The Cross Section of MBS Returns*

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Abstract

We present a simple, linear asset pricing model of the cross section of Mortgage-Backed Security (MBS) returns. MBS earn risk premia as compensation for their exposure to prepayment risk. We measure prepayment risk and estimate risk loadings using prepayment forecasts vs. realizations. Estimated loadings on prepayment risk decrease monotonically in securities' coupons relative to the par coupon, consistent with the predicted effect of prepayment on bond value. Prepayment risk appears to be priced by specialized MBS investors. The price of prepayment risk changes sign over time with the sign of a representative MBS investor's exposure to prepayment shocks.

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The market for Mortgage-Backed Securities (MBS) represents over $7.3 Trillion in market value.[1] Accordingly, MBS are a very important part of fixed income portfolios. They constitute about one quarter of the Bloomberg Barclays US Aggregate Bond Index, a key benchmark for fixed income portfolio allocations. Despite the size and importance of the MBS market, relatively little work has been done to systematically explain the cross section variation in MBS returns. Our study is one of the first empirical studies of the returns to Mortgage-Backed Securities over a long time series and broad cross section. And, to our knowledge, our paper is the very first study of the cross section of MBS returns using average monthly returns to measure expected returns, as opposed to model-generated option-adjusted spreads (OAS). We provide a simple, linear asset pricing model of the cross section of treasury-hedged returns to Mortgage-Backed Securities, and find robust empirical support for the model's main implications. We use data on agency pass-through MBS, which is by far the largest and most liquid category of the market for asset-backed securities.

MBS are a promising place to look for evidence of asset pricing by specialized investors in segmented markets for several reasons. First, Mortgage-Backed Securities are complex assets that attract sophisticated investors, and have low participation by non-experts.[2] Duarte, Longstaff, and Yu (2006) provide convincing evidence that the active management of MBS requires significant intellectual capital, and find that MBS strategies have the highest returns of the five fixed income arbitrage strategies they study. Second, the exposures of MBS to prepayment shocks, one of the key drivers of MBS returns, not only varies in the cross section, but it actually changes sign between securities with coupons below and above par. As a result, as the composition of the market changes, the exposure of the aggregate MBS market portfolio, and specialized MBS investors, to prepayment shocks changes from positive to negative. Thus, using MBS, it is possible to provide evidence for intermediary asset pricing that not only shows that the magnitude of risk premia varies over time, but that also the sign changes.

We study the returns to agency MBS, for which prepayment risks are the primary risks borne by active investors. Default risk is borne by the agencies rather than by MBS investors, in exchange for a guarantee fee. In addition, changes in bond valuations and prepayments due to interest rate movements of government securities can be hedged with US Treasury

[1]See `www.sifma.org/research/statistics.aspx`. We report the value of agency-backed pass-through MBS from the Table describing US Mortgage-Related Issuance and Outstanding.

[2]Theories in which the marginal investor in risky assets holds a specialized portfolio are developed in a growing literature, including important contributions by Shleifer and Vishny (1992, 1997), Gromb and Vayanos (2002), Allen and Gale (2005), Gabaix, Krishnamurthy, and Vigneron (2007), Brunnemeier and Pedersen (2009), and He and Krishnamurthy (2013).

derivatives, up to model error. However, it is challenging, if not impossible, to hedge against prepayment risk driven by shocks to systematic factors which do not have corresponding traded derivatives, such as spreads between government and mortgage rates, changing credit conditions, house price appreciation, and regulatory changes. As a result, we expect MBS which load on the unhedgeable component of prepayment risk to earn prepayment risk premia even if returns are effectively duration and prepayment hedged to US treasuries.

Agency MBS are created when mortgage lenders deliver pools of similar mortgage loans to Fannie Mae, Freddie Mac, or Ginnie Mae, in exchange for an MBS with an agency default guarantee. An investor in a pass-though agency MBS receives the interest and principal payments from the mortgages in the pool, and is prepaid in the event of a default or voluntary prepayment. For example, a mortgage originator might make a large number of loans to borrowers at a mortgage rate of 4.5%. The mortgage servicer, who collects and forwards interest and principal payments, must keep a 0.25% coupon strip as an incentive, known as base servicing. The agencies then require a 0.25-0.50% guarantee fee to insure the pool of loans and to forward payments to MBS investors in the event of delinquencies or defaults. Thus, an MBS backed by mortgage loans with loan rates of about 4.5% will typically have a coupon of 4%. As mortgage rates change, MBS with various coupons are issued. MBS are issued in 0.5% increments. Our data consists of a cross section of about seven coupon-level portfolios of MBS each month.

We explain the returns in the MBS cross section using a simple, easy to interpret, linear asset pricing model which features cross section variation in prepayment risk exposures, and a prepayment risk premium which varies with the composition of the MBS market. We start by following the prior literature (Levin and Davidson (2005) and Chernov, Dunn, and Longstaff (2015)), who propose two prepayment risk factors. The first risk factor is a level factor, corresponding to a level shift of prepayments across all coupon levels. The second factor is an incentive-sensitivity factor. In the cross section of borrowers, at any given time, low mortgage rate borrowers have a prepayment option which is out-of-the-money, whereas high mortgage rate borrowers' prepayment options are in-the-money. The incentive-sensitivity factor determines how sensitive borrowers with in-the-money options are to their particular rate incentive. Although active MBS investors duration hedge, they cannot hedge shocks to the level of prepayments, for example driven by house price appreciation, or shocks to borrowers' sensitivity to a given rate incentive, which can change with credit availability.

We construct time series for the two prepayment risk factors using the differences between forecast and realized prepayment data. We define MBS securities at the coupon level, normalizing coupons relative to the current par coupon so that discount securities have a negative relative coupon, and premium securities have a positive relative coupon. We then estimate MBS securities' loadings on prepayment shocks using time series regressions of coupon-level MBS returns on the prepayment risk factors. Exposure to prepayment risk varies in the MBS cross section in a way that is highly intuitive from the perspective of a simple partial equilibrium model. A positive prepayment shock essentially moves agency MBS values closer to par (100). For securities with low coupons, which trade below par (say at 98), prepayments at par are value increasing. On the other hand, for securities with high coupons, which trade above par (say at 102), prepayments at par are value decreasing. Thus, loadings on prepayment risk, which measure the change in valuation as prepayment shocks realize, should be around zero for securities near par, positive for securities with coupons below the par coupon (discount securities) and negative for securities with coupons above the par coupon (premium securities). Moreover, the absolute value of the effect of prepayment on MBS value should monotonically decrease with the absolute value of a security's coupon relative to the par coupon. We find strong evidence, robust to several different estimation and data choices, for these predictions.

In support of theories of market segmentation or intermediary asset pricing, we show that the sign of the price of prepayment risk depends on whether a positive prepayment shock is wealth increasing or wealth decreasing for a specialized investor who is solely invested in the aggregate MBS portfolio. As mortgage rates move, and the composition of the MBS market between discount and premium securities changes, whether a high prepayment shock is good news or bad news for the value of the aggregate MBS portfolio also changes. We show empirically that the composition of the market between discount and premium securities drives the sign of prepayment risk premia. This idea, first proposed by Gabaix, Krishnamurthy, and Vigneron (2007), makes sense in the context of segmented markets for active investors in complex assets, and specialized MBS investors.[3]

In particular, when the majority of the MBS market trades at a discount, a positive prepayment shock is wealth increasing for a representative MBS investor who holds the MBS universe. Accordingly, during these months, we find that the price of prepayment risk is positive (higher prepayment states have low state prices), and the prepayment risk premium is positive. Thus, in discount months, the pattern of average returns in the cross section is downward sloping; discount securities have higher average returns, while premium securities have lower average returns. On the other hand, when the majority of the MBS market trades at a premium, early prepayment decreases the wealth of such an investor. During

[3]Gabaix et al. (2007), Adrian, Etula, and Muir (2014), He, Kelly, and Manela (2017), Kargar (2019) and Haddad and Muir (2019) provide complementary empirical support for models in which the marginal investor is a financial intermediary. Mitchell, Pedersen, and Pulvino (2007) and Mitchell and Pulvino (2012) provide evidence of slow moving capital. Eisfeldt et al. (2019) provide a model of complex arbitrage and apply it to the market for MBS.

these months, the price of prepayment risk is negative (higher prepayment states have high state prices) and the prepayment risk premium is negative. The pattern of average returns in the cross section during premium market months is upward sloping, with premium securities outperforming discount ones. One way of interpreting our results is that the market for MBS is subject to limited prepayment-risk-bearing capacity. When the overall market is discount-heavy, investors require additional compensation for buying more discount securities and further exposing themselves to the risk that prepayments are lower than expected. When the market is comprised by more premium securities, investors are conversely exposed to the risk that prepayments realize *higher* than expected, and therefore demand additional compensation for taking on additional premium securities. We find that a model which accounts for the changing sign of prepayment risk premia cuts pricing errors by 64% relative to an MBS market model with constant risk prices.

The size of the Mortgage-Backed Security market and its importance in fixed income portfolios speak to the importance of understanding of MBS risk premia. Aside from this, risk premia in secondary mortgage markets are important determinants of the mortgage rates paid by homeowners and the pass-through rate of monetary policy. In addition, our study makes several contributions relative to the existing literature.[4] First, and most importantly, our broad cross section and long time series describing the returns of the largest and most liquid segment of the MBS market provides the most promising laboratory to document the changing sign of prepayment risk premia. MBS average realized returns, as well as MBS option adjusted spreads (OAS), exhibit a U-shaped pattern across relative coupons in pooled time series cross section data. We argue, and provide substantial evidence, that the U-shaped unconditional average return pattern is driven by conditional patterns of returns that are downward sloping in relative coupon in discount markets, and upward sloping in premium markets, leading to a U-shape in the pooled time series cross section. The unconditional U-shaped pattern is emphasized by Boyarchenko, Fuster, and Lucca (2017), however our explanation, that the OAS smile reflects prepayment risk premia which change sign over time, stands in contrast to their proposed explanation based on constant risk premia. Accordingly, we show that a "Prepayment Risk Premium" portfolio, which exploits the changing pattern of returns in the cross section, has a Sharpe ratio which is 2.7 times that of a passive, value-weighted MBS index, and 1.72 times higher than a passive portfolio that is long the highest available coupon, and short the lowest available coupon. Moreover, failing to account for the sign changes in prepayment risk premia leads to estimates for expected returns which

[4]For completeness, we note that our study follows a large literature which studies prepayment behavior and is aimed at developing prepayment models with minimal pricing errors. Important examples include Dunn and McConnell (1981a), Dunn and McConnell (1981b), Schwartz and Torous (1992), Stanton (1995), Longstaff (2005), Downing, Stanton, and Wallace (2005), and Agarwal, Driscoll, and Laibson (2013).

are misleading because positive expected returns are biased towards zero.

Second, most prior papers, including Gabaix, Krishnamurthy, and Vigneron (2007), Song and Zhu (2016), and Boyarchenko, Fuster, and Lucca (2017) use Option Adjusted Spreads (OAS) to proxy for expected returns. By contrast, and consistent with the vast literature examining the cross section of equity returns, we use average realized monthly returns in our study.[5]

Third, we are the first to measure prepayment risk loadings in the cross section of MBS using data on prepayment surprises. In particular, our study employs actual realized vs. forecasted prepayment data to measure innovations to prepayment risk factors. That is, we use real variables as factors, rather than model errors, or price or return data.[6] Chernov, Dunn, and Longstaff (2015) use a structural model to derive more accurate MBS prices. They provide convincing evidence that there are systematic shocks to the level and incentive-sensitivity of prepayments, and that these shocks are important determinants of the level of MBS prices.[7] Our focus is complementary to theirs, as our study's explicit focus is on understanding the cross section of MBS returns, in the spirit of connecting to the large literature on the cross section of equity returns.

Our study is most closely related to Gabaix, Krishnamurthy, and Vigneron (2007). Their study provides convincing evidence that the returns to Collateralized Mortgage Obligations are driven in large part by limits to arbitrage, as proposed by Shleifer and Vishny (1997). The main differences between our study and theirs are that they use a shorter time period, during which prepayment risk does not change sign, they use OAS rather than average returns, and they study Collateralized Mortgage Obligations (CMO's), rather than pass-through securities. Pass-through securities constitute 90% of MBS outstanding, while CMO's comprise the remaining 10%. We greatly extend their results on the cross section and time series of MBS returns by using a long time series and broad cross section of MBS pass-through returns. Finally, Gabaix, Krishnamurthy, and Vigneron (2007) measure prepayment risk as errors from a stylized prepayment model, rather than using actual data on prepayment forecasts and realizations as our study does.

[5]The Internet Appendix Diep, Eisfeldt, and Richardson (2019) shows that OAS on agency MBS pass-throughs displayed almost no cross sectional variation prior to 2007. Moreover, OAS are model-implied yields. Due to differences across dealers' prepayment models, the variation within a coupon across dealers is large, most often larger than the variation across coupons for a single dealer.

[6]See Chen, Roll, and Ross (1986).

[7]See also Levin and Davidson (2005), who develop and calibrate a model of MBS option adjusted spreads which includes turnover and refinancing risk factors. The notion of systematic, priced, non-interest rate prepayment risk is also proposed by Boudoukh, Richardson, Stanton, and Whitelaw (1997).

1 Data Description

The following is a brief introduction to our data sources and methodology. The Appendix contains a detailed description of the data and its construction.

We utilize two sources for prepayment data. The first is Bloomberg's monthly report of the median dealer prepayment forecast by coupon. Bloomberg collects these data via survey. We collect realized prepayment data for Fannie Mae 30-year fixed-rate securities by coupon monthly from eMBS. To compute rate-based incentives to prepay, and the incentive-sensitivity prepayment shocks, we also measure the moneyness of borrowers' prepayment options for each MBS coupon. To do this, we collect data on weighted average coupons (WAC) for each MBS coupon. These WAC's measure the underlying borrower loan rates. Borrowers' rate incentive is given by the WAC relative to the current mortgage rate as reported weekly by Freddie Mac in their Primary Mortgage Market Survey (PMMS). We use a monthly average of the weekly primary mortgage rates as the current mortgage rate.

Our primary returns data are excess returns obtained from the coupon-level sub-indices of the Bloomberg Barclays MBS Index. Bloomberg Barclays' fixed income indices are the most commonly used fixed income benchmarks. Index returns are available at a monthly frequency dating back to 1994. The index is constructed by grouping individual TBA deliverable fixed-rate MBS pools into aggregates based on program, coupon, and vintage.[8] Maturity and liquidity criteria are then applied to determine which aggregates qualify for inclusion in the index. Daily pricing for index pool aggregates is provided directly by the Barclays MBS trading desk via two pricing components: (i) TBA prices are provided for each agency, program and coupon combination within the index, and (ii) an additional payup spread for each agency, program, coupon and origination year combination is provided and added to the TBA price to adjust pricing for pools that are unlikely to be TBA delivered due to their special characteristics. Each coupon-level index is thus essentially an index portfolio of individual MBS with the same coupon.

We use the interest rate hedged returns of coupon-level aggregates of Fannie Mae 30-year fixed-rate MBS pools to measure excess returns to MBS. Fannie Mae is the largest agency MBS issuer. Hedged returns, denoted excess returns, are computed by Barclays using a term structure-matched position in Treasuries based on a key-rate duration approach. In the Online Appendix, we report results for prepayment risk loadings using Bloomberg Barclays total index returns hedged with a simple empirical hedging model, and for alternative return data sources including Bank of America Merrill Lynch indices and TBA returns.

[8] See Vickery and Wright (2013) for a detailed description of the TBA market. Gao et al. (2017) study the relation between the TBA and cash MBS market. Song and Zhu (2016) studies MBS financing rates implied by TBA market prices.

A given coupon may trade at a premium or discount depending on current mortgage rates. Thus, we define securities by their coupon relative to the current par coupon in order to obtain securities with more stable exposures to prepayment risk. Specifically, we compute the difference between each liquid MBS's coupon at each date, and the par coupon on that date. We compute the par coupon using the TBA prices of securities trading near par. We then use data from eMBS to compute the remaining principal balance (RPB) for each MBS relative coupon. Table 1 displays summary statistics for each coupon relative to par, from -2% to 3.5%. Unconditionally, average MBS returns are highest for the coupons with the largest absolute distances from par, on both sides. However, we will show that this is due to an upward sloping pattern of average returns in premium markets, and a downward sloping pattern in discount markets.

2 Theoretical Framework

We develop a linear pricing model in which risk premia and expected excess returns are earned for loading (β) on priced prepayment risk with prepayment risk premia (λ). In particular, following Levin and Davidson (2005) and Chernov, Dunn, and Longstaff (2015), to measure prepayment risk shocks and exposures, we posit a two-factor model, in which prepayment shocks arise from innovations to the level of prepayments, x, and innovations to the sensitivity of prepayments to interest rate incentives, y. It is important to understand that the incentive-sensitivity shock y does not capture sensitivity to interest rates. Instead, the incentive-sensitivity shock captures how likely a borrower with an in-the-money prepayment option is to refinance or prepay, conditional on a given rate incentive. Active MBS investors use a dynamic interest rate hedge to earn the excess returns to MBS. They price and hedge their portfolios using pricing models in which interest rates are the main (and often only) stochastic state variable. However, other aggregate variables which drive borrowers prepayment decisions, such as house price appreciation and credit conditions, do not have traded derivatives, making hedging changes in these systematic state variables costly, imperfect, or infeasible. Thus, although MBS investors duration hedge, the value of their portfolios are still exposed to systematic variation in the level and incentive-sensitivity of prepayments, conditional on interest rate realizations. Our model is aimed at pricing prepayment risk in treasury-hedged MBS.[9]

[9]See Hanson (2014) for complementary evidence that duration risk premia in treasury markets vary with the supply of MBS. When the supply of duration risk in MBS increases, active MBS investors increase their demand for interest rate risk hedges (short treasury futures), and passive MBS investors reduce their demand for treasuries. Vayanos and Vila (2009) provide a theory of preferred habitat which builds on theories of segmented markets and specialized investors, to explain limited market capacity for duration risk. We

Further, we assume a segmented market in which the stochastic discount factor (SDF) arises from a representative MBS investor whose portfolio consists of the universe of agency pass-through MBS, net of a dynamic treasury hedge. Such a stochastic discount factor can be motivated by specialized investors as in Gabaix, Krishnamurthy, and Vigneron (2007) and He and Krishnamurthy (2013).[10] In particular, we assume the following SDF:

$$\frac{d\pi_t}{\pi_t} = -r_f dt - \gamma_{x,\mathrm{M}}\, dZ_t^x - \gamma_{y,\mathrm{M}}\, dZ_t^y \tag{1}$$

where $\gamma_{x,\mathrm{M}}$ is the price of risk for the "level" prepayment risk factor, x_t, and $\gamma_{y,\mathrm{M}}$ is the price of risk for "incentive-sensitivity" risk, y_t, and $M \in \{DM, PM\}$ indicates that risk prices are conditional on market type; either discount (DM) or premium (PM). We assume the Wiener processes for the level and incentive-sensitivity of prepayments, dZ_t^x and dZ_t^y, are independent, since, as we will show below, the empirical correlation between the two shocks is 0.13 and statistically insignificant.[11] Market type is determined by which security type is predominant, either discount (price below par) or premium (price above par). The type of security which is predominant in terms of remaining principal balance determines whether prepayment is either value increasing or decreasing for the overall MBS market. State prices are high in bad states of the world for the value of the aggregate MBS portfolio. When the market is discount (premium), bad states are states with lower (higher) than expected prepayment. For example, in a discount market, lower prepayment states ($dZ_t^k < 0$) are bad states. In discount markets, $\gamma_{k,\mathrm{DM}} > 0$, indicating that such states have a high state price deflator according to Equation (1).

We then derive our linear asset pricing model by computing the difference in drifts in expected MBS returns under the physical and risk-neutral measure as follows:

$$E_M[R^{ei}dt] = \underbrace{\gamma_{x,\mathrm{M}}\,\sigma_x}_{\lambda_x} \overbrace{\frac{\partial P^i}{\partial x}\frac{1}{P^i}}^{\beta_x^i} dt + \underbrace{\gamma_{y,\mathrm{M}}\,\sigma_y}_{\lambda_y} \overbrace{\frac{\partial P^i}{\partial y}\frac{1}{P^i}}^{\beta_y^i} dt, \tag{2}$$

emphasize that our excess returns are in net of the interest rate risk premium studied in these papers.

[10]Supporting the importance of specialized active investors in MBS pricing, MBS dealer research regularly reports the "net supply" of MBS, i.e. the supply that exceeds the stable demand from passive buy and hold investors, and which must be absorbed by the marginal active investors such as hedge funds. See, for example Jozoff, Maciunas, Ye, and Kraus (2017).

[11]If x and y were indeed correlated, one would expect the correlation between the level and incentive-sensitivity of prepayments to be positive, since we show below that both appear to be driven in the same direction by macroeconomic variables such as house price appreciation and bank lending standards. Our theory is qualitatively unchanged in this case, since a positive covariance does not change the sign of the risk premia.

where we use the notation $E_M[R^{ei}]$ to denote expected excess returns conditional on market type $M \in \{DM, PM\}$, and where e denotes the excess return after treasury hedging, and i denotes the security. Prepayment risk premia, $\lambda_{k,\mathrm{M}} \equiv \gamma_{k,\mathrm{M}}\, \sigma_k$, which compensate investors for the covariation of payoffs with good and bad prepayment states, have the same sign as prepayment risk prices, $\gamma_{k,\mathrm{M}}$. Equations (1) and (2) imply that positive excess returns are earned by securities whose payoffs have a negative instantaneous covariance with the stochastic discount factor, i.e. those securities which have a high payoff in states with low state prices.

We define securities by the coupon of the MBS security relative to the par coupon. Simplifying notation, this leads to the following conditional linear model, familiar-looking from linear equity pricing models, for the cross section of treasury-hedged MBS returns:[12]

$$E_M[R^{ei}] = \lambda_{x,\mathrm{M}}\beta_x^i + \lambda_{y,\mathrm{M}}\beta_y^i. \tag{3}$$

Following, Gabaix, Krishnamurthy, and Vigneron (2007), we develop the intuition for our model using a first order approximation of MBS prices around the no prepayment uncertainty case. There is a constant par coupon rate, r, which represents the opportunity cost of capital for the representative, specialized, MBS investor who can reinvest portfolio proceeds in par MBS securities, as in Fabozzi (2006). There is a securitized mortgage pool (MBS) i with prepayment rate ϕ^i and coupon c^i. We normalize the initial mortgage pool balance b_0^i to one. The change in the remaining principal balance, b_t^i, is:

$$\frac{db_t^i}{dt} = -\phi^i b_t^i. \tag{4}$$

The first order linear approximation of the value of the MBS pass-through around the no-prepayment-uncertainty case is then given by:

$$P_0^i \approx \int_0^\infty e^{-rt}\left(b_t^i c^i - db_t^i\right) dt = b_0^i + (c^i - r)\int_0^\infty e^{-\left(r+\phi^i\right)t}\, dt.$$

Simplifying, we get the following intuitive representation of the value of the MBS as its par value plus the value of the coupon strip:

$$P_0^i \approx 1 + \frac{c^i - r}{r + \phi^i}. \tag{5}$$

[12]See Cochrane (2005) for a textbook description of the theory and econometrics of linear asset pricing models, including models with conditioning information for risk prices. Jagannathan and Wang (1996) and Nagel and Singleton (2011) document the importance of conditioning information in equity markets, and provide econometric frameworks for evaluating competing conditional models. Although the continuous time β's are not exactly OLS, we preserve notation for expositional purposes.

The value of the coupon strip increases in the difference between the coupon and current rates, and it is negative for discount securities and positive for premium securities, since discount securities have coupons lower than the par coupon, while premium securities have coupons higher than the par coupon. Accordingly, the value of the coupon strip decreases with the speed of prepayment if $c^i - r$ is positive, and increases with the speed of prepayment if $c^i - r$ is negative.

3 Prepayment Risk Factors and Factor Loadings

This section first derives the main predictions from the theoretical framework outlined in Section 2 for security risk loadings on the two prepayment risk factors. We derive the implied theoretical loadings from Equation (5). The fundamental intuition for the theoretical results describing security risk loadings is straightforward given the right hand side of this equation. The prepayment rate ϕ^i acts like an additional discount rate for the cash flows in the numerator. When $c^i < r$ (discount securities), the numerator is negative and an increase in the prepayment rate essentially discounts that negative cash flow more, increasing the value of the discount MBS. When $c^i > r$ (premium securities), the numerator is positive, and an increase in discounting in the denominator reduces the value of the premium MBS. Thus, Equation (5) has the following two key implications for prepayment risk loadings: First, any shock that increases prepayments will raise the value of discount securities, and decrease the value of premium securities. Second, the absolute value of the effect of any prepayment shock on the value of the security should be monotonically decreasing in the absolute value of the difference between that MBS's coupon and the current par MBS coupon.

These basic predictions do not depend on what model is specified for prepayment, however, to estimate empirical loadings we need time series data on prepayment shocks. To this end, we specify a simple, piece-wise linear prepayment model which is motivated by the prior literature, and is also consistent with prepayment "S-curves" used by practicioners. Our prepayment model features two shocks, a level shock and an incentive-sensitivity shock. Using this simple prepayment model, we construct our empirical measures for surprises in the level and incentive-sensitivity of prepayments. Finally, we test the main predictions of the model using the time series of prepayment surprises and monthly returns on coupon-level indices for duration hedged MBS.

Our theoretical and empirical results for security-level factor loadings on prepayment risk suggest that a simple characteristic, negative relative coupon, or $r - c^i$, effectively captures the sensitivity of coupon-level MBS to prepayment shocks.

3.1 Theoretical Predictions: Factor Loadings

Approximate expressions for the factor loadings on the level and incentive-sensitivity shocks, β_x^i and β_y^i in Equation (3), can be derived from the first-order approximation in Equation (5) as follows:

$$\beta_x^i = \frac{\partial P^i}{\partial x}\frac{1}{P^i} = \frac{\partial P^i}{\partial \phi^i}\frac{\partial \phi^i}{\partial x}\frac{1}{P^i} = \frac{r - c^i}{(r+\phi^i)(\phi^i + c^i)}\frac{\partial \phi^i}{\partial x}, \tag{6}$$

and,

$$\beta_y^i = \frac{\partial P^i}{\partial y}\frac{1}{P^i} = \frac{\partial P^i}{\partial \phi^i}\frac{\partial \phi^i}{\partial y}\frac{1}{P^i} = \frac{r - c^i}{(r+\phi^i)(\phi^i + c^i)}\frac{\partial \phi^i}{\partial y}. \tag{7}$$

Given that a positive shock to either x or y implies an increase in prepayment, these expressions give us the first testable hypothesis of our model, which we state in Proposition 1:

Proposition 1. *If $c^i - r > 0$, then $\beta_x^i < 0$ and $\beta_y^i < 0$. If $c^i - r < 0$, then $\beta_x^i > 0$ and $\beta_y^i \geq 0$.*

In other words, premium securities, for which $c^i - r > 0$, will have negative loadings on level and incentive-sensitivity risk. Intuitively, these securities have coupons that are above current mortgage rates, and so their value deteriorates with faster prepayment. On the other hand, discount securities, for which $c^i - r < 0$, load positively on prepayment risk. Discount securities have coupon rates that are below the opportunity cost of re-invested capital, and hence their value increases if prepayment speeds increase.

We further specify the following stylized model for prepayment, where our notation now allows prepayment to vary over time in order make the connection with our empirical work clear:

$$\phi_t^i = x_t + y_t \max\left(0, l^i - l_t\right). \tag{8}$$

We use l^i to denote the borrowers' loan rates for the loans underlying the MBS with coupon i (i.e. the coupon i MBS's "Weighted Average Coupon" or WAC), and l_t to denote the current mortgage loan rate (measured by the Freddie Mac Primary Mortgage Market Survey rate, for example). We assume that $c^i - r = l^i - l_t$, so that the moneyness of the borrowers' long prepayment options matches that of the MBS investors' short options. This assumption is not crucial but it helps facilitate exposition. Although we abstract from variation in the spread between the MBS coupons, c^i, and the underlying borrowers' loan rates, l^i, we will use separate data on each of these rates in our empirical work and so we use separate notation for clarity. The moneyness of borrowers' prepayment options ("borrower moneyness") is measured by $l^i - l_t$. The moneyness from investors' perspective ("investor monenyess"), or relative coupon, $c^i - r$ captures how the security's value changes with prepayment, which moves the security's value closer to par value. We use borrower moneyness to estimate the prepayment risk factors, since the borrowers themselves make the prepayment decisions. Then, to define securities, and to study financial payoffs and returns to these securities, we use relative coupon, or investor moneyness.

Figure 1 plots prepayment as a function of borrower moneyness and the realization of the x and y prepayment factors. Using this model, we have for discount securities:

$$\phi_t^{i,\text{disc}} = x_t, \tag{9}$$

and for premium securities

$$\phi_t^{i,\text{prem}} = x_t + y_t \max\left(0, l^i - l_t\right). \tag{10}$$

Superscripts denote securities i by relative coupon, $i = c^i - c^{\text{par}}$, and $_{\text{prem}}$ indicates that the MBS is a premium security, i.e. $c^i - c^{\text{par}} > 0$. Further, we have that for discount securities,

$$\frac{\partial \phi^{i,\text{disc}}}{\partial x} = 1 \qquad \text{and} \qquad \frac{\partial \phi^{i,\text{disc}}}{\partial y} = 0. \tag{11}$$

For premium securities, we have

$$\frac{\partial \phi^{i,\text{prem}}}{\partial x} = 1 \qquad \text{and} \qquad \frac{\partial \phi^{i,\text{prem}}}{\partial y} = \left(l^i - l_t\right). \tag{12}$$

Combining the expressions for how prepayment changes with shocks to x and y in Equations (11) and (12) with the expressions for β_x^i and β_y^i in Equations (6) and (7), we have the following additional testable implications for the two prepayment risk factor loadings:

Proposition 2. *For discount securities, using i to denote the security defined by $c^i - r$ where for discounts $c^i - r < 0$, we have:*

(i) $\beta_x^{i,disc}$ *is monotonically decreasing in c^i. That is, we expect securities which trade at a larger discount to par to have larger positive loadings on the level prepayment risk factor.*

(ii) $\beta_y^{i,disc} = 0$.

For premium securities, using i to denote the security defined by $c^i - r$ where for premiums $c^i - r > 0$ we have:

(iii) $|\beta_x^{i,prem}|$ *is monotonically increasing in c^i. That is, we expect securities which trade at a larger premium relative to par to have more negative loadings on the level prepayment risk factor.*

(iv) $|\beta_y^{i,prem}|$ *is monotonically increasing in* c^i*. That is, we expect securities which trade at a larger premium relative to par to have more negative loadings on the incentive-sensitivity prepayment risk factor.*

Proposition 2 says that prepayment risk loadings increase in absolute value as one moves away from the par coupon in either direction.

3.2 Empirical Results: Risk Factors and Factor Risk Loadings

We test these theoretical predictions from Propositions 1 and 2 using data on prepayment risk factors and the excess returns to MBS securities defined by their coupon relative to the par coupon. This requires us to construct time series for the prepayment risk factors, which we acheive using data on realized vs. predicted prepayments along with the parsimonious prepayment model in Equation (8).

3.2.1 Constructing Prepayment Risk Factors

In order to measure the prepayment risk factor loadings, β_x^i and β_y^i, using time series regressions, we need time series for shocks to x_t and y_t. To construct these series, we use differences between forecasted and realized prepayments as reported on Bloomberg. Each month, dealers provide Bloomberg with their forecasts for prepayments for each MBS coupon. We use the Bloomberg-reported median of these coupon-level forecasts. We obtain realized prepayments for each MBS coupon from eMBS. Realized prepayments are reported on the eMBS website on the 4th business day of the month for the prior month. The Appendix contains further details on the data and our methodology.

The difference between prepayment forecasts and realized prepayments measures innovations in prepayments relative to market participants' forecast models, or, "prepayment surprises". The basic idea behind the estimation of the level and incentive-sensitivity prepayment risk factors is to estimate the prepayment function in Equation (8) at each date using the forecast and realized prepayment data by coupon. The difference between the realized and forecasted "intercept" of prepayments represents a surprise in the level of prepayments, x_t. Forecasters may underestimate the level of prepayments if they underestimate house price appreciation, for example. The difference between the realized and forecasted "slope" of prepayments as a function of borrowers' interest rate incentives represents a surprise in the incentive sensitivity of prepayments, y_t. For example, some months prepayment occurs at much higher rates for borrowers with a 2% rate incentive than for borrowers with no rate incentive (a high slope), while in other months all borrowers prepay at similar rates (a low slope). The difference between the realized and forecasted y_t captures the median prepayment modeler's error in forecasting this slope. Forecasters may underestimate the slope of prepayments if there is an unanticipated loosening of credit standards, for example. It is crucial to note that for both factors, prepayment surprises do not measure rate surprises, but rather surprises in how borrowers behave conditional on their loan rate relative to current mortgage rates.

Specifically, we estimate innovations to the level and incentive-sensitivity prepayment risk factors as follows. First, we estimate the following cross section regression across available underlying borrower loan rates using the forecast data in each month:

$$ppmt_t^{i,\text{forecast}} = x_t^{\text{forecast}} + y_t^{\text{forecast}} \max\left(0, l^i - l_t^{\text{PMMS}}\right) + \epsilon_t^i. \tag{13}$$

We use the Weighted Average Coupon (WAC) of the loans underlying MBS with a particular coupon i to measure borrower loan rates l^i. The prevailing mortgage rate l_t^{PMMS} is obtained from the Freddie Mac Primary Mortgage Market Survey (PMMS). The second term is positive for MBS with underlying borrower loan rates which are above prevailing rates, and zero otherwise. In this regression, the estimated intercept, $\hat{x}_t^{\text{forecast}}$ measures the forecasted level of prepayments, while the forecasted slope on the rate incentive for borrowers' with in-the-money prepayment options is estimated by $\hat{y}_t^{\text{forecast}}$. Next, we run the same regression in realized prepayment data for each month:

$$ppmt_t^{i,\text{realized}} = x_t^{\text{realized}} + y_t^{\text{realized}} \max\left(0, l^i - l_t^{\text{PMMS}}\right) + \epsilon_t^i. \tag{14}$$

For parsimony, we use the notation x_t and y_t to denote these innovations. Innovations in the realized relative to forecasted level of prepayments x_t are measured as

$$x_t = \hat{x}_t^{\text{realized}} - \hat{x}_t^{\text{forecast}}. \tag{15}$$

Similarly, innovations in the realized relative to forecasted incentive-sensitivity of prepayments y_t are measured as:

$$y_t = \hat{y}_t^{\text{realized}} - \hat{y}_t^{\text{forecast}}. \tag{16}$$

Figure 2 presents a graphical representation of the estimation of x_t and y_t. Figure 3 presents four sample months of the forecast and realized prepayment curves that are used for estimation.

Figure 4 plots the time series for the two prepayment risk factors. The correlation between the innovations in x and y is low, at 0.13. The series are, however, autocorrelated (0.78 for x and 0.66 for y). We argue that despite this measured autocorrelation, these innovations should be considered "surprises" in the context of MBS price setting behavior, and we use the raw surprise series in our baseline estimation. However, results using errors from first-order autoregressions, reported in the Internet Appendix, are nearly identical. Given industry practices, it is clear why prepayment forecast errors, or surprises, are persistent. It is standard for dealers and investors to use statistical models to forecast prepayment. When data which is inconsistent with the model arrives, they face a tradeoff in the decision to update their model. If they update the model too often, then it is not a model, but instead just a statistical description of current data. On the other hand, if the data consistently contradicts the model over a longer time period, parameters are updated. This behavior leads to slow-to-update prepayment models, and persistent prepayment model errors. Despite being persistent, then, prepayment errors are correlated with returns because investors' prepayment-model output feeds directly into MBS pricing on both the buy and sell side. We show that the prepayment errors constructed using Equations (15) and (16) have the theoretically predicted relationship to coupon-level excess returns using time series regressions, supporting the interpretation of the x_t and y_t series as shocks, since expected prepayment should not drive returns. The largest innovations also confirm this interpretation. The largest x_t innovation occurs in January of 2009, when refinancing prepayments declined due to tight credit. The largest y_t innovation occurs in March of 2010, when prepayments increased due to Fannie Mae's buyouts of delinquent loans with higher coupons.

Our paper is the first to provide time series of prepayment surprises, measured using data on forecasted vs. actual prepayments, and to show that these prepayment surprises have the theoretically predicted relationship to coupon-level excess returns. This contribution is important, because, although prepayment risk is known to be the most important risk factor driving excess returns to MBS, the empirical link between actual prepayment surprises and realized returns has not been previously documented. We also link our measure of prepayment surprises to the underlying systematic macroeconomic drivers. Although interest rates are a key stochastic state variable governing borrowers' prepayment decisions, prepayment varies considerably over time, even conditional on rate realizations.

Practicioners sometimes refer to systematic prepayment waves net of interest rate incentives (i.e. from level or incentive-sensitivity shocks) as a "media effect". However, we show that the level and incentive-sensitivity of prepayments are statistically significantly related to intuitively appealing underlying aggregate state variables. Table 2 presents the correlation of the change in the national US house price index, real personal consumption expenditure growth, the CRSP value weighted excess return on the stock market, the change in bank mortgage lending standards, and the Baa-Aaa credit spread with the estimated level and incentive-sensitivity prepayment risk factors. As expected, prepayment is positively correlated with changes in the house price index, and the relationship between house price appreciation and both the level and incentive-sensitivity of prepayments is highly statistically significant. The correlation between the level of prepayments and house price appreciation is particularly high (0.57) and statistically significant (t-stat of 11.44), which is consistent with the notion that cash-out refinancing drives borrowers to prepay regardless of their rate incentive (or dis-incentive) when house prices rise substantially. Both the level and rate-sensitivity of prepayments are also positively correlated with personal consumption expenditure growth, an effect that may be either related to consumer sentiment, or to cash-out refinancing. On the other hand, both the level and incentive-sensitivity of prepayments decline when credit spreads widen, or when banks tighten lending standards, which makes sense since wider spreads and tighter standards inhibit refinancing. We note that the relationship between all of these macroeconomic drivers and prepayment appears to be stronger for the level factor, both in terms of magnitude and statistical significance. This is consistent with the findings in Chernov, Dunn, and Longstaff (2015), who report a higher risk premium for turnover, or level, prepayment risk.

The fact that prepayment, which drives the value of premium securities down, tends to be higher in states of the world that are "good" for the representative household (high house price appreciation, positive consumption growth, and good credit conditions) was also pointed out by Gabaix, Krishnamurthy, and Vigneron (2007), who showed a positive correlation between consumption growth and prepayments. The fact that prepayments increase in good times for consumers makes the high average observed excess returns of premium securities particularly surprising. Because premium securities decline in value when prepayments increase, they are a hedge against bad house price, consumption, or credit condition states, and this would drive returns down in a representative consumer/investor asset-pricing model.[13] We show in the Internet Appendix that the price of risk in the cross section of MBS estimated using a value-weighted equity market CAPM model is indeed negative, providing further support for segmented markets, and specialized investors, for MBS.

3.2.2 Estimating Factor Loadings

With time series data on the prepayment level and incentive-sensitivity factors in hand, we estimate prepayment risk factor loadings using the following time series regression for each relative coupon i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i. \tag{17}$$

[13]Table 1 shows that, unconditionally, the deep premiums display the highest excess returns in the cross section.

Our baseline estimation uses the Barclays MBS Index Excess Returns, available at the coupon level. In the Internet Appendix, we show that estimations using Bank of America Merrill Lynch (BAML) MBS Index Excess Returns, Barclays returns that are hedged using empirical rate sensitivities, and TBA returns as reported by a major dealer bank, hedged with US treasury futures using that dealer's reported analytical key rate durations, yield very similar results. We use Barclays excess returns as our baseline return data because Barclays has the best time series and cross section coverage, and because using their analytical hedge gives us fewer free parameters relative to an empirically constructed hedge.[14] Barclays uses a proprietary prepayment model to compute key-rate durations, and constructs hedged MBS returns using these key-rate durations and US treasury returns. Details regarding the index returns construction can be found in Phelps (2015). We also provide further detail in the Appendix, including the precise timing of measurement for each variable. We define securities by their coupon relative to the par coupon, rather than by their absolute coupon. This is because the sensitivities of securities' values with respect to prepayment (the risk factor loadings) vary less over time for securities defined by their relative coupon than by their absolute coupon, as can be seen in Proposition 2. For example, an MBS with a 5% coupon has varied from being discount to being premium over our sample. When the 5% coupon was discount, its value increased with prepayment speeds, and vice versa when it became premium. In fact, we will show that the characteristic we use to define securities, relative coupon, has the theoretically predicted declining relationship with prepayment risk factor loadings. This supports our model as well as using relative coupon to define a "security".

Table 3 presents our estimated loadings when we impose the restriction that $\beta_y^{\text{disc}} = 0$, as in a strict interpretation of our model.[15] First, we test Proposition 1, using a one-sided test that prepayment risk factor loadings are positive for discount securities and negative loadings for premium securities, and a two-sided test that loadings are not significantly different from zero for securities near par. We find substantial support for Proposition 1. In particular, the loadings on the level factor are statistically significantly positive at the 5% level for the -1.0% and -0.5% discount securities. The loadings for the remaining two discount securities are also positive, but the small number of observations for those coupons limits statistical significance. Loadings are near zero, and not statistically significantly different from zero, for the par coupon, and for the relative coupons just above par, from 0.5% to

[14] The Internet Appendix also reports results using short term prepayment forecasts from a single dealer, and results for Barclays excess returns empirically hedged to rates and rate volatility.

[15] The intercepts in all regressions used to estimate factor loadings are less than 0.1%, and insignificant, for all securities, and so we do not report them. Due to data limitations, we use full sample estimates for the factor loadings. However, we provide evidence of fixed loadings for securities defined by relative coupons in the Internet Appendix.

1% premium. Fixed costs to refinancing imply that borrower rate incentives need to exceed zero by a positive amount for their prepayment option to be in the money, so it makes sense that loadings are statistically insignificant for par and only slightly premium coupons. The results for more premium securities also support Proposition 1. Loadings on the level factor are statistically significantly negative at the 10% level for securities more than 1% above par, and at the 1% level for securities 3% or more above par. Loadings on the rate-sensitivity factor are statistically significantly negative at the 1% level for securities 2% or more above par.

Proposition 1 uses only the pricing model, without a specific model for how x and y affect prepayments across the coupon stack. Turning to the predictions of Proposition 2, which uses the prepayment model in Equation (10), we see that the results also closely match each of the more detailed predictions of the model stated in Proposition 2. Not only do the signs match the model's predictions, but also most all of the estimated loadings for both x and y are indeed decreasing in the absolute value of the relative coupon. Figure 5 plots the coefficients, along with their standard errors, for a visual description of the fit between the model's predictions and our empirical findings. In results from an unrestricted regression, shown in the Internet Appendix, none of the discount securities' loadings on the incentive-sensitivity factor, y are statistically significantly different from zero, confirming Part (ii) of Proposition 2. We provide two statistical tests for the remaining predictions of Proposition 2, namely Parts (i), (iii), and (iv). First, we run cross section regressions of estimated loadings on relative coupon. The slope of the level factor loadings on relative coupon is -1.19% and is highly significant at the 0.01% level. Similarly, the slope of the incentive-sensitivity factor loadings on relative coupon is -1.96% and is also highly significant at the 0.01% level.

Second, we run a much stricter test for the monotonicity of the factor loadings by testing whether the factor loadings for each relative coupon are statistically significantly different from the loadings on each of the other coupons, in the expected direction. Specifically, we use dummy regressions to test for the significance and signs of the differences between coefficients on the level and incentive-sensitivity factors across the relative-coupon stack. The test consists of twelve panel regressions, one for each "base" coupon from 2% discount to 3.5% premium. In each panel regression, we designate one coupon as the base coupon, and drop all the terms associated with that coupon from each summation. Each regression can be stated as:

$$R_t^{ei} = a + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \delta_i + \beta_x x_t + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \phi_i x_t + \mathbb{1}_{\text{base}\in\{0.0\%:3.5\%\}} \beta_y y_t + \sum_{i=0.0\%}^{3.5\%} \mathbb{1}_i \theta_i y_t + \epsilon_t^i, \tag{18}$$

where the notation $\mathbb{1}_i$ is used to denote dummies equal to one for each included coupon i. The coefficients δ_i measure the intercept for each included coupon, relative to the base (dropped) coupon. The coefficients ϕ_i measure the differences in loadings on the level factor x, for each included coupon relative to the base coupon. Then, β_x measures the loading on the level factor for the base coupon, which has no associated dummy interaction with x_t. The coefficients θ_i measure the difference in loadings on the incentive-sensitivity factor y, for each included coupon relative to the base coupon. We restrict loadings on the incentive-sensitivity factor to be zero for discount securities. For premium coupons, β_y measures the loading on the incentive-sensitivity factor for the base coupon, which has no associated dummy interaction with y_t.

We verify that the coefficients β_x and β_y on x_t and y_t indeed match the loadings for the base coupon from Table 3 for each of the 11 regressions. We use one-sided tests of whether the coefficients ϕ_i and θ_i, which measure the difference in the level and incentive-sensitivity factors relative to the base coupon, are significant and have the expected sign. Our test is based on standard errors clustered by time. Tables 4 and 5 present the t-statistics on the ϕ and θ coefficients, respectively, and show that the estimated loadings show statistically significant differences, with the expected sign for all coupons with sufficient data and/or sufficient distance from the base coupon.[16]

This test is very stringent, since it relies on relative coupon being the only cross section differences in prepayment exposures. In practice, vintage and other effects also play a role, and, in addition to introducing noise, this can diminish the spread in betas. This is particularly true for close coupons which may have similar unmeasured characteristics. Furthermore, we note that the theoretical loadings in Equations (6) and (7) are approximations that rely on the stylized, piecewise-linear prepayment model.[17] Still, we find statistically significant differences, with the expected sign, for the majority of the estimated loadings.

Next, we discuss robustness checks. In the Internet Appendix, we also show that the

[16]The associated coefficients are reported in the Internet Appendix.

[17]In addition, the implied values depend on expectations of prepayment and interest rates, which are difficult to measure, and, in practice should differ by relative coupon depending on the months that any particular relative coupon appears in our sample.

predicted pattern of loadings holds using different hedging methods, different return sources, a different prepayment forecast source, in an unrestricted regression, and controlling for within-month interest rate changes which may affect realized returns. Here, we present results showing that the same pattern of loadings holds when controlling for standard asset pricing factors. Table 6 presents the results. The loadings are very similar to those in Table 3, and continue to follow the pattern from Proposition 1 and Proposition 2 even with the additional controls.

Perhaps the most interesting results in Table 6 are those for the tradable intermediary asset pricing factor. The loadings are significant, but fairly flat. The loadings are, however, slightly higher for the coupons around par, which earn the *lowest* returns in the cross section. We show in the Internet Appendix that, when not controlling for prepayment shocks, the price of risk for the intermediary factor is indeed significantly *negative* in the cross section of MBS returns.[18] We use the tradable intermediary return series provided by He et al. (2017) (HKM), which is available monthly. These intermediary returns are at the bank holding company level, and while banks are exposed to prepayment risk, they also make fees on the mortgage origination side that can offset prepayment effects. Ideally, one would want to use the returns of the trading desk, or the broker-dealer segment of the bank, as in Adrian, Etula, and Muir (2014), as well as allowing loadings to change sign as the predominance of discount or premium securities in the overall market (and thus the trading desk's portfolio) changes. However, data limitations using the quarterly data of Adrian et al. (2014) make such analysis challenging.[19] Another important consideration is that banks' trading desks are exposed to equity and credit risks. Prepayment, which affects premium securities negatively, tends to occur when equity markets and credit markets are healthy (see Table 2).

In general, there are two main channels through which intermediary wealth or returns may affect asset returns, namely through active trading or through intermediation. We argue that prepayment risk in the cross section of MBS is priced by active traders which may only be a small part of overall bank holding company returns. Teasing out the intermediation vs. trading role of intermediaries in asset pricing presents an interesting challenge for future research. Haddad and Muir (2019) is a promising step in this direction.

In summary, in support of Proposition 1, we present the following results in the main text: (1) One-sided tests that factor loadings in our baseline estimation are positive for discount coupons, and negative for premium coupons (Table 3)[20] and (2) Similar loading

[18]Below, we show that the price of risk is negative, but insignificant, when controlling for prepayment shocks.

[19]We found no evidence of intermediary factor loadings changing signs with market type using either the He et al. (2017) or the Adrian et al. (2014) measure.

[20]Analogous results with unrestricted loadings on y appear in the Internet Appendix.

estimates when controlling for standard asset pricing factors (Table 6). The following additional evidence in support of Proposition 1 appears in the Internet Appendix: (3) Similar loading estimates using an empirical rate hedge and an empirical rate and volatility hedge (4) Similar loading estimates from TBA returns and BAML index returns (5) Similar loadings using short-term forecasts from a single dealer (6) Similar loading estimates using AR(1) errors in the x and y series, and (7) Similar loading estimates controlling for within-month interest rate changes. In support of Proposition 2, we have presented the following results: (1) Regression tests that the slope of the factor loadings are negative across the relative coupon stack, (2) Tests for the sign and statistical significance for the differences in loadings between each relative coupon and all other coupons (Tables 4 and 5). Taken together, we argue the results of these tests strongly support the theoretically predicted patterns of prepayment risk loadings across relative coupons.

4 Factor Risk Premia

The goal of this section is to document the fact that the risk premium on prepayment risk changes sign with the market composition of MBS. Figure 6 plots the market composition over time, and shows that the contribution of discount and premium securities to the overall MBS market portfolio varies considerably. When the market is primarily composed of discount securities, the value of the overall MBS market increases, ceteris paribus, when prepayment increases. By contrast, when the market is primarily premium, an increase in prepayment causes a deterioration in the value of the overall MBS market. We argue that active, specialized MBS investors, who hold a treasury-hedged MBS portfolio, are the marginal investors in MBS, and that the sign of their exposure to prepayment risk drives the sign of prepayment risk premia.

Simple evidence for this is given in Table 7, which presents summary statistics by relative coupons and for the subsamples defined by whether the predominant security in terms of remaining principal balance (RPB) is premium or discount. As can be seen in the top panel, when the market is primarily discount, MBS investors are concerned that prepayment will realize too low, and require higher returns to hold discount securities, which increase their exposure to low prepayment states. By contrast, premium securities provide a hedge against low prepayment states, and earn negative returns on average in discount markets. In premium markets, the opposite is true, as shown in the bottom panel. During premium markets, investors are concerned about high prepayment states, and require higher returns for premium securities whose value declines when prepayment is higher than expected. Discount securities provide a hedge and earn slightly negative returns on average in premium markets.

Figure 7 shows this pattern visually, by plotting average returns by relative coupon for all months (green solid line), and then by averaging within discount (red dashed line), and within premium months (blue short-dashed line) only. The downward sloping pattern of average returns as a function of relative coupon in discount markets, and the upward sloping pattern in premium markets, is readily apparent. We also note that averaging returns unconditionally leads to biased expected return estimates. In particular, unconditional averaging leads to a U-shaped pattern for expected returns, as can be seen in the green solid line in Figure 7 and in Table 1. This U-shape underestimates the positive returns that can be earned by holding a portfolio of MBS which places higher weights on the predominant coupon-type, while underweighting or shorting the less-representative coupon type. We document the returns to such a strategy in Section 4.4.

4.1 Theoretical Results: Factor Risk Premia

We proceed by estimating factor risk premia using a baseline single-factor model motivated by our theory, namely a model in which prepayment exposures are summarized by negative relative coupon, $r - c^i$. The main results of Section 3.1, presented in Propositions 1 and 2, show that loadings on both the level and incentive-sensitivity prepayment factors depend monotonically on $r - c^i$. This can be readily seen in Equations (6) and (7). Any independent variation in factor loadings comes from the specification of how prepayment varies with each shock, namely the terms $\frac{\partial \phi^i}{\partial x}$ and $\frac{\partial \phi^i}{\partial y}$. Our simple, piecewise-linear prepayment model yields Equations (11) and (12) for these terms. It is clear from these equations that, in cross-section or panel regressions, the loadings on the level and incentive-sensitivity factors should be highly correlated. This makes it challenging to estimate separate risk premia for each factor. We confirm this high correlation empirically. We present the distribution of the cross section correlation between the two factor loadings by month in the Internet Appendix. Only 6% of months have a cross section correlation between factor loadings of less than 50%, and one third of the correlations are above 70%. Given the highly correlated level and incentive-sensitivity loadings, we focus our estimation of time varying prepayment risk premia on a characteristic-based model, using $r - c^i$, or negative relative coupon, as the single characteristic. Still, an important contribution of our paper is to show that this characteristic indeed captures exposure to prepayment risk, measured using data on prepayment surprises, as documented in Section 3.2. An additional benefit of the characteristic model is that it avoids estimated regressors. We provide results, consistent with the theory, using the estimated empirical loadings on the level and incentive-sensitivity shocks in the Internet Appendix.

Using the characteristic model, expected returns are given by:

$$E_M[R^{ei}] = \lambda_{\mathrm{M}}\,(r - c^i), \tag{19}$$

where $_{\mathrm{M}}$ denotes the market type, either premium or discount.[21] Whether a high prepayment state is a "good" or "bad" state of the world (i.e. whether the price of prepayment risk γ in Equation (1) is either positive or negative) depends on whether the overall MBS portfolio is discount or premium, i.e. the prices of prepayment risk are determined by the sign of the change in wealth for a representative, specialized MBS investor who invests in the universe of MBS securities. To fix ideas, consider that, in a strictly segmented market and under the standard assumptions necessary to guarantee the existence of a representative agent, we can write the wealth of the representative MBS investor that holds the MBS portfolio as:

$$W = \sum_i P^i \ \mathrm{RPB}^i$$

where P^i is given in equation (5), and RPB^i denotes the remaining principal balance of security i. It is clear that $\frac{\partial W}{\partial \phi}$, or the change in the value of the MBS portfolio with a change in prepayment, inherits the sign of the partial derivative of the price of the majority RPB security type with respect to the shock. As long as the representative investor dislikes states of the world in which their wealth declines, we have that investors will put a high value on states of the world in which wealth declines. That is, if $\frac{\partial W}{\partial \phi} < 0$, as is true in a premium-heavy market, then the state price for a positive prepayment shock γ_{M} will be negative, and the risk premium λ_{M} will be negative, implying a higher expected return for securities which load negatively on prepayment shocks (decline in value given a positive prepayment shock). In other words, investors will require compensating positive risk premia for holding securities whose returns are positively correlated with changes in their wealth, and which security type this is changes with the overall MBS market composition.[22] MBS investors will require positive risk premia for the predominant security type, either discount or premium.

[21] While the sign of prepayment risk depends only on the predominant security type, our baseline estimation allows for the magnitude to vary with how heavily discount or premium the market composition is. However, here, we drop the subscript t for parsimony, and condition only on the predominant security type.

[22] Note that we do not need strict market segmentation. High state prices when investor wealth declines can be motivated by value at risk constraints, or compensation concerns. See Shleifer and Vishny (1997), Gromb and Vayanos (2002), Allen and Gale (2005), Brunnemeier and Pedersen (2009) or He and Krishnamurthy (2013) for models in which the wealth of specialized investors drives the returns to complex assets. Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) provide empirical support for these theories.

Thus, in a premium heavy market, we expect that

$$E_{\text{PM}}[R^{ei,\text{prem}}] = \lambda_{\text{PM}}(r - c^i)^{i,\text{prem}} > 0, \tag{20}$$

where we use $_{\text{PM}}$ to denote the expectation conditional on "premium market" dates, namely dates at which more than 50% of total MBS remaining principal balance trades at a premium. Again, superscripts denote securities by relative coupon, $i = c^i - r$ and $_{\text{prem}}$ indicates that the MBS is a premium security, i.e. $c^i - r > 0$. Since $(r - c^i)$ is negative for premium securities (and $\beta_x^{i,\text{prem}}$ and $\beta_y^{i,\text{prem}}$ are both negative,) we expect that λ_{PM} is negative.

By contrast, in a discount market, we expect that:

$$E_{\text{DM}}[R^{ei,\text{disc}}] = \lambda_{\text{DM}}(r - c^i)_x^{i,\text{disc}} > 0 \tag{21}$$

where we use $_{\text{DM}}$ to denote the expectation conditional on "discount market" dates, namely dates at which 50% or more of total MBS remaining principal balance trades at a discount. Superscripts denote securities by relative coupon, $i = c^i - r$ and $_{\text{disc}}$ indicates that the MBS is a discount security, i.e. $c^i - r < 0$. Since $(r - c^i)$ is positive for discount securities (and $\beta_x^{i,\text{disc}}$ is positive while $\beta_x^{i,\text{disc}}$ is zero), this implies that λ_{DM} is positive. Then, we have the following hypothesis regarding the signs of the prices of prepayment risk:

Hypothesis 1. *High prepayment states are wealth increasing for the aggregate MBS portfolio in discount markets, and wealth decreasing in premium markets. As a result, we expect the following signs for prepayment risk prices and prepayment risk premia, depending on market type:*

(i) ***Premium Market:*** *When the market is comprised mainly of premium securities, high prepayment states are bad states, and thus the risk price γ_{PM} for prepayment shocks is negative and the risk premium on prepayment risk exposure λ_{PM} is negative. The representative investor requires compensation for bearing the risk that prepayment is higher than expected. Since $\lambda_{PM} < 0$, the signs for $r - c^i$ by relative coupon, and the predictions for the signs of the risk loadings (β's) from Proposition 1, imply that $E_{PM}[R^{ei,prem}] > 0$ and $E_{PM}[R^{ei,disc}] < 0$.*

(ii) ***Discount Market:*** *When the market is comprised mainly of discount securities, high prepayment states are good states, and thus the risk price γ_{DM} for prepayment shocks is positive and the risk premium on prepayment risk exposure λ_{DM} is positive. The representative investor requires compensation for bearing the risk that prepayment is lower than expected. Since $\lambda_{DM} > 0$, the signs for $r - c^i$ by relative coupon, and the predictions for the signs of the risk loadings (β's) from Proposition 1 imply that $E_{DM}[R^{ei,prem}] < 0$ and $E_{DM}[R^{ei,disc}] > 0$.*[23]

[23]Technically, since discount securities do not load on the y factor, it is possible that premium securities

4.2 Empirical Results: Factor Risk Premia

Our baseline estimation of the sign of prepayment risk premia (or, the sign of the price of prepayment risk) as a function of market type is given by the following pooled time series, cross section, regression over all relative coupons and across all months:

$$R_t^{ei} = a + \kappa(r - c^i) + \delta(r - c^i)\left(\%RPB^{\text{disc}}_{\text{t,BoM}} - 50\%\right) + \epsilon_t^i. \tag{22}$$

The interaction term captures the effect of market type on prepayment risk premia. We use $_{\text{BoM}}$ to denote observation at the beginning of the month, emphasizing that this is a predictive regression. When the market is perfectly balanced between discount and premium securities, $\%RPB^{\text{disc}} - 50\% = 0$, and κ should thus be zero. The risk to MBS investors' premium securities from prepayment being too high is offset by the risk to MBS investors' discount securities from prepayment being too low. With little or no prepayment risk exposure, investors do not require significant prepayment risk premia. On the other hand, we expect that δ should be positive, indicating a positive prepayment risk premium in discount markets, and a negative prepayment risk premium in premium markets. The coefficient δ on the interaction term effectively captures the market-type dependent sign of the prepayment risk premium (and hence the market-type dependent sign of the prepayment risk price), since it changes sign with market composition. In discount heavy months, $\%RPB^{\text{disc}} - 50\% > 0$, and since discount securities have positive prepayment risk loadings, as captured by the characteristic of negative relative coupon, $r - c^i > 0$, a positive δ leads to the model-implied higher expected returns for discount securities in discount months. Similarly, in premium heavy months, $\%RPB^{\text{disc}} - 50\% < 0$, and since premium securities have negative loadings, as captured by $r - c^i < 0$, positive δ leads to the model-implied higher expected returns for premium securities in premium months. Table 8 presents our baseline results. We present results both with and without time fixed effects in order to highlight the fact that our model can predict monthly returns with an R^2 of 1.2% without time fixed effects. However, in addition to the risk factors which change the shape of expected returns in the cross section, there are likely to be shocks or risk factors that move the entire coupon stack of returns. Thus, although the results are similar between the two specifications, we emphasize the results with time fixed effects. We also note that the coefficient of interest, δ, increases in magnitude and significance when time fixed effects are included in order to focus on the cross sectional variation. We present standard errors clustered by time.[24] As predicted,

determine the price of incentive-sensitivity shocks, and that, as a result, premium securities may have positive expected returns even in discount markets. However, our empirical results indicate that this is not the case.

[24]In an asset pricing context, we expect it to be most important to cluster errors in the time dimension, see Petersen (2011). Standard errors are smaller using coupon and time clusters, however the size of the

the κ is zero, and δ is positive, and significant at the 1% level using a one-sided test that the coefficient is positive as predicted by Hypothesis 1. Finally, we also present results with security fixed effects, and confirm our results for time-varying risk premia remain very similar in magnitude and significance.

We present several robustness checks, and confirm that δ remains positive, and statistically significant. First, we show that our results remain essentially unchanged excluding the crisis period. Table 9 presents the results. Next, we report results controlling for other standard asset pricing factors in Table 10. Again, the magnitude and significance of the prepayment risk premium estimate is very similar to the baseline estimate in each case. This is not surprising, since the factor loadings on standard asset pricing factors reported in Table 6 display so little cross section variation. As a result, these factor loadings add little or no explanatory power to the cross section. Although, as reported in Table 6, the returns to the overall MBS market are correlated with these other systematic factors, the effect is common across the coupon stack.

One over-arching concern with using average returns to measure expected returns is that realized returns each month are the sum of expected returns, plus a shock. This concern is partially alleviated by studying portfolios of individual securities, as is common in the vast literature studying the cross section of equity returns. Our data consists of coupon-level portfolios of returns, i.e. coupon-level index returns. In addition, we directly address the concern that our results on time-varying risk premia are driven by coincidental prepayment or rate shocks, rather than expected returns from risk premia. In particular, we show that including shocks to interest rates and the level and incentive-sensitivity prepayment risk factors (1) captures the effect of such shocks on realized returns, but (2) does not change our estimates of risk prices. Table 11 adds controls to our baseline model in Table 8 for the main shocks affecting realized returns, namely prepayment shocks x and y, and interest rate shocks.[25] As expected, the level and incentive-sensitivity prepayment shocks affect realized returns with the expected signs, and significantly for the level factor. However, risk prices are unchanged with the inclusion of these contemporaneous prepayment surprises. If the interest rate hedge were perfect, the effect of interest rate shocks would be zero. The table shows that the Barclays excess return series, hedged using their proprietary OAS model, still display a significant exposure to contemporaneous rate shocks. However, the effect of these shocks on the estimated risk price is basically zero.[26]

We also note that prior work provides a sort of out-of-sample test for our theory. Duarte,

clusters becomes small.

[25]We use the change in the Primary Mortgage Market Survey borrowing rate, normalized by its full-sample standard deviation to measure the rate shock driving realized prepayments.

[26]The Internet Appendix contains similar results using empirically hedged returns.

Longstaff, and Yu (2006) compute interest rate hedged returns to discount, par and premium portfolios using data from 1996 to 2004. They find that the discount strategy has the highest average returns, followed by the par strategy, with the premium strategy having the lowest average returns. Using our sample from 1994 to the present, we find the opposite ranking, consistent with the findings in Gabaix, Krishnamurthy, and Vigneron (2007), who find positive premia for interest only coupon strips (IO's). The difference is due to variation in the composition of the MBS market over time. Discount securities were more prevalent in the period studied by Duarte, Longstaff, and Yu (2006), in contrast to the more premium heavy sample later studied here and in Gabaix, Krishnamurthy, and Vigneron (2007). Our analysis explains why, and is consistent with, the fact that studies using different time samples find different rankings amongst MBS strategies which are long either discount, par, or premium securities.

4.3 Relative Pricing Errors vs. Constant Risk Price Models

Another way to assess how important time varying prepayment risk premia are for pricing the cross section of MBS is to compare the pricing errors of models which are consistent with our theory to benchmark models with constant risk prices. The first benchmark model uses the return on the RPB weighted MBS market return as the single factor. The second constant risk premium benchmark model uses the return on a spread asset constructed by going long the maximum coupon in each month, and short the minimum coupon in each month. We scale this spread asset so that its return has equal leg volatility and constant volatility over time. The intuition for this benchmark model is that it makes use of the predicted monotonicity of the prepayment risk factor loadings, but not the time varying prepayment risk prices. We compare these models to theory-implied models with risk premia that vary conditionally with whether the market is comprised primarily of discount or premium securities. The first theory-implied model utilizes both prepayment risk factors, the level factor x, and the incentive-sensitivity factor y. The second theory-implied model uses the characteristic of negative relative coupon (i.e. $(r - c^i)$) to measure prepayment risk.

To provide graphical results in addition to root mean squared errors, we estimate each model using Fama and MacBeth (1973). First, we estimate factor loadings via time series regressions for each relative coupon. Then, we estimate risk premia by taking the time series average of the monthly risk premia estimates from cross section regressions of returns on factor loadings at each date. For the models with time varying risk premia, we estimate a separate risk premium for discount and premium markets by averaging using only data from either discount markets (DM), or premium markets (PM). We measure market composition using the percent of remaining principal balance (RPB) that is discount at the beginning of the month. We classify a month as discount if greater than 50% of the outstanding MBS balance trades at a discount, and premium otherwise. Since the panel of relative coupons is unbalanced, time series averages are computed by weighting monthly cross sections by the number of coupons that month, relative to the total number of coupon-month observations.[27]

Figure 8 presents scatter plots of the results for the two benchmark models with constant risk prices for the value weighted MBS market risk factor (left panel) and the passive max-min risk factor (right panel) conditional on market type, and over the full sample. Each column is one model, and rows plot different market types, discount or premium. The left column of Figure 8 plots the benchmark model using the return on the RPB weighted market-level return to MBS as the single factor. The right column of Figure 8 plots the benchmark model using the return on a spread asset constructed by going long the maximum coupon in each month, and short the minimum coupon in each month. As is clear in the figure, both of the constant risk price models perform very poorly in discount months. Since risk prices over the entire sample are more heavily influenced by the (more prevalent) premium months, both constant prepayment risk premium models get the slope of expected returns in the cross section wrong in discount months. Moreover, the max-min model, which has slightly lower pricing errors, performs well in premium months, as expected, because the loadings on the max-min portfolio are monotonically increasing in relative coupon, negative for discount securities and positive for premium securities. The estimated unconditional prepayment risk premium is negative. Then, in premium markets this model correctly predicts that premium securities should have higher expected returns. In discount markets, predicted returns are the same, however realized returns have the opposite pattern and this model gets the wrong sign for the slope of returns across relative coupons. As a result, the overall performance is poor, as can be seen in the plot for the full sample, in the bottom row of the figure.

Figure 9 plots the results for the two theory-implied models with time varying risk prices described in Equation (3) (left panel) and Equation (19) (right panel) conditional on market type, and over the full sample. The superior performance of the theory-implied models with time varying risk premia can clearly be seen by the improvement in fit seen in Figure 9 relative to Figure 8. The left column of Figure 9 plots the results for the model described in Equation (3), with level and incentive-sensitivity risk factors.[28] Two things improve the fit of this model. First, this model produces a larger spread in β's than either benchmark model. Second, allowing the price of risk to vary by market type allows the model to match

[27] This weighing effectively weights each observation more equally, vs. weighting months equally. It also has the advantage of weighting months with larger cross section variation in prepayment risk exposures more heavily.

[28] See the Internet Appendix for the factor loadings for this model.

the slope of average returns in the cross section of relative coupons in both market types, and hence in the full sample. The right column of Figure 9 plots the results for the model described in Equation (19), with relative coupon as the single factor/characteristic. This model is also implied by our theory, and has a good fit. Thus, the two models which are consistent with our theory offer a substantial improvement in fit over the benchmark models with passive indices and constant risk premia.

The better performance of the two models we propose can be measured by the improvement in the average root mean squared pricing errors for each model for the full sample, corresponding to the figures plotted in the bottom row of Figures 8 and 9. Both models with constant risk prices have pricing errors that are more than double our single-factor model with time-varying risk premia. Root mean squared errors are 0.88% for the value weighted market model, 0.84% for the Max-Min model. By contrast, pricing errors allowing risk premia to vary with market type, discount vs. premium, are 0.53% for the two-factor model, and 0.32% for the single-factor model.[29]

4.4 Time Series Results: Prepayment Risk Premium Portfolio

The results of our estimated model

$$E_M[R^{ei}] = \lambda_{\mathrm{M}}\,(r - c^i)$$

suggest implementing an active strategy consisting of a long-short spread asset which changes direction with market type. Since loadings are monotonic in coupon, and given our estimated time varying risk prices, the results suggest going long the deepest discount security and short the most premium security in discount heavy markets, and vice versa in premium markets. Intuitively, this spread asset is designed to harvest the prepayment risk premium earned for bearing prepayment risk that is hard to hedge with US treasuries. Hence, we label this portfolio the "Prepayment Risk Premium" or "PRP" portfolio. To construct the Prepayment Risk Premium portfolio, we restrict the spread asset to have a constant volatility over time, and to have equal volatility in the long and short legs, which is standard. Table 12 presents results for the Sharpe ratios of the PRP portfolio, passive long-short comparison spread assets, and passive indices over the full sample, and within discount and premium months.

[29] To account for the unbalanced panel, and for the fact that pricing errors are conditional on market type, RMSE's are computed for each security by taking the weighted average of squared deviations in discount and premium months, weighted by the number of months of each type, for each security. This security-level weighted average is then averaged across securities before taking the square root.

The Sharpe (1966) ratio of the PRP portfolio is 0.76. This is 2.62 times the Sharpe ratio of a passive value weighted MBS index. The final row of Table 12, using the full sample, shows the superior performance of the Prepayment Risk Premium portfolio over all other strategies. The conditional Sharpe ratios are also informative, since the Sharpe ratio for any strategy that is always long discount securities has a Sharpe ratio that is positive in discount months, and negative in discount months. The converse is true for any strategy that is always long premium securities.

We also present information ratios, a version of the active Sharpe ratio which controls for the correlation between the actively managed PRP portfolio and a passive benchmark since it is the excess return relative to the standard deviation of the PRP return less the benchmark return:

$$\frac{E\left[R^{\text{PRP}} - R^{\text{Benchmark}}\right]}{\sigma\left(R^{\text{PRP}} - R^{\text{Benchmark}}\right)}$$

where $R^{\text{Benchmark}}$ is the benchmark return. Table 13 displays the excess return, tracking error, and information ratio for the PRP portfolio relative to three passive benchmarks, namely, a passive long maximum premium coupon short minimum discount coupon portfolio with constant volatility and equal-leg volatility, a passive long maximum premium coupon short par portfolio with constant volatility and equal-leg volatility, and the remaining principal balance weighted MBS index. In all cases, the information ratio is about 0.3, indicating that the simple PRP strategy generates an information ratio of a similar magnitude as traditional market risk premia such as the equity risk premium, term premium or credit risk premium.

To study the magnitude of risk loadings and α's with respect to passive benchmarks, we regress the PRP portfolio returns on four passive benchmarks. That is, we estimate:

$$R_t^{\text{PRP}} = \alpha + \beta^{\text{Benchmark}} R_t^{\text{Benchmark}} + \epsilon_t \tag{23}$$

where $R_t^{\text{Benchmark}}$ is one of four benchmark returns, namely, the remaining principal balance weighted MBS index, VW_{all} , the remaining principal balance weighted MBS index amongst premium securities only, VW_{prem}, an untimed long maximum premium coupon short minimum discount coupon portfolio with constant volatility and equal-leg volatility, Max - Min, and an untimed long maximum premium coupon short par coupon portfolio with constant volatility and equal leg volatility, Max - Par. Table 14 presents the results. The monthly α's are all highly statistically significant. We note that, importantly, the returns to the Prepayment Risk Premium portfolio are largely independent of the passive benchmark returns. In particular, the loading on the remaining principal balance weighted MBS market portfolio is -0.08 and the R^2 of this regression is only 1%. The highest loading of the PRP strategy, 0.45, is on the Max-Par benchmark, and this regression has an R^2 of 22%. All of these results are consistent with our finding that neglecting to control for the time varying prices of prepayment risks biases estimates of positive average returns towards zero.

Finally, we compute the cumulative returns from investing in the model-implied Prepayment Risk Premium portfolio, vs. the alternative cumulative returns from the three passive benchmark strategies with the next highest Sharpe ratios, namely, a passive long maximum premium coupon short minimum discount coupon portfolio with constant volatility and equal-leg volatility, a passive long maximum premium coupon short par portfolio with constant volatility and equal-leg volatility, and the remaining principal balance weighted MBS index. Figure 10 plots the results, and shows that the cumulative PRP portfolio returns over the last twenty years have been almost double that of the next best strategy. Note that the difference in cumulative returns between the Max-Min strategy (blue line), and the optimal strategy (black line) is entirely driven by optimally switching the long and short legs, conditional on market type. The market has been dominated by premium securities since 2009, so the difference in cumulative returns over this time between these two strategies is constant. The market type will change to discount if rates increase in the future, and at that point the cumulative returns will again diverge. One lesson from Figure 10 is that the performance of the PRP portfolio depends on the avaliable spread in relative coupons, which has been more limited in recent years. Recall also that these cumulative returns are net of treasury returns, and so are compensation for prepayment risk only.

5 Conclusion

Our study provides new evidence of segmented markets for mortgage-backed securities, populated by specialized investors who price market-specific risks. In particular, we show that the price of prepayment risk appears to be determined by whether prepayment is wealth increasing or wealth decreasing for a representative MBS investor who holds the MBS market.

Our evidence provides support for theories of limits to arbitrage and intermediary asset pricing in general, however we do not find evidence that traditional intermediary asset pricing factors price the cross section of MBS returns. We argue that this is because prepayment risk is priced by specialized traders of MBS. Banks have exposure to mortgage prepayment both through trading, but also through origination. Moreover, whether intermediary wealth prices assets because of trading or intermediation remains an open, and interesting, question.

We proceed by presenting the first simple, linear asset pricing model for the cross section of MBS returns, and by estimating the model's parameters using average monthly realized returns to proxy for expected returns. We measure level and incentive-sensitivity prepayment risk factors using surprises in prepayment realizations relative to prepayment forecasts.

A simple pricing model implies that, quite generally, the values of discount securities, which trade below par, increase with positive prepayment shocks. Similarly, the values of premium securities, which trade above par, decrease with positive prepayment shocks. We find robust support for these predicted prepayment risk exposures using our measured level and incentive-sensitivity prepayment risk factors.

As a result of the variation in the exposure of discount and premium securities to prepayment shocks in the cross section, and the fact that the composition of the MBS market varies substantially over time between being discount vs. premium heavy, the exposure of the overall value of the MBS market to prepayment shocks varies over time. When the market is primarily discount, a positive prepayment shock increases the value of the aggregate MBS portfolio. However, when the market is primarily comprised of premium securities, a positive prepayment shock decreases the value of the aggregate MBS portfolio. Therefore, an investor whose wealth is highly exposed to changes in the value of the MBS market prices prepayment shocks with opposite signs depending on the predominant type of security. A high prepayment shock is wealth increasing in discount markets, but wealth decreasing when the market is more premium.

We estimate prepayment risk prices conditional on the composition of the market between discount and premium securities at the beginning of the month. The conditional risk price estimates support the hypothesis of pricing by specialized investors in MBS. The price of prepayment risk is positive in discount markets, and negative in premium markets. This leads to a downward sloping pattern of expected returns in the cross section of MBS coupons relative to the par coupon in discount markets, and an upward sloping pattern in premium markets. Overall, in the pooled time series cross section, the resulting pattern for the cross section of returns is U-shaped in relative coupon. As a result, failing to account for the market composition, and the associated prices of prepayment risk, leads to estimates of average returns, and risk premia, which are biased. In particular, estimates are biased downwards when they are positive conditional on market type; discount securities' average returns are underestimated in discount markets and premium securities' average returns are underestimated in premium markets. The model also implies a "Prepayment Risk Premium" portfolio which is long the deepest discount security and short the most premium security in discount heavy markets, and vice versa in premium markets. This portfolio offers substantially improved Sharpe and information ratios over passive benchmarks.

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A. Appendix: Data Description

Constructing Prepayment Risk Factors

This section provides a detailed description of the construction of the level and incentive-sensitivity prepayment risk factors, as well as results using an alternative source of prepayment forecasts.

Prepayment Forecasts For our study, we use historical prepayment forecasts obtained from Bloomberg. Specifically, we use a Bloomberg-computed median of prepayment projections submitted by contributing dealers. Projections are available for generic TBA securities defined by agency/program/coupon. In this paper, we focus on prepayment projections for Fannie Mae 30-year TBA securities.

Dealers have the option of updating their prepayment projections on Bloomberg on a daily basis and do so at their own discretion. Bloomberg computes a daily median prepayment forecast based on whatever dealer projections are available at the time. On average, there are about 8-10 contributing dealers. Bloomberg median prepayment forecasts can be downloaded historically with a monthly frequency (i.e. a monthly snapshot on the 15th).

Dealer prepayment forecasts are available for a range of interest rate scenarios. In addition to the base case that assumes rates realize at forward rates, forecasts are also made assuming parallel shifts in the yield curve of $+/-$ 50, 100, 200, 300 basis points. We utilize the base case projection for our main analysis. Using realized rates requires conditioning on future rate realizations. However, because rates rarely move over 50bps within the month, results using the forecast for the realized rate scenario, available upon request, are very similar.

The dealer prepayment forecasts on Bloomberg are quoted according to the PSA convention. We convert that to an annualized constant prepayment rate (CPR) using the standard conversion formula:

$$CPR = PSA * \min(6\%, 0.2\% * \text{weighted-average loan age}).$$

For reference, we provide a more detailed description of PSA and CPR:[30]

- Constant Prepayment Rate (CPR) and the Securities Industry and Financial Markets Association's Standard Prepayment Model (PSA curve) are the most popular models used to measure prepayments.

- CPR represents the annualized constant rate of principal repayment in excess of scheduled principal amortization.

- The PSA curve is a schedule of prepayments that assumes that prepayments will occur at a rate of 0.2 percent CPR in the first month and will increase an additional 0.2 percent CPR each month until the 30th month and will prepay at a rate of 6 percent CPR thereafter ("100 percent PSA").

[30] See `http://www.fanniemae.com/resources/file/mbs/pdf/basics-sf-mbs.pdf`.

- PSA prepayment speeds are expressed as a multiple of this base scenario. For example, 200 percent PSA assumes annual prepayment rates will be twice as fast in each of these periods; 0.4 percent in the first month, 0.8 percent in the second month, reaching 12 percent in month 30 and remaining at 12 percent after that.

Realized Prepayments Historical realized prepayment rates are obtained via eMBS. The realized prepayment rate is computed based on the pool factors that are reported by the agencies on the fourth business day of each month. The pool factor is the ratio of the amount of remaining principal balance relative to the original principal balance of the pool. Using the pool factors and the scheduled balance of principal for a pool, one can calculate the fraction of the pool balance that was prepaid, that is the unscheduled fraction of the balance that was paid off by borrowers. The prepayment rates reported on eMBS are a 1-month CPR measure. In other words, prepayments are measured as the fraction of the pool at the beginning of the month that was prepaid during that month, yielding a single monthly mortality (SMM) rate. The SMM is then annualized to get the constant prepayment rate (CPR).

Borrower Moneyness We define borrower moneyness or rate-based prepayment incentive to be the rolling 3-month average of the difference between the weighted-average coupon (WAC) of a Fannie Mae 30-year coupon aggregate and the Freddie Mac Primary Mortgage Market Survey (PMMS) rate for 30-year fixed-rate mortgages.

The Fannie Mae 30-year coupon aggregate is formed by grouping Fannie Mae 30-year MBS pools that have the same specified coupon. The WAC of a MBS pool is defined to be the weighted-average of the gross interest rates of the underlying mortgages in the pool, weighted by the remaining principal balance of each mortgage. Similarly, the WAC of the coupon aggregate is defined to be the weighted-average of the WAC of the underlying MBS pools, weighted by the remaining principal balance of each MBS pool. We obtain historical WAC data for Fannie Mae 30-year coupon aggregates from eMBS. The data is available with monthly frequency and represents an end-of-month snapshot.

The Freddie Mac Primary Mortgage Market Survey (PMMS) is used as an indicator of current mortgage rates. Since April 1971, Freddie Mac has surveyed lenders across the nation weekly to determine the average rates for conventional mortgage products. The survey obtains indicative lender quotes on first-lien prime conventional conforming home purchase mortgages with a loan-to-value of 80 percent. The survey is collected from Monday through Wednesday and the national average rates for each product are published on Thursday morning. Currently, about 125 lenders are surveyed each week; lender types consist of thrifts, credit unions, commercial banks and mortgage lending companies. The mix of lender types surveyed is approximately proportional to the volume of mortgage loans that each lender type originates nationwide. In our study, we use the historical monthly average PMMS rate for 30-year fixed-rate mortgages, available from Freddie Mac's website.[31]

We use a 3-month average to measure the borrower incentive because we recognize that there is a lag between a refinance application and the resulting closing and actual mortgage

[31] See `http://www.freddiemac.com/pmms/pmms30.htm`.

prepayment. Refinancing a mortgage can take a considerable amount of time due to the various steps involved, such as credit checks, income verification, and title search.[32] Borrowers can choose to lock in their rate during this time by requesting a rate lock from their lender. The rate locks usually range from 30 to 90 days. In our regression in Equations (13) and (14), the borrower moneyness of a security is determined at the beginning at the month and we only include securities with at least USD 1bn outstanding in RPB as a liquidity filter.

Correlations of Prepayment Factors with Macroeconomic Variables
Macroeconomic data were collected from the following sources: The change in the national US house price index is constructed as the change the in the levels data from FRED at: `https://fred.stlouisfed.org/series/CSUSHPINSA`. Real consumption growth is computed using the change in real personal consumption expenditures from FRED at: `https://fred.stlouisfed.org/series/PCEC96`. The change in bank mortgage lending standards is the concatenation of the following three series from the Senior Loan Officer Opinion Survey on Bank Lending Practices from the BLS: (1) Net Percentage of Banks Tightening Standards for Mortgage Loans (2) Net Percentage of Domestic Banks Tightening Standards for Prime Mortgage Loans (3) Net Percentage of Domestic Banks Tightening Standards for GSE-Eligible Mortgage Loans. These are available from FRED at `https://fred.stlouisfed.org/series/HOSUBLPDHMSNQ`, `https://fred.stlouisfed.org/series/DRTSPM` and `https://fred.stlouisfed.org/series/SUBLPDHMSENQ`. Results are similar for the main SLOOS series for Commercial and Industrial loans available as a continuous series at `https://fred.stlouisfed.org/series/DRTSCILM`. The Baa-Aaa corporate credit spread is constructed by forming the difference in these two yield series available from FRED at `https://fred.stlouisfed.org/series/BAA` and `https://fred.stlouisfed.org/series/AAA`. Finally, the excess return on the market is obtained from Kenneth French's website (Fama and French (2017)) at:`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/F-F_Research_Data_Factors_CSV.zip`.

MBS Return Data and Estimation of Factor Loadings

Bloomberg Barclays Coupon-Level Hedged Return Indices
We obtain monthly MBS returns from the coupon-level sub-indices of the Bloomberg Barclays MBS Index. Index returns are available at a monthly frequency dating back to 1994. The index is constructed by grouping individual TBA deliverable fixed-rate MBS pools into aggregates based on program, coupon, and vintage. Maturity and liquidity criteria are then applied to determine which aggregates qualify for inclusion in the index. The Barclays MBS trading desk provides daily index pricing for pool aggregates based on their underlying non-specified pools. The trading desk provides two pricing components: (i) TBA prices are provided for each agency, program and coupon combination within the index, and (ii) an additional payup spread for each agency, program, coupon and origination year combination is provided and added to the TBA level.

As a liquidity filter, we also exclude monthly returns from coupons that have less than \$1BN outstanding in RPB at the beginning of the month. The following is a brief description

[32] See Hayre and Young (2004).

of the restriction that securities in the index are TBA-deliverable. More than 90 percent of agency MBS trading occurs in the to-be-announced (TBA) forward market. In a TBA trade, the buyer and seller agree upon a price for delivering a given volume of agency MBS at a specified future date. The characteristic feature of a TBA trade is that the actual identity of the securities to be delivered at settlement is not specified on the trade date. Instead, participants agree upon only six general parameters of the securities to be delivered: issuer, maturity, coupon, price, par amount, and settlement date. The exact pools to be delivered are "announced" to the buyer two days before settlement. The pools delivered are at the discretion of the seller, but must satisfy SIFMA good delivery guidelines, which specify the allowable variance in the current face amount of the pools from the nominal agreed-upon amount, the maximum number of pools per $1 million of face value, and so on. Because of these eligibility requirements, "TBA-deliverable" pools can be considered fungible because a significant degree of actual homogeneity is enforced among the securities deliverable into any particular TBA contract.[33]

Absolute coupon return series are converted into a relative coupon return series. We define relative coupon to be the difference between the TBA coupon and the par coupon at the beginning of the month. The implied par coupon is determined from TBA prices by finding the TBA coupon that corresponds to a price of 100, linearly interpolating when needed. For example, if the 4.0 coupon has a price of 95 and the 4.5 coupon has a price of 105, the implied par coupon would be equal to 4.25. After computing the relative coupon (z) for each absolute coupon, we map it to a relative coupon in increments of 0.5 centered around zero. For example:

- $-0.75 <= z < -0.25$ maps to relative coupon -0.5 %
- $-0.25 <= z < 0.25$ maps to relative coupon 0.0% (par is centered around zero)
- $0.25 <= z < 0.75$ maps to relative coupon 0.5%

It is important to note that in Step 1 of our Fama-MacBeth regression, we regress returns against 1-month lagged prepayment risk factors. For example, if the LHS is the 1-month return for the month of January, we regress that against the prepayment shocks measured for the month of December. The reason for the lag is to account for the fact that the Bloomberg Barclays MBS Index convention uses same day settlement prices with paydowns estimated throughout the month, as opposed to the market's convention of PSA settlement. Because prepayment data for a given month is reported after index results have been calculated, paydown returns in the MBS Index are reported with a one-month delay. As an example, the paydown return for January will reflect December prepayment data (which were made available by the agencies during January) since complete factor (or prepayment) data for January will be not available until the middle of February (due to PSA settlement). The MBS Index reflects an estimate of paydowns in the universe on the first business day of the month and the actual paydowns after the 16th business day of a month. See Phelps (2015) for a detailed discussion of the index construction and timing conventions.

[33] See Vickery and Wright (2013), Hayre et al. (2010), or `http://www.sifma.org/uploadedfiles/services/standard_forms_and_documentation/ch08.pdf?n=42389`.

Estimating Risk Prices

Defining Market Type We define market type based on the market composition between discount and premium Fannie Mae 30-year MBS securities. At the beginning of each month, we measure the remaining principal balance (RPB) for each these two types of securities. For computing root mean squared errors in models with conditional risk premia, we use the following dichotomous classification: If the total RPB for discount securities is greater than the total RPB for premium securities, we classify that month as a discount market; otherwise the month is deemed to be a premium market. By this measure of market type, the market has been in a premium market state about 70% of the time during our sample period (Jan 1994 to June 2016).

Spread Assets

We scale all long short portfolios to have, in expectation, constant volatility and equal leg volatility. We predict monthly volatility for each leg, for each month using an exponentially weighted moving average (six month center of mass) of past realized monthly volatility. We predict correlations using an exponentially weighted moving average (twelve month center of mass) of past realized correlations. Correlations tend to be more stable than volatilities, hence we use the longer window for correlations. If any volatility or correlation is missing for a leg/month observation, we use the estimate of the closest coupon or coupon pair in that month to replace the missing value. Each leg in the spread assets is scaled to target 1% volatility, and each spread asset is scaled to target 1% volatility in each month.

Figures

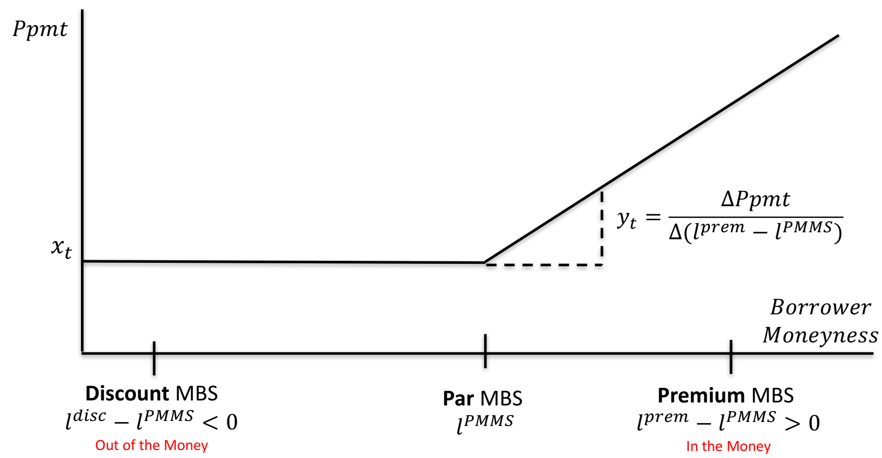


Figure 1: This figure plots prepayment as a function of borrower moneyness and a realization of the level (x), and incentive-sensitivity (y) prepayment factors, $\phi_t^i = x_t + y_t \max\left(0, l^i - l^{\text{PMMS}}\right)$.

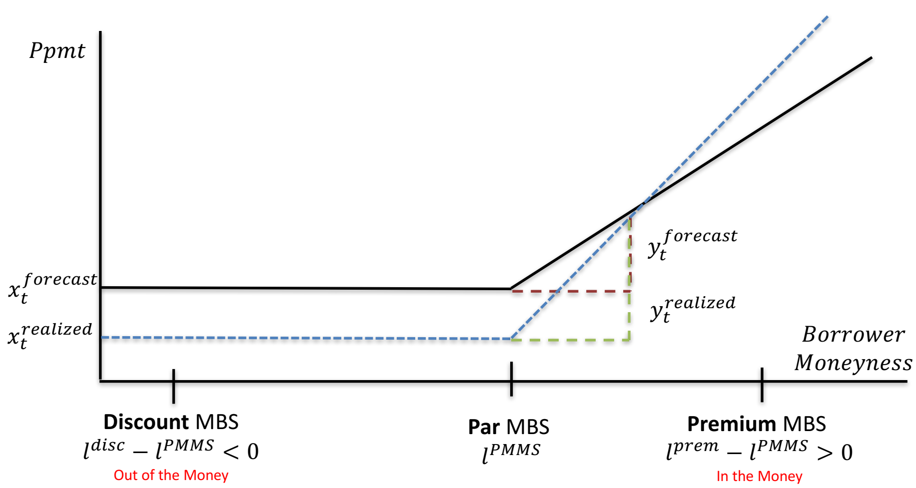


Figure 2: This figure plots forecast and realized prepayment as a function of borrower moneyness and a realization of the level (x), and incentive-sensitivity (y) prepayment factors. Prepayment shocks are measured as the difference between realized and forecasted factors, $x_t = \hat{x}_t^{\text{realized}} - \hat{x}_t^{\text{forecast}}$, and $y_t = \hat{y}_t^{\text{realized}} - \hat{y}_t^{\text{forecast}}$.

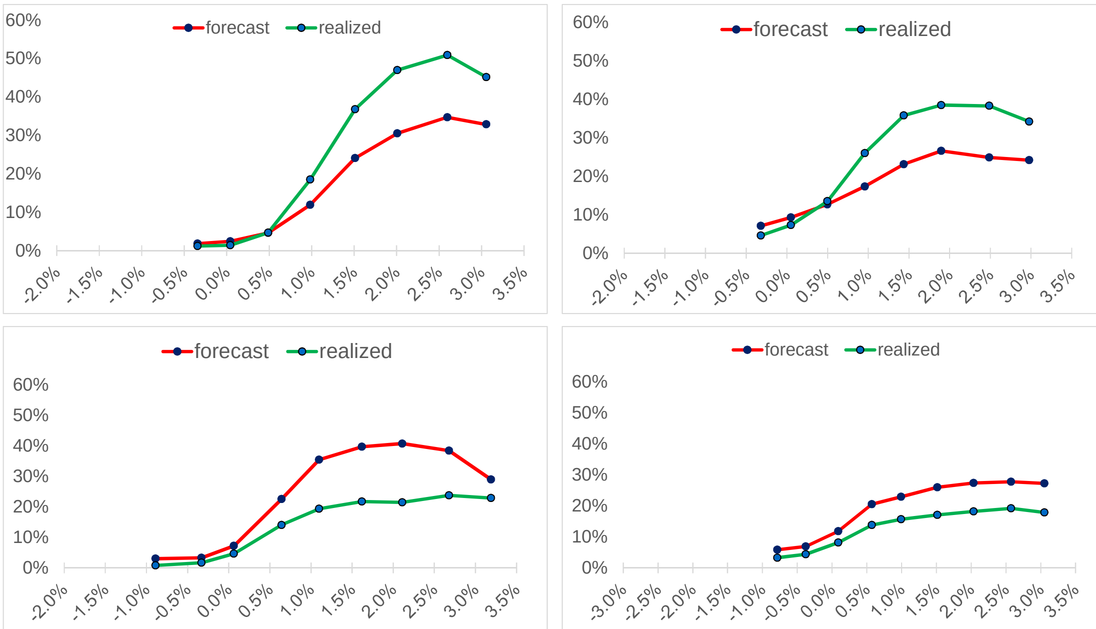


Figure 3: This figure plots four examples of the monthly forecast and realized conditional prepayment rate data used to estimate the innovations to the level and incentive-sensitivity prepayment risk. From top left to bottom right the data are from January 1994, May 1998, January 2010, and January 2015. The y-axis is prepayment rates in percent, and the x-axis is $m^i - m_t^{\text{PMMS}}$, or borrower moneyness.

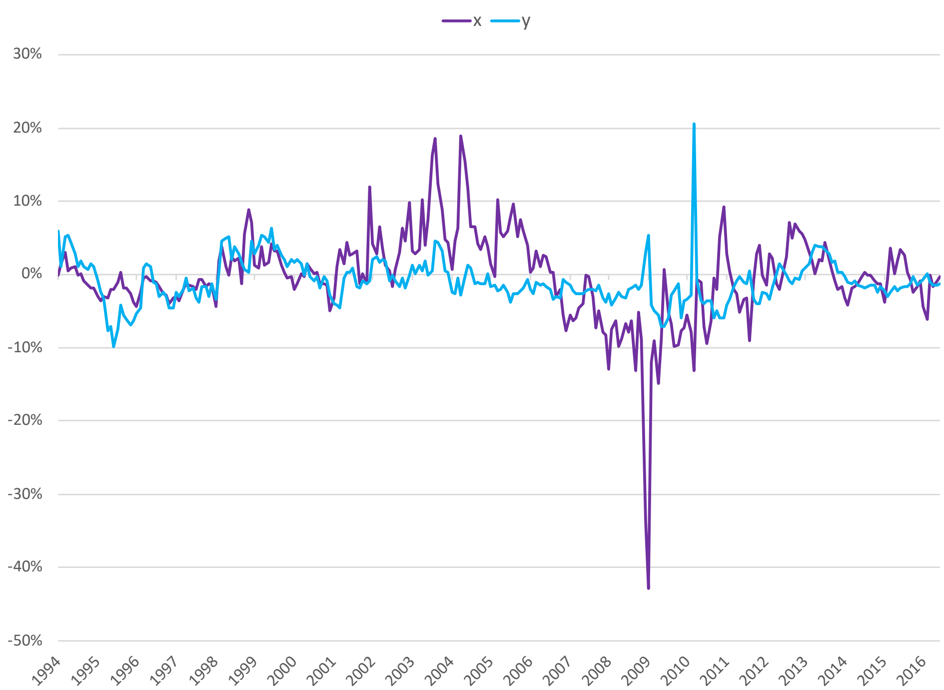
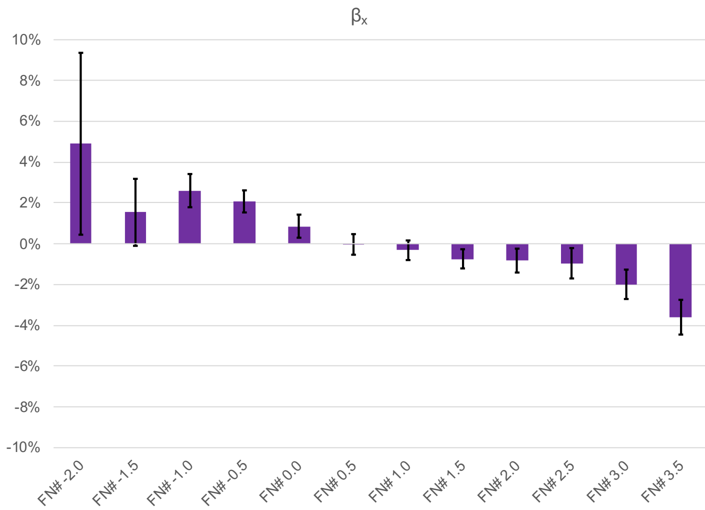


Figure 4: This figure plots the estimated time series for the two prepayment risk factors, level (x), and incentive-sensitivity (y). Each series is the difference between realized and forecasted conditional prepayment rates in percentage terms, or prepayment surprises.



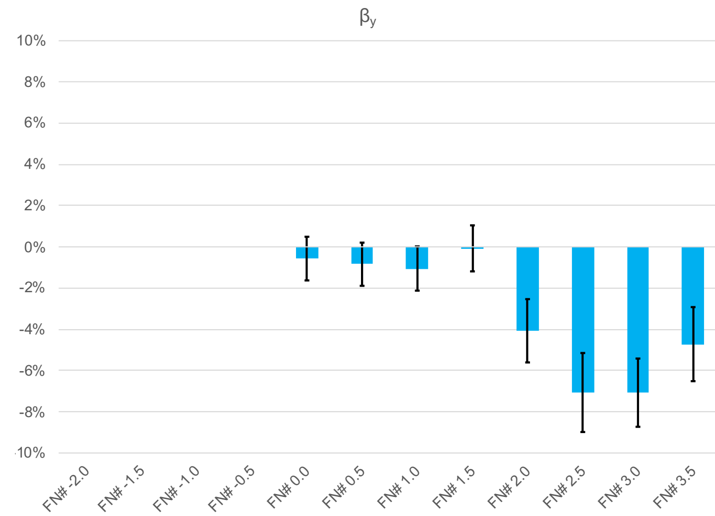


Figure 5: This figure plots the results for the loadings on the two prepayment risk factors, level (x), and incentive-sensitivity (y), by relative coupon. Colored bars depict estimated loading values. Thin bars represent standard errors for estimated loadings.

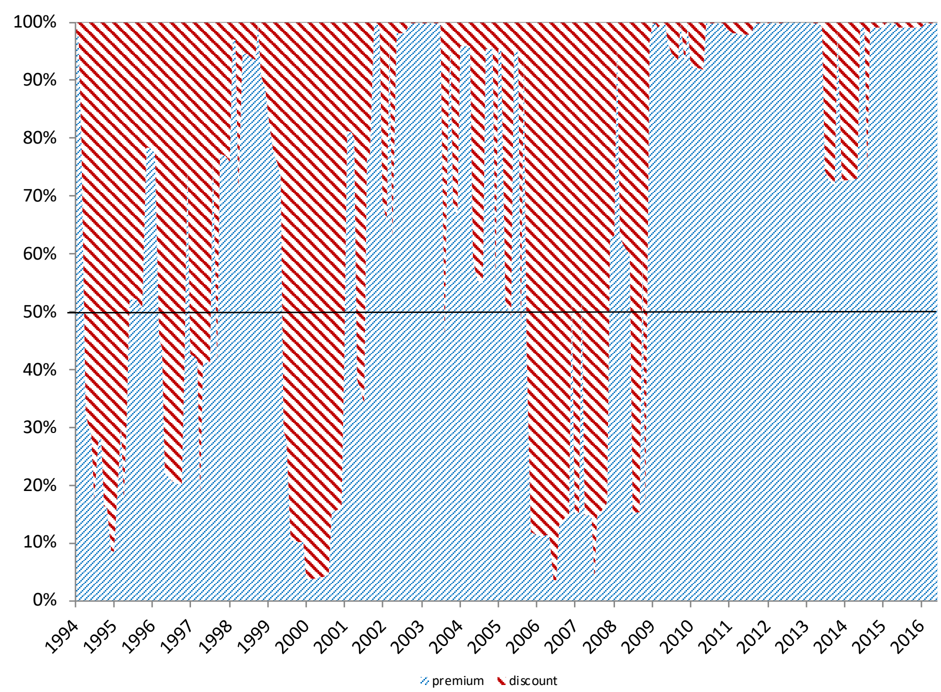


Figure 6: This figure plots the Fannie Mae 30 year MBS market composition between discount and premium securities. We define market type by classifying any month in which more than 50% of total remaining principal balance is discount at the beginning of the month as a discount market (DM). The remaining months are classified as premium markets (PM).

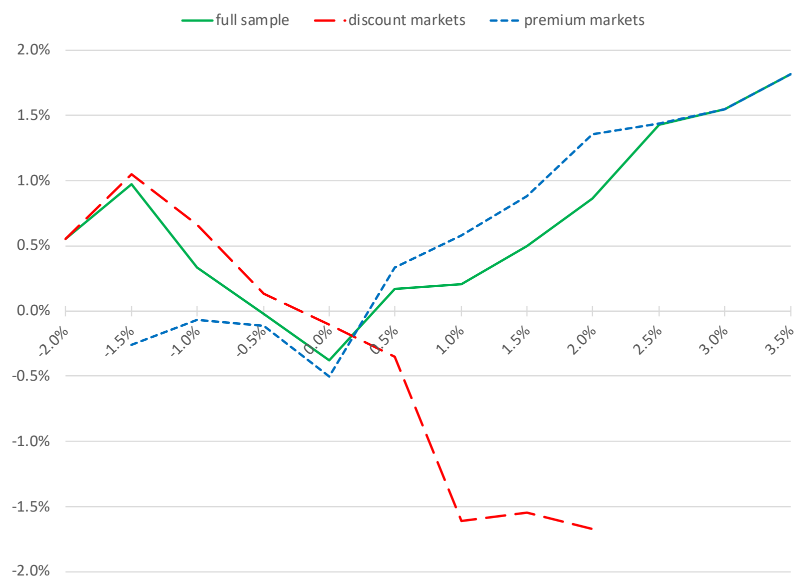


Figure 7: This figure plots annualized average monthly returns for the full sample, and within discount months and premium months only. The pattern of average returns is U-shaped overall, declining in discount markets, and increasing in premium markets. We exclude coupons which would require averaging over less than five observations in a particular market type.

$$\widehat{E[R^{ei}]} = \hat{a} + \hat{\beta}^{i,\text{VW}_{all}} \hat{\lambda}^{\text{VW}_{all}} \qquad\qquad \widehat{E[R^{ei}]} = \hat{a} + \hat{\beta}^{i,\text{Max-Min}} \hat{\lambda}^{\text{Max-Min}}$$

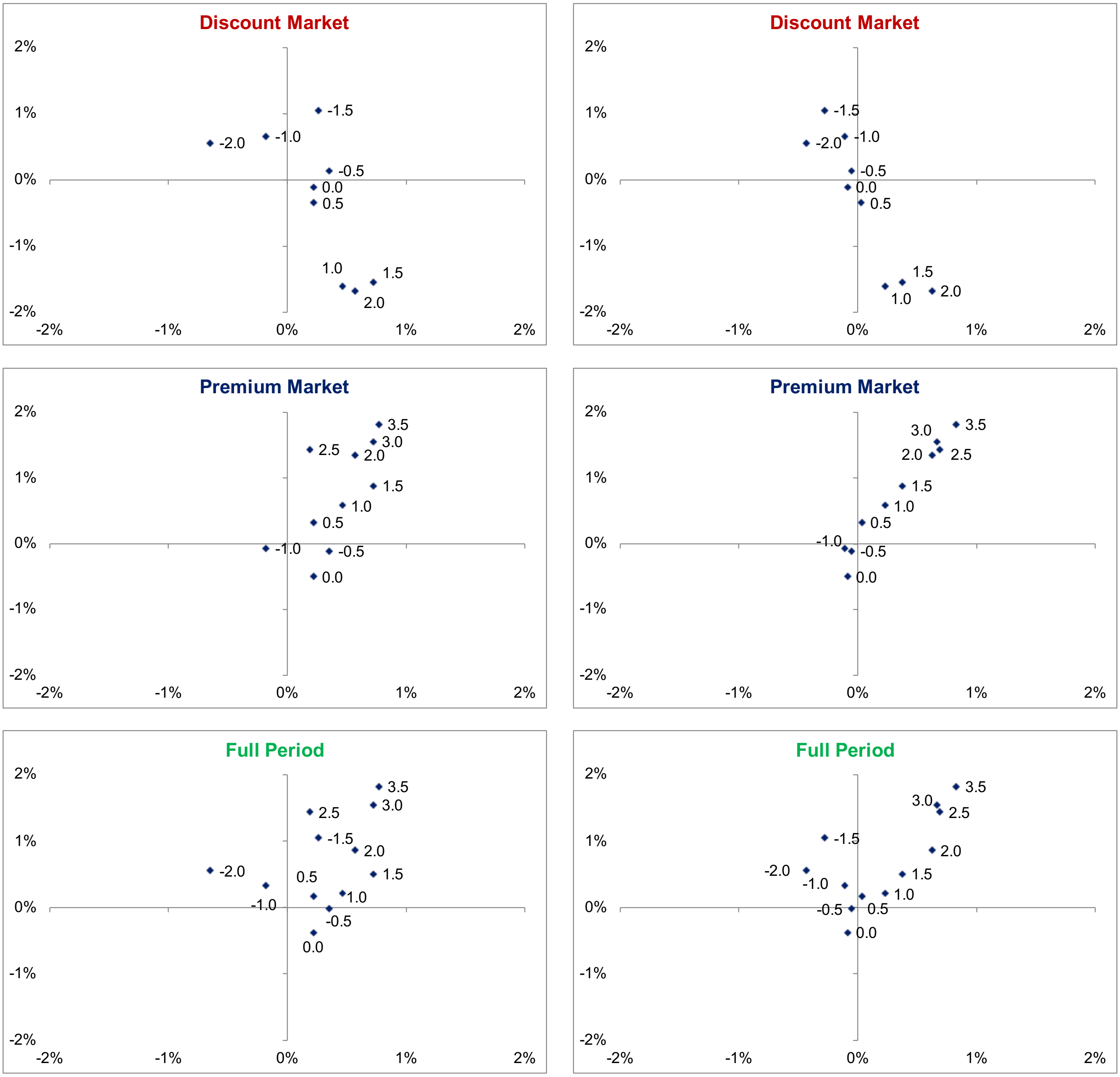


Figure 8: This figure plots annualized realized returns vs. predicted returns for two passive benchmark models, by market type, and for the full sample.

$$\widehat{E[R^{ei}]}_{\mathrm{M}\in\{\mathrm{DM,PM}\}} = \hat{a}_{\mathrm{M}\in\{\mathrm{DM,PM}\}} + \hat{\lambda}_{x,\mathrm{M}\in\{\mathrm{DM,PM}\}}\hat{\beta}^i_x + \hat{\lambda}_{y,\mathrm{M}\in\{\mathrm{DM,PM}\}}\hat{\beta}^i_y \qquad \widehat{E[R^{ei}]}_{\mathrm{M}\in\{\mathrm{DM,PM}\}} = \hat{a}_{\mathrm{M}\in\{\mathrm{DM,PM}\}} + \hat{\lambda}_{c,\mathrm{M}\in\{\mathrm{DM,PM}\}}\left(r - c^i\right)$$

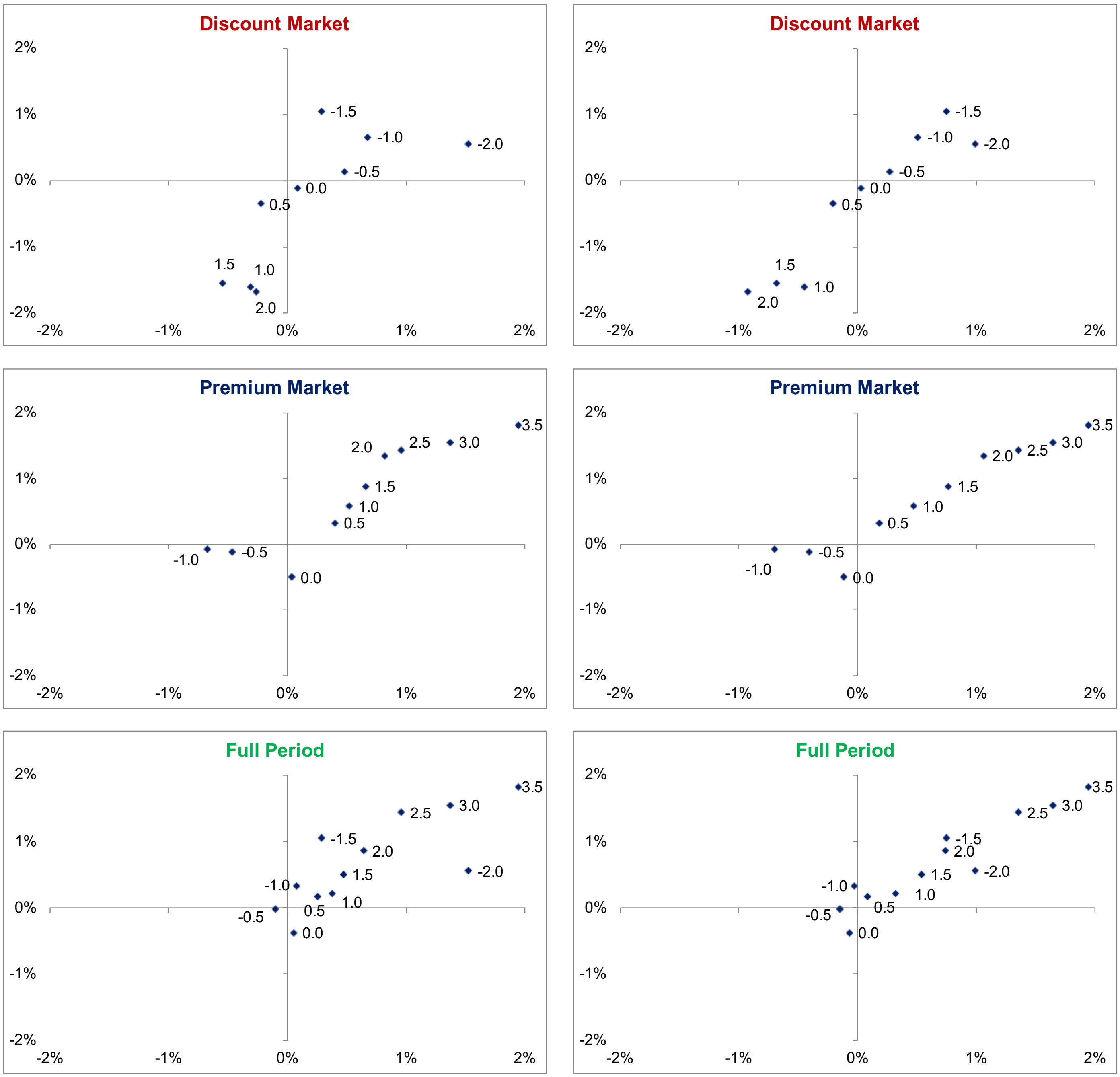


Figure 9: This figure plots annualized realized returns vs. predicted returns for the two and one factor models implied by our theory, by market type, and for the full sample.

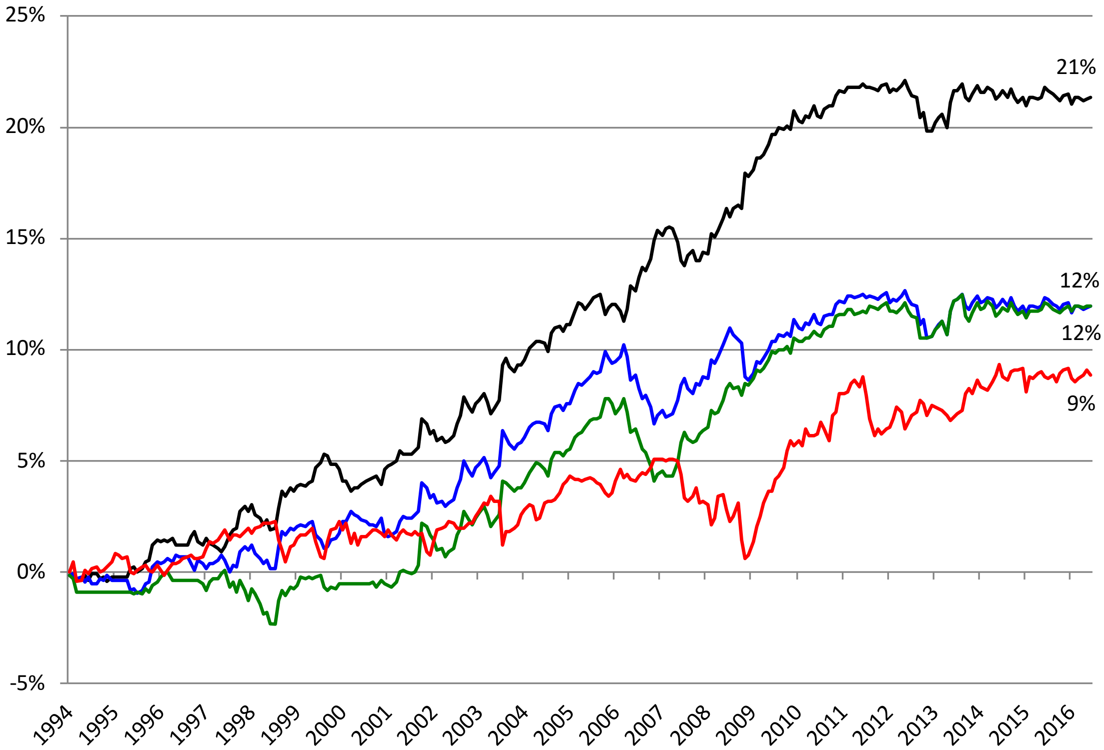


Figure 10: This figure plots cumulative returns for our model-implied PRP portfolio (black) relative to three passive benchmarks. Max - Min (blue) is a passive long maximum premium coupon short minimum discount coupon portfolio, Max - Par (green) is a passive long maximum premium coupon short par portfolio, VW_{all} (red) is the RPB weighted MBS index.

Tables

Table 1: Annualized returns, volatility, and Sharpe ratios, as well as number of observations for MBS by relative coupon, defined as own coupon relative to par coupon.

	-2.0%	-1.5%	-1.0%	-0.5%	0.0%	0.5%	1.0%	1.5%	2.0%	2.5%	3.0%	3.5%
ann. ret	0.56%	0.97%	0.34%	-0.02%	-0.38%	0.17%	0.21%	0.50%	0.86%	1.43%	1.55%	1.82%
ann. vol	1.70%	1.82%	1.87%	1.67%	1.78%	1.71%	1.63%	1.59%	1.97%	2.45%	2.10%	2.21%
SR	0.33	0.53	0.18	-0.01	-0.21	0.10	0.13	0.32	0.44	0.58	0.74	0.82
n	41	87	153	217	248	238	217	199	172	139	112	92

Table 2: Correlation of the change in the national US house price index, real personal consumption expenditure growth, the CRSP value weighted excess return on the stock market, the change in bank mortgage lending standards, and the Baa-Aaa credit spread with the estimated level (x) and incentive-sensitivity (y) risk factors.

Macroeconomic Variable	Correlation with x	t-stat$_x$	Correlation with y	tstat$_y$
Δ US house price index	0.57	11.44	0.24	4.05
Δ Real PCE	0.19	2.78	0.13	1.87
Baa-Aaa Credit Spread	-0.43	-7.80	-0.08	-1.38
CRSP VW Mkt - R$_f$	0.11	1.83	-0.03	-0.47
% of Banks Tightening Mortgage Lending Standards	-0.58	-6.66	-0.12	-1.10

Table 3: Factor loadings by relative coupon. β_y^{disc} is restricted to equal zero. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i \text{ with } \beta_y^{\text{disc}} \equiv 0.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-2.0%	4.90%	1.10	0	0	41	3.0%
-1.5%	1.54%	0.94	0	0	87	1.0%
-1.0%	2.60%	3.20	0	0	153	6.3%
-0.5%	2.07%	3.83	0	0	216	6.4%
0.0%	0.86%	1.52	-0.57%	-0.54	247	1.0%
0.5%	-0.04%	-0.07	-0.84%	-0.8	237	0.3%
1.0%	-0.32%	-0.67	-1.05%	-0.98	216	0.7%
1.5%	-0.74%	-1.57	-0.07%	-0.07	198	1.3%
2.0%	-0.83%	-1.41	-4.07%	-2.65	172	5.2%
2.5%	-0.96%	-1.29	-7.07%	-3.69	139	10.1%
3.0%	-1.99%	-2.76	-7.07%	-4.27	112	18.0%
3.5%	-3.60%	-4.23	-4.72%	-2.63	92	19.6%

Table 4: Results for test of Proposition 2's prediction for level factor loadings. T-statistics are reported for one-sided tests that loadings on the level factor, x, for the comparison coupons are different than the base coupon, in the expected direction. Proposition 2 states that these differences should be negative if the base coupon has a higher relative coupon $c^i - r$ (above the diagonal), and positive if the base coupon has a lower relative coupon $c^i - r$ (below the diagonal), relative to the comparison coupon. Significance at the 1%, 5%, and 10% level are denoted by ***, **, and *, respectively. The test consists of twelve panel regressions, one for each "base" coupon from 2% discount to 3.5% premium. In each panel regression, we designate one coupon as the base coupon, and drop all the terms associated with that coupon from each summation. See the main text for further details. Each panel regression has the following form, and statistics are reported for ϕ:

$$R_t^{ei} = a + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \delta_i + \beta_x x_t + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \phi_i x_t + \mathbb{1}_{\text{base}\in\{0.0\%:3.5\%\}} \beta_y y_t + \sum_{i=0.0\%}^{3.5\%} \mathbb{1}_i \theta_i y_t + \epsilon_t^i$$

	Comparison Coupon											
Base Coupon	-2.0%	-1.5%	-1.0%	-0.5%	0.0%	0.5%	1.0%	1.5%	2.0%	2.5%	3.0%	3.5%
-2.0%		-0.82	-0.64	-0.80	-1.14	-1.39*	-1.48*	-1.60*	-1.61*	-1.61*	-1.88**	-2.37***
-1.5%	0.82		0.44	0.20	-0.25	-0.57	-0.68	-0.84	-0.85	-0.87	-1.21	-1.83**
-1.0%	0.64	-0.44		-0.58	-1.53*	-2.21**	-2.47***	-2.98***	-2.87***	-2.62***	-2.81***	-4.26***
-0.5%	0.80	-0.20	0.58		-2.33***	-3.50***	-4.03***	-5.04***	-4.43***	-3.32***	-3.67***	-5.57***
0.0%	1.14	0.25	1.53*	2.33***		-2.42***	-2.93***	-3.48***	-2.93***	-2.14**	-2.91***	-5.24***
0.5%	1.39*	0.57	2.21**	3.50***	2.42***		-1.34*	-2.10**	-1.66**	-1.19	-2.27**	-5.09***
1.0%	1.48*	0.68	2.47***	4.03***	2.93***	1.34*		-2.25**	-1.19	-0.81	-1.79**	-4.41***
1.5%	1.60*	0.84	2.98***	5.04***	3.48***	2.10**	2.25**		-0.19	-0.26	-1.25	-3.63***
2.0%	1.61*	0.85	2.87***	4.43***	2.93***	1.66**	1.19	0.19		-0.27	-1.51*	-3.82***
2.5%	1.61*	0.87	2.62***	3.32***	2.14**	1.19	0.81	0.26	0.27		-1.60*	-3.30***
3.0%	1.88**	1.21	2.81***	3.67***	2.91***	2.27**	1.79**	1.25	1.51*	1.60*		-2.53***
3.5%	2.37***	1.83**	4.26***	5.57***	5.24***	5.09***	4.41***	3.63***	3.82***	3.30***	2.53***	

Table 5: Results for test of Proposition 2's prediction for incentive-sensitivity factor loadings. T-statistics are reported for one-sided tests that loadings on the incentive-sensitivity factor y, for the comparison coupons are different than the base coupon, in the expected direction. Proposition 2 states that these differences should be negative if the base coupon has a higher relative coupon $c^i - r$ (above the diagonal), and positive if the base coupon has a lower relative coupon $c^i - r$ (below the diagonal), relative to the comparison coupon. Significance at the 1%, 5%, and 10% level are denoted by ***, **, and *, respectively. The test consists of twelve panel regressions, one for each "base" coupon from 2% discount to 3.5% premium. In each panel regression, we designate one coupon as the base coupon, and drop all the terms associated with that coupon from each summation. Loadings on the incentive-sensitivity factor y are restricted to equal zero for discount securities. See the main text for further details. Each panel regression is of the following form, and statistics are reported for θ:

$$R_t^{ei} = a + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \delta_i + \beta_x x_t + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \phi_i x_t + \mathbb{1}_{\text{base}\in\{0.0\%:3.5\%\}} \beta_y y_t + \sum_{i=0.0\%}^{3.5\%} \mathbb{1}_i \theta_i y_t + \epsilon_t^i$$

	Comparison Coupon							
Base Coupon	0.0%	0.5%	1.0%	1.5%	2.0%	2.5%	3.0%	3.5%
0.0%		-0.53	-0.59	0.48	-1.41*	-1.77**	-2.54***	-2.35***
0.5%	0.53		-0.39	0.95	-1.34*	-1.72**	-2.52***	-2.39***
1.0%	0.59	0.39		1.57*	-1.46*	-1.82**	-2.78***	-2.41***
1.5%	-0.48	-0.95	-1.57 *		-1.73**	-1.96**	-2.93***	-3.42 ***
2.0%	1.41*	1.34*	1.46*	1.73**		-2.16**	-3.33***	-0.26
2.5%	1.77**	1.72**	1.82**	1.96**	2.16**		-0.01	0.67
3.0%	2.54***	2.52***	2.78***	2.93***	3.33***	0.01		1.06
3.5%	2.35***	2.39***	2.41***	3.42***	0.26	-0.67	-1.06	

Table 6: Factor loadings by relative coupon. β_y^{disc} is restricted to equal zero. All regressions include an (unreported, insigificant) intercept. S&P500 is returns to the S&P500 index, 2YTSY is the return to two year treasury futures, 10TSY is the return to ten year treasury futures, short vol is short interest rate volatility returns constructed using returns from shorting three month maturity swaption straddles, delta hedged, on ten year USD LIBOR, Baa-Aaa is the credit spread between the seasoned Baa and Aaa Moody's corporate bond yields as reported by FRED at the Federal Reserve Bank of St. Louis, HKM is the tradable intermediary asset pricing factor from He et al. (2017), PS Liq is the liquidity factor from Pastor and Stambaugh (2003), SMB, HML, and MOM are the FF4 factors from Fama and French (2017) as in Fama and French (1992), Asness (1994), and Carhart (1997). Due to space constraints, the coefficients on the market, very similar to those the S&P 500 model, have been suppressed in the FF4 results. The number of observations for each coupon is the same as in the baseline estimation in Table 3.

					S&P 500						
Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	$\beta_{S\&P500}$	t-stat$_{S\&P500}$					R^2
-2.0%	5.69%	1.25			1.81%	0.86					4.9%
-1.5%	1.55%	0.94			-0.66%	-0.42					1.2%
-1.0%	2.50%	3.21			3.95%	3.98					15.3%
-0.5%	1.73%	3.32			3.53%	4.84					15.7%
0.0%	0.53%	0.96	0.09%	0.09	3.61%	4.95					10.0%
0.5%	-0.43%	-0.89	-0.20%	-0.20	3.42%	4.81					9.3%
1.0%	-0.68%	-1.45	-0.51%	-0.49	3.11%	4.35					8.9%
1.5%	-1.14%	-2.51	0.50%	0.47	3.33%	4.74					11.5%
2.0%	-1.25%	-2.14	-3.56%	-2.37	3.30%	3.32					11.0%
2.5%	-1.40%	-1.88	-6.50%	-3.45	3.59%	2.72					14.8%
3.0%	-2.31%	-3.17	-6.57%	-3.97	2.73%	2.00					20.9%
3.5%	-3.98%	-4.67	-4.00%	-2.23	3.27%	2.18					23.7%

TSY											
Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	β_{2yTSY}	t-stat$_{2yTSY}$	β_{10yTSY}	t-stat$_{10yTSY}$	$\beta_{shortvol}$	t-stat$_{shortvol}$	R^2
-2.0%	4.60%	0.92			21.71%	1.06	-15.02%	-0.86	2.66%	0.09	6.0%
-1.5%	2.76%	1.70			0.05%	0.00	1.64%	0.15	-37.66%	-2.95	13.8%
-1.0%	2.38%	2.90			-18.25%	-1.93	14.12%	1.78	2.16%	0.23	9.1%
-0.5%	1.49%	2.97			-14.99%	-2.36	9.25%	1.75	34.79%	5.33	23.6%
0.0%	0.04%	0.09	-0.41%	-0.43	-5.18%	-0.82	2.12%	0.42	47.59%	7.39	22.0%
0.5%	-0.47%	-1.04	-0.74%	-0.81	0.13%	0.02	-0.78%	-0.16	48.82%	8.17	24.5%
1.0%	-0.70%	-1.63	-0.98%	-1.04	3.28%	0.55	-5.87%	-1.24	44.93%	7.67	24.8%
1.5%	-1.02%	-2.54	-0.13%	-0.14	6.90%	1.21	-15.15%	-3.31	41.43%	7.41	31.1%
2.0%	-0.89%	-1.65	-3.92%	-2.83	12.83%	1.58	-22.47%	-3.57	34.24%	4.47	24.3%
2.5%	-0.83%	-1.15	-6.77%	-3.73	13.28%	1.10	-26.09%	-2.94	27.68%	2.34	21.1%
3.0%	-1.99%	-3.13	-6.87%	-4.94	19.57%	1.63	-38.19%	-5.13	12.90%	1.40	43.9%
3.5%	-3.47%	-5.66	-4.42%	-3.47	1.26%	0.09	-41.18%	-5.53	4.37%	0.51	61.2%

Credit											
Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	$\beta_{Baa-Aaa}$	t-stat$_{Baa-Aaa}$					R^2
-2.0%	4.92%	1.13			26.5%	1.79					10.5%
-1.5%	1.53%	0.93			4.8%	0.65					1.5%
-1.0%	2.01%	2.83			23.3%	7.12					30.0%
-0.5%	1.97%	3.97			17.0%	6.46					21.7%
0.0%	0.84%	1.60	-0.14%	-0.14	17.0%	6.54					15.8%
0.5%	0.30%	0.62	-0.77%	-0.79	14.2%	6.02					13.7%
1.0%	-0.04%	-0.10	-0.95%	-0.94	12.1%	5.30					12.3%
1.5%	-0.46%	-1.05	0.06%	0.06	12.2%	5.54					14.7%
2.0%	-0.50%	-0.92	-3.90%	-2.74	14.5%	5.39					19.2%
2.5%	-0.51%	-0.73	-6.83%	-3.84	17.3%	4.80					23.2%
3.0%	-0.81%	-1.14	-6.21%	-4.07	20.0%	4.70					31.9%
3.5%	-2.03%	-2.25	-3.43%	-2.01	18.8%	3.76					30.7%

Intermediary

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	β_{HKM}	t-stat$_{HKM}$					R^2
-2.0%	5.60%	1.22			1.04%	0.75					4.4%
-1.5%	1.48%	0.91			-1.22%	-1.21					2.7%
-1.0%	2.39%	3.01			2.32%	3.25					12.5%
-0.5%	1.62%	3.16			2.75%	5.64					18.6%
0.0%	0.43%	0.81	0.50%	0.49	2.80%	6.03					13.9%
0.5%	-0.54%	-1.12	0.13%	0.13	2.44%	5.38					11.3%
1.0%	-0.79%	-1.70	-0.26%	-0.26	2.21%	4.84					10.6%
1.5%	-1.25%	-2.75	0.71%	0.67	2.29%	5.13					13.1%
2.0%	-1.39%	-2.39	-3.37%	-2.27	2.39%	3.90					13.1%
2.5%	-1.53%	-2.04	-6.28%	-3.33	2.39%	2.93					15.4%
3.0%	-2.46%	-3.43	-6.22%	-3.81	2.18%	2.88					23.8%
3.5%	-4.04%	-4.87	-3.58%	-2.03	2.42%	2.97					26.9%

PS liq

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	$\beta_{S\&P500}$	t-stat$_{S\&P500}$	β_{PSliq}	t-stat$_{PSliq}$			R^2
-2.0%	6.27%	1.36			2.36%	1.08	-2.32%	-0.98			7.2%
-1.5%	1.76%	1.07			0.03%	0.02	-2.14%	-1.31			3.2%
-1.0%	2.50%	3.20			3.97%	3.90	-0.12%	-0.11			15.3%
-0.5%	1.72%	3.30			3.45%	4.64	0.49%	0.60			15.8%
0.0%	0.53%	0.97	0.10%	0.10	3.65%	4.90	-0.27%	-0.31			10.1%
0.5%	-0.44%	-0.88	-0.20%	-0.20	3.42%	4.70	-0.01%	-0.01			9.3%
1.0%	-0.68%	-1.44	-0.51%	-0.49	3.09%	4.24	0.11%	0.13			8.9%
1.5%	-1.11%	-2.44	0.44%	0.42	3.20%	4.49	0.87%	1.01			12.0%
2.0%	-1.21%	-2.07	-3.61%	-2.40	3.11%	3.06	1.01%	0.87			11.4%
2.5%	-1.33%	-1.77	-6.49%	-3.44	3.43%	2.58	1.57%	0.97			15.4%
3.0%	-2.15%	-2.96	-6.44%	-3.94	2.82%	2.09	3.18%	1.91			23.5%
3.5%	-3.70%	-4.24	-3.80%	-2.13	3.38%	2.27	2.75%	1.39			25.4%

FF4												
Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	β_{SMB}	t-stat$_{SMB}$	β_{HML}	t-stat$_{HML}$	β_{MOM}	t-stat$_{MOM}$	R^2
-2.0%	7.02%	1.50			3.56%	1.20	3.93%	1.31	1.98%	0.76	19.4%
-1.5%	1.57%	0.94			0.21%	0.12	-2.87%	-1.34	-0.03%	-0.02	5.6%
-1.0%	2.48%	3.19			2.04%	1.67	0.14%	0.10	-0.81%	-0.89	17.3%
-0.5%	1.72%	3.28			1.77%	1.95	0.67%	0.64	-1.03%	-1.45	17.8%
0.0%	0.44%	0.79	0.23%	0.22	1.33%	1.39	1.81%	1.61	-0.54%	-0.83	11.8%
0.5%	-0.59%	-1.15	-0.04%	-0.04	0.80%	0.70	1.64%	1.47	-0.18%	-0.27	10.4%
1.0%	-0.92%	-1.89	-0.37%	-0.35	0.79%	0.66	2.26%	1.88	0.13%	0.20	10.6%
1.5%	-1.43%	-3.02	0.61%	0.57	0.83%	0.66	2.51%	2.09	0.52%	0.75	13.8%
2.0%	-1.36%	-2.20	-3.67%	-2.41	1.07%	0.60	0.94%	0.51	0.46%	0.47	11.4%
2.5%	-1.30%	-1.62	-6.71%	-3.50	1.98%	0.76	-0.93%	-0.35	0.03%	0.03	15.2%
3.0%	-1.87%	-2.34	-6.70%	-3.97	3.08%	1.29	-2.86%	-1.10	-1.26%	-1.06	23.4%
3.5%	-3.85%	-3.96	-4.37%	-2.40	5.50%	2.06	0.61%	0.21	-0.63%	-0.45	27.7%

Table 7: Annualized returns, volatility, and Sharpe ratios, as well as number of observations for MBS by relative coupon, defined as own coupon relative to par coupon, conditional on the market type. The market is defined as a Discount Market if > 50% of RPB is discount, and a Premium Market otherwise.

Discount Market	-2.0%	-1.5%	-1.0%	-0.5%	0.0%	0.5%	1.0%	1.5%	2.0%	2.5%	3.0%	3.5%
ann. ret	0.56%	1.05%	0.66%	0.13%	-0.11%	-0.35%	-1.61%	-1.54%	-1.67%	1.14%		
ann. vol	1.70%	1.87%	1.56%	1.29%	1.25%	1.36%	1.57%	1.85%	1.99%	0.47%		
SR	0.33	0.56	0.42	0.10	-0.09	-0.25	-1.03	-0.83	-0.84 2	0.42		
n	41	82	85	83	78	56	37	31	28	3		
Premium Market	-2.0%	-1.5%	-1.0%	-0.5%	0.0%	0.5%	1.0%	1.5%	2.0%	2.5%	3.0%	3.5%
ann. ret		-0.26%	-0.07%	-0.12%	-0.50%	0.33%	0.58%	0.88%	1.35%	1.44%	1.55%	1.82%
ann. vol		0.84%	2.20%	1.87%	1.98%	1.80%	1.63%	1.52%	1.94%	2.48%	2.10%	2.21%
SR		-0.31	-0.03	-0.06	-0.25	0.18	0.36	0.58	0.70	0.58	0.74	0.82
n		5	68	134	170	182	180	168	144	136	112	92

Table 8: Prices of Risk, Pooled Time Series Cross Section Regression, Negative Relative Coupon Characteristic. For the results with time fixed effects, the intercept a is excluded, and for the results with security fixed effects, the κ term is excluded as well.

$$R_t^{ei} = a + \kappa(r - c^i) + \delta(r - c^i)\left(\%RPB^{\text{disc}}_{\text{t,BoM}} - 50\%\right) + \epsilon_t^i.$$

		t-stat & clustering			t-stat & clustering			t-stat & clustering	
	Coefficient	none	time	Coefficient	none	time	Coefficient	none	time
a	0.00%	-0.10	-0.06						
κ	0.00%	0.33	0.20	0.01%	0.71	0.30			
δ	0.11%	3.89	2.18	0.14%	5.82	2.42	0.16%	4.72	2.30
time f.e.	no			yes			yes		
security f.e.	no			no			yes		
n	1915			1915			1915		
R^2	1.2%			60.4%			60.5%		

Table 9: Prices of Risk, Pooled Time Series Cross Section Regression, Negative Relative Coupon Characteristic, Excluding Crisis Period. Crisis period is defined as the one year window centered around November 2008. Time fixed effects are included, and standard errors are clustered by time.

$$R_t^{ei} = a + \kappa(r - c^i) + \delta(r - c^i)\left(\%RPB^{\text{disc}}_{\text{t,BoM}} - 50\%\right) + \epsilon_t^i.$$

	Excluding Crisis	Full Sample	Crisis Period
κ	0.00%	0.01%	0.03%
t-stat κ	0.02	0.30	0.22
δ	0.10%	0.14%	0.62%
t-stat δ	2.08	2.42	1.67
n	1810	1915	105
R^2	59.8%	60.4%	68.0%

Table 10: Prices of Risk, Pooled Time Series Cross Section Regression, Negative Relative Coupon Characteristic, with the loadings on standard asset pricing factors (as reported in Table 6) as controls. Time fixed effects are included, and standard errors are clustered by time. S&P500 is returns to the S&P500 index, 2YTSY is the return to two year treasury futures, 10TSY is the return to ten year treasury futures, Short vol is short interest rate volatility returns constructed using returns from shorting three month maturity swaption straddles, delta hedged, on ten year USD LIBOR, Baa-Aaa is the credit spread between the seasoned Baa and Aaa Moody's corporate bond yields as reported by FRED at the Federal Reserve Bank of St. Louis, HKM is the tradable intermediary asset pricing factor from He et al. (2017), PS Liq is the liquidity factor from Pastor and Stambaugh (2003), SMB, HML, and MOM are the FF4 factors from Fama and French (2017) as in Fama and French (1992), Asness (1994), and Carhart (1997). Each regression is estimated on 1915 monthly relative-coupon return observations.

	S&P 500			TSY		
	Variable	Coefficient	t-stat	Variable	Coefficient	t-stat
	$(r-c^i)$	0.01%	0.27	$(r-c^i)$	-0.02%	-0.89
	$(r-c^i)\left(\%RPB^{\mathrm{disc}}_{\mathrm{t,BoM}}-50\%\right)$	0.14%	2.36	$(r-c^i)\left(\%RPB^{\mathrm{disc}}_{\mathrm{t,BoM}}-50\%\right)$	0.16%	2.30
	S&P500	-0.17%	-0.21	2YTSY	0.20%	0.94
				10YTSY	0.40%	1.32
				Short Vol	-0.04%	-0.63
R^2	60.4%			60.5%		
	Credit			Intermediary		
	Variable	Coefficient	t-stat	Variable	Coefficient	t-stat
	$(r-c^i)$	0.01%	0.34	$(r-c^i)$	0.01%	0.23
	$(r-c^i)\left(\%RPB^{\mathrm{disc}}_{\mathrm{t,BoM}}-50\%\right)$	0.14%	2.45	$(r-c^i)\left(\%RPB^{\mathrm{disc}}_{\mathrm{t,BoM}}-50\%\right)$	0.13%	2.33
	Baa-Aaa	-0.21%	-1.05	HKM	-0.41%	-0.41
R^2	60.4%			60.4%		
	Liquidity			FF4		
	Variable	Coefficient	t-stat	Variable	Coefficient	t-stat
	$(r-c^i)$	0.00%	0.08	$(r-c^i)$	0.01%	0.26
	$(r-c^i)\left(\%RPB^{\mathrm{disc}}_{\mathrm{t,BoM}}-50\%\right)$	0.14%	2.40	$(r-c^i)\left(\%RPB^{\mathrm{disc}}_{\mathrm{t,BoM}}-50\%\right)$	0.16%	2.31
	S&P500	-0.18%	-0.16	S&P500	0.24%	0.23
	PS Liq	-0.60%	-0.32	SMB	-1.50%	-1.07
				HML	-0.08%	-0.08
				MOM	-0.48%	-0.23
R^2	60.4%			60.5%		

Table 11: Prices of Risk, Pooled Time Series Cross Section Regression, Negative Relative Coupon Characteristic. Subscripts on coefficients denote variable interacted with negative relative coupon. Including effect of rate shock on realized returns does not change estimated risk premia in expected returns. Standard deviations for each variable appear in the last column. OAD stands for Option Adjusted Duration.

$$R_t^{ei} = a + \kappa(r - c^i) + \delta_{\left(\%RPB_{\text{BoM}}^{\text{disc}} - 50\%\right)}(r - c^i)\left(\%RPB_{\text{t,BoM}}^{\text{disc}} - 50\%\right) \\ + \delta_x(r - c^i)\, x_t + \delta_y(r - c^i)\, y_t + \delta_{\Delta r}(r - c^i)\, \Delta r_t + \epsilon_t^i.$$

	Barclays OAD Hedged			Empirically Hedged			Interaction
		t-statistic clustering			t-statistic clustering		Variable
	Coefficient	none	time	Coefficient	none	time	StdDev
κ	0.03%	2.85	1.18	0.00%	0.05	0.02	
$\delta_{\left(\%RPB_{\text{BoM}}^{\text{disc}} - 50\%\right)}$	0.15%	6.64	2.84	0.13%	5.46	2.19	0.35
δ_x	0.79%	7.47	3.14	0.50%	4.22	2.07	0.06
δ_y	1.46%	6.56	1.89	1.55%	5.97	2.68	0.03
$\delta_{\Delta r}$	-0.44%	-11.04	-4.32	-0.11%	-2.46	-0.75	0.19
time f.e.	yes			yes			
n	1910			1652			
R^2	64.7%			71.0%			

Table 12: Sharpe Ratios for the Prepayment Risk Portfolio (PRP), Passive Spread Assets, and Indices. Max - Min is a passive long maximum premium coupon short minimum discount coupon portfolio, Max - Par is a passive long maximum premium coupon short par portfolio, Min - Par is a passive long minimum premium coupon short par portfolio, PRP is an active portfolio which is long maximum premium coupon short minimum discount coupon when > 50% of outstanding RPB is premium at the beginning of the month and long minimum discount coupon short maximum premium coupon otherwise. VW_{all} is the RPB weighted MBS index, VW_{ex-par} is the RPB weighted MBS index excluding par coupon, VW_{disc} is the RPB weighted MBS index of discount securities only, VW_{prem} is the RPB weighted MBS index of premium securities only. All long short portfolios are scaled to have constant volatility and equal leg volatility.

	Max - Min	Max - Par	Min - Par	**PRP**	VW_{all}	VW_{ex-par}	VW_{disc}	VW_{prem}
Discount (M=DM)	-0.47	-0.28	0.49	**0.47**	0.12	0.18	0.27	-0.50
Premium (M=PM)	0.91	0.73	-0.42	**0.91**	0.36	0.41	-0.08	0.47
Full Sample	0.44	0.48	-0.02	**0.76**	0.29	0.35	0.03	0.26

Table 13: Excess returns, tracking errors, and information ratios for the Prepayment Risk Portfolio (PRP) relative to three passive benchmarks. Max - Min is a passive long maximum premium coupon short minimum discount coupon portfolio, Max - Par is a passive long maximum premium coupon short par portfolio, VW_{all} is the RPB weighted MBS index.

	Benchmark		
PRP	Max - Min	Max - Par	VW_{all}
Active excess return	0.36%	0.41%	0.48%
Tracking Error	1.35%	1.22%	1.82%
Information Ratio	0.27	0.33	0.26

Table 14: Loadings of the Prepayment Risk Portfolio (PRP) returns on, and α's with respect to, four passive benchmarks, namely, the remaining principal balance weighted MBS index (VW_{all}), the remaining principal balance weighted MBS index amongst premium securities only (VW_{prem}), an untimed long maximum premium coupon short minimum discount premium portfolio with constant volatility and equal-leg volatility (Max - Min), and an untimed long maximum premium coupon short par portfolio with constant volatility and equal leg volatility (Max - Par).

Benchmark	α	t-stat$_\alpha$	$\beta^{\text{Benchmark}}$	t-stat$_\beta$	n	R^2
Max - Min	0.06%	3.11	0.30	5.16	270	9%
Max - Par	0.06%	3.12	0.45	8.14	238	22%
VW_{all}	0.07%	3.75	-0.08	-1.48	270	1%
VW_{prem}	0.08%	3.90	-0.15	-2.59	241	3%

B Internet Appendix to "The Cross Section of MBS Returns"

This Internet Appendix contains additional results and robustness checks.[34]

B.1 Factor Loadings: Additional details and robustness checks

Robustness: Unrestricted β_y^i We present estimated factor loadings for the case in which β_y^i is unrestricted in Table B1. As can be seen, the results are very similar to the case in which β_y^i is restricted to be zero for coupons at or below par, and the R^2 do not change much between the unconstrained and constrained specifications.

Table B1: Factor loadings by relative coupon. β_y^{disc} is unrestricted. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-2.0%	2.73%	0.49	2.52%	0.66	41	4.10%
-1.5%	1.53%	0.86	0.04%	0.02	87	1.00%
-1.0%	2.42%	2.89	1.22%	0.95	153	6.90%
-0.5%	2.08%	3.79	-0.01%	-0.01	216	6.40%
0.0%	0.86%	1.52	-0.57%	-0.54	247	1.00%
0.5%	-0.04%	-0.07	-0.84%	-0.8	237	0.30%
1.0%	-0.32%	-0.67	-1.05%	-0.98	216	0.70%
1.5%	-0.74%	-1.57	-0.07%	-0.07	198	1.30%
2.0%	-0.83%	-1.41	-4.07%	-2.65	172	5.20%
2.5%	-0.96%	-1.29	-7.07%	-3.69	139	10.10%
3.0%	-1.99%	-2.76	-7.07%	-4.27	112	18.00%
3.5%	-3.60%	-4.23	-4.72%	-2.63	92	19.60%

[34] Citation format: Diep, Peter, Eisfeldt, Andrea L. and Richardson, Scott, Internet Appendix to "The Cross Section of MBS Returns," Journal of Finance [DOI STRING]. Please note: Wiley is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

Robustness: Empirical Interest Rate Hedge For our study, we use Treasury-hedged returns of coupon-level aggregates of Fannie Mae 30-year fixed-rate MBS pools. Hedged returns are computed by Barclays using a term structure-matched position in Treasuries based on a key-rate duration approach. Results are similar using returns hedged using empirical durations. We construct the empirical-duration hedged series by starting with the Barclays MBS total index returns by absolute coupon. We compute empirical hedge ratios by estimating three year rolling betas for these index returns on 2 and 10 year US Treasury Futures returns. To extend the sample back to the start of the Barclays index return sample, we use 2 year Treasury Index returns from CRSP prior to 5/1996. Table B2 displays the results for security loadings on empirically hedged returns, and shows that these results are very similar to those using the hedged series provided by Barclays. We note that the negative loadings for the -1.5% coupon are due to the shortened sample induced by the rolling window.

Table B2: Factor loadings by relative coupon for empirically hedged returns. β_y^{disc} is restricted to equal zero. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i \text{ with } \beta_y^{\text{disc}} \equiv 0.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-2.0%	1.98%	0.35	0	0	32	0.40%
-1.5%	-4.03%	-1.49	0	0	71	3.13%
-1.0%	2.11%	1.42	0	0	110	1.84%
-0.5%	2.91%	2.56	0	0	130	4.88%
0.0%	0.67%	1.15	0.24%	0.22	181	0.82%
0.5%	-1.03%	-1.97	-0.86%	-0.77	209	2.31%
1.0%	-1.14%	-2.22	-1.85%	-1.60	207	3.94%
1.5%	-1.49%	-3.21	-1.14%	-1.02	197	5.76%
2.0%	-1.39%	-2.70	-4.67%	-3.47	172	10.57%
2.5%	-1.35%	-2.08	-7.44%	-4.44	139	15.03%
3.0%	-2.21%	-4.39	-7.20%	-6.23	112	32.92%
3.5%	-3.14%	-6.49	-4.11%	-4.03	92	36.47%

Robustness: Empirical Interest Rate and Volatility Hedge Our results are also robust to including an empirical hedge for interest rate volatility. Table B3 reports factor loadings for Barclays excess returns hedged with respect to short volatility returns constructed using the returns from shorting three month maturity straddles constructed using ten year maturity US treasury swaptions. As with the results for the empirical rate hedge, the pattern of risk factor loadings is very similar to our baseline results. Again, we note that the negative loadings for the -1.5% coupon are due to the shortened sample induced by the rolling window. Note that, in unreported results, we also find that security return loadings on short volatility returns are highest around par, and decrease in the tail coupons. This is intuitive since vega is likely to be highest near par. We think that exposure to volatility risk is unlikely to be driving our results, since, in addition to par securities having the lowest average returns in both market types, the correlation between short volatility returns and our x and y factors is approximately zero (0.02 and 0.09 respectively over the period January 1994 to June 2016). Likewise, if we add short volatility returns as an additional factor in our step one regressions, the loadings on x and y display the same robust declining pattern as in our baseline specification. Again, the loadings on the short volatility returns are largest and most significant around par.

Table B3: Factor loadings by relative coupon for Barclays excess returns, hedged to short volatility returns. β_y^{disc} is restricted to equal zero. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i \text{ with } \beta_y^{\text{disc}} \equiv 0.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-2.0%	8.23%	1.03	0	0	24	4.57%
-1.5%	-5.01%	-1.66	0	0	56	4.85%
-1.0%	2.36%	1.52	0	0	91	2.54%
-0.5%	2.37%	2.29	0	0	113	4.51%
0.0%	0.70%	1.49	-0.63%	-0.64	166	1.48%
0.5%	-0.57%	-1.62	-0.15%	-0.18	198	1.39%
1.0%	-0.78%	-1.81	-0.90%	-0.90	203	2.17%
1.5%	-1.13%	-2.64	-0.21%	-0.20	197	3.53%
2.0%	-1.06%	-1.83	-3.95%	-2.61	172	5.84%
2.5%	-0.98%	-1.29	-7.05%	-3.60	139	9.71%
3.0%	-1.89%	-2.41	-6.91%	-3.83	112	14.78%
3.5%	-3.33%	-3.46	-4.66%	-2.30	92	14.46%

Robustness: Alternative Return Data Sources We report factor loadings estimated using alternative sources for relative-coupon level MBS excess returns. Results are similar to the baseline results using Barclays Coupon-Level MBS Index Excess Returns, which have the greatest time series and cross section coverage. Table B4 reports results using Bank of America Merrill Lynch Coupon-Level MBS Index Excess Returns. Table B5 reports results using TBA returns as reported by a major dealer bank, hedged with US treasury futures using that dealer's reported analytical key rate durations. All data starts in 1998, due to data availability. To ensure comparability and data quality, we require coupons to pass the Barclays data filters, i.e. we include coupon-months where available for which Barclays reports data and for which there is greater than 1BN in RPB outstanding. For comparison, we report the results using Barclays Excess returns starting in 1998 in Table B6.

Table B4: Factor loadings by relative coupon for BAML Excess Returns. β_y^{disc} is restricted to equal zero. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i \text{ with } \beta_y^{\text{disc}} \equiv 0.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-2.0%	14.51 %	1.49	0	N/A	20	10.9 %
-1.5%	1.83 %	0.87	0	N/A	51	1.5 %
-1.0%	2.85 %	3.06	0	N/A	99	8.8 %
-0.5%	2.96 %	4.34	0	N/A	166	10.3 %
0.0%	1.20 %	2.14	-0.61 %	-0.51	199	2.3 %
0.5%	-0.04 %	-0.07	-0.43 %	-0.33	209	0.1 %
1.0%	-0.26 %	-0.46	-0.62 %	-0.47	205	0.2 %
1.5%	-0.76 %	-1.51	0.56 %	0.46	194	1.2 %
2.0%	-1.05 %	-1.89	-3.05 %	-2.13	148	5.4 %
2.5%	-1.66 %	-2.28	-3.55 %	-1.97	125	6.8 %
3.0%	-3.13 %	-3.45	-4.54 %	-1.73	105	12.9 %
3.5%	-3.22 %	-2.20	-6.02 %	-1.47	59	12.1 %

Table B5: Factor loadings by relative coupon for TBA returns as reported by a major dealer bank, hedged with US treasury futures using that dealer's reported analytical key rate durations. β_y^{disc} is restricted to equal zero. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i \text{ with } \beta_y^{\text{disc}} \equiv 0.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-2.0%	10.48 %	1.10	0	N/A	20	6.3 %
-1.5%	4.25 %	1.99	0	N/A	51	7.5 %
-1.0%	3.74 %	3.50	0	N/A	107	10.5 %
-0.5%	2.96 %	3.99	0	N/A	171	8.6 %
0.0%	1.66 %	2.26	0.04 %	0.02	207	2.5 %
0.5%	0.54 %	0.83	-0.02 %	-0.01	211	0.3 %
1.0%	0.40 %	0.65	-0.39 %	-0.27	205	0.2 %
1.5%	-0.26 %	-0.42	-0.33 %	-0.22	197	0.1 %
2.0%	-0.57 %	-0.87	-1.26 %	-0.73	170	0.8 %
2.5%	-0.86 %	-1.21	-3.06 %	-1.68	139	3.1 %
3.0%	-0.94 %	-1.09	-4.91 %	-2.47	112	5.9 %
3.5%	-2.77 %	-1.98	-8.91 %	-2.06	78	9.1 %

Table B6: Factor loadings by relative coupon for Barclays Excess Return data starting in 1998. β_y^{disc} is restricted to equal zero. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i \text{ with } \beta_y^{\text{disc}} \equiv 0.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-2.0%	12.94 %	1.43	0	N/A	20	10.2 %
-1.5%	1.48 %	0.71	0	N/A	51	1.0 %
-1.0%	2.70 %	2.91	0	N/A	107	7.4 %
-0.5%	2.12 %	3.60	0	N/A	171	7.1 %
0.0%	0.91 %	1.52	-0.98 %	-0.76	207	1.3 %
0.5%	0.00 %	-0.01	-0.96 %	-0.81	211	0.3 %
1.0%	-0.30 %	-0.62	-1.17 %	-1.06	205	0.8 %
1.5%	-0.73 %	-1.56	-0.29 %	-0.26	197	1.3 %
2.0%	-0.83 %	-1.41	-4.07 %	-2.65	172	5.2 %
2.5%	-0.96 %	-1.29	-7.07 %	-3.69	139	10.1 %
3.0%	-1.99 %	-2.76	-7.07 %	-4.27	112	18.0 %
3.5%	-3.60 %	-4.23	-4.72 %	-2.63	92	19.6 %

Robustness: Results using Single Dealer Prepayment Forecasts Projections reported to Bloomberg, while heavily weighting the first month forward and with approximately exponential decay thereafter, cover the life of the security. We use these forecasts for the main analysis because we can remove dealer-specific noise by using the median forecast, and, even more importantly, because these forecasts are available for a broad cross section and for the entire time period covered by the Barclays MBS Index Returns. Correctly estimating prepayment shocks requires that we include data for a wide sample of coupons in both premium and discount markets. Short term forecasts can sometimes be obtained at the dealer level, but the quality, sample length, and coupon coverage, varies widely. The longest real-time time series of short term forecasts we are able to obtain come from a major dealer and cover the period from January 2001 to June 2016.[35] For that time period, these data cover almost the same broad cross section as the Bloomberg forecast data. This dealer provided us daily data containing the short term forecasts for their models in real time under the assumption that interest rates follow the forward rate at the time of the forecast. Table B7 presents the prepayment risk factor loadings using the single-dealer one month forward forecast from the 15th of each month January 2001 to June 2016, and shows very similar results to our main analysis. Some significance is lost for discount securities due to the shorter sample which excludes the earlier years in which discount securities were more prevalent.

Table B7: Factor loadings by relative coupon using single-dealer prepayment forecasts. β_y^{disc} is restricted to equal zero. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i x_t + \beta_y^i y_t + \epsilon_t^i \text{ with } \beta_y^{\text{disc}} \equiv 0.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-1.5%	0.06%	0.03	0	0	32	0.0%
-1.0%	0.56%	0.63	0	0	81	0.5%
-0.5%	1.21%	2.09	0	0	136	3.2%
0.0%	1.79%	2.15	1.5%	1.28	171	2.7%
0.5%	0.91%	1.21	1.2%	1.11	183	0.9%
1.0%	-0.07%	-0.10	0.5%	0.47	186	0.3%
1.5%	-0.98%	-1.40	-0.5%	-0.46	182	1.4%
2.0%	-2.07%	-2.39	-1.4%	-0.98	171	3.4%
2.5%	-2.16%	-1.84	-1.7%	-0.76	139	2.4%
3.0%	-2.65%	-2.03	-5.1%	-1.89	112	4.2%
3.5%	-3.20%	-1.93	-3.7%	-1.16	92	4.1%

Robustness: AR(1) Errors for x and y Prepayment Factors Table B8 presents estimated prepayment factor loadings using the errors from full-sample autoregressions on

[35]We also explored historical forecast data from other peer dealers. Electronically available data from one peer dealer's API uses their current prepayment model rather than the model which was used on the historical date. A shorter sample of real-time forecasts from this dealer can be obtained from pdf files back to December 2008, however the cross section coverage is very limited.

the x and y time series as prepayment risk factors. The pattern in loadings closely matches the pattern from the baseline estimation, with the exception of the lowest discount coupon, for which there are relatively few observations.

Table B8: Factor loadings by relative coupon using AR(1) innovations in the x and y prepayment factors, denoted υ_t^x and υ_t^y, respectively. β_y^{disc} is restricted to be zero. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta_x^i \upsilon_t^x + \beta_y^i \upsilon_t^y + \epsilon_t^i.$$

Relative Coupon	β_x	t-stat$_x$	β_y	t-stat$_y$	n	R^2
-2.0%	-11.72 %	-1.59	0	N/A	41	6.1 %
-1.5%	3.98 %	1.36	0	N/A	87	2.1 %
-1.0%	2.63 %	1.81	0	N/A	153	2.1 %
-0.5%	2.23 %	2.36	0	N/A	215	2.6 %
0.0%	1.21 %	1.25	0.89 %	0.61	246	0.7 %
0.5%	-0.46 %	-0.55	-0.45 %	-0.32	236	0.1 %
1.0%	-1.10 %	-1.38	-1.96 %	-1.39	215	1.3 %
1.5%	-1.71 %	-2.14	-0.50 %	-0.35	197	2.4 %
2.0%	-2.86 %	-2.84	-8.32 %	-4.60	172	11.7 %
2.5%	-3.05 %	-2.40	-12.13 %	-5.48	139	18.1 %
3.0%	-4.35 %	-3.67	-11.41 %	-5.93	112	24.9 %
3.5%	-5.02 %	-3.51	-7.57 %	-3.39	92	15.1 %

Robustness: Time Varying Exposures We present a conditional asset pricing model of MBS returns, and emphasize the role of time-varying risk prices, given fixed risk loadings. The fact that our full-sample estimates of prepayment risk exposures are strongly consistent with the predictions of Propositions 1 and 2, and the fact that the fixed characteristic, negative relative coupon, appears to measure exposures as well or better than the estimated loadings, supports using fixed prepayment exposures for securities defined by relative coupon. However, it is theoretically possible that even within a single month, changes in interest rates may change the relative coupon of all MBS, hence changing each security's exposure to prepayment risk. Therefore, for robustness, we directly address the concern that exposures may vary with interest rate changes, and that resulting changes in exposures can explain our results. First, we show that allowing for within-month variation in exposures leaves our estimates of fixed prepayment exposures essentially unchanged. Second, we show that controlling for prepayment and interest rate shocks that effect realized returns, our results for expected returns from exposures multiplied by risk premia remain unchanged.

First, we measure the effect of changes in interest rates on exposures. That is, we decompose the prepayment risk exposures by relative coupon into a fixed component, and a component that varies with interest rates in a way consistent with the predictions of Equations (6) and (7). We find that including the effect of time varying exposures leaves the estimates presented in Table 3 and Table B1 essentially unchanged, and that the theoretically possible effects of interest rate changes on measured prepayment exposures within the month are statistically insignificant. Specifically, we run a pooled time series cross section regression of monthly hedged returns by coupon on fixed prepayment exposures, and the change in exposure within the month. Table B9 presents the results from a pooled time series cross section regression that uses relative coupon dummy interactions with the prepayment risk factors to estimate the fixed exposures, and double interactions between coupon dummies, rate changes, and the prepayment risk factors to measure the change in exposures within months. The interest rate changes are measured by changes in the PMMS 30 year fixed-rate primary mortgage rate. These rate changes measure any change in the moneyness of borrowers' prepayment options, and hence prepayment risk exposure, within the month. The interaction with negative relative coupon allows for the theoretically predicted opposite sign of rate changes on discount and premium securities. This specification also allows for a larger effect the further the security is from par, consistent with the estimated pattern of exposures. As expected, given that interest rate changes rarely exceed 50bps within any given month, the pattern of estimated prepayment risk factor loadings is essentially unchanged relative to our main analysis. Moreover, the double interactions between interest rate changes and relative coupon dummies with the prepayment risk factors are insignificant.

Table B9: Fixed and time varying prepayment risk exposures, Pooled Time Series Cross Section Regression. Coefficients on relative coupon dummies capture fixed prepayment risk exposures, which are similar to the baseline results in Tables 3 and B1. Coefficients representing the effects on returns from changes in exposures due to interest rate changes are not significant.

$$R_t^{ei} = a + \boldsymbol{\phi^i_{(c^i-r)*x}} \mathbb{1}_{(c^i-r)}\, x_t + \boldsymbol{\phi^i_{(c^i-r)*y}} \mathbb{1}_{(c^i-r)}\, y_t + \phi_{\Delta r*(r-c^i)*x}\, \Delta r_t \left(r - c^i\right) x_t + \phi_{\Delta r*(r-c^i)*y}\, \Delta r_t \left(r - c^i\right) y_t + \epsilon_t^i.$$

Variable	ϕ coefficient	t-stat	time-clustered t-stat
intercept	0.02%	1.44	0.69
$\mathbb{1}_{-2.0\%} * x$	2.25%	0.41	0.47
$\mathbb{1}_{-1.5\%} * x$	1.23%	0.70	0.41
$\mathbb{1}_{-1.0\%} * x$	2.43%	2.91	2.03
$\mathbb{1}_{-0.5\%} * x$	2.08%	3.42	3.13
$\mathbb{1}_{0.0\%} * x$	0.85%	1.49	1.29
$\mathbb{1}_{0.5\%} * x$	-0.04%	-0.08	-0.08
$\mathbb{1}_{1.0\%} * x$	-0.34%	-0.64	-0.69
$\mathbb{1}_{1.5\%} * x$	-0.76%	-1.42	-1.70
$\mathbb{1}_{2.0\%} * x$	-0.86%	-1.57	-1.26
$\mathbb{1}_{2.5\%} * x$	-1.02%	-1.78	-1.00
$\mathbb{1}_{3.0\%} * x$	-2.08%	-3.10	-1.90
$\mathbb{1}_{3.5\%} * x$	-3.66%	-5.00	-4.86
$\mathbb{1}_{-2.0\%} * y$	2.87%	0.75	0.75
$\mathbb{1}_{-1.5\%} * y$	-0.67%	-0.33	-0.32
$\mathbb{1}_{-1.0\%} * y$	0.98%	0.79	0.94
$\mathbb{1}_{-0.5\%} * y$	0.08%	0.08	0.09
$\mathbb{1}_{0.0\%} * y$	-0.09%	-0.09	-0.10
$\mathbb{1}_{0.5\%} * y$	-0.69%	-0.66	-0.90
$\mathbb{1}_{1.0\%} * y$	-0.91%	-0.80	-1.12
$\mathbb{1}_{1.5\%} * y$	-0.21%	-0.18	-0.24
$\mathbb{1}_{2.0\%} * y$	-3.96%	-2.97	-2.05
$\mathbb{1}_{2.5\%} * y$	-7.08%	-5.06	-2.47
$\mathbb{1}_{3.0\%} * y$	-6.95%	-4.68	-3.56
$\mathbb{1}_{3.5\%} * y$	-4.40%	-2.85	-2.91
$\Delta r * (r - c^i) * x$	0.36%	0.67	0.29
$\Delta r * (r - c^i) * y$	1.54%	1.25	0.56
n	1910		
R^2	6.8%		

Additional evidence against the importance of time varying exposures is that the correlation between rate changes and the state variable determining the sign of the price of prepayment risk, $\%RPB_{\text{disc}}$ is basically zero. Jagannathan and Wang (1996) provide a theoretical econometric framework to consider the effect of time varying exposures on the estimation of asset pricing models in the context of equity markets. They show precisely how unconditional estimates of expected returns will be biased by the covariance between time varying exposures and risk prices if this covariance is non-zero. The correlation between $\%RPB_{\text{disc}}$ and interest rate changes, measured as the change in the primary mortgage rate from the Freddie Mac Primary Mortgage Market Survey is very low, at 0.10, and is statistically insignificant. Although exposures may be most different from their average following a large interest rate shock, such a shock does not necessarily move the $\%RPB_{\text{disc}}$, which determines risk prices, far from its average. Thus, a back of the envelope calculation based on the theory in Jagannathan and Wang (1996), suggests that it is unlikely that the change in risk prices is correlated with changes in prepayment exposures arising from changes in interest rates.

Coefficients for the test of Proposition 2. T-statistics appear in the main text. The test consists of twelve panel regressions, one for each "base" coupon from 2% discount to 3.5% premium. In each panel regression, we designate one coupon as the base coupon, and drop all the terms associated with that coupon from each summation. See the main text for further details.

Table B10: Level factor loading differences: Each panel regression is of the following form, and coefficients are reported for ϕ. Coefficients match those in Table 3 for own coupon (diagonal):

$$R^{ei}_t = a + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \delta_i + \beta_x x_t + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \phi_i x_t + \mathbb{1}_{\text{base}\in\{0.0\%:3.5\%\}} \beta_y y_t + \sum_{i=0.0\%}^{3.5\%} \mathbb{1}_i \theta_i y_t + \epsilon^i_t$$

$$R^{ei}_t = a + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \delta_i + \beta_x x_t + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \phi_i x_t + \mathbb{1}_{\text{base}\in\{0.0\%:3.5\%\}} \beta_y y_t + \sum_{i=0.0\%}^{3.5\%} \mathbb{1}_i \theta_i y_t + \epsilon^i_t$$

	Comparison Coupon											
Base Coupon	-2.0%	-1.5%	-1.0%	-0.5%	0.0%	0.5%	1.0%	1.5%	2.0%	2.5%	3.0%	3.5%
-2.0%	4.90%	-3.36%	-2.30%	-2.82%	-4.04%	-4.93%	-5.22%	-5.64%	-5.73%	-5.86%	-6.89%	-8.50%
-1.5%	3.36%	1.54%	1.06%	0.54%	-0.68%	-1.57%	-1.86%	-2.28%	-2.37%	-2.50%	-3.53%	-5.14%
-1.0%	2.30%	-1.06%	2.60%	-0.53%	-1.74%	-2.64%	-2.92%	-3.34%	-3.43%	-3.56%	-4.59%	-6.21%
-0.5%	2.82%	-0.54%	0.53%	2.07%	-1.22%	-2.11%	-2.40%	-2.82%	-2.90%	-3.03%	-4.07%	-5.68%
0.0%	4.04%	0.68%	1.74%	1.22%	0.86%	-0.89%	-1.18%	-1.60%	-1.69%	-1.82%	-2.85%	-4.46%
0.5%	4.93%	1.57%	2.64%	2.11%	0.89%	-0.04%	-0.29%	-0.71%	-0.79%	-0.92%	-1.96%	-3.57%
1.0%	5.22%	1.86%	2.92%	2.40%	1.18%	0.29%	-0.32%	-0.42%	-0.51%	-0.64%	-1.67%	-3.28%
1.5%	5.64%	2.28%	3.34%	2.82%	1.60%	0.71%	0.42%	-0.74%	-0.09%	-0.22%	-1.25%	-2.86%
2.0%	5.73%	2.37%	3.43%	2.90%	1.69%	0.79%	0.51%	0.09%	-0.83%	-0.13%	-1.16%	-2.78%
2.5%	5.86%	2.50%	3.56%	3.03%	1.82%	0.92%	0.64%	0.22%	0.13%	-0.96%	-1.03%	-2.64%
3.0%	6.89%	3.53%	4.59%	4.07%	2.85%	1.96%	1.67%	1.25%	1.16%	1.03%	-1.99%	-1.61%
3.5%	8.50%	5.14%	6.21%	5.68%	4.46%	3.57%	3.28%	2.86%	2.78%	2.64%	1.61%	-3.60%

Table B11: Incentive-sensitivity factor loading differences: Each panel regression is of the following form, and coefficients are reported for θ. Coefficients match those in Table 3 for own coupon (diagonal). Loadings on the incentive-sensitivity factor y are restricted to equal zero for discount securities:

$$R_t^{ei} = a + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \delta_i + \beta_x x_t + \sum_{i=-2.5\%}^{3.5\%} \mathbb{1}_i \phi_i x_t + \mathbb{1}_{\text{base}\in\{0.0\%:3.5\%\}} \beta_y y_t + \sum_{i=0.0\%}^{3.5\%} \mathbb{1}_i \theta_i y_t + \epsilon_t^i$$

	Comparison Coupon							
Base Coupon	0.0%	0.5%	1.0%	1.5%	2.0%	2.5%	3.0%	3.5%
0.0%	-0.57%%	-0.27%	-0.48%	0.50%	-3.50%	-6.50%	-6.51%	-4.15%
0.5%	0.27%	-0.84%	-0.21%	0.77%	-3.23%	-6.22%	-6.23%	-3.88%
1.0%	0.48%	0.21%	-1.05%	0.98%	-3.02%	-6.02%	-6.02%	-3.67%
1.5%	-0.50%	-0.77%	-0.98%	-0.07%	-4.00%	-6.99%	-7.00%	-4.65%
2.0%	3.50%	3.23%	3.02%	4.00%	-4.07%	-3.00%	-3.00%	-0.65%
2.5%	6.50%	6.22%	6.02%	6.99%	3.00%	-7.07%	-0.01%	2.35%
3.0%	6.51%	6.23%	6.02%	7.00%	3.00%	0.01%	-7.07%	2.35%
3.5%	4.15%	3.88%	3.67%	4.65%	0.65%	-2.35%	-2.35%	-4.72%

B.2 Risk Premia: Additional details and robustness checks

Robustness: Defining Market Type Although there are several ways one could classify market type, they are all highly correlated. Since we use the percent of the market that is discount to define market type, we define the alternative measures to be positive when the market is more discount heavy. We analyzed the following alternative measures of market type: (1) Current mortgage rates less RPB weighted WAC, or "negative borrower moneyness", (2) negative RPB weighted relative coupon, or "negative investor moneyness", and (3) ten year treasury yield minus RPB weighted relative coupon, which is the negative of the measure used in Gabaix et al. (2007). The correlation of these measures with the percentage of RPB that trades at a discount are 0.84, 0.89, and 0.77 respectively. Since the correlation of market type defined by percentage of RPB that trades at a discount with all other measures is very high, our risk premia estimation results are, unsurprisingly, fairly similar across these specifications, as shown in Table B12.[36]

Table B12: Prices of Risk, Pooled Time Series Cross Section Regression, Negative Relative Coupon Characteristic for different market type definitions.

$$R_t^{ei} = \kappa(r - c^i) + \delta(r - c^i)\,(\text{Market Type}) + \epsilon_t^i.$$

	Negative Borrower Moneyness			Negative Investor Moneyness			Negative Gabaix et al. (2007)		
		t-stat & clustering			t-stat & clustering			t-stat & clustering	
	Coefficient	none	time	Coefficient	none	time	Coefficient	none	time
κ	0.02%	1.81	0.82	0.01%	1.40	0.61	0.12%	4.18	1.79
δ	0.09%	6.40	2.45	0.06%	5.79	2.31	0.07%	5.39	2.13
time f.e.	yes			yes			yes		
n	1915			1915			1910		
R^2	60.6%			60.4%			60.3%		

[36]The Gabaix et al. (2007) measure uses the remaining principal balance and WAC for all three agencies, Fannie, Freddie, and Ginnie, while the other measures use Fannie only. Using all agencies eliminates one month of data, resulting in 1910 vs. 1915 observations.

Multicollinearity of x and y Factor Loadings Table B13 presents the distribution of the monthly cross section correlation between the loadings on the level and incentive-sensitivity factors. There is little independent information in the two separate loadings, as can be seen by the high frequency of correlations over 50%. In seven months, only discount securities trade, so there is no variation in the loadings on the incentive-sensitivity factor.

Table B13: Cross Section Correlation of x and y Factor Loadings by Month. This table presents the frequency of cross section correlations between level and incentive-sensitivity loadings by month.

bin	count	pdf
0% to 10%	0	0%
10% to 20%	0	0%
20% to 30%	0	0%
30% to 40%	0	0%
40% to 50%	15	6%
50% to 60%	109	40%
60% to 70%	58	21%
70% to 80%	48	18%
80% to 90%	0	0%
90% to 100%	33	12%
N/A	7	3%

Robustness: Realized vs. Expected Returns As discussed in the main text, one concern with using average monthly returns to proxy for expected returns is that average realized returns can be a noisy proxy of expected returns. Realized returns are the sum of the expected return, or drift, plus the effect of current shocks. Thus, we also consider whether the realization of interest rate shocks can explain our results. We show that our estimates of risk prices are unchanged by controlling for the effect of interest rate and prepayment shocks on realized returns. To elaborate on the possible effect of a change in exposures within the month on realized returns, consider an MBS with a 6% coupon that has a relative coupon $(c^i - r)$ of 2%. Assume that the market is premium, so that premium securities have positive expected excess returns. Consider the effect of an increase in interest rates. As interest rates increase, high coupon premium securities move closer to par, i.e. $(c^i - r)$ decreases. Their prepayment risk exposure declines, reducing the required discount rate and leading to a positive contemporaneous return. The concern is, then, that changes in interest rates drive changes in exposures, and also drive realized returns. Although such effects would be consistent with the theory, we find that our results are essentially unchanged when controlling for the effect of within-month changes in interest rates on realized returns. We use the characterisic negative relative coupon to measure each relative coupon's fixed prepayment exposure.

Table 8 presents our baseline results with fixed prepayment exposures measured by negative relative coupon. Table B14 adds controls for the main shocks affecting realized returns, namely prepayment shocks x and y, and interest rate shocks, and adds columns with results using an empirical hedge to the table in the main text. We present the results using the empirically hedged series in the last three columns of Table B14. Using the empirically hedged series, the effect of interest rate shocks is indeed zero. We note that the risk prices are essentially unchanged, the effect of interest rate shocks on realized returns is insignificant in the cross section (when standard errors are clustered by time, as advocated by Petersen (2011)), and that the effect of the prepayment shocks remain, or gain, significance relative to the results using the analytically hedged returns. The superior performance of empirical hedges in neutralizing interest rate shocks has been pointed out by Breeden (1994). We utilize the Barclays hedged series for our baseline analysis because it allows us fewer degrees of freedom in measurement, and because analytical duration hedging is more common in practice.

Table B14: Prices of Risk, Pooled Time Series Cross Section Regression, Negative Relative Coupon Characteristic, controlling for contemporaneous prepayment and rate shocks. Subscripts on coefficients denote variable interacted with negative relative coupon. Including effect of rate shock on realized returns does not change estimated risk premia in expected returns. Standard deviations for each variable appear in the last column. OAD stands for Option Adjusted Duration.

$$R_t^{ei} = a + \kappa(r - c^i) + \delta_{\left(\%RPB_{\text{BoM}}^{\text{disc}} - 50\%\right)}(r - c^i)\left(\%RPB_{\text{t,BoM}}^{\text{disc}} - 50\%\right)$$
$$+\delta_x(r - c^i)\,x_t + \delta_y(r - c^i)\,y_t + \delta_{\Delta r}(r - c^i)\,\Delta r_t + \epsilon_t^i.$$

	Barclays OAD Hedged			Empirically Hedged			Interaction
		t-statistic clustering			t-statistic clustering		Variable
	Coefficient	none	time	Coefficient	none	time	StdDev
κ	0.03%	2.85	1.18	0.00%	0.05	0.02	
$\delta_{\left(\%RPB_{\text{BoM}}^{\text{disc}} - 50\%\right)}$	0.15%	6.64	2.84	0.13%	5.46	2.19	0.35
δ_x	0.79%	7.47	3.14	0.50%	4.22	2.07	0.06
δ_y	1.46%	6.56	1.89	1.55%	5.97	2.68	0.03
$\delta_{\Delta r}$	-0.44%	-11.04	-4.32	-0.11%	-2.46	-0.75	0.19
time f.e.	yes			yes			
n	1910			1652			
R^2	64.7%			71.0%			

Robustness: Fama MacBeth Results for Characteristic Model Table B15 presents the results for the second stage Fama MacBeth estimation of the risk premia used to compute root mean squared errors. Consistent with our theory, the price of prepayment risk for discount securities is positive in discount months and negative in premium months, and vice versa for premium securities. All intercepts (unreported) are very close to zero and statistically insignificant. Using a one-sided test that the price of prepayment risk is statistically significantly negative in premium markets, we confirm the prediction of Hypothesis 1 at the 1% significance level. We also confirm that the price of prepayment risk is positive in discount markets, but here the significance is lower (6%) due to the smaller number of discount months.

Table B15: Prices of Risk, Negative Relative Coupon Characteristic. Risk prices are time series averages of cross section regression coefficients conditional on market type $M \in (DM, PM)$. We use c to denote the price of the negative relative coupon (c)haracteristic. The following regression is estimated at each date t, and average risk prices are computed within each market type, with months weighted by the number of available securities:

$$R^{ei}_{t,\mathrm{M}} = a_{t,\mathrm{M}} + \lambda_{t,c,,\ \mathrm{M}} \left(r - c^i\right) + \epsilon^i_t.$$

Market Type	λ_c	t-stat	n
Discount	3.98%	1.61	85
Premium	-4.90%	-2.77	185

Robustness: Fama MacBeth Results for x and y Factor Model Table B16 presents the Fama MacBeth results for the two-factor model. As expected, we find that the price of x, the shock to the level of prepayments is positive in discount markets and negative in premium markets, with significance at the 5% and 1% levels respectively. We also find that the price of the incentive-sensitivity shock, y is negative, but insignificant, in both market types. The negative sign is expected, since only premium securities load on this shock. The standard errors for all coeficients are biased upward due to the high positive correlation between the factor loadings in each cross section, as documented in Table B13.

Table B16: Prices of Risk, Fama MacBeth Estimation, two-factor model. Risk prices are time series averages of cross section regression coefficients conditional on market type $M \in (DM, PM)$. Monthly observations are weighed by the number of coupons available in that month. The following regression is estimated at each date t:

$$R^{ei}_{t,\mathrm{M}} = a_{t,\mathrm{M}} + \lambda_{t,x,\mathrm{M}} \hat{\beta}^i_x + \lambda_{t,y,\mathrm{M}} \hat{\beta}^i_y + \epsilon^i_t.$$

Market Type	λ_x	t-stat$_x$	λ_y	t-stat$_y$	n
Discount (M=DM)	3.07%	1.65	-.66%	-0.26	85
Premium (M=PM)	-3.31%	-2.60	-.26%	-0.18	185

Robustness: Pooled Time Series Cross Section Results for x and y Factor Model With the caveat that the x and y loadings exhibit strong multicollinearity, biasing significance downward, we present the pooled time series cross section results for time-varying level and incentive-sensitivity risk premia here. We focus on the results with time fixed effects and using t-statistics from time-clustered standard errors (right-most column). We find that the risk premia estimates are of the expected sign and are significant using a one-sided test at the 5% and 10% level, respectively. The two risk premia coefficients are jointly significant at the 5% level.

Table B17: Prices of Risk, Pooled Time Series Cross Section Regression. F-statistics for joint statistical significance of δ_x and δ_y are computed using the Wald statistic.

$$R_t^{ei} = a + \kappa_x \beta_x^i + \kappa_y \beta_y^i + \delta_x \beta_x^i \left(\%RPB_{\text{BoM}}^{\text{disc}} - 50\%\right) + \delta_y \beta_y^i \left(\%RPB_{\text{BoM}}^{\text{disc}} - 50\%\right) + \epsilon_t^i.$$

		t-statistic clustering			t-statistic clustering	
	Coefficient	none	time	Coefficient	none	time
κ_x	-0.30%	-0.31	-0.27	-0.15%	-0.18	-0.13
κ_y	0.30%	0.27	0.20	0.73%	0.79	0.60
δ_x	4.87%	2.11	1.49	6.88%	3.18	2.22
δ_y	3.28%	1.45	0.92	3.81%	1.79	1.34
a	0.01%	0.68	0.45			
time f.e.	no				yes	
n	1915				1915	
R^2	1.08%				60.29%	
F-stat δ_x and δ_y	84%				95%	

B.3 Additional Evidence: Segmented Markets for MBS

We provide additional support for segmented markets for MBS by demonstrating that securities that load more *positively* on systematic equity market risk earn *lower* returns on average. The price of equity market risk is negative (and significant) in the MBS cross section. Our findings are consistent with Gabaix et al. (2007), who show that prepayment risk is negatively correlated with consumption growth. Given these findings, it is unlikely that the marginal investor in MBS shares the same marginal rate of substitution as a representative consumer or equity investor. Tables B18 and B19 present the step one and two results of the Fama and MacBeth (1973) estimation.[37]

[37] Data for the value-weighted CRSP excess market return are from Fama and French (2017).

Table B18: Factor loadings by relative coupon from a CRSP value weighted excess equity return CAPM model. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta^i_{\text{eCRSPVW}} R_t^{\text{eCRSPVW}} + \epsilon^i_t.$$

Relative Coupon	β^i_{eCRSPVW}	t-stat$_{\text{eCRSPVW}}$	n	R^2
-2.0%	2.56%	1.35	41	4.46%
-1.5%	0.11%	0.07	87	0.01%
-1.0%	4.15%	4.17	153	10.32%
-0.5%	3.91%	5.45	217	12.14%
0.0%	3.66%	5.24	248	10.03%
0.5%	3.31%	4.90	238	9.23%
1.0%	3.02%	4.41	217	8.29%
1.5%	3.01%	4.44	199	9.08%
2.0%	3.15%	3.21	172	5.73%
2.5%	3.66%	2.75	139	5.25%
3.0%	2.80%	2.00	112	3.50%
3.5%	2.70%	1.73	92	3.22%

Table B19: Prices of Risk, CRSP value weighted excess equity return CAPM model. Risk prices are time series averages of cross section regression coefficients. We use eCRSPVW to denote the price of the CRSP value weighted excess equity return. The following regression is estimated at each date t, and risk prices are computed as the time series average of $\lambda_{t,\text{eCRSPVW}}$:

$$R_t^{ei} = a_t + \lambda_{t,\text{eCRSPVW}} \beta^i_{\text{eCRSPVW}} + \epsilon^i_t.$$

λ_{eCRSPVW}	t-stat	n
-7.35%	-2.81	270

B.4 Additional Evidence: Price of Intermediary Returns Negative in MBS Cross Section

The following Tables B20 and B21 show that the price of intermediary capital is negative in the cross section of MBS returns. We use the tradable intermediary asset pricing factor from He, Kelly, and Manela (2017).[38] Similar to the results for the equity market model, the loadings on the intermediary factor are fairly flat in the cross section, positive, and significant for relative coupons -1.0% and higher. However, although the loadings are fairly flat, they are highest for the coupons near par. Since these coupons also earn the lowest returns on average, the price of the intermediary factor is *negative* in the cross section of MBS returns. This might seems surprising given the fact that banks are major holders of mortgages. However, the role of banks in mortgage markets (as opposed to the mortgage trading desks of banks, prior to the Volcker Rule), is mainly to originate and hold mortgage loans, rather than to dynamically trade them. It is notable that mortgage origination tends to occur at coupons at or near the par coupon, consistent with the idea that banks are mainly long par mortgages. Haddad and Muir (2019) show that, in the time series, a substantial amount of variation in the risk premium of a hedged MBS index is due to variation in the intermediary asset pricing factor. Our coupon-level results show that although intermediary wealth measured by banking data appears to matter for time series variation in the overall MBS market return, it cannot explain the cross section in MBS returns.

Table B20: Factor loadings by relative coupon from a single factor Intermediary Asset Pricing model of the cross section of MBS returns. The following time series regression is estimated for each security, i:

$$R_t^{ei} = a^i + \beta^i_{\text{HKM}} R_t^{\text{HKM}} + \epsilon^i_t.$$

Relative Coupon	β^i_{HKM}	t-stat$_{\text{HKM}}$	n	R^2
-2.0%	0.69%	0.50	41	0.65%
-1.5%	-1.24 %	-1.23	87	1.76%
-1.0%	2.50%	3.43	153	7.22%
-0.5%	3.00%	6.12	217	14.85%
0.0%	2.80%	6.20	248	13.52%
0.5%	2.34%	5.36	238	10.84%
1.0%	2.06%	4.67	217	9.21%
1.5%	2.00	4.56	199	9.56%
2.0%	2.19%	3.60	172	7.09%
2.5%	2.33%	2.84	139	5.55%
3.0%	2.13%	2.68	112	6.13%
3.5%	2.00%	2.29	92	5.51%

[38] The authors note in their data description that this tradable intermediary asset pricing factor is "The value-weighted investment return to a portfolio of NY Fed primary dealers' publicly-traded holding companies. Unlike the intermediary capital risk factor, this portfolio is tradable, and performed similarly as a pricing factor."

Table B21: Prices of Risk, single factor Intermediary Asset Pricing model. Risk prices are time series averages of cross section regression coefficients. We use HKM to denote the price of the HKM tradable intermediary factor. The following regression is estimated at each date t, and risk prices are computed as the time series average of $\lambda_{t,\text{HKM}}$:

$$R_t^{ei} = a_t + \lambda_{t,\text{HKM}} \beta_{\text{HKM}}^i + \epsilon_t^i.$$

λ_{HKM}	t-stat	n
-9.06%	-2.54	270

B.5 OAS vs. Average Realized Returns as Expected Return Proxies

In most of the empirical asset pricing literature, it is standard to measure expected returns using average monthly returns, rather than yields, however our paper appears to be the first in this tradition in the literature on the cross section of returns to Mortgage Backed Securities. Several prior papers, including Gabaix, Krishnamurthy, and Vigneron (2007), Song and Zhu (2016), and Boyarchenko, Fuster, and Lucca (2017) use Option Adjusted Spreads (OAS) to proxy for expected returns. This may have been due to limited data availability in the past. Option-adjusted spread (OAS) is a yield spread which MBS industry participants back out from market prices using their proprietary pricing models. Specifically, it is the constant spread which must be added to a benchmark yield curve to generate a discount rate which justifies the market price of an MBS security given forecasted security cash flows. Security cash flow forecasts are specified by each dealer to account for variation in interest rates and borrower prepayment using the dealer's proprietary prepayment model, term structure and rate volatility model. Prepayment models, in particular, vary across dealers, and within dealers over time. As a result, the OAS for a given MBS coupon varies considerably across dealers.

We argue that this using OAS to proxy for expected returns is problematic for examining the cross section of MBS pass-throughs, especially prior to the financial crisis. To show this, we collected OAS data from six major dealers from January 1994 to June 2016. To alleviate the effect of outliers, we use the median of OAS quotes across dealers for each coupon in each month, however results using means are essentially unchanged.

For our analysis, we aggregate the OAS data across dealers' models to form a single OAS time-series per coupon. We collect end-of-month OAS data for Fannie Mae 30-year TBA securities from six different dealers. We use OAS computed with respect to the Treasury curve to be consistent with our analysis of treasury-hedged returns. To alleviate the effect of outlying dealer-level OAS quotes, we compute the median OAS in the cross-section of available dealers at each point in time for each coupon. The six dealers' data become available sequentially in 1994, 1996, 1997, 1998 2001 and 2005. As a liquidity filter, we also exclude coupons that have less than one billion outstanding in RPB at the beginning of the month.

Figure B1 plots the median OAS by coupon from January 1994 to June 2016. Clearly, there is very little cross-coupon variation in OAS in the first half of the sample, prior to the financial crisis. Accordingly, Table B22 presents results from a pooled time series cross section regression of monthly hedged MBS returns on OAS at the end of the prior month, including time fixed effects, and shows that OAS has no explanatory power for the cross section returns prior to 2007. Finally, we note that the variation across dealers' individual OAS quotes for a single coupon is typically larger than the variation in OAS across coupons. The observed large variation in dealers' OAS quotes for a single coupon is due to the fact that dealers' prepayment models vary widely. To show this, Figure B2 plots the standard deviation of OAS across coupons vs. the within-coupon, across-dealer standard deviation for each coupon from January 1996 to June 2016.[39] To illustrate the magnitude of the variation

[39] Due to variation in coverage, prior to 1996, the data contain only one dealer's quotes.

across dealer OAS quotes relative to the level of each coupon's OAS, Table B23 displays the median standard deviation across dealers' OAS quotes by coupon, the time series median of the median OAS across dealers by coupon, , and the ratio of the two. Note that the amount of variation across dealers is nearly as large as the median OAS for deep premium coupons; the disagreement is as large as the level. Moreover, disagreement across dealers in the prepayment forecasts underlying dealers' OAS models has been shown to predict returns by Carlin, Longstaff, and Matoba (2014).

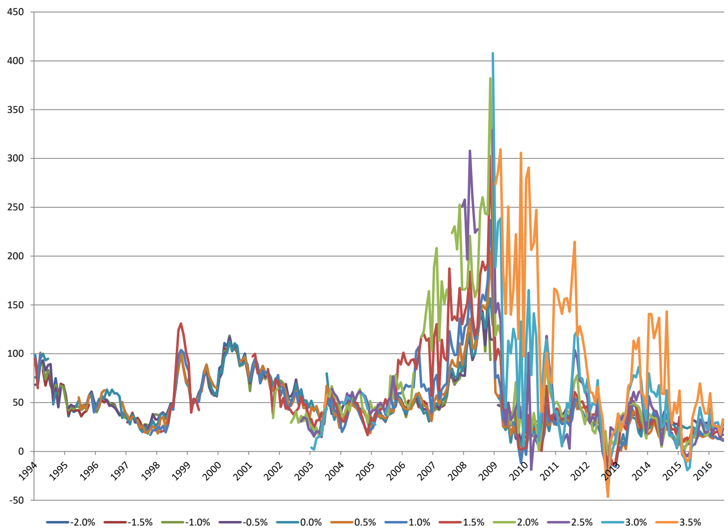


Figure B1: This figure plots the median across dealers of their model's Option Adjusted Spread (OAS) by relative coupon. There is very little variation across coupons in the first half of the sample. We plot OAS for all coupon-months with greater than $1BN in remaining principal balance outstanding.

Table B22: OAS does not predict the cross section of hedged MBS returns in a regression of excess MBS returns on OAS prior to 2007. Time fixed effects are included, and standard errors are clustered by time to illustrate the lack of predictability in the cross section pre-financial crisis.

$$R_t^{ei} = a_t + b_{\text{OAS}} OAS_{t-1}^i + e_t^i$$

Sample Period	b_{OAS}	t-stat$_{\text{OAS}}$	n	R^2
January 1994-December 2006	0.11%	0.6	949	69.90%
January 2007-June 2016	0.18%	2.69	966	56.10%
January 1994-June 2016	0.17%	2.73	1915	60.20%

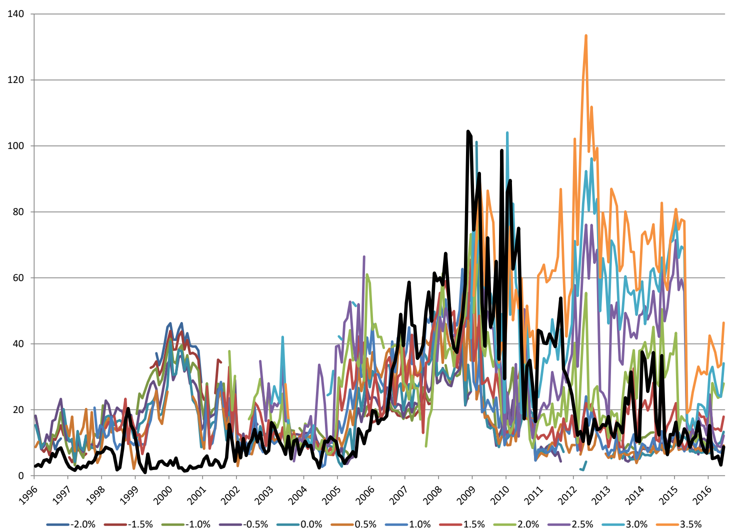


Figure B2: This figure plots the standard deviation across dealers of their model's Option Adjusted Spread (OAS) by relative coupon (colored lines), along with the standard deviation across coupons at each date (black line). The within-coupon standard deviation across dealers often exceeds the across coupon standard deviation. We plot OAS for all coupon-months with greater than $1BN in remaining principal balance outstanding for all dealers reporting for that coupon-month. Within coupon disagreement across dealers exceeds cross-coupon variation for the majority of coupon-months.

Table B23: Time series median of monthly median OAS across dealers by relative coupon and time series median of monthly cross section standard deviation of OAS across dealers by relative coupon. The third column reports the ratio of the time series median of the standard deviation of OAS across dealers (numerator) to the time series median of the cross section median of OAS across dealers (denominator) to show that the across dealer standard deviation is large relative to the median coupon level OAS, in particular for premium coupons. We use medians instead of averages to reduce the influence of outlying dealer quotes.

Relative Coupon	Time Series Median of Median OAS Across Dealers	Time Series Median of Standard Deviation of OAS Across Dealers	Standard Deviation/ Median
-2.0%	68	37	55%
-1.5%	55	21	38%
-1.0%	49	19	39%
-0.5%	47	16	33%
0.0%	44	13	29%
0.5%	41	12	29%
1.0%	40	13	32%
1.5%	43	17	40%
2.0%	42	26	61%
2.5%	39	34	86%
3.0%	45	47	105%
3.5%	70	62	89%