The Impact of Unconventional Monetary Policy on Real Estate Markets*

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Abstract

We use a structural factor-augmented vector autoregression (FAVAR) model and a large dataset of daily time series to study the impact of unconventional monetary policy on residential and non-residential real estate and related markets. Our findings indicate that an expansionary unconventional monetary policy shock lowers key housing market interest rates; raises equity market returns for homebuilders and real estate investment trusts (REITs); reduces the cost to insure subprime mortgage-backed and commercial real estate debt; and increases housing sentiment. Research findings also suggest that the estimated effects are generally large in magnitude and similar in size to those found for equity markets. Further, the impact of unconventional monetary policy shocks on housing markets differs in magnitude across risk-levels and US geographies. Finally, results indicate that successive rounds of monetary easing may be necessary during an extended period of economic weakness, in that the impact of an unconventional monetary shock attenuates rather quickly with an estimated half-life that is generally less than three months.

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During the 2000s meltdown of housing and the global economy, the Federal Reserve employed conventional and unconventional methods to stem the crisis, calm financial markets, and return the economy to full employment. Indeed, the Fed engaged in multiple rounds of quantitative easing, inclusive of substantial purchase of long-term government and mortgage-backed securities, and provided new guidance regarding the future direction of monetary policy. In the wake of those efforts, the Federal Reserve's balance sheet exploded from $880 billion in January of 2008 to over $4 trillion in December of 2013. Even with the massive monetary accommodation, the Fed faced substantial uncertainty as to the benefits of the policy innovations for the economy and the financial markets.[1] While long-term bond purchases were significantly directed to the ailing housing sector, many elements of the housing finance system were in disarray, resulting in limited ability to calibrate likely policy outcomes.

This paper aims to fill this gap via assessment of the effects of unconventional monetary policy on housing, real estate, and related markets. Specifically, we build a structural factor-augmented vector autoregression (FAVAR) model to analyze the impact of monetary policy on crucial real estate aggregates over the 2000s crisis period and its aftermath. Research findings indicate that unconventional monetary policy shocks are associated with (1) reductions in key housing market interest rates including Fannie Mae MBS yields and the Fannie Mae mortgage commitment rate;[2] (2) elevated returns on homebuilder and REIT stocks;[3] (3) lower costs of insuring subprime mortgage and commercial real estate debt; and (4) increased levels of housing and mortgage market sentiment across states and for the United States overall. Further, the estimated monetary policy effects differ in magnitude across US states and MBS credit tranches. Indeed, the results indicate that a surprise unconventional monetary easing greatly reduces the cost to insure AAA rated subprime mortgage debt, but has little effect on insurance prices for subprime debt with a higher exposure to collateral loss. Moreover, results provide new insights into the geographic incidence of monetary policy. A surprise monetary eas-

[1]Similarly, substantial uncertainty was associated with the efficacy of the Bank of Japan's unconventional monetary stimulus in the 1990s (Bowman et al. (2011)) and the Bank of England's ongoing unconventional monetary stimulus.

[2]As described in more detail below, the Fannie Mae commitment rate is the required net yield on mortgages to be sold to Fannie Mae by mortgage lenders.

[3]REIT stock returns track equity market returns for real estate investment trusts (REITs).

ing leads to much higher levels of housing market sentiment for bubble states such as California and Florida relative to less volatile housing markets like those in New York and Texas. Finally, results suggest that the monetary policy shocks attenuate relatively quickly as the half-life for the real estate related dynamic responses is generally less than three months. Overall, our findings highlight the importance of new, unconventional monetary policy interventions during the 2000s crisis period and aftermath in support of ailing real estate markets.

The FAVAR model (Bernanke, Boivin, and Eliasz (BBE; 2005) and Boivin, Giannoni, and Mihov (BGM; 2009)) allows us to evaluate numerous time series, including several proxies of real estate, housing, and mortgage market performance. Hence, the model employs a large database of daily time series that is likely to span the information sets used by practitioners and policymakers. As noted by BBE and BGM, this reduces the potential omitted variable bias found in the standard VAR setup and allows for a more accurate measurement of monetary policy shocks. Indeed, our dataset contains a large number of government, corporate, and housing interest rate series; exchange rates; equity market proxies; CDS spreads; and measures of housing distress. Altogether, these data include 31 daily time series that capture information in real estate, equity, and bond markets.

In assessment of the real estate market effects of unconventional monetary policy, we include key interest rate variables such as the yields on Fannie Mae mortgage-backed securities (MBS), the spread between Fannie Mae MBS and the 30-year Treasury, and the Fannie Mae mortgage commitment rate. The Fannie Mae commitment rate tracks the required net yield on home mortgages sold to Fannie Mae by mortgage lenders. We also evaluate the effects of monetary policy shocks on other housing and real estate proxies including the returns on an equity index of homebuilders and returns on an index of real estate investment trusts (REITs). The data also include indices that track the cost of CDS in both housing and non-residential real estate markets. In that regard, we consider ABX indices that track the cost to insure subprime mortgage debt of a certain investment grade.[4] These CDS measures are closely watched on Wall Street and reflect the beliefs of mortgage and housing investors regarding the future performance

[4]Specifically, the prices on credit-default swap (CDS) spreads.

of subprime mortgage debt.[5] Similarly, we use the CMBX indices to track the cost to insure commercial real estate debt. Lastly, our data include measures of housing and mortgage market sentiment, the Housing Distress Indices (HDIs) compiled by Chauvet, Gabriel, and Lutz (CGL; 2014). The HDI indices use the relative frequency of Google search queries for terms like "foreclosure help" or "mortgage help" to measure distress at the household level. Indeed, CGL find that the HDIs are key leading indicators of the turmoil that pervaded the housing and financial markets over the recent period. In this paper, we extend the HDIs developed by CGL to the daily frequency for the US overall and for states with the largest populations, including California, Florida, New York, and Texas. Thus, through national and state-level HDIs, we can examine the impact of unconventional monetary policy on household-level distress and test for heterogeneous geographic effects of monetary policy actions; two important issues that are unexplored in the recent literature.

With our dataset in hand, we estimate a FAVAR model using a two-step approach. In the first step, principal component analysis (PCA) is used to extract a set of latent factors that capture the dynamics of financial markets. More specifically, we assume that financial markets are affected by a basket of key interest rates, a vector of observed factors, and a set of latent factors; where the latent factors are derived from our large time series database using PCA. In the second step, we estimate a standard vector autoregression using the latent factors and our set of key interest rate variables. This process, which mirrors that used by BBE and BGM during conventional times, yields a reduced-form VAR in the latent and observed factors. From there, we identify structural monetary shocks by allowing the variance-covariance matrix of the VAR residuals to be heteroskedastic across monetary policy event and non-event days as in Wright (2012), Rigobon and Sack (2003, 2004, 2005), and Rigobon (2003). The key assumption is that the variance of the structural monetary shock is especially high on event days. In other words, news regarding monetary shocks arises in a "lumpy manner" (Wright (2012)). After identification, structural impulse response functions (IRFs) can then be computed for all variables in the dataset. Overall, the novel combination of the FAVAR model and

[5] *The Wall Street Journal*. June 21, 2007. "Index With Odd Name Has Wall Street Glued; Morning ABX.HE Dose."

the event identification strategy allows us to analyze both the initial and longer-term response of a large set of important real estate, housing, and mortgage market variables to an identified unconventional monetary policy shock.

As previously noted, a surprise unconventional monetary easing has a large and favorable impact on housing, real estate, and related markets. For example, research findings indicate that an unconventional monetary policy shock associated with an immediate 25 basis point reduction in the yield on the 10-year Treasury serves to lower the yield on Fannie MBS by 36 points. That same shock lowers the Fannie commitment rate by 41 basis points; produces abnormal returns for homebuilders and REITs relative to the S&P500 of approximately seven percentage points; and reduces the upfront cost to insure $10 million of AAA-rated subprime mortgage and commercial mortgage-backed securities by over 377,000 and 262,000 dollars, respectively. In other results, the unconventional policy shock reduces the growth rate of internet searches that signal housing distress by over 30 percent (nearly 3 standard deviations), an effect whose magnitude is similar to that found in other housing market variables. Further, through the forecast error variance decomposition (FEVD) from the VAR, our results indicate that the contribution of unconventional monetary policy shocks to the forecast error variance for key real estate variables is large in magnitude and similar to that found for equity market proxies; suggesting that the size of the estimated effects is similar across equity and real estate markets. Moreover, while the immediate policy effects are sizable, results also indicate that the effects attenuate relatively quickly with an estimated half-life that is generally less than three months. Finally, as also suggested above, the impact of unconventional monetary policy shocks varies by geography. For example, we find that the magnitude of the reduction in the growth rate of housing distress is approximately 1.5 standard deviations larger in the bubble states of California and Florida than in less speculative housing markets such as New York and Texas.

This paper builds on a sizable recent literature that examines the effects of unconventional monetary policy on financial markets.[6] Yet our work is most closely related

[6]Papers in this literature include those by Doh (2010), Fuster and Willen (2010), Neely (2010), Gagnon et al. (2011), Hancock and Passmore (2011, 2012, 2014), Krishnamurthy and Vissing-Jorgenson (2011), Swanson (2011), Hamilton and Wu (2012), D'Amico et al. (2012), D'Amico and King (2013), Glick and Leduc (2013), Duygan-Bump et al. (2013), and Swanson and Williams (2014).

to Wright (2012). Wright uses a structural VAR to study the effects of unconventional monetary policy on long-term interest rates. He identifies a structural monetary shock by assuming heteroskedasticity across event and non-event days, as we do in this paper. His results indicate that an expansionary shock lowers yields, but that the effects attenuate relatively quickly.

Yet our paper diverges from prior work in a number of important ways. First, we assess unconventional policy effects on housing, mortgage, and non-residential real estate markets, all key areas of focus for Fed crisis management. Moreover, our analysis is, to the best of our knowledge, the first to cover not only all three rounds of quantitative easing (QE), but also the recent so-called "taper" period. To evaluate policy effects, we employ a structural factor-augmented vector autoregression (FAVAR) model that can accommodate numerous variables from a variety of markets and geographies. Also, in estimating that model, we include a much larger and more comprehensive dataset than those used in prior papers. Thus, unlike other studies, we provide new evidence regarding the spatial incidence of unconventional monetary policy. Together, these innovations allow us to assess the effects of unconventional monetary policy on key indicators that track the performance of national and local real estate markets.

The rest of this paper is organized as follows: We provide an overview of the econometric methodology and identification in section 1; section 2 describes unconventional monetary policy over the recent sample and the dataset; the main results are in section 3; we consider a number of extensions and robustness checks in section 4; and section 5 concludes.

1 Econometric Methodology: Factor Augmented Vector Autoregression

In this section, we describe the methodology used to estimate the impact of unconventional monetary shocks on the real estate markets over the November 2008 through December 2013 period. During that time frame, the fed funds rate, the target of conventional policy, was held at its zero lower bound. Our approach is to estimate a factor-augmented vector autoregression (FAVAR) model (see Bernanke, Boivin, and Eliasz (BBE; 2005) and

Boivin, Giannoni, and Mihov (BGM; 2009)) with structural identification of monetary shocks through the assumption of heteroskedasticity across event and non-event days as in Rigoban (2003), Rigoban and Sack (2003, 2004, 2005), and Wright (2012). First, we outline the specifics of the FAVAR model; identification is discussed in more detail below.

A key benefit of the FAVAR model is that it allows us to consider a broad set of daily time series that extend to equity, government and corporate debt, housing, and commercial real estate markets all within a single comprehensive econometric framework. Thus, we include an expansive dataset that is likely to span the information sets used by both central bankers and private sector practitioners. This approach allows us to more accurately measure the effects of unconventional monetary policy shocks on the variables of interest. As noted by BBE and BGM, our large dataset and the FAVAR framework also allows us circumvent the potential omitted variable bias issues commonly found in standard VARs (e.g. the "price puzzle" of Sims (1992)). Furthermore, through the FAVAR methodology we can identify structural unconventional monetary policy shocks via heteroskedasticity in the variance of structural monetary shocks across policy announcement and non-announcement days.

With regard to the estimation of the FAVAR model, we assume that financial markets are affected by a basket of key interest rates, the observed factors, and a set of latent factors. Together, the latent and observed factors are assumed capture dynamics of financial markets over the sample period. In general, this approach mirrors that used by BBE and BGM during conventional times. However, before we can derive the latent factors and estimate the model, we must identify the interest rates that constitute the set of observed factors. Here, we follow Wright (2012) and let the key interest rate series include the 2-year Treasury, the 10-year Treasury, the five-year TIPS breakeven, the forward-five-to-ten-year TIPS breakeven, and the Moody's AAA and BAA seasoned corporate bond yields. These variables are described in more detail below in section 2. The robustness of this choice for the observed factors is examined in section 4.

Given the specified set of observed factors, we can proceed with estimation and identification. First, the set of informational time series is comprised of all variables in the dataset except for the interest rate series that constitute the observed factors. This leaves

25 variables in our set of informational time series. These variables are described in more detail below in section 2. Estimation, structural identification, and computation of the impulse response functions (IRFs) requires the following steps:

1. Extract a set of factors from the informational time series using principal components. These factors will represent the latent factors.

2. Estimate a reduced-form VAR using the observed factors and the latent factors from step (1).

3. Identify structural monetary policy shocks by assuming that the reduced-form FAVAR residuals are heteroskedastic across event and non-event days (discussed below in section 1.1).

4. Calculate the impulse response functions for the latent and observed factors using the structural identification from step (3).

5. Compute the impulse response functions for all the variables in the set of informational time series by multiplying the identified impulse response functions from step (4) by the factor loadings estimated in step (1).

To set up the reduced-form VAR used for the FAVAR model, we first extract a set of common components from our set of informational time series. More specifically, let X_t be a de-meaned $N \times 1$ vector of "informational time series" at time t that contains all variables in the dataset except for the key interest rates that constitute the observed factors. Further, assume that financial markets are affected by a $(K + 6) \times 1$ set of common factors, C_t, that comprise the latent and observed factors:

$$C_t = \begin{bmatrix} F_t \\ S_t \end{bmatrix} \tag{1}$$

where F_t is a $K \times 1$ vector representing the latent factors and S_t is a 6×1 vector of observed factors. Here, C_t, the common component, is assumed to capture the evolution of financial markets at the daily frequency over the sample. As noted above, this approach is analogous to that used by BBE and BGM during conventional times. Then, in line with step (1) above, we estimate the following observation equation via principal component

analysis:

$$X_t = \Lambda C_t + e_t \tag{2}$$

where Λ is an $N \times (K+6)$ matrix of factor loadings and e_t is an $N \times 1$ vector representing the idiosyncratic component to each time series. Note that we follow BGM and impose the constraint that S_t is one of the common factors.[7]

Then, with the common component, C_t, in hand, we estimate a reduced-form VAR via the following measurement equation:

$$C_t = \Phi(L)C_{t-1} + v_t \tag{3}$$

where $\Phi(L)$ is a conformable polynomial lag of finite order and v_t is a $K \times 1$ vector of reduced-form errors. Further, let $\eta_{i,t}$ be the ith structural shock at time t and assume that the structural shocks are independent over both i and t.[8] Then, as in Wright (2012), we let the reduced-form errors be a linear combination of structural shocks, $\eta_{i,t}$:

$$v_t = \sum_{i=1}^{p} R_i \eta_{i,t} \tag{4}$$

where R_i is a $K \times 1$ vector to be estimated. Finally, as is standard in the literature, we assume that the parameters Λ, $\Phi(L)$, and $\{R_i\}_{i=1}^{p}$ are all constant over time.

1.1 Identification and Impulse Response

To identify the structural monetary shock in equation 4, we follow Rigobon (2003), Rigobon and Sack (2003, 2004, 2005), and Wright (2012) and assume that the variance of the monetary shock differs across event and non-event days where the events are monetary policy announcements (e.g. FOMC meetings or major policy speeches). Intuitively, this identification strategy relies upon assumption that monetary announcements are exogenous and occur by accident of the calendar, so that news about monetary policy events surfaces in a "lumpy manner" (Wright (2012)). More concretely, let the structural monetary policy shock be ordered first (for convenience) and have mean zero with

[7] As in BGM, we impose this constraint using the following algorithm: (1) extract the first K principal components from X_t, denoted $F_t^{(0)}$; (2) regress X_t on $F_t^{(0)}$ and S_t to obtain $\tilde{\lambda}_S^{(0)}$, the regression coefficient on S_t; (3) define $\tilde{X}_t^{(0)} = X_t - \tilde{\lambda}_S^{(0)} S_t$; (4) calculate the first K principal components of $\tilde{X}_t^{(0)}$ to get $F_t^{(1)}$; (5) Repeat steps (2) to (4) multiple times.

[8] This allows for other independent shocks to occur on monetary policy event days. See Wright (2012) for more details.

variance σ_1^2 on event days and variance σ_0^2 on non-event days.[9] Then the key assumption for identification is that $\sigma_0^2 \neq \sigma_1^2$; that the variance of the structural monetary shock is heteroskedastic across event and non-event days. Finally, assume that all other structural shocks are identically distributed with mean zero and variance 1 on all days. This latter assumption also follows directly from the notion that monetary events occur by accident of the calendar, so that the variance of all other structural shocks should be identical across event and non-event days.

In order to facilitate identification, we need to determine R_1, the parameter vector in equation 4 that relates the reduced-form errors to the structural shocks. First, let Σ_1 and Σ_0 be the variance-covariance matrices of the reduced-form forecast errors on event and non-event days, respectively. Then, following from equation 4, we see that

$$\Sigma_1 - \Sigma_0 = R_1 R_1' \sigma_1^2 - R_1 R_1' \sigma_0^2 = R_1 R_1' (\sigma_1^2 - \sigma_0^2) \tag{5}$$

As $R_1 R_1'$ and $(\sigma_1^2 - \sigma_0^2)$ are not separately identified, we follow Wright (2012) and normalize $(\sigma_1^2 - \sigma_0^2)$ to be equal to 1. Then, to estimate R_1 within our econometric framework, we solve the corresponding minimum distance problem:

$$\hat{R}_1 = \underset{R_1}{\operatorname{argmin}} [vech(\hat{\Sigma}_1 - \hat{\Sigma}_0) - vech(R_1 R_1')]' [\hat{V}_0 + \hat{V}_1]^{-1} [vech(\hat{\Sigma}_1 - \hat{\Sigma}_0) - vech(R_1 R_1')] \tag{6}$$

where the $vech(\cdot)$ operator stacks the lower triangular matrix of a square matrix into a vector, $\hat{\Sigma}_0$ and $\hat{\Sigma}_1$ are sample estimates of the variance-covariance matrices for the reduced-form residuals on non-event and event days, and $\hat{V}_0$ and $\hat{V}_1$ are the estimates of the variance-covariance matrices of $vech(\hat{\Sigma}_0)$ and $vech(\hat{\Sigma}_1)$. Essentially, equation 6 is similar to a weighted least-squares problem with unknown parameter vector R_1. Lastly, as we are not attempting to identify the other structural shocks, $(\eta_2, \ldots, \eta_p)$, no further model assumptions are required.

With $\hat{R}_1$ in hand, we can then compute the dynamic responses of the variables of interest to an unconventional monetary policy shock. First, we obtain the impulse response functions for the VAR described in equation 3 in the usual way; this yields the IRFs for the observed factors. Then, as in BBE and BGM, we calculate the impulse response functions for all the variables in the set of informational time series, X_t, by simply multiplying

[9] Ordering the monetary policy shock first for structural identification is just for convenience as the shocks will be identified via the heteroskedasticity of the monetary shock across event and non-event days.

the aforementioned IRFs by the factor loadings obtained from the observation equation (equation 2). As the VAR employs "generated regressors," confidence intervals for the IRFs will be computed using the two-step bootstrapping algorithm of Kilian (1998). To preserve any potential residual autocorrelation, we follow Wright (2012) and use the stationary block bootstrap of Politis and Romano (1994) and set the block length to 10 days. Altogether, this approach will allow us to then assess the impact of a monetary policy shock on key proxies of housing and real estate market performance.

Finally, we implement statistical tests to ensure that the variance-covariance matrices are different across event and non-event days and that there is a single monetary policy shock. First, we test for heteroskedasticity in the reduced-form residuals via the null hypothesis that $\Sigma_0 = \Sigma_1$. Clearly, a rejection of the null would indicate heteroskedasticiy. The corresponding test statistic is

$$[vech(\hat{\Sigma}_1 - \hat{\Sigma}_0)]'[\hat{V}_0 + \hat{V}_1]^{-1}[vech(\hat{\Sigma}_1 - \hat{\Sigma}_0)] \tag{7}$$

Statistical significance is then evaluated based on a bootstrapped distribution. Next, to test for a single monetary shock, we evaluate the hypothesis that $\Sigma_1 - \Sigma_0 = R_1 R_1'$. The relevant test statistic is as follows:

$$[vech(\hat{\Sigma}_1 - \hat{\Sigma}_0) - vech(R_1 R_1')]'[\hat{V}_0 + \hat{V}_1]^{-1}[vech(\hat{\Sigma}_1 - \hat{\Sigma}_0) - vech(R_1 R_1')] \tag{8}$$

We assess the null in equation 8 using a bootstrapped distribution based on the two-step bias adjusted resampling algorithm of Kilian (1998). See Wright (2012) for more details. Failure to reject the null provides support for a single monetary shock.

In general, there are several advantages to identifying the structural shocks through heteroskedasticity across monetary policy event and non-event days. First, this identification strategy only requires the dates when the FOMC releases policy-related information and therefore circumvents the need to measure market expectations regarding the Fed policy statements. This feature is crucial for our purposes as measuring housing and real estate investors' expectations for Fed policy is a decidedly difficult task, especially as these investors span multiple markets and asset classes. Next, as noted above, identifying the structural shocks through heteroskedasticity allows us to compute impulse response functions and hence assess the initial impact and longer run effects of the unconventional monetary policy shocks. Lastly, this framework allows for other macroeconomic or finan-

cial shocks to occur on monetary policy events days; minimizing endogeneity concerns in our measurement of the monetary policy shocks.[10]

Through our identification strategy, we measure the total effect of unconventional monetary policy actions on real estate markets. These monetary policy actions are inclusive of large-scale purchases of US government debt and mortgage backed securities, forward guidance regarding the future direction of monetary policy, and the various credit and lending facilities pursued by the Federal Reserve over the sample period. Further, it should be noted that our aim is somewhat different than event studies that also assess the effects of unconventional monetary policy.[11] These event studies often attempt to determine the channels through which FOMC policies impacted financial markets. Yet the event study approach requires researchers to measure market expectations regarding the direction of Fed policy (a notably difficult task) and cannot provide estimates for the persistence of monetary policy shocks. Further, event studies are vulnerable to endogeneity concerns if other financial market or macroeconomic shocks occur around the release of FOMC statements.

2 Data

We consider a number of daily housing, real estate, and financial market data series for the recent period over which the FOMC implemented it unconventional monetary stimulus. Table 1 in the data appendix lists all of the variables in our dataset. We discuss the recent monetary policy actions and the data in turn.

2.1 Unconventional Monetary Policy

In the wake of conventional easing resulting in a zero fed funds rate in 2008, the Federal Reserve employed unconventional tools in an effort to achieve its dual policy goals of full employment and stable prices. Specifically, major actions by the FOMC have included the purchase of long-term government and mortgage-backed securities as well as new guidance regarding the future direction of monetary policy. We list the most important monetary events over the sample period from November 2008, when the FOMC initiated

[10] See Wright (2012) for more details.

[11] See Gagnon et al. (2010), Krishnamurthy and Vissing-Jorgenson (2011), Swanson (2011), and Glick and Leduc (2013).

its first long-term asset purchase program, to December 2013 in table 3 of appendix C.[12] These events are sorted by the various QE programs as well as the "taper" period where the Fed first signaled that it would reduce its monetary stimulus. Hence, our data covers nearly the full cycle of unconventional monetary policy over the recent period. As in Wright (2012) and Glick and Leduc (2013), the policy events include all FOMC meetings and major speeches by Chairman Bernanke; this allows us to capture all major monetary announcements over the sample period. In total, we consider 47 monetary events with the 15 most important events highlighted in table 3. For the presentation of our main results below, we identify the structural monetary shocks using all 47 events; then in section 4.5, we extend our baseline analysis and use just the major announcements for identification.

2.2 ABX Indices

The ABX indices reflect the price of credit default swaps on subprime mortgage-backed securities. These indices are tabulated by Markit and are closely watched on Wall Street.[13] More specifically, each ABX index tracks the cost to insure an equally-weighted basket of 20 subprime mortgage-backed securities. The ABX series are identified by time of issuance and credit tranche. For this paper, we consider the ABX indices based on mortgage-backed securities issued in the second half of 2007 with ratings of either AAA or AA, henceforth the ABX AAA and ABX AA indices, respectively. These indices are plotted in figure 1. We focus only on the higher quality AAA and AA ABX indices as the underlying securities that comprise these indices are more frequently traded. Further, the vast majority of subprime mortgage-backed securities were rated AAA. Indeed, Hull (2010) contends that 90 dollars of AAA rated securities were created from each 100 dollars of subprime mortgages. The ABX indices are pegged at 100 on the day of issuance and then fall as mortgage and housing investors become more pessimistic about housing and mortgage market performance. Hence, the AAA ABX index fell by substantially less during the housing bust and largely recovered in the aftermath of the crisis; its AA rated counterpart, on the other hand, crashed and remained damped through the end of

[12] This table is updated from Glick and Leduc (2013).

[13] *The Wall Street Journal*. June 21, 2007. "Index With Odd Name Has Wall Street Glued; Morning ABX.HE Dose."

the sample period. In addition to the raw ABX indices, we also consider an ABX risk premium defined as the difference in the AAA ABX index and the AA index. Larger values in the ABX risk premium indicate higher relative insurance costs for lower rated subprime mortgage-backed securities. We describe the ABX indices in more detail in appendix F as well as how the values of the ABX indices correspond to the insurance costs for subprime mortgage-backed debt.

2.3 CMBX Index

Also, we consider the Markit CMBX indices. The CMBX indices are similar to the ABX indices, but track the cost to insure commercial mortgage-backed, rather than subprime mortgage-backed debt. We use the AAA-rated CMBX index based on a basket of 25 commercial mortgage-backed securities that were issued in the second half of 2006. This was the only CMBX index with sufficient levels of liquidity and trading volume over the sample period. As with the ABX indices, the CMBX indices start at 100 on the day of issuance and decline as investors become more pessimistic regarding commercial real estate loan performance. For more details on the CMBX indices see appendix F.

2.4 Housing Distress Index (HDI)

In addition to the ABX and CMBX indices, our dataset also includes a measure of housing and mortgage market sentiment, the Housing Distress Index (HDI) of Chauvet, Gabriel, and Lutz (CGL; 2014). The HDI is the relative Google search frequency of a basket of internet search terms that signal housing or mortgage distress.[14] Thus, unlike other variables in the housing literature, the HDI captures mortgage and foreclosure distress as directly revealed by the internet search queries of households. This makes the HDI unique compared to other variables in the housing literature. Moreover, the use of the HDI is advantageous for our purposes as search query data from Google can be compiled in real time (Choi and Varian (2012)).

We extend the original HDI from CGL in two directions. First, daily data from Google Trends are used to build a daily HDI, matching the periodicity of the other variables in

[14]The search terms include the following: "foreclosure," "foreclosure assistance," "foreclosure help government," "foreclosure help," "government assistance mortgage," "government mortgage help," "help for mortgage," "help with mortgage," "home mortgage assistance," "home mortgage help," "housing assistance," "mortgage assistance program," "mortgage assistance programs," "mortgage assistance," "mortgage foreclosure help," "mortgage government help," "mortgage help."

the dataset. Accordingly, the HDI comprises a unique, real-time, and high periodicity measure of housing sentiment. Second, we construct the HDI not only for the United States overall, but also for California, Florida, New York, and Texas. These local HDIs allow us to test for a heterogeneous spatial impact of unconventional monetary policy shocks, an issue not previously explored in the literature.

To construct the daily HDIs, we download the internet search query data from Google Trends.[15] Data from Google Trends are published in the form of a "Search Volume Index" (SVI) that ranges from 0 to 100, where values of 100 indicate peak relative search frequency. See Choi and Varian (2012) or CGL for more details on the search query data from Google Trends. To obtain the search query data at the daily frequency, we enter the relevant search terms into Google Trends one quarter at a time; this yields the daily SVI for each quarter between 2008 and 2013. To make the data comparable across quarters, the SVIs are then transformed into growth form using the log first-difference, producing a time series that represents the daily percentage change in Housing Distress over the sample period. This process leaves missing values at the beginning of each quarter for which the growth in the daily HDI cannot be computed. As the dates for these missing values occur by accident of the calendar, they can be treated as "missing at random" and are imputed by bootrapping the EM algorithm of Dempster, Laird, and Rubin (1977) as in Honaker and King (2010). The state-level HDIs are then constructed by restricting the search query data to originate from the relevant geography. All search query data are seasonally adjusted by retaining the residuals from a regression of the daily HDI measure on day of the week and month dummy variables. Lastly, the HDI proxies are standardized to have zero mean and unit variance so that they are easily comparable across states.

We plot the cumulative returns of daily National HDI index in figure 1. The index is normalized so that December 31, 2013 has a value of 10. As noted by CGL, the HDI closely tracks housing distress over the sample period. Indeed, queries for housing distress related search terms were high during housing crisis and then fell substantially as the crisis abated. Finally, we consider an HDI Geographic Risk Premium, which is the

[15]In Google Trends, we restrict searches to originate from the relevant geography and enter the following into the search box (without quotes): "foreclosure+foreclosure assistance+foreclosure help government+foreclosure help+government assistance mortgage+home mortgage assistance+home mortgage help+housing assistance+mortgage assistance program+mortgage assistance+mortgage foreclosure help+mortgage help."

average of the growth of the HDIs for California and Florida less the average the growth of the HDIs for New York and Texas.[16]

In a robustness check below, we entertain an alternative formulation for the HDIs based on the log of the cumulative returns of each HDI index minus a 100 moving average. The results are similar to those that just use the HDI indices in growth form.

2.5 Other Housing and Real Estate Data

Our dataset also includes a number of other variables that measure housing, real estate, or mortgage market performance. First, we consider the yields on Fannie Mae 30-year current coupon mortgage backed securities (MBS) and the Fannie Mae 30-year 60 day commitment rate. The Fannie MBS rates represent the yields on mortgage backed securities packaged and sold by Fannie Mae, while the Fannie Mae commitment rate measures the required net yield on 30-year mortgage loans to be delivered by lenders within 30 to 60 days to Fannie Mae. Together, we use these series to capture the interest rate dynamics in the housing market. Further, our data also include equity market proxies for housing and real estate market performance. More specifically, we use the returns on the SPDR S&P Homebuilders ETF (NYSE symbol: XHB) to represent the equity market performance of home builders, and the returns on the First Trust S&P REIT Index ETF (NYSE symbol: FRI) to measure the performance of real estate investment trusts. With their broad holdings, these index funds should capture the expectations of equity market investors regarding future housing and real estate market performance.

2.6 Other Data

In addition to the aforementioned housing market proxies, the dataset also includes a number of other financial market indicators tabulated from various equity and debt markets. Indeed, our data include nominal and inflation-indexed government securities, corporate bond yields and spreads, exchange rate measures, stock returns, and a proxy for expected stock market volatility. With regard to interest rates, as in Wright (2012), we consider the yields on the nominal 2- and 10-year zero coupon US Treasuries, Moody's AAA and BAA rated seasoned corporate bond yields, the five-year TIPS breakeven, and

[16]HDI Geographic Risk Premium = mean(HDICA,HDIFL) - mean(HDINY,HDITX).

the five-to-ten-year forward TIPS breakeven.[17] Together, this basket of key interest rates represents our set of observed factors in the FAVAR model.[18] Furthermore, we also include the returns on the S&P500 and the Dow Jones Industrial Average (DJIA), the VIX index, the US-Euro, US-Pound, and US-Yen exchange rates, the BAA-AAA corporate bond spread, the spread between the Fannie MBS yields and the 30-year US Treasury Rate, and the ten-to-two year and the thirty-to-two year US Treasury spreads. The stock returns signal equity market performance, the VIX index measures expected risk in the stock market, the exchange rates capture the dynamics of the US Dollar, the BAA-AAA spread represents corporate default risk, the Fannie MBS-30 year Treasury spread is a risk and liquidity premium proxy for the mortgage market, and the Treasury spreads signal the slope of the yield curve. Altogether, our large dataset includes a number of important financial market indicators and is likely to span the information sets used by policymakers or financial market practitioners.

3 Main Results

We first estimate the FAVAR model over the November 2008 to December 2013 sample period. The monetary policy event data includes 47 events in total and covers QE1, QE2, QE3, and the subsequent so-called "taper" period. Also, the analysis below in section 4 considers a number of model extensions and robustness checks including alternative factor specifications and a test of only major monetary events. In general, our results suggest that unconventional monetary easing results in substantially lower interest rates on housing debt, increased stock returns for homebuilders and REITs, reduced costs to insure housing or real estate debt, and lower levels of housing distress. Further, the results differ in magnitude across risk-levels and US states.

3.1 Estimation of Latent Factors

To build our FAVAR model and compile the corresponding impulse response functions, we first estimate the latent factors using the observation equation. As in BBE and BGM, we choose five latent factors for the observation equation, yielding 11 total variables in

[17] See Wright (2012) and the references therein for more details.

[18] We consider alternative specifications for the set of observed factors below in section 4.

the vector C_t. Equation 2 is then estimated by principal component analysis.[19] Thus, we estimate a matrix Λ that relates each element of the set of informational time series, X_t, to the common component C_t. Table 1 shows the proportion of the variation in each member of the set of informational time series that is explained by the observation equation via the R^2 and adjusted R^2 statistics. In general, the common component appears to capture a large portion of the variation in the informational time series. Indeed, the R^2 statistics are all large in magnitude for the interest rate series, the equity return series, exchange rates, the AAA ABX index, ABX risk premium, the HDI variables, and the HDI Geographic Risk Premium.[20] Thus, five factors appears appropriate for our econometric specification. Below in section 4.4, we consider a model with an alternative number of latent factors.

3.2 Estimation of the VAR and Identification of the Structural Monetary Shocks

To compute the dynamic responses of the variables of interest to a structural monetary shock, we first estimate the reduced-form VAR outlined in equation 3 using the five latent factors and the basket of key interest rates described above. One lag is chosen for the reduced-form VAR by minimizing the Bayesian Information Criterion (BIC). R_1 is identified by solving the minimum distance problem in equation 5 and then the structural impulse response functions are traced out. To assess the hypotheses that the variance-covariance matrix of the reduced-form errors is heteroskedastic across event and non-event days and that there is a single monetary shock, we evaluate the test statistics outlined in equations 7 and 8 relative to their bootstrapped distributions. First, we reject the null that $\Sigma_0 = \Sigma_1$ with a bootstrapped Wald statistic of 19.60 and a corresponding bootstrapped p-value of 0.015. Hence, using the test statistic from equation 7, we reject the null of equal variances across event and non-event days. Next, the null that $\Sigma_1 - \Sigma_0 = R_1 R_1'$ is evaluated using the test statistic in equation 8. The bootstrapped Wald statistic is 7.70 and its bootstrapped p-value is 0.94. Hence, the null of a single monetary shock is not rejected.

[19] To let the members of X_t vary with both the observed and unobserved factors, we use the algorithm outlined above in section 1.

[20] As expected, the R^2 is equal to 1 when the ten-to-two year Treasury interest rate spread or when the corporate bond spread serve as the dependent variable as these measures are just a linear combination of the components of C_t.

3.3 Impulse Response

We calculate the impulse response functions (IRFs) for all variables in our dataset and conduct inference using bootstrapped confidence intervals as described above in section 1.1. Response dynamics are first computed for the observed factors, the basket of key interest rates, and then for all variables in the set of informational time series, X_t. As previously noted, the IRFs for the observed factors are obtained in the usual fashion, while the responses for the components of X_t are estimated by multiplying the IRFs from C_t by the factor loadings, Λ, calculated as in equation 2. This process yields an impulse response function for all 31 variables in our dataset. The identified monetary shock is normalized to reduce the 10-year Treasury yield instantaneously by 25 basis points as in Wright (2012). We trace out the dynamic responses for 750 periods, equivalent to approximately 3 years of daily data.[21] Below, in sections 3.3.1, 3.3.2, 3.3.3, 3.3.4, and 3.3.5, we analyze the dynamic responses of the interest rate series, the financial market variables, the housing market variables, the CDS spreads, and the housing distress indices in turn.

3.3.1 Interest Rates

Figure 2 shows the dynamic responses for the observed factors, the set of key interest rates. As indicated above, the identified unconventional monetary shock is standardized to lower the yield on the 10-year Treasury rate by 25 basis points instantaneously. The top-left and middle-left panels show the responses by the 2- and 10-year Treasuries to the identified monetary shock. As expected, the initial decrease in the 10-year Treasury is 25 basis points. In comparison, the initial decline in the 2-year Treasury is 15.6 basis points, while the corporate bond rates, the five-year TIPS breakeven, and the five-to-ten-year forward TIPS breakeven rates increase slightly. These latter effects then reverse quickly. Indeed, BAA corporate bond yield falls by 20 basis points after 20 days, the AAA corporate bond yield falls by 10 basis points after 30 days, and the lower confidence bounds five-year TIPS breakeven and the five-to-10-year forward TIPS breakeven both cross zero after just 30 days. These latter results support the findings of Krishnamurthy and Vissing-Jorgenson and Wright (2012) who provide some evidence that breakeven

[21] Assuming 250 trading days per year.

rates rise in response to a unconventional monetary shock. Further, the effects of the monetary shock on the Treasury yields attenuate relatively quickly as the estimated half-life for the IRFs in the 2- and 10-year Treasuries is approximately just 85 and 80 days, respectively. Hence, in order for unconventional policy to be efficacious over the recent period of economic weakness, policymakers may have needed multiple rounds of monetary stimulus. Overall, the results in this sections are similar to those found by Wright (2012) who considers a structural VAR with only interest rate series.

3.3.2 Financial Market Variables

Next, we show the structural impulse response functions for important financial market variables over the sample period using all monetary events in figure 3. The variables of interest here include the S&P500 and DJIA stock returns, the VIX index, the Dollar-Euro and Dollar-Pound exchange rates, and the BAA - AAA Corporate default spread. All of the dynamic responses in figure 3 are normalized so that initial decline in the 10-year Treasury yield is 25 basis points. As evinced in table 1, the variation in these financial variables, which are all included in our set of informational time series, X_t, is well explained by the five latent factors and the observed factors; indicating that the IRFs for these variables are likely to be reliably estimated via the FAVAR model (BBE). First, as seen in the left panel of the figure, an unconventional monetary policy shock that lowers the 10-year Treasury by 25 basis points increases stock returns and lowers stock market volatility. Indeed, the initial increase in stock returns is 12.7 percent for the S&P500 and 11.2 percent for the Dow Jones Industrial Average. Interestingly, Bernanke and Kuttner (2005) find that a 100 basis point surprise decrease in the fed funds rate is associated with an 11.3 percent increase in excess stock returns. Thus, our results indicate that an unconventional monetary shock that reduces the 10-year Treasury yield by 25 basis points has a similar effect on stock returns as an unexpected 100 basis point cut in the fed funds rate. Moreover, an unconventional monetary shock lowers the VIX index, a proxy for expected stock market volatility. The initial estimated reduction in the VIX is over 15 points. This estimated response is large in magnitude and economically meaningful as the all-time high of the VIX is 80.86. The effect, however, quickly dies off and the upper confidence bound for the IRF crosses the zero-line after just about

100 days. Next, the right panel of the figure shows the structural dynamic responses of the Dollar-Euro and Dollar-Pound exchange rates and the BAA - AAA corporate default spread. As expected and in line with Glick and Leduc (2013), we find that a surprise unconventional monetary easing leads to a depreciation of the dollar relative to the Euro and the Pound. Lastly, the unconventional shock lowers the corporate default spread about 12 basis points after 30 days, but the estimated confidence intervals are relatively wide. Indeed, the upper confidence interval crosses the zero line after just 40 days.

3.3.3 Housing Market Variables

Figure 4 displays the dynamic responses of key housing market variables to the identified structural monetary policy shock. Here we consider the IRFs for Fannie Mae MBS yields, the spread between the Fannie Mae MBS yields and the yields on the 30-year Treasury, the Fannie Mae Commitment Rate, and equity returns on an index of homebuilders and an index of real estate investment trusts (REITs). The top-left and middle-left panels of the figure show the dynamic responses of the Fannie Mae MBS yields and the spread between the Fannie Mae MBS yields and the 30-year Treasury. Clearly, an unconventional monetary shock that lowers the 10-year Treasury by 25 basis points has a large initial impact on housing market interest rates: The estimated initial reduction of Fannie MBS yields is 36 basis points, while the spread between the Fannie MBS yields and those for the 30-year Treasury also falls by around 36 basis points. These effects, however, do appear to attenuate relatively quickly with an estimated half-life that is less 60 days. Similarly, the Fannie commitment rate, which represents the required net yield on 30-year mortgage loans to be delivered to Fannie Mae, fell initially by 41 basis points, but quickly reversed course with an estimated half-life of around just 30 days. Lastly, the right panel of the figure shows the estimated IRFs for equity returns on the XHB and FRI series which track stock prices for homebuilders and REITs, respectively. As evidenced by the figure, the initial response to an identified unconventional monetary shock is large in magnitude; indicating that a surprise monetary easing that lowers the 10-year Treasury by 25 basis points is associated with an increase in housing and real estate related stock returns of nearly 20 percent. As discussed above, the estimated increase in S&P500 equity returns was 12.7 percent. Thus, a surprise unconventional monetary policy easing that initially

lowers the 10-year Treasury by 25 basis points produces abnormal returns of about 7 percent in homebuilder and REIT stocks.

3.3.4 CDS Spreads

In figure 5, we present the responses of the housing and real estate CDS indices. Recall that ABX and CMBX indices fall as it becomes more expensive to insure subprime-mortgage or commercial real estate debt. The left panel of the figure shows the plots for the dynamic responses of the ABX AAA and the ABX AA indices, while the top-right plot presents the IRF for the ABX risk premium, the spread between the AAA and AA rated ABX indices. First, there is a large initial increase in the AAA ABX index; indicating that unconventional monetary shocks reduce to cost to insure subprime-mortgage debt. Indeed, after just 5 periods the AAA ABX index rises by about 6 points, indicating that the cost to insure 10 million dollars in AAA-rated subprime-mortgage debt falls by 600,000 dollars.[22] This estimated effect then quickly reverses with a half-life of about 25 days and then slowly decays and nearly completely dies off after 750 days. Next, as evidenced in the bottom-left panel, the impact of an unconventional monetary shock on the AA ABX index is relatively small in magnitude, suggesting that monetary policy has less of an effect on lower-rated debt. These previous findings are summarized in the top-left panel of the figure via the ABX Risk Premium, the difference between the AAA ABX and AA ABX indices. Indeed, the ABX Risk Premium jumps initially in response to an unconventional monetary shock and then quickly reverses course. Overall, the differences in the estimated responses between the AAA and AA ABX indices are not surprising. As previously noted, a large majority of subprime mortgage-backed securities were in fact rated AAA.

Finally, the bottom-right panel shows the estimated response of the AAA CMBX index to an identified structural monetary shock. Recall that the CMBX index tracks the prices on commercial real estate credit default swaps and falls as the cost to insure commercial real estate debt increases. The plot of the IRF indicates that there is a large initial increase in the AAA CMBX; suggesting that an unconventional monetary policy shock that lowers the 10-year Treasury by 25 basis points reduces the cost to insure 10

[22]See appendix F for more details on how the ABX indices relate to the cost to insure subprime mortgaged-backed securities.

million dollars of commercial real estate debt by approximately 262,000 dollars. Yet this effect falls off fairly quickly with an estimated half-life of approximately just 60 days. The effect nearly perishes completely after 750 trading days.

3.3.5 Housing Distress

Finally, figure 6 presents the structural dynamic responses of the Housing Distress Indices (HDIs) to an identified unconventional monetary shock. Recall that the HDIs serve as proxies of housing and mortgage market sentiment and act as leading indicators of housing and mortgage markets (CGL). First, as evidenced in the top-left panel of the figure, an unconventional monetary shock that lowers the 10-year Treasury by 25 basis points leads to a decline in the growth rate of US Housing Distress of nearly 2.95 standard deviations. The magnitude of this effect, which is statistically significant and economically meaningful, is in line with what we expect given the dynamic responses of other crucial housing or financial variables. Indeed, the nearly 20 percent initial increase in the homebuilder or REIT stock returns outlined above is equivalent to an increase in returns of approximately 9 standard deviations, while the 3.95 point initial response in the AAA ABX index is equivalent to a 7.25 standard deviation increase in that ABX index. Given that the standard deviation of the raw US HDI series is 10.3 percent; this translates into a decrease in search queries for housing distress related search terms of approximately 30 percent. Hence, the decline of Housing Distress associated with an unexpected unconventional monetary easing is congruent with that found in other key housing market variables.

Next, the middle-left plot shows the IRF for the HDI Geographic Risk Premium, the difference in the average growth rates for California and Florida relative to Texas and New York.[23] Indeed, computation of Housing Distress at the state level enables assessment of variation in unconventional monetary policy effects across geographically disparate markets. Clearly, there is a large initial decline in the HDI Geographic Risk Premium, indicating that the effects of unconventional monetary shocks are geographically heterogeneous across local housing markets. In other words, QE stimulus leads to larger reductions in Housing Distress for the most volatile housing markets, such as

[23]HDI Geographic Risk Premium = mean(HDICA,HDIFL) - mean(HDINY,HDITX).

those for California and Florida. The remainder of the Impulse Response Function plots, which show the dynamic responses for the state-level HDIs, further indicate that a surprise expansionary unconventional monetary easing lowered housing distress, but that these effects were much larger for California and Florida. Indeed, the initial decline in the growth rate of Housing Distress was larger than 1.5 standard deviations in magnitude for California and Florida, but less than one standard deviation in magnitude for New York and Texas.

Overall, these results are consistent with previous findings that suggest that Fed policy affects agent sentiment and has a larger impact on distressed assets.[24] Further, while the Fed cannot geographically target monetary policy, results are consistent with Fed interests in bolstering economic activity in weak areas. Altogether, the results indicate that expansionary unconventional monetary shocks lower Housing Distress, but that the effects are most prominent in more distressed, speculative markets.

3.4 Forecast Error Variance Decomposition

Lastly, we summarize the impact of unconventional monetary policy shocks on the variables of interest using the forecast error variance decomposition (FEVD). The FEVD is the portion of the forecast error variance attributable to unconventional monetary policy shocks. For the key interest rate series that constitute the observed factors, we calculate the FEVD in the usual way and normalize the monetary shocks to account for 10 percent of the one-day forecast error variance in the 10-year Treasury as in Wright (2012).[25] To calculate the FEVD for the informational time series, we use the modified formula from BBE. This alternative formula augments the standard FEVD specification for each variable i in the set of informational time series using the factor loadings estimated in equation 2. As noted by BBE, this approach is advantageous as the structural monetary shock is assessed only relative to the common factors and not the idiosyncratic component in each time series for which common economic and financial market determi-

[24]For example, Chen (2007) finds that monetary policy has a larger effect in bear markets and Kurov (2010) contends that monetary actions alter investor sentiment in the stock market and have a bigger effect on firms that are more sensitive to credit market conditions.

[25]This normalization is necessary as the size of the monetary shock is not identified. See Wright (2012) for more details.

nants should have no influence.[26] Hence, the augmented formula should provide a more accurate measurement of the relative importance of the monetary policy shocks.

Table 2 shows the results for observed factors and the informational time series at various forecast horizons. The top panel in the table shows FEVD for the key interest rate variables. In general, the results are similar to those obtained by Wright (2012). Unconventional monetary policy shocks that account for 10 percent of the forecast error variation in the 10-year Treasury explain approximately 8.9, 1.2, 1.1, 0.3, and 1.4 percent of the one-day forecast error variance in the 2-Year Treasury, the AAA and BAA corporate bond yields, and the five-year and forward-five-to-ten-year TIPS breakeven rates. Further, the monetary shocks account for a slightly larger portion of the forecast error variation in the observed factors at longer horizons; ranging from 1.6 percent for the forward-five-to-ten-year TIPS breakeven to 18.4 percent for the 2-year Treasury.

Next, the bottom panel in the table lists the FEVD calculations for the informational time series. First, unconventional monetary shocks that account for 10 percent of the one-day forecast error variation in the 10-year Treasury explain approximately 40.4, 54.7, 48.3, 47.6, 41.8, 52.4, and 51.3 percent of the one-day forecast error variance in the Fannie MBS Yields, the Fannie Commitment Rate, the AAA ABX index, the ABX risk premium, the CBMX index, the XHB stock returns (homebuilders), and the FRI stock returns (REITs). These results are large in magnitude and suggest that the impact of unconventional monetary policy shocks on housing and real estate markets are roughly similar in magnitude as those for equity markets. For example, the contribution of the aforementioned monetary shocks to the forecast error variance for the S&P500 and the VIX is 51.9 and 46.7 percent, respectively. Further, unconventional monetary policy shocks appear to have little impact on substantially underwater and lower rated subprime debt as the one-day FEVD for the ABX AA is just 0.7 percent. Additionally, our results indicate that the contribution of unconventional monetary policy shocks to the forecast error variance for the HDIs is similar to that found for the interest rate series that constitute the observed factors. Indeed, unconventional monetary shocks that explain 10 percent of the forecast error variation in the 10-year Treasury contribute approximately

[26]Note also that standard FEVD formula for the informational time series can be obtained by multiplying the FEVD results in table 2 by the R^2 values listed in table 1. See BBE for more details.

6.3, 4.7, 6.4, 0.9, 0.5, and 1.6 percent to the one-day forecast error variance for HDI US, HDI CA, HDI FL, HDI NY, HDI TX, and the HDI Geographic Risk Premium, respectively. Moreover, the unconventional monetary shocks explain a substantially larger portion of the forecast error variance for California and Florida relative to New York and Texas; suggesting, as above, that the effects of unconventional monetary policy shocks differ across geographies and are largest for more speculative housing markets. Lastly, our FEVD findings also imply that the effects of unconventional monetary policy shocks attenuate fairly quickly and have a minimal long-run impact on key housing and real estate variables.

4 Extensions and Robustness Checks

In this section, we analyze a number of extensions to assess the robustness of our main results. More specifically, these extensions include various alternative specifications for the observed and latent factors, a stricter definition of monetary events as suggested by those in table 3, and a different formulation for the Housing Distress Indices. Overall, the findings from this section are substantially similar to those estimated above. Accordingly, the results in this section highlight the robustness of our results to various alternative specifications for the FAVAR model, a different set of dates used for identification of the structural shocks, and alternative data methodologies.

4.1 Fannie Mae MBS Yields as an Observed Factor

First, we use the yields on Fannie Mae MBS, rather than the AAA and BAA corporate bond yields, in our set of observed factors. Thus, the corporate bond yields are relegated to the set of informational time series, X_t. Figure 7 in appendix E displays the dynamic responses for the real estate and housing variables. Overall, the results are substantially similar to those from section 3. Hence, our main findings are robust to the use of the Fannie MBS yields, rather than the corporate bond yields, in our set of observed factors.

4.2 Fannie Mae MBS Yields and the Fannie Mae Commitment Rate as Observed Factors

Next, we let the set of observed factors include the Fannie Mae MBS yields and the Fannie Mae commitment rate. Thus, our reduced-form VAR model will consist of 11

variables in total; six observed factors and five latent factors. Figure 8 in appendix E displays the dynamic responses for the housing and real estate variables. Overall, the results are qualitatively similar to those discussed above; indicating that our findings are robust to the use of the Fannie Mae MBS yields and the Fannie Mae commitment rate as observed factors.

4.3 Only Government Securities used as Observed Factors

In this section, the set of observed factors only includes the yields on US government securities: The 2- and 10-year Treasuries, five-year TIPS breakeven, and the forward-five-to-10-year TIPS breakeven. Thus, the reduced-form VAR estimated using equation 3 contains only 9 variables including the latent factors. The structural Impulse Response Functions for the housing and real estate market variables are presented in figure 9 in appendix E. In general, the shape and magnitude of the IRFs are substantially similar to those estimated above. This implies that the use of only the yields on government securities in the set of observed factors does not affect our results.

4.4 Alternative Latent Factor Specification

We also consider an alternative latent factor specification. Specifically, seven latent factors, rather than five latent factors, are used in the estimation of the FAVAR model. This implies that we will use 13 variables in our reduced-form VAR from equation 3. Figure 10 in appendix E shows the results. The IRFs are qualitatively similar to those estimated above, but the effects are slightly larger in magnitude. Overall, our findings appear robust to different specifications for the number of latent factors in the FAVAR model.

4.5 Major Events

Here, only major policy events are used to identify the structural monetary shocks. These events are listed in table 3. The corresponding IRFs for the housing market variables are presented in figure 11 in appendix E. In general, the IRFs are similar in shape to those estimated above, but the effects are larger in magnitude. Overall, these larger estimated effects are not surprising and are in line with the previous literature. Indeed, Wright (2012) finds that the change in the yields on corporate debt securities is over twice as

large in response to an identified monetary shock when he considers only major policy events similar to those listed in table 3.

4.6 Log Detrended HDIs

In the last robustness check, we consider an alternative formulation for the HDIs. More specifically, the HDIs are now computed as the log of the cumulative returns of each HDI detrended using a 100 day moving average. The results are displayed in figure 12 in appendix E. Overall, the results are substantially similar to those discussed above and indicate that expansionary unconventional monetary policy shocks lower housing distress but that the results are asymmetric across US states. Indeed, as evidenced by the dynamic response for the HDI Geographic Risk Premium, the monetary shock leads to larger reductions in housing distress for California and Florida. Further, the effects attenuate rather quickly and nearly completely dissipate after 200 days.

5 Conclusion

In this paper, we use a structural factor-augmented vector autoregression (FAVAR) model to study the impact of unconventional monetary policy on real estate and related markets. The use of the FAVAR framework allows us to consider a large number of daily real estate, housing, and financial time series; this yields a more accurate measurement of monetary policy shocks and reduces the potential for omitted variable bias often found in standard VARs (BBE, BGM). To facilitate identification, we assume that the structural monetary shock is heteroskedastic across event and non-event days. In more intuitive terms, this assumption is based on the notion that news regarding monetary policy is revealed to markets in "lumpy manner" (Wright (2012)). Together, this econometric methodology provides key insights into the relationship between unconventional monetary policy and real estate markets.

Our results indicate that expansionary unconventional monetary policy shocks reduce housing and mortgage interest rates; lead to excess equity returns for stock market indices based on homebuilders and REITs relative to the S&P500; reduce the cost to insure subprime mortgage debt and commercial real estate debt; and lower housing distress. Research findings further suggest that the effects of unconventional monetary shocks differ in

magnitude across risk-levels and geographies. For example, we find that a surprise monetary easing leads a large reduction in the cost to insure higher-rated subprime mortgage debt via the dynamic response of the AAA ABX index, but that unconventional monetary policy has little impact on the lower rated AA ABX index. Moreover, the results with regard to housing and mortgage market sentiment as measured by housing distress differ in magnitude across US states. Specifically, a surprise unconventional monetary easing leads to a much lower growth rate in indices of housing distress for California and Florida markets relative to those for New York and Texas. Thus, unconventional monetary policy appears to have a larger impact on more speculative local housing markets. Further, we find that the contribution of monetary shocks to the forecast error variance for key real estate variables is large in magnitude and similar to that found in equity markets; indicating that the size of the effects associated with monetary policy shocks is similar for both equity and real estate markets. Finally, findings indicate that the estimated half-life of the effects is generally less than three months. Overall, the results in this paper provide new evidence highlighting the importance of unconventional monetary policy actions during the 2000s recession and aftermath in support of ailing real estate markets.

References

[1] B. S. Bernanke, J. Boivin, and P. Eliasz. Measuring the effects of monetary policy: a factor-augmented vector autoregressive (favar) approach. *The Quarterly Journal of Economics*, 120(1):387–422, 2005.

[2] J. Boivin, M. P. Giannoni, and I. Mihov. Sticky prices and monetary policy: Evidence from disaggregated us data. *The American Economic Review*, 99(1):pp. 350–384, 2009.

[3] D. Bowman, F. Cai, S. Davies, and S. Kamin. *Quantitative easing and bank lending: evidence from Japan*. Board of Governors of the Federal Reserve System, 2011.

[4] M. Chauvet, S. Gabriel, and C. Lutz. Fear and loathing in the housing market: Evidence from search query data. *Working Paper*, 2013.

[5] S.-S. Chen. Does monetary policy have asymmetric effects on stock returns? *Journal of Money, Credit and Banking*, 39(2-3):667–688, 2007.

[6] H. Choi and H. Varian. Predicting the Present with Google Trends. *Economic Record*, 88(s1):2–9, 2012.

[7] S. D'Amico, W. English, D. López-Salido, and E. Nelson. The federal reserve's large-scale asset purchase programmes: Rationale and effects. *The Economic Journal*, 122(564):F415–F446, 2012.

[8] S. D'Amico and T. B. King. Flow and stock effects of large-scale treasury purchases: Evidence on the importance of local supply. *Journal of Financial Economics*, 108(2):425–448, 2013.

[9] A. P. Dempster, N. M. Laird, D. B. Rubin, et al. Maximum likelihood from incomplete data via the em algorithm. *Journal of the Royal statistical Society*, 39(1):1–38, 1977.

[10] T. Doh. The efficacy of large-scale asset purchases at the zero lower bound. *Federal Reserve Bank of Kansas City Economic Review*, 95(2):5–34, 2010.

[11] B. Duygan-Bump, P. Parkinson, E. Rosengren, G. A. Suarez, and P. Willen. How effective were the federal reserve emergency liquidity facilities? evidence from the asset-backed commercial paper money market mutual fund liquidity facility. *Journal of Finance*, 68(2):715–737, 2013.

[12] A. Fuster and P. S. Willen. $1.25 trillion is still real money: Some facts about the effects of the federal reserve's mortgage market investments. Technical report, Public policy Discussion Papers, Federal Reserve Bank of Boston, 2010.

[13] J. Gagnon, M. Raskin, J. Remache, and B. Sack. The financial market effects of the federal reserves large-scale asset purchases. *International Journal of Central Banking*, 7(1):3–43, 2011.

[14] R. Glick and S. Leduc. The effects of unconventional and conventional us monetary policy on the dollar. *Manuscript, Federal Reserve Bank of San Francisco*, 2013.

[15] R. S. Gürkaynak, B. Sack, and J. H. Wright. The tips yield curve and inflation compensation. *American Economic Journal: Macroeconomics*, pages 70–92, 2010.

[16] J. D. Hamilton and J. C. Wu. The effectiveness of alternative monetary policy tools in a zero lower bound environment. *Journal of Money, Credit and Banking*, 44(s1):3–46, 2012.

[17] D. Hancock and S. W. Passmore. The federal reserve's portfolio and its effects on mortgage markets. *Working Paper*, 2012.

[18] D. Hancock and W. Passmore. Did the federal reserve's mbs purchase program lower mortgage rates? *Journal of Monetary Economics*, 58(5):498–514, 2011.

[19] D. Hancock and W. Passmore. How the federal reserves large-scale asset purchases (lsaps) influence mortgage-backed securities (mbs) yields and us mortgage rates. Technical report, Board of Governors of the Federal Reserve System (US), 2014.

[20] J. Honaker and G. King. What to do about missing values in time-series cross-section data. *American Journal of Political Science*, 54(2):561–581, 2010.

[21] L. Kilian. Small-sample confidence intervals for impulse response functions. *Review of Economics and Statistics*, 80(2):218–230, 1998.

[22] A. Krishnamurthy and A. Vissing-Jorgensen. The effects of quantitative easing on interest rates: Channels and implications for policy. *Brookings Papers on Economic Activity*, pages 215–287, 2011.

[23] A. Kurov. Investor sentiment and the stock markets reaction to monetary policy. *Journal of Banking & Finance*, 34(1):139–149, 2010.

[24] S. Kwan. Inflation expectations: how the market speaks. *FRBSF Economic Letter*, 2005.

[25] C. J. Neely. The large-scale asset purchases had large international effects. *Federal Reserve Bank of St. Louis Working Paper Series*, 2010.

[26] D. N. Politis and J. P. Romano. The stationary bootstrap. *Journal of the American Statistical Association*, 89(428):1303–1313, 1994.

[27] R. Rigobon. Identification through heteroskedasticity. *Review of Economics and Statistics*, 85(4):777–792, 2003.

[28] R. Rigobon and B. Sack. Measuring the reaction of monetary policy to the stock market. *The Quarterly Journal of Economics*, 118(2):639–669, 2003.

[29] R. Rigobon and B. Sack. The impact of monetary policy on asset prices. *Journal of Monetary Economics*, 51(8):1553–1575, 2004.

[30] R. Rigobon and B. Sack. The effects of war risk on us financial markets. *Journal of Banking and Finance*, 29(7):1769–1789, 2005.

[31] C. A. Sims. Interpreting the macroeconomic time series facts: the effects of monetary policy. *European Economic Review*, 36(5):975–1000, 1992.

[32] J. H. Stock and M. W. Watson. Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2):147–162, 2002.

[33] E. T. Swanson. Let's twist again: A high-frequency event-study analysis of operation twist and its implications for qe2. *Brookings Papers on Economic Activity*, pages 151–207, 2011.

[34] E. T. Swanson and J. C. Williams. Measuring the effect of the zero lower bound on medium- and longer-term interest rates. *American Economic Review*, 104(10):3154–3185, 2014.

[35] J. H. Wright. What does monetary policy do to long-term interest rates at the zero lower bound? *The Economic Journal*, 122(564):F447–F466, 2012.

A Tables

Table 1: Portion of the Variation of the Informational Time Series explained by the Latent and Observed Factors

	R^2	R^2 Adj
10 Year Yield Curve	1.000	1.000
30 Year Yield Curve	0.948	0.948
BAA Corp - AAA Corp	1.000	1.000
S&P500 Returns	0.941	0.940
DJIA Returns	0.908	0.907
VIX	0.876	0.875
XHB Stock Returns	0.826	0.825
FRI Stock Returns	0.752	0.750
ABX AAA	0.969	0.969
ABX AA	0.571	0.567
ABX Risk Premium	0.965	0.965
CMBX AAA	0.914	0.913
USD/JPY	0.625	0.621
USD/EURO	0.901	0.900
USD/GBP	0.875	0.874
Fannie MBS	0.974	0.974
Fannie MBS - 30 Year Treas	0.820	0.818
Fannie Commitment Rate	0.964	0.964
HDI US	0.766	0.764
HDI CA	0.537	0.533
HDI FL	0.520	0.516
HDI NY	0.519	0.515
HDI TX	0.528	0.523
HDI Risk Premium	0.998	0.998

Notes: R^2 and adjusted R^2 statistics from a regression of a given variable in the set of the informational time series (left column) on the five latent factors and the set of observed factors.

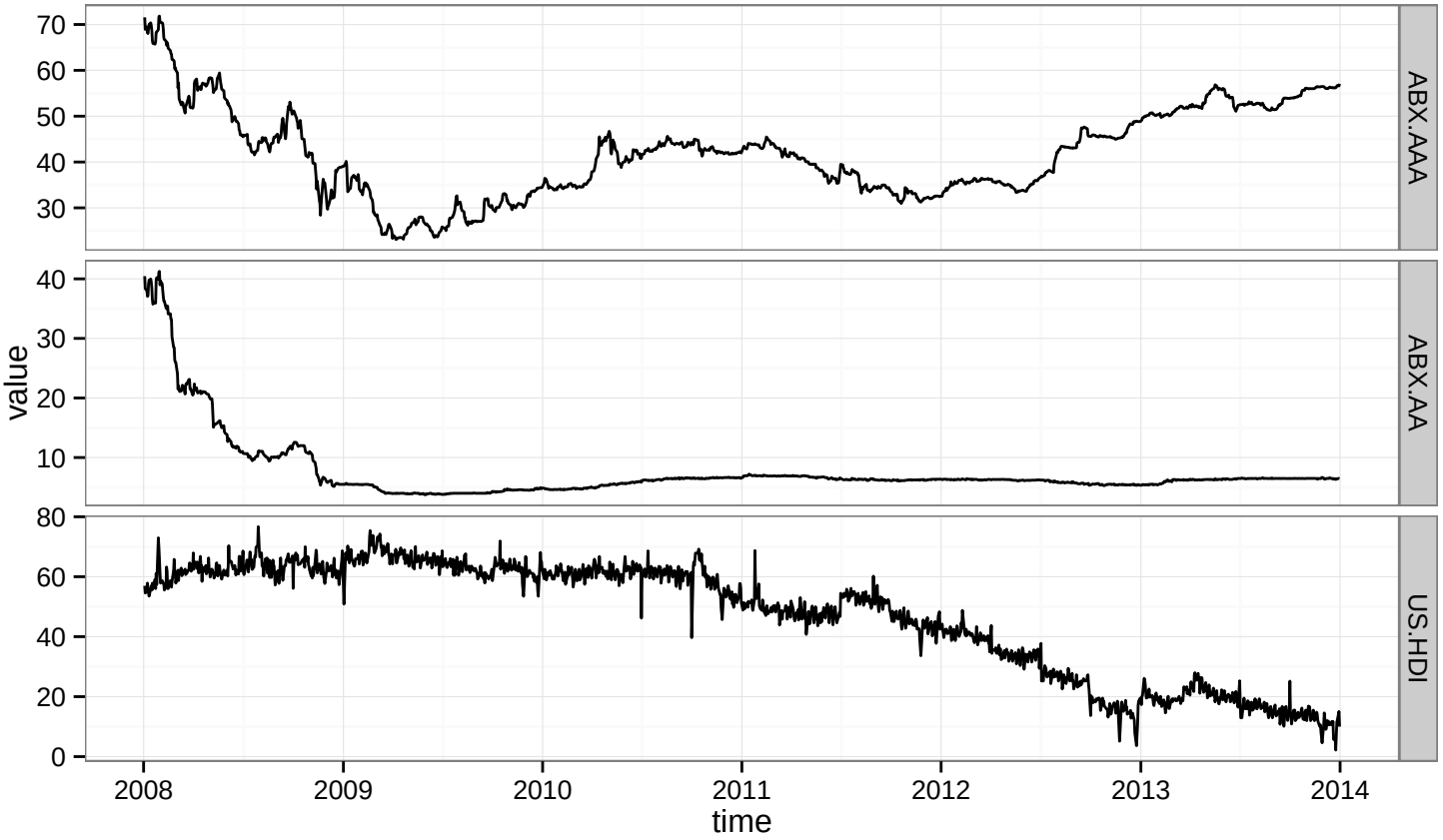
Table 2: Forecast Error Variance Decomposition

	Forecast Horizon (In Days)					
	1 Day	50 Days	100 Days	250 Days	500 Days	750 Days
2 Year Treasury	0.089	0.184	0.201	0.195	0.186	0.184
10 Year Treasury	0.100	0.079	0.068	0.053	0.048	0.047
AAA Corporate Yields	0.012	0.044	0.053	0.050	0.046	0.046
BAA Corporate Yields	0.011	0.070	0.107	0.126	0.126	0.125
5 Year Breakeven	0.003	0.012	0.018	0.026	0.028	0.028
5-10 Forward Breakeven	0.014	0.007	0.009	0.014	0.015	0.016
	Informational Time Series					
10 Year Yield Curve	0.054	0.009	0.004	0.000	0.000	0.000
30 Year Yield Curve	0.001	0.000	0.000	0.000	0.000	0.000
BAA Corp - AAA Corp	0.339	0.079	0.066	0.023	0.003	0.000
S&P500 Returns	0.519	0.000	0.000	0.000	0.000	0.000
DJIA Returns	0.516	0.000	0.000	0.000	0.000	0.000
VIX	0.467	0.009	0.005	0.001	0.000	0.000
XHB Stock Returns	0.524	0.000	0.000	0.000	0.000	0.000
FRI Stock Returns	0.513	0.000	0.000	0.000	0.000	0.000
ABX AAA	0.483	0.187	0.104	0.030	0.002	0.000
ABX AA	0.007	0.035	0.021	0.006	0.000	0.000
ABX Risk Premium	0.476	0.151	0.084	0.024	0.002	0.000
CMBX AAA	0.418	0.123	0.074	0.019	0.001	0.000
USD/JPY	0.149	0.003	0.001	0.001	0.000	0.000
USD/EURO	0.115	0.002	0.004	0.001	0.000	0.000
USD/GBP	0.139	0.000	0.000	0.000	0.000	0.000
Fannie MBS	0.404	0.081	0.039	0.004	0.000	0.000
Fannie MBS - 30 Year Treas	0.182	0.023	0.010	0.003	0.000	0.000
Fannie Commitment Rate	0.547	0.089	0.044	0.004	0.000	0.000
HDI US	0.063	0.000	0.000	0.000	0.000	0.000
HDI CA	0.047	0.000	0.000	0.000	0.000	0.000
HDI FL	0.064	0.000	0.000	0.000	0.000	0.000
HDI NY	0.009	0.000	0.000	0.000	0.000	0.000
HDI TX	0.005	0.000	0.000	0.000	0.000	0.000
HDI Risk Premium	0.016	0.000	0.000	0.000	0.000	0.000

Notes: This table shows the forecast error variance decomposition (FEVD) for the observed factors and the informational time series. The FEVD is the portion of the forecast error variance explained by the monetary policy shock. The size of the monetary shock is normalized so that the FEVD for the 10-year Treasury is 10 percent (0.100). The FEVD for the informational time series is calculated as in BBE.

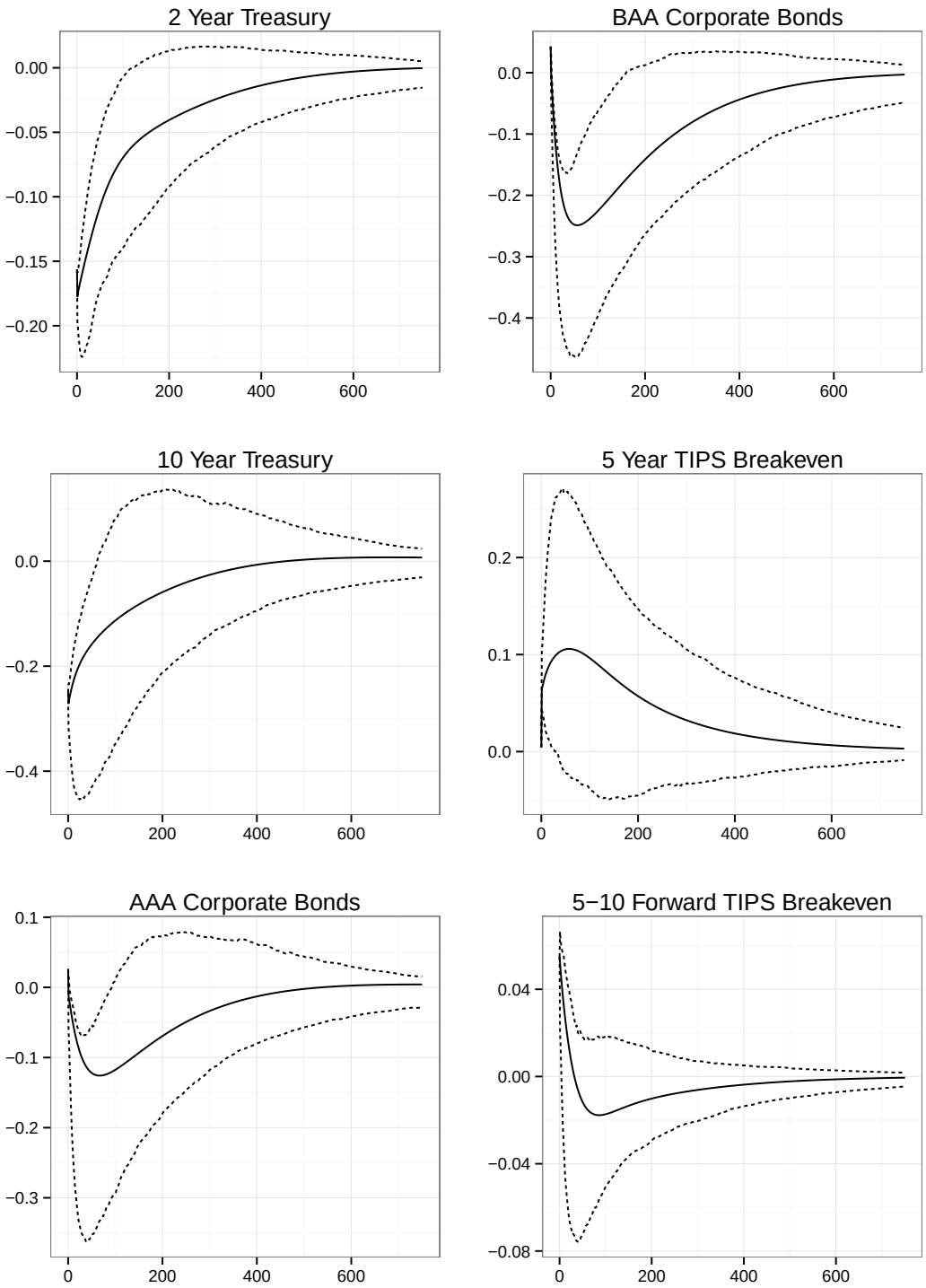
B Figures

Figure 1: Plots of ABX and HDI Indices



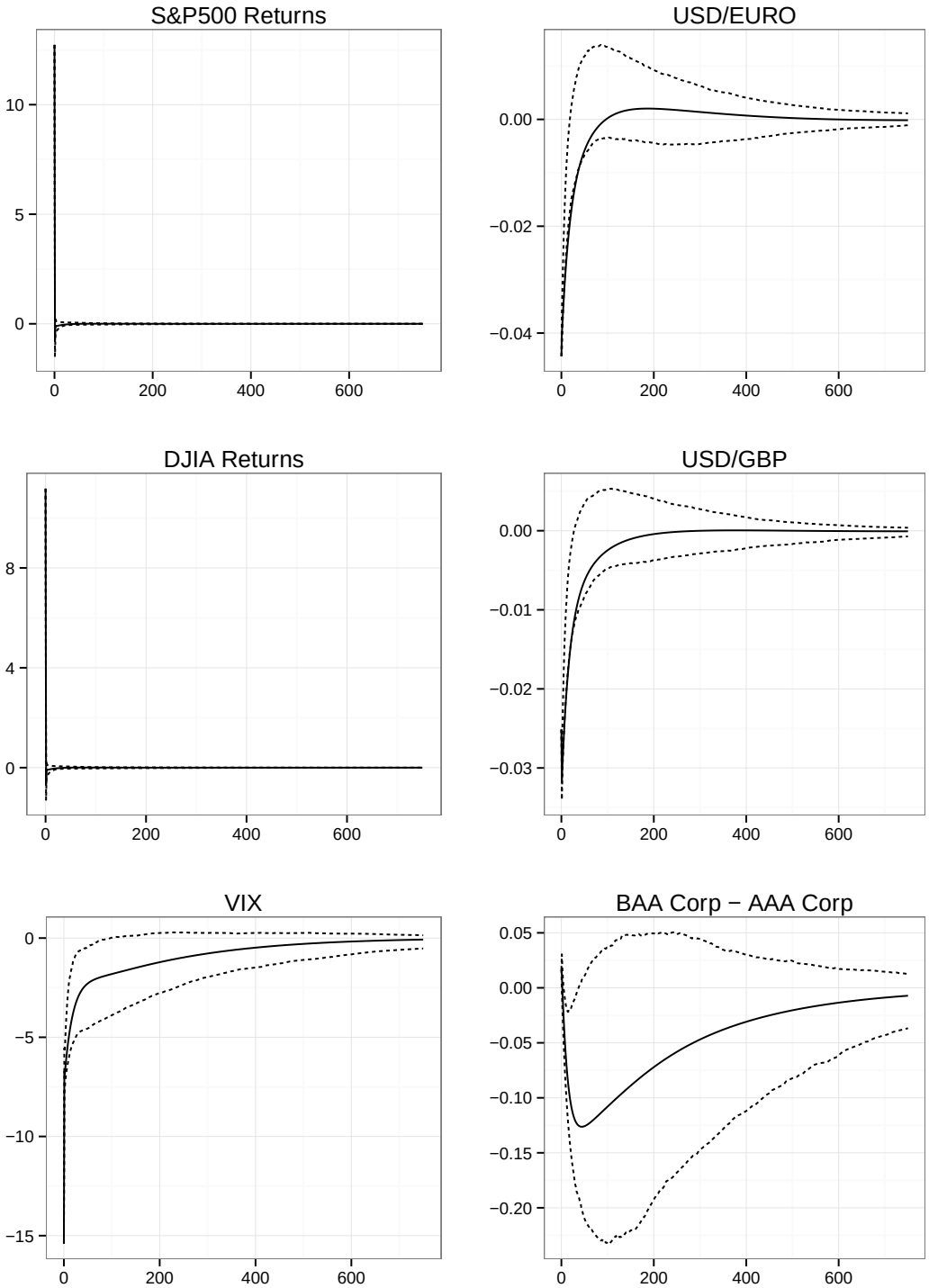
Notes: Plots of the daily ABX and HDI indices. The HDI is normalized so that December 31, 2013 has a value of 10.

Figure 2: Estimated Impulse Responses of Interest Rates to an Identified Unconventional Monetary Policy Shock – Full Sample



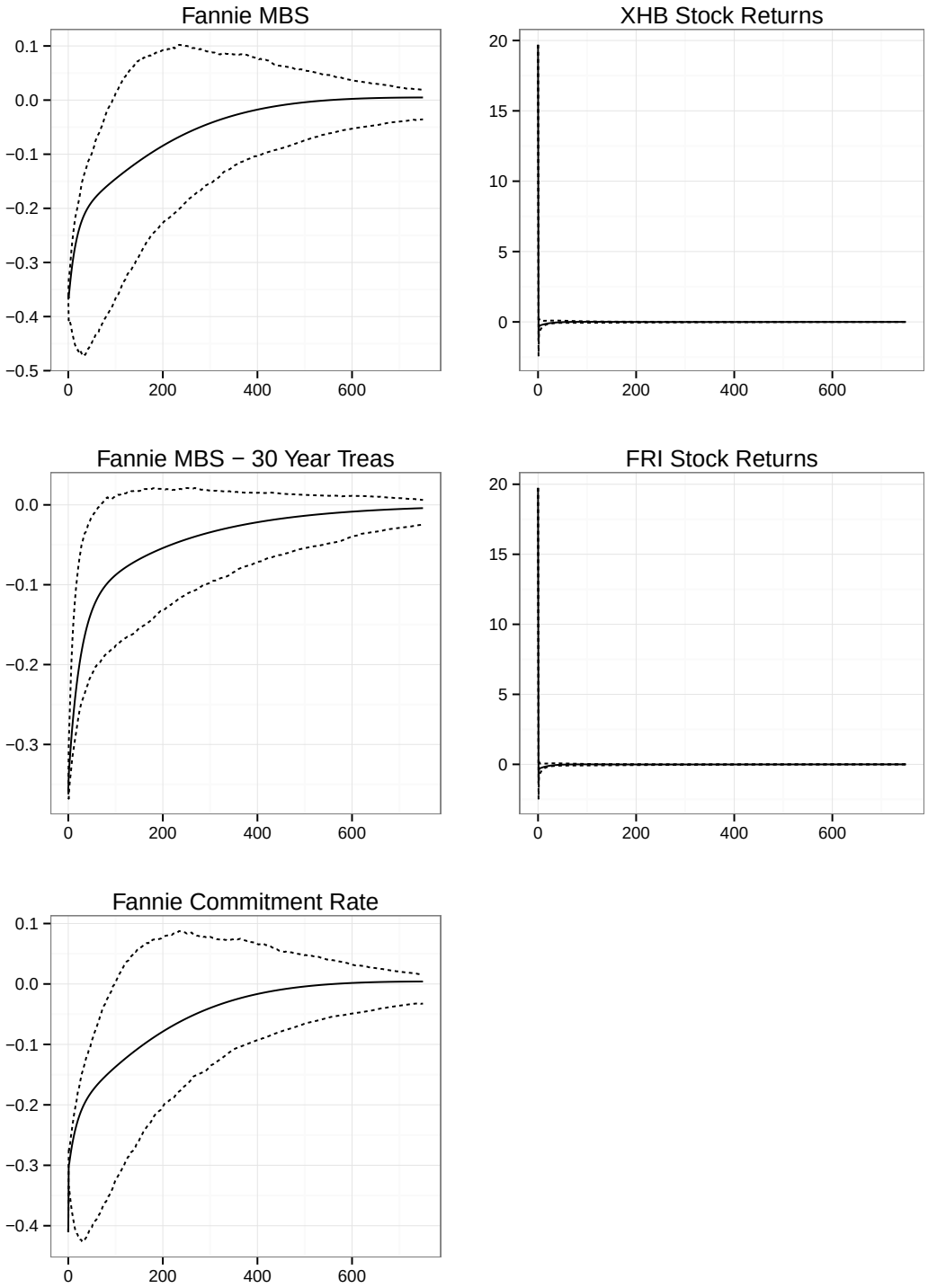
Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points.

Figure 3: Estimated Impulse Responses of Financial Variables to an Identified Unconventional Monetary Policy Shock – Full Sample



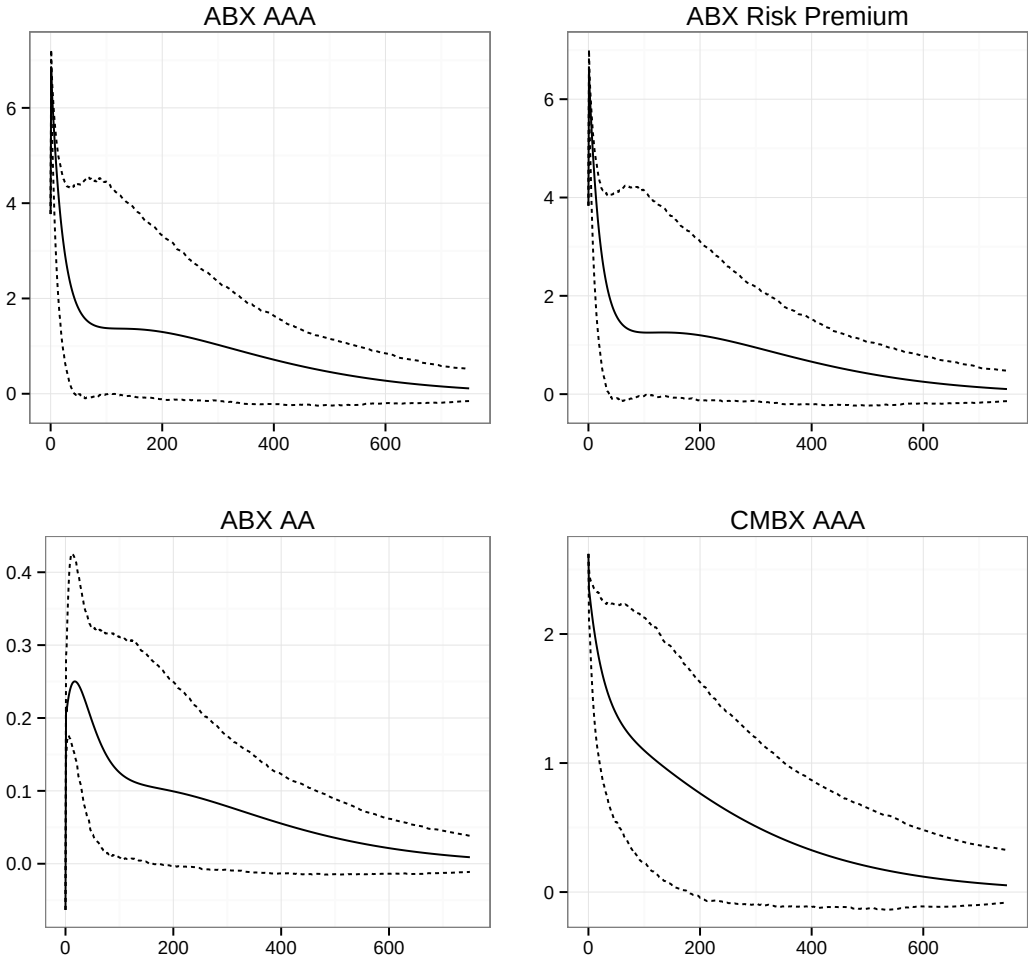
Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points.

Figure 4: Estimated Impulse Responses of Housing Variables to an Identified Unconventional Monetary Policy Shock – Full Sample



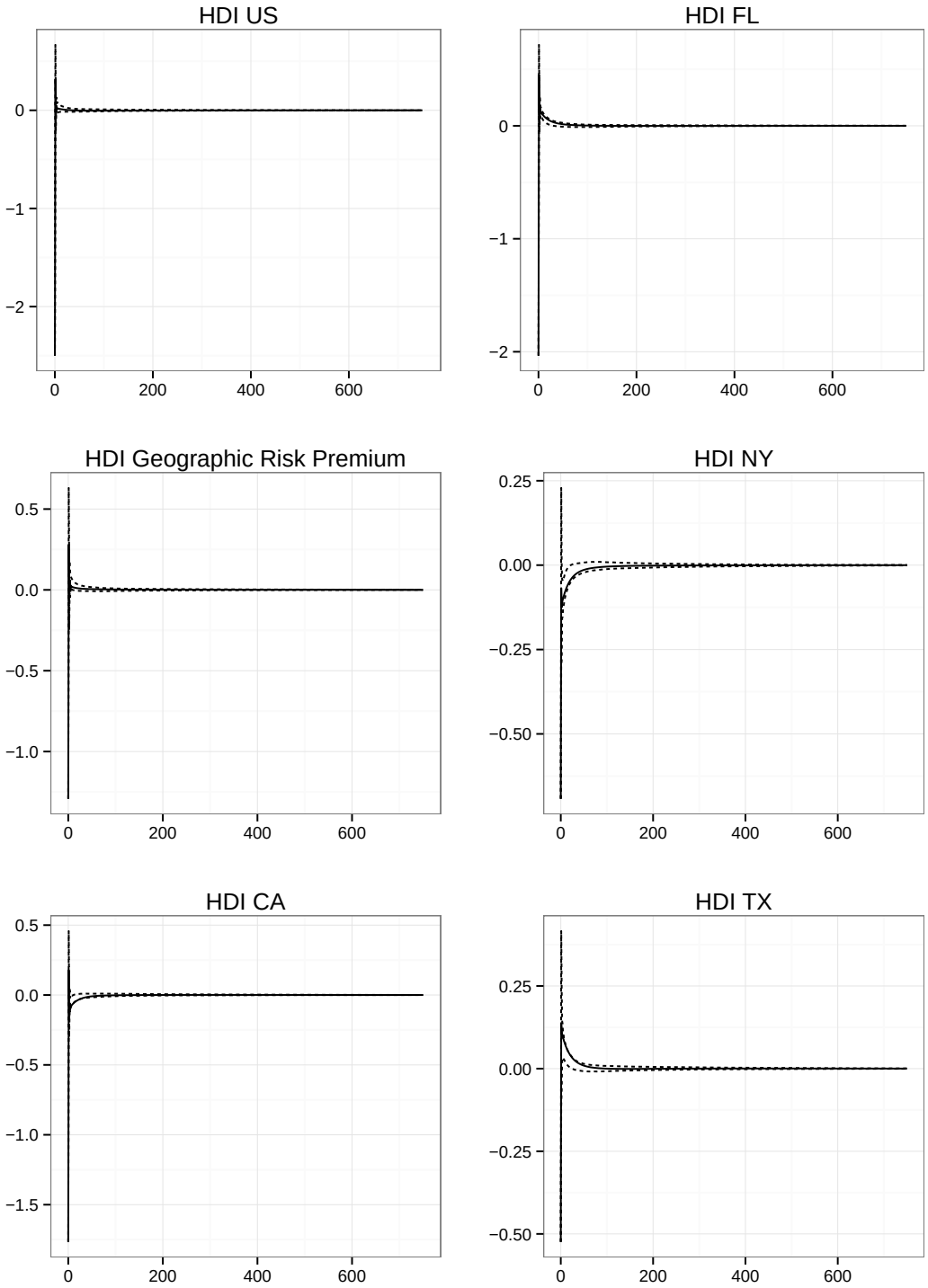
Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points.

Figure 5: Estimated Impulse Responses of CDS Variables to an Identified Unconventional Monetary Policy Shock – Full Sample



Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points.

Figure 6: Estimated Raw Impulse Responses of HDI Variables to an Identified Unconventional Monetary Policy Shock – Full Sample



Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points.

C Monetary Policy Events–For Online Publication Only

Table 3: Major QE Events

Event Date	Time (EST)	QE Round	Event	Event Description
11/25/2008	8:15 AM	1	QE1 Announcement	FOMC announces planned purchases of $100 billion of GSE debt and up to $500 billion in MBS
12/1/2008	1:40 PM	1	Bernanke Speech In Texas	Bernanke announces that the Fed may purchase long-term US Treasuries
12/16/2008	2:15 PM	1	FOMC Statement	FOMC first suggests that long-term US Treasuries may be purchased
1/28/2009	2:15 PM	1	FOMC Statement	FOMC indicates that it will incrase its purchases of agency debt and long-term US Treasuries
3/18/2009	2:15 PM	1	FOMC Statement	FOMC announces that will purchase an additional $750 billion in agency MBS, up to an additional $100 billion of agency debt, and up to $300 billion of long-term US Treasuries
8/10/2010	2:15 PM	2	FOMC Statement	FOMC announces that it will roll over the Fed's holdings of US Treasuries
8/27/2010	10:00 AM	2	Bernanke Speech In Jackson Hole	Bernanke signals that monetary easing will be continued
9/21/2010	2:15 PM	2	FOMC Statement	FOMC announces that it will roll over the Fed's holdings of US Treasuries
10/15/2010	8:15 AM	2	Bernanke Speech at Boston Fed	Bernanke signals that monetary easing will be continued
11/3/2010	2:15 PM	2	FOMC Statement	FOMC announces it plan to purchase $600 billion of long-term US Treasuries by the end of the 2011 Q2
8/31/2012	10:00 AM	3	Bernanke Speech at Jackson Hole	Bernanke announces intention for further monetay easing
9/13/2012	12:30 PM	3	FOMC Statement	FOMC announces that it will expand its QE policies by purchasing mortgaged-backed securities at a rate of $40 billion per month
12/12/2012	12:30 PM	3	FOMC Statement	FOMC extends monthly purchases to long-term Treasuries and announces numerical threshold targets
5/22/2013	10:00 AM	Taper	Bernanke Congressional Testimony	Bernanke first signals that FOMC may reduce its quantitative stimulus
6/19/2013	2:15 PM	Taper	Bernanke Press Conference & FOMC statement	Bernanke suggests that the FOMC will moderate asset purchases later in 2013
12/12/2013	2:00 PM	Taper	FOMC Statement	FOMC announces that it will reduce its purchases of longer term Treasuries and mortgage-backed securities by $10 billion dollars per month

Notes: Major FOMC announcements or speeches by Chairman Bernanke. Event dates, times, and descriptions updated from Glick and Leduc (2013).

D Data Appendix–For Online Publication Only

Table 1: Data List

Variable	Description	Source	Symbol	Transformation
	Observed Factors			
2 Year Treasury	USD Treasury Actives Zero Coupon Yield 2 Year	Bloomberg	I02502Y	none
10 Year Treasury	USD Treasury Actives Zero Coupon Yield 10 Year	Bloomberg	I02510Y	none
5 Year Breakeven	Five year TIPS breakeven	Bloomberg		none
5-10 Forward Breakeven	Five-to-ten-year forward TIPS breakeven	Bloomberg		none
AAA Corporate Bond Yields	Moody's Seasoned AAA Corporate Bond Yield	Bloomberg	MOODCAAA	none
BAA Corporate Bond Yields	Moody's Seasoned BAA Corporate Bond Yield	Bloomberg	MOODCBAA	none
	Intformational Time Series			
10 Year Yield Curve	Yield Curve – 10 Year Treasury versus 2 Year Treasury	Bloomberg		none
30 Year Yield Curve	Yield Curve – 30 Year Treasury versus 2 Year Treasury	Bloomberg		none
MOODCBAA - MOODCAAA	BAA - AAA Corporate Bond Risk Premium	Bloomberg		none
S&P500	S&P500 Stock Market Index	FRED	SP500	return
Dow Jones Industrial Average	DJIA Stock Market Index	FRED	DJIA	return
VIX	CBOE Volatility Index - VIX	FRED	VIXCLS	none
XHB	SPDR S&P Homebuilders ETF	Yahoo	XHB	return
FRI	First Trust S&P REIT ETF	Yahoo	FRI	return

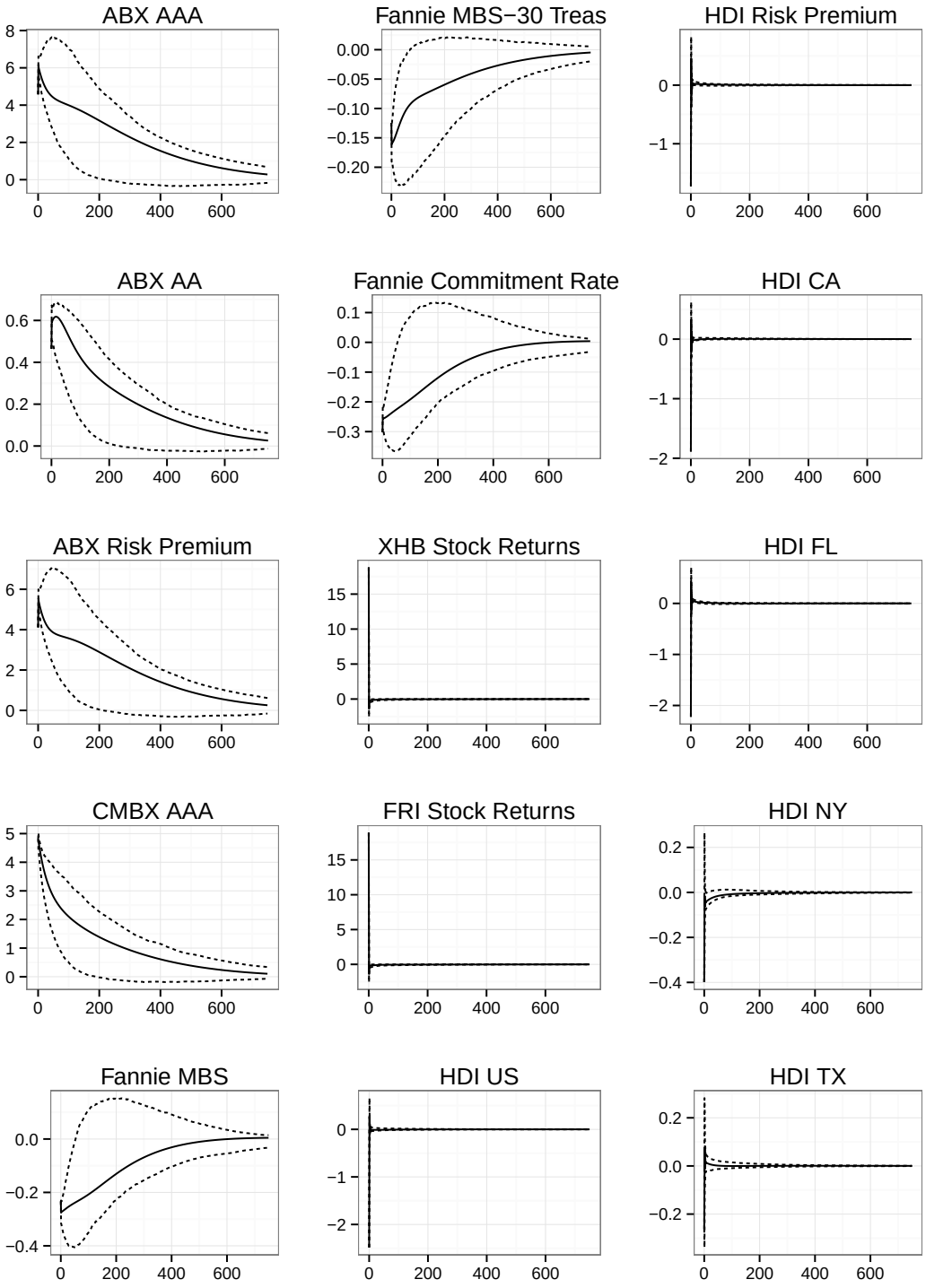
Notes: **Continued on next page.** Observed factors and informational time series. Transformations from Wright (2012), BBE, BGM, and Stock and Watson (2002).

Table 2 Continued

Variable	Description	Source	Symbol	Transformation
ABX AAA	ABX Index for AAA rated securities issued in the second half of 2007	Bloomberg	ABX.HE.AAA.07-2	none
ABX AA	ABX Index for AA rated securities issued in the second half of 2007	Bloomberg	ABX.HE.AA.07-2	none
ABX AAA - ABX AA	MBS CDS Risk Premium	Bloomberg		none
CMBX AAA	CMBX Index for AAA rated securities for the second half of 2006	Bloomberg	CBX3A11	none
HDI - National	Housing Distress Index (HDI) for the United States	Google Trends (CGL)	HDIUS	return
HDI - California	Housing Distress Index (HDI) for California	Google Trends (CGL)	HDICA	return
HDI - Florida	Housing Distress Index (HDI) for Florida	Google Trends (CGL)	HDIFL	return
HDI - New York	Housing Distress Index (HDI)for New York	Google Trends (CGL)	HDINY	return
HDI - Texas	Housing Distress Index (HDI) for Texas	Google Trends (CGL)	HDITX	return
HDI Geographic Risk Premium	mean(HDICA + HDIFL) - mean(HDINY + HDITX)	Google Trends		none
FM 30 Year Fixed Commitment rate - 60 Day	Fannie Mae Commitment Rates 30 Year Fixed Rate 60 Day	Bloomberg	FCR3060	none
Fannie Mae MBS	Fannie Mae 30-year Current-coupon MBS	Bloomberg	MTGEFNCL	none
MTGEFNCL - 30 Year Treas	Fannie Mae MBS Risk Premium	Bloomberg		none
US/Euro exchange rate		Bloomberg	USDEUR	none
US/UK exchange rate		Bloomberg	USDGBP	none
US/Yen exchange rate		Bloomberg	USDJPY	none

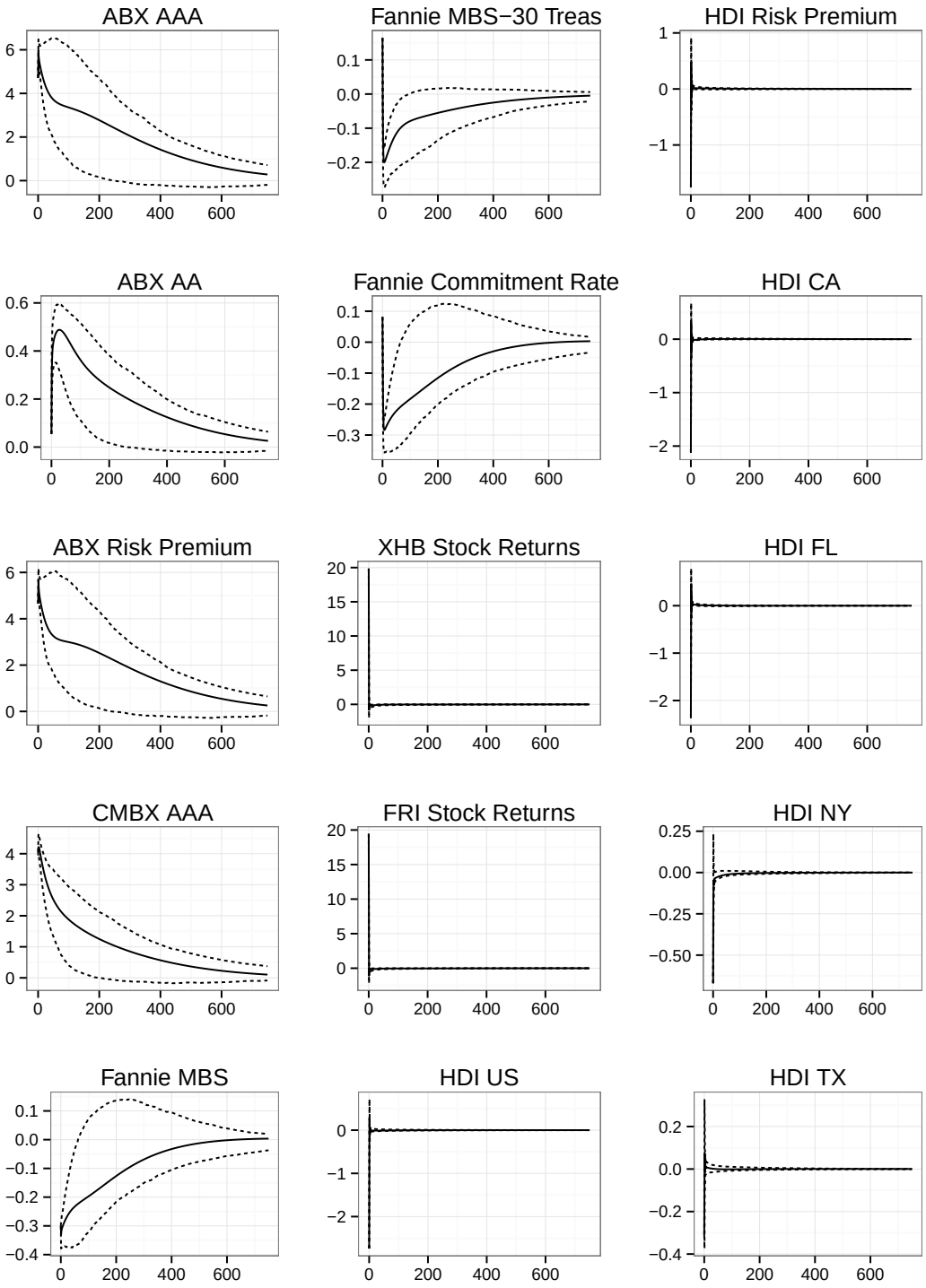
E Appendix: Extensions and Robustness Checks–For Online Publication Only

Figure 7: Estimated Impulse Responses of Housing Variables to an Identified Unconventional Monetary Policy Shock – Fannie MBS Yields as an observed factor



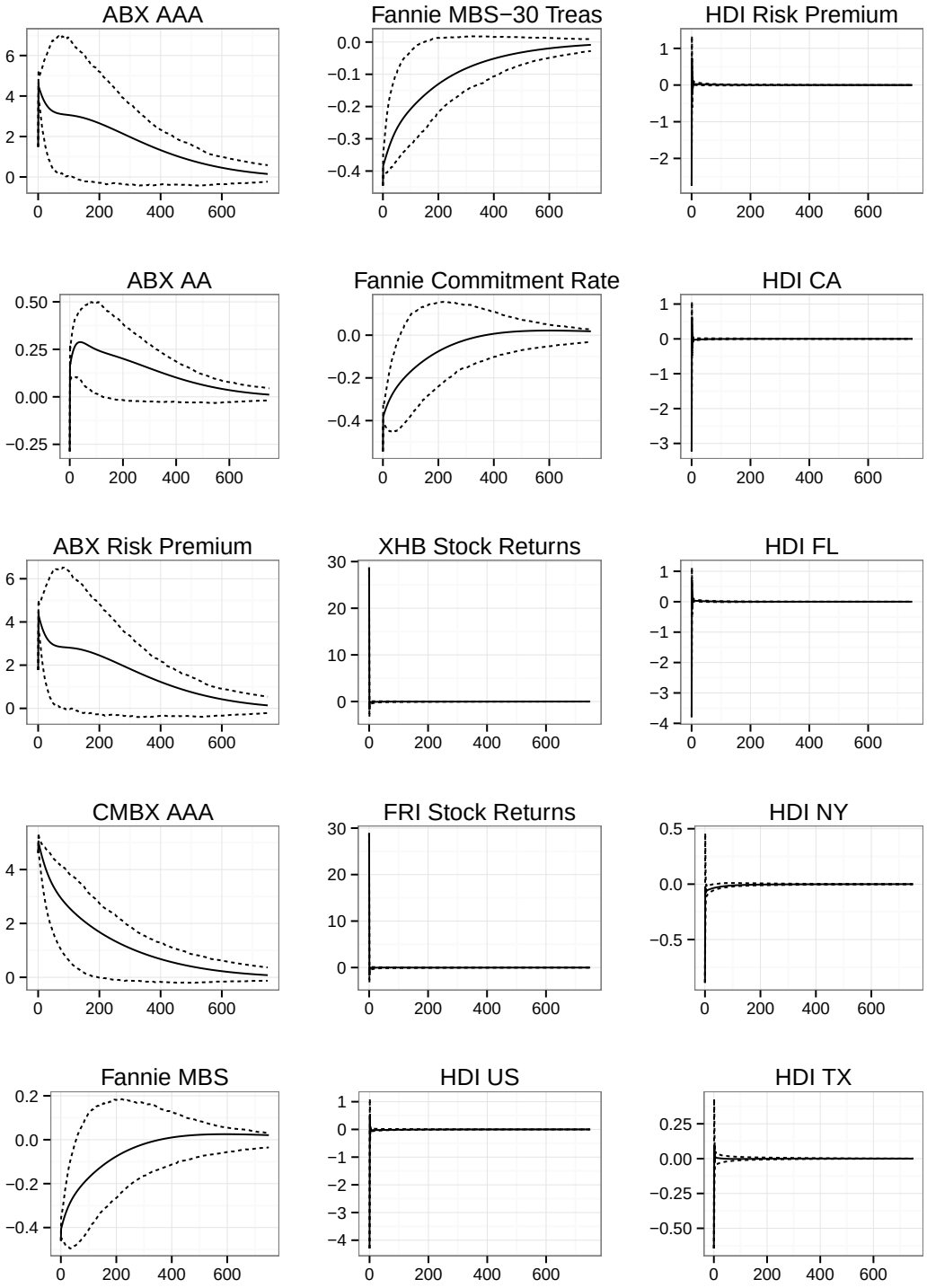
Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points. In the computation of the IRFs, the Fannie Mae MBS yields are included in the set of observed factors while the corporate bond yields are in the set of informational time series.

Figure 8: Estimated Impulse Responses of Housing Variables to an Identified Unconventional Monetary Policy Shock – Fannie MBS Yields and Fannie Commitment Rate as observed factors



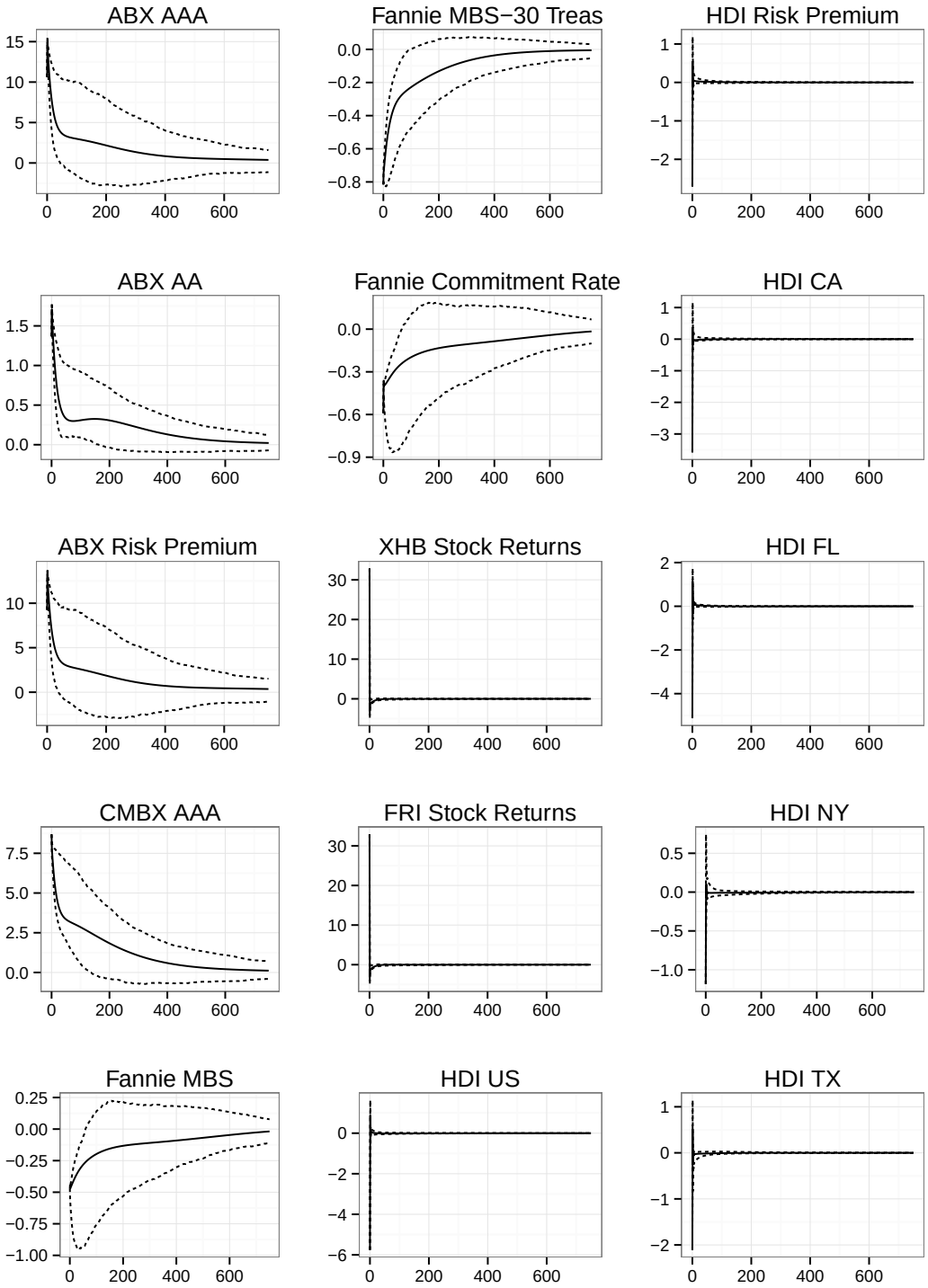
Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points. In the computation of the IRFs, the Fannie Mae MBS yields and the Fannie commitment rate are included in the set of observed factors while the corporate bond yields are in the set of informational time series.

Figure 9: Estimated Impulse Responses of Housing Variables to an Identified Unconventional Monetary Policy Shock – Only Yields on Government Bonds used as observed factors



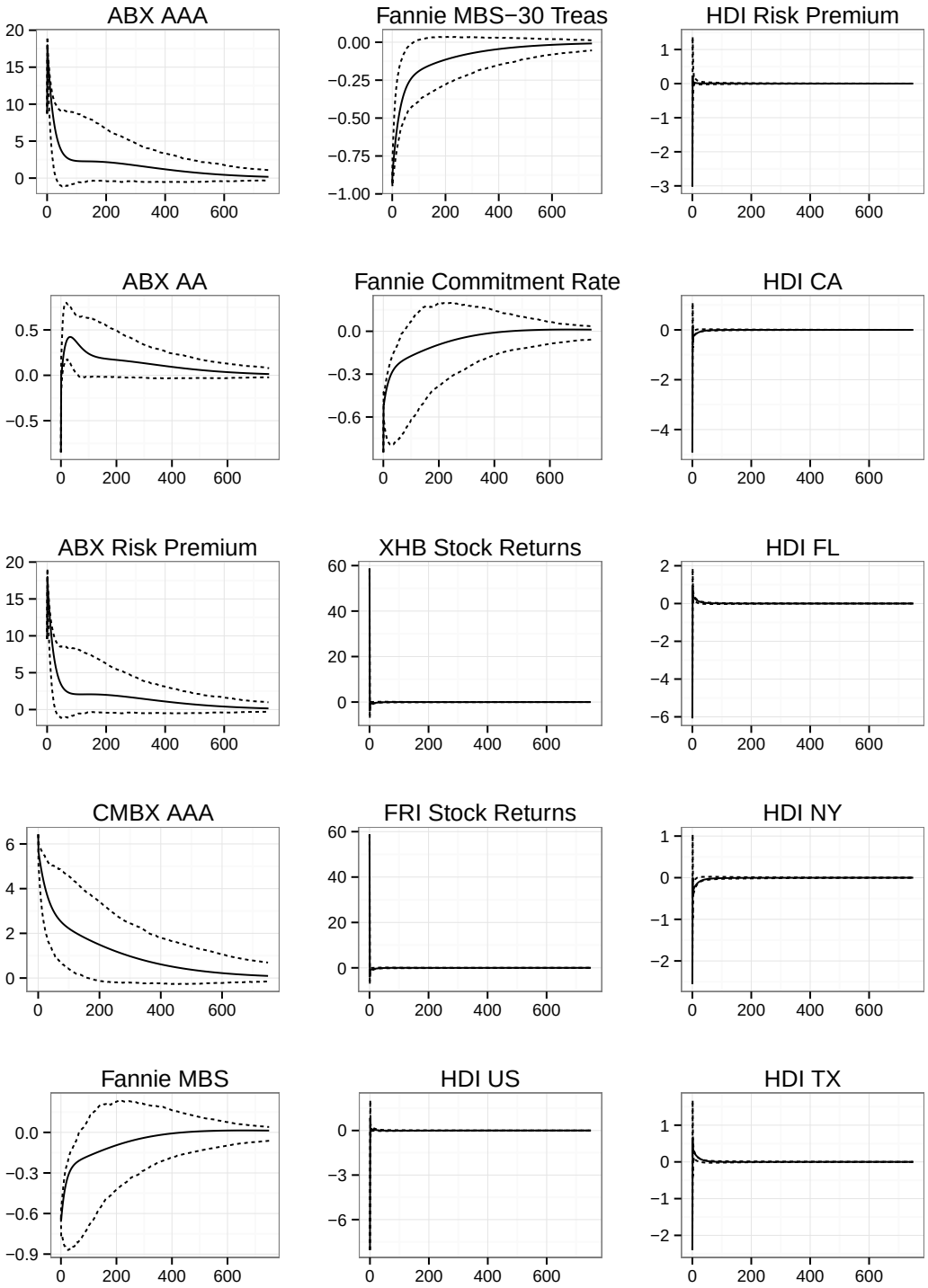
Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points. In the computation of the IRFs, only Government Bond Yields are included in the set of observed factors.

Figure 10: Estimated Impulse Responses of Housing Variables to an Identified Unconventional Monetary Policy Shock – 7 Latent Factors



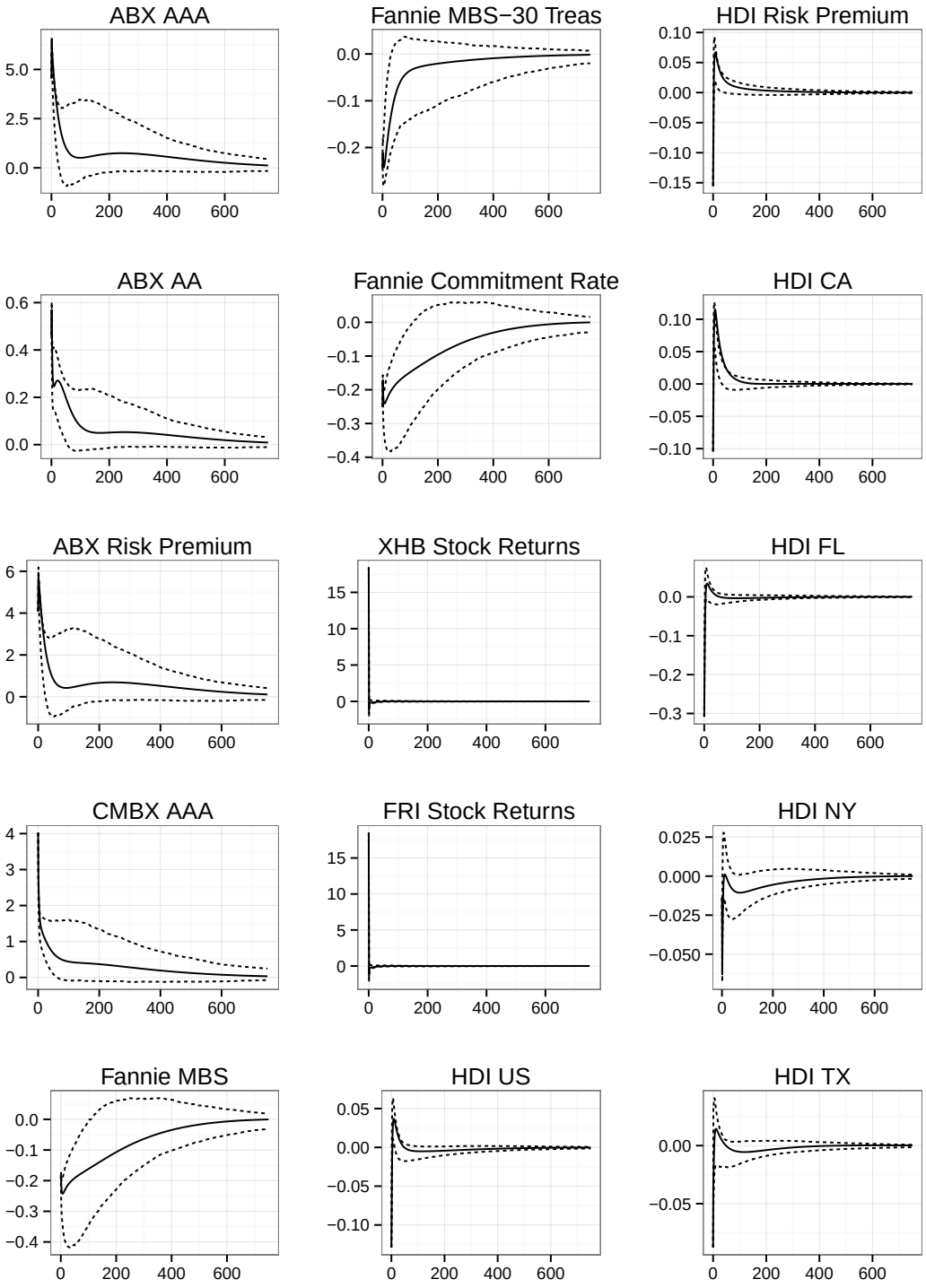
Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points.

Figure 11: Estimated Impulse Responses of Housing Variables to an Identified Unconventional Monetary Policy Shock – Major Events



Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points. The monetary events are restricted to the major announcements listed in the table 3.

Figure 12: Estimated Impulse Responses of Housing Variables to an Identified Unconventional Monetary Policy Shock – Log Detrended HDIs



Notes: Plots of the structural Impulse Response Functions. The IRFs are traced out for 750 periods and normalized so that the initial decrease in the 10-year Treasury is 25 basis points. The HDIs are log of the cumulative returns of each HDI index detrended using a 100 day moving average.

F Appendix: The ABX and CMBX Indices–For Online Publication Only

In this appendix, we briefly describe the ABX and CMBX indices. Each ABX index tracks the cost to insure a basket of 20 subprime mortgage backed securities, equally weighted. Similarly, the CMBX indices are based on the cost to insure a basket of 25 commercial mortgage-backed securities. These two measures are constructed in a similar fashion, so we'll just describe the ABX indices here.

The ABX indices are split up based on investment quality and time of issuance. The ratings are synonymous to those in the bond industry: AAA is the highest and BBB- is the lowest. The 2007-02 set of ABX indices that we use in this paper is comprised of loans made in the second half of 2007. We can interpret $(100 - ABX)$ as the upfront payment above the coupon required to insure certain mortgage loans.

To exactly understand how the ABX relates to the cost for insurance we first define the following variables:

- The value for the ABX index (ABX). The ABX is always 100 on the day of issuance.
- The $Loan$: The amount of mortgage backed securities to be insured.
- The $Coupon$: The annual fixed payment for the insurance, reported in basis points.
- The $Factor$: The proportion of the principal currently outstanding. This equals one on the day of issuance.

Using the above variables we can calculate the cost to insure a given amount of mortgage backed securities:

$$\begin{aligned} \text{Insurance Cost} &= (100 - ABX) \cdot Loan \cdot Factor + Loan \cdot Factor \cdot Coupon \\ &= (100 - ABX + Coupon) \cdot Loan \cdot Factor \end{aligned} \tag{9}$$

The derivative of equation 9 with respect to ABX is negative. Hence, it becomes more costly to insure mortgage backed securities as ABX falls. In other words, the ABX indices fall as investors become more pessimistic about mortgage backed securities. Finally, we can calculate the change in the up-front cost to insure debt by simply multiplying $Loan$ by the change in the ABX index represented as a percent.[27]

[27]See, for example, "Subprime Mortgage Bond Derivatives Fall After NovaStar's Loss." *Bloomberg News*, February 21, 2007. Also, "Goldman Pushes Subprime ABX Index as Housing Rebounds: Mortgages." *Bloomberg News*, November 30, 2012.