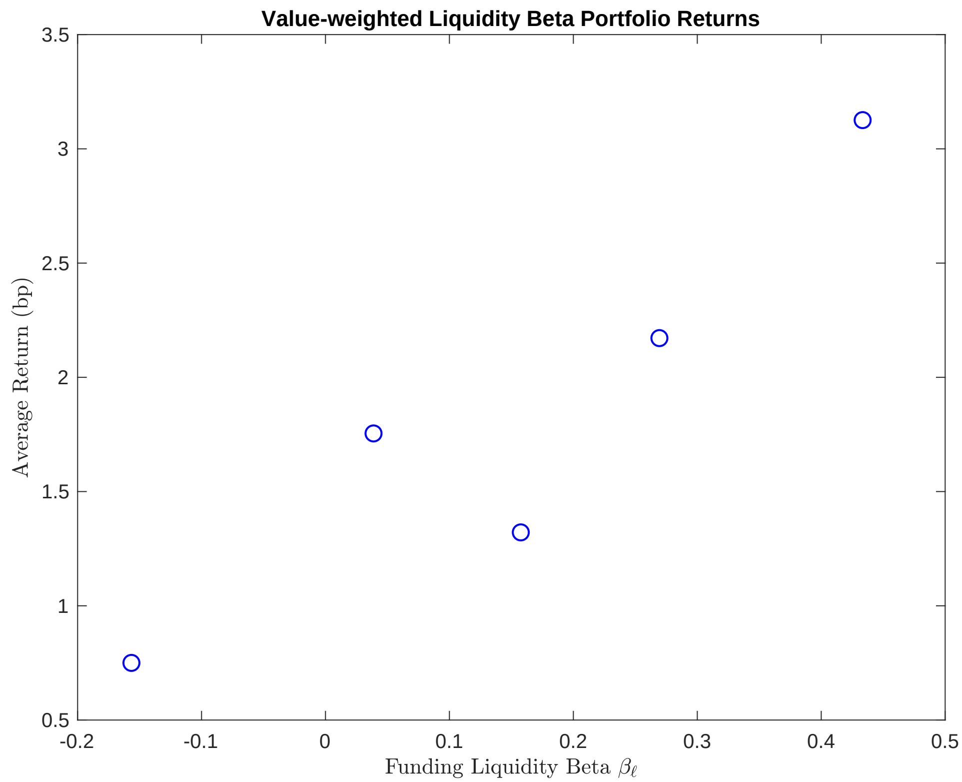


Figure 2 displays our measure of funding liquidity, F_t, derived from the unobserved-components model for the dollar roll specialness of agency MBS securities presented in Section 2.3. The data is weekly and covers the period between 1998 and November 2017.

Figure 3: Estimated Funding Liquidity Beta and Average Monthly Returns



This scatter plot reports the full sample average hedged returns against the estimated funding liquidity betas β^l. The test assets include Fannie Mae (FNMA) and Freddie Mac (FHLM) agency MBS with at least 5 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 hedged returns on each security i on a constant and funding liquidity shocks in the MBS market. The estimates are obtained using weekly data. The returns are expressed in basis points. The hedged return sample varies by security and covers the period between January 2000 to March 2017.

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 repo 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 Unobserved-Components Model For the IFR

Panel A: Observation Equation

Security	κ_i	R^2
FNMA 7.5	1.478	0.567
FNMA 7.0	0.418	0.315
FNMA 6.5	0.669	0.433
FNMA 6.0	0.890	0.752
FNMA 5.5	0.308	0.106
FNMA 5.0	0.551	0.344
FNMA 4.5	0.424	0.389
FNMA 4.0	0.094	0.096
FNMA 3.5	0.425	0.913
FNMA 3.0	0.150	0.269
FHLM 7.5	1.623	0.636
FHLM 7.0	0.424	0.381
FHLM 6.5	0.657	0.441
FHLM 6.0	0.530	0.281
FHLM 5.5	0.247	0.080
FHLM 5.0	0.331	0.190
FHLM 4.5	0.176	0.114
FHLM 4.0	0.009	0.000
FHLM 3.5	0.349	0.740
FHLM 3.0	0.109	0.092

Panel B: State Equation

	Estimate
ρ	0.965

Panel A of Table 2 presents the loading κ_i estimated from the unobserved-components model for the spread between the MBS GC repo rate (r_t) and the contract-specific dollar roll IFR ($f_{i,t}$),

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

The last column of Panel A presents the variance of each IFR explained by the aggregate factor F_t as captured by the R^2. Panel B presents the estimate of the common factor's first-order autocorrelation. The estimates are based on weekly data that covers the period between January 1998 and November 2017.

Table 3: Funding Liquidity As a Predictor For Market Liquidity

	Δ Volume	Δ Amihud
ϕ	0.129	-0.025
	[2.03]	[-1.82]
T	331	328

Table 3 presents the estimated slope coefficient from the following regression,

$$\Delta L_{t+4} = \alpha + \phi\, \ell_t + \epsilon_{t+4}$$

where L_t is a proxy variable for market liquidity and ℓ_t is a shock to funding liquidity implied by the unobserved-components model for the dollar roll specialness presented in Section 2.3. Columns (1) and (2) present the response of trading volume and the Amihud measure of price impact for FNMA securities to a funding liquidity shock, respectively. The dependent variables are standardized. The corresponding t-statistics robust to autocorrelation using the Newey-West standard error correction are show in brackets. The regression is estimated using weekly data for the period covering May 2011 and October 2017.

Table 4: 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 5: Average Returns For Portfolios Sorted on Funding Liquidity Beta

	High-β_ℓ	2	3	4	Low	High minus Low-β_ℓ
				Funding Liquidity Beta		
β_ℓ	0.433	0.269	0.158	0.039	-0.157	0.590
	(0.069)	(0.050)	(0.041)	(0.044)	(0.081)	(0.114)
				Average Monthly Returns		
$\bar{R}$	3.240	2.172	1.321	1.754	0.750	2.673
						(1.237)
				Sharpe Ratio		
$\frac{\bar{R}}{\sigma(R)}$	0.152	0.102	0.070	0.079	0.038	0.134
						(0.060)

Table 5 reports the average pre-ranking funding liquidity beta, β_ℓ, along with the average value-weighted hedged returns and the Sharpe ratio for five portfolios formed on the exposure to funding liquidity shocks. The last column reports the spread in the liquidity betas and the measures of expected return between the High-β_ℓ and Low-β_ℓ portfolios. Standard errors, shown in parenthesis, are computed using the stationary bootstrap of Politis and Romano (1994) and take into account the autocorrelation of returns and estimated betas by sampling data in blocks. Our standard errors for inference are computed using 1000 bootstrap replications. The data covers January 1998 through November 2017.

Table 6: Characteristics of Portfolios Sorted on Funding Liquidity Beta

	High	2	3	4	Low	High minus Low
$c - r$	0.904	0.931	1.052	0.979	0.889	0.016
						(0.320)
WALA	45.811	44.462	52.231	55.575	53.908	-8.097
						(7.675)
CPR	18.867	19.544	24.511	24.324	21.289	-2.423
						(2.435)
OAS	0.597	0.601	0.624	0.622	0.672	-0.075
						(0.051)
Duration	3.368	3.173	2.824	3.005	3.533	-0.166
						(0.282)

Table 6 presents average characteristics of the underlying mortgage pools for portfolios formed on the exposure to funding liquidity shocks. The last column reports the spread in the average characteristics between the High-β_ℓ and Low-β_ℓ portfolios. Standard errors, shown in parenthesis, are computed using the stationary bootstrap of Politis and Romano (1994) and take into account the autocorrelation of characteristics by sampling data in blocks. Our standard errors for inference are computed using 1000 bootstrap replications. The data covers January 1998 through November 2017.

Table 7: Average Returns and Selected Characteristics For Portfolios Sorted on Past Prepayment and Funding Liquidity Beta

	High Prepayment			Low Prepayment		
	High-β_ℓ	Low-β_ℓ	High minus Low	High-β_ℓ	Low-β_ℓ	High minus Low
β_ℓ	0.297	0.065	0.232	0.330	-0.078	0.408
	(0.063)	(0.063)	(0.038)	(0.080)	(0.092)	(0.084)
$\bar{R}$	9.723	3.898	5.729	2.156	-0.298	2.412
			(2.510)			(0.990)
$\frac{\bar{R}}{\sigma(R)}$	0.194	0.148	0.153	0.072	-0.011	0.138
			(0.068)			(0.059)
Portfolio Characteristics						
$c - r$	1.719	1.678	0.041	0.280	0.250	0.030
			(0.135)			(0.187)
WALA	69.174	68.314	0.860	32.658	37.316	-4.658
			(4.873)			(5.477)
CPR	26.116	26.675	-0.559	16.607	16.734	-0.127
			(0.924)			(1.955)

Table 7 table presents the average excess return 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 two years of monthly hedged returns before year t and the average prepayment as captured by the average 1-month CPR over two 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 20th percentile and 80th percentile. After assigning securities to the double-sorted portfolios, we compute the hedged returns on the portfolios for the next 12 months, from January to December of year t. The table reports value-weighted hedged returns. The characteristics are simple averages of characteristics of the underlying securities. The data covers January 1998 through December 2017.

Table 8: Market Price of Funding Liquidity Risk

Panel A: Funding Liquidity Beta

Portfolio	β_ℓ	$t-$value
High-β_ℓ	0.130	[2.92]
2	0.083	[1.72]
3	0.060	[2.05]
4	0.075	[2.60]
Low-β_ℓ	0.035	[1.32]

Panel B: Funding Liquidity Risk Premium

	Estimate	Std.Err.	Conf. Int. [5%	95%]	R^2
λ_ℓ	0.204	0.080	[0.056	0.322]	0.594

Table 8 table presents the estimates of our benchmark linear factor model for mortgage-backed securities that includes funding liquidity as a risk factor

$$E[R_i] = \lambda_\ell \beta_{i,\ell}.$$

Panel A reports the average funding liquidity betas β_ℓ along with t-statistics, which come from a time-series regression of security i's hedged return on funding liquidity shocks in the MBS market. Panel B reports the average cross-sectional estimates of the market price of liquidity risk from a regression of the average hedged return on our test assets on the estimated β_ℓs. The data is monthly and covers the period between January 2000 to November 2017.