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Government-Backed Mortgage Insurance, Financial Crisis, and the Recovery from the Great Recession

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Abstract

The Great Recession provides an opportunity to test the proposition that government mortgage insurance programs mitigated the effects of the financial crisis and enhanced the economic recovery from 2009 to 2014. We find that government-sponsored mortgage insurance programs have been responsible for better economic outcomes in counties that participated heavily in these programs. In particular, counties with high levels of participation from government-sponsored enterprises and the Federal Housing Authority had relatively lower unemployment rates, higher home sales, higher home prices, lower mortgage delinquency rates, and less foreclosure activity, both in 2009 (soon after the peak of the financial crisis) and in 2014 (six years after the crisis) than did counties with lower levels of participation. The persistence of better outcomes in counties with heavy participation in federal government programs is consistent with a view that lower government liquidity premiums, lower government credit-risk premiums, and looser government mortgage-underwriting standards yield higher private-sector economic activity after a financial crisis.

JEL CODES: G01, G21, G28

KEY WORDS: Financial crisis, Great Recession, mortgages, government policy

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1. Introduction

The United Sates government has a long history of involvement in mortgage finance. During the 1930s, the government created the Federal Home Loan Banks (FHLBs), the Federal Housing Administration (FHA), and the Federal National Mortgage Association (Fannie Mae). Since then, these programs have grown in size and scope, and the government has introduced additional programs, e.g. the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Government National Mortgage Association (Ginnie Mae). Green and Wachter (2005) provide an analysis and timeline of the federal legislation that created mortgage programs from 1933 to 1989.[2]

The housing programs created during the Great Depression were taken as background fixtures during the Great Recession. However, the Great Recession provides an opportunity to assess the importance of these housing programs during and after a financial crisis. Most of these programs were created with the objective of limiting damage to households during the Great Depression and speeding economic recovery. How well did they perform this role during the Great Recession?

During the most recent financial crisis, government focus concerning mortgage finance was primarily on mortgage debt relief and mortgage refinancing, particularly for households that had experienced large declines in house values. In particular, the Home Affordable Modification Program (HAMP) and the Home Affordable Refinance Program (HARP) helped homeowners who experienced losses in income, unaffordable increases in expenses, or declines in home values. Most of the analytical work concerning these programs focused on re-defaults and strategic behavior by homeowners (Holden, *et. al*, 2012).

The traditional channel for a financial crisis to affect the real economy is that the crisis raises the cost of financial intermediation and lowers the value of borrower collateral, causing banks to raise interest rates and decrease credit availability (Bernanke, 1983, Bernanke and Gertler, 1989). In theory, these traditional housing recovery programs, by using government guarantees and financing, should stabilize and moderate the cost of credit for certain types of loans, allowing an economic recovery to take hold and proceed more quickly.[3] In addition, the designers of the

[2] Official histories can be found at http://fhfaoig.gov/LearnMore/History and at http://www.hud.gov/offices/adm/about/admguide/history.cfm.

[3] Of course, providing government guarantees for the performance of financial assets has well-known moral hazard problems. However, well-targeted government insurance programs (clear participation requirements and relatively

government mortgage housing programs during the Great Depression hoped to limit the economic contraction resulting from tightening bank underwriting standards, mainly by extending mortgages under less onerous underwriting standards (Rose, 2011).[4] Finally, government programs effectively "cap" the price of credit risk in primary mortgage markets because these programs swap mortgages for government-backed, mortgage-backed securities (MBS) in return for a fixed-credit-risk premium.

Do government programs promote faster economic recovery? We can empirically test this proposition in US mortgage markets by focusing on mortgage insurance and guarantee programs. In particular, we focus on the FHA and the government-sponsored enterprises (GSEs), Fannie Mae and Freddie Mac. We characterize the mortgage market by four methods of origination and financing: (1) FHA/Ginnie Mae; (2) private mortgage originators/Fannie Mae/Freddie Mac; (3) banks; and (4) private-market origination and securitization (referred to as private-label securities or PLS).

These four mortgage origination channels can be ranked by their government-backed financing and the underwriting standards. FHA/Ginnie Mae uses government-guaranteed financing and has the most generous underwriting standards. Fannie Mae/Freddie Mac have tighter underwriting standards than FHA, and their government financing is more limited than FHA's direct government backing. As for banks, they have government deposit insurance for some of their liabilities, but also rely on non-government-backed liabilities. In addition, their underwriting for fixed-rate mortgages held in their own portfolios typically "overlays" either the FHA or GSE underwriting standards, and thus is stricter than the standards used by government institutions alone.[5] Finally, PLS has no government-backing and has the tightest underwriting standards, at least during the post-crisis period.

In sum, we find that government-sponsored mortgage insurance programs seem to have been responsible for better economic outcomes in counties that participated more heavily in these

small target-populations) in non-crisis states can potentially limit moral hazard concerns, while mitigating negative consequences during a crisis (Hancock and Passmore, 2011, Krishnamurthy, 2010).

[4] Theoretical support for this view is provided by Allen and Gale (1998), who show that when long assets are risky, bank runs can be triggered by a negative outlook on future returns for these assets. Substituting government underwriting for private sector underwriting may mitigate this problem, although government intervention can cause many other problems through the distribution of implicit or explicit subsidies among private market participants.

[5] Part of the motivation for these stricter standards is a desire to maintain the option to sell the mortgages to the government later if needed.

programs. In particular, counties with high levels of FHA participation had relatively lower unemployment rates, higher home sales, higher home prices, and lower mortgage delinquency and foreclosure rates, both in 2009 (right after the financial crisis) and in 2014 (six years after the crisis). To a lesser extent, counties with substantial participation in GSE programs also had better economic outcomes. In contrast, counties reliant on banks' and PLS' methods of mortgage origination lagged during the economic recovery. The persistence of better outcomes with government programs is consistent with a view that the liquidity provided by government-backed financing and the government's less pro-cyclical government underwriting standards can promote economic recovery. We proceed as follows: Section 2 describes the FHA, Fannie Mae, and Freddie Mac. Section 3 describes the data and our empirical technique, and summarizes our results. Section 4 concludes.

2. FHA, Fannie Mae, and Freddie Mac

The FHA provides mortgage insurance for mortgages extended by FHA-approved lenders. At the end of the 2015 fiscal year (September 30, 2015), the FHA had $1.3 trillion of insurance-in-force.[6] FHA mortgages are securitized by Ginnie Mae or held in the portfolios of banks. Ginnie Mae MBS trade with the full faith and credit of the United States government.

Fannie Mae and Freddie Mac are GSEs that purchase mortgages either to hold in their portfolios or create MBS to sell to investors. Almost all mortgages securitized by the GSEs are 30-year, fixed-rate mortgages.[7] As of the end of the December 2014, Fannie Mae held $413 billion of mortgage-related assets in its portfolio and guaranteed $2.80 trillion of MBS, while Freddie Mac held $408 billion in mortgage-related assets in its portfolio and guaranteed $1.66 trillion of MBS.[8]

Fannie Mae and Freddie Mac are implicitly subsidized by the government (Acharya, et. al., 2011, Burgess, Sherlund and Passmore, 2005, Passmore, 2005). On September 6, 2008, the

[6] A full review of the FHA's finances can be found at http://portal.hud.gov/HUD.
[7] Government financing eliminates investors' concerns about the credit risk of fully-amortizing, long-term, fixed-rate mortgages, and thus the 30-year, fixed-rate mortgage is established with the creation of FHA and the precursor of Fannie Mae during the Great Depression (Green and Wachter, 2005).
[8] Fannie Mae income and balance sheet statements can be found at http://www.fanniemae.com/portal/about-us/investor-relations/quarterly-annual-results.htm and Freddie Mac at http://www.freddiemac.com/investors.

Federal Housing Finance Agency placed Fannie Mae and Freddie Mac into conservatorship and the Department of the Treasury agreed to provide strong financial support for these entities. Currently, Fannie Mae and Freddie Mac both remain under government conservatorship.[9]

Mortgage originators (e.g. banks, thrifts, credit unions and mortgage bankers) can either hold the mortgage in their portfolio after origination or sell the mortgage into the secondary mortgage markets. Most sold mortgages are sold to either the FHA, Fannie Mae, or Freddie Mac. An originator who plans to sell mortgages must follow the underwriting guidelines of the purchaser of the mortgage.[10] The relative cost and ease of the securitization determines which method of mortgage finance dominates.[11]

As shown in Figure 1, the bulk of mortgage outstanding in the United States are held in banks' portfolios or purchased and securitized by Fannie Mae and Freddie Mac. As is well-known, private-label mortgage-backed securitization grew rapidly in the pre-crisis period and then plummeted, with a significant impact on the mortgage markets (Mayer, Pence and Sherlund, 2009, Nadauld and Sherlund, 2013). The FHA was a relatively small portion of the mortgage market in the pre-crisis period; it grew in the post-crisis period but it still insures a smaller part of aggregate mortgage holdings.

As described above, government-backed mortgage insurance programs can influence the costs of mortgage financing in three ways: (1) by providing readily-available and low-cost financing for mortgages using government guarantees; (2) by having less strict underwriting standards; and (3) by directly capping the price of credit risk. Each of these factors might play a role in faster economic growth: (1) government liquidity can substitute when the private-sector is unwilling to finance mortgages; (2) government underwriting standards may allow more borrowers to increase their household leverage; and (3) government pricing of the credit risks embedded in the primary mortgage may make mortgage rates lower.

Moreover, as noted by Tirole (2011), securitization certifies the quality of mortgage underwriting decisions and thus allows the mortgage to become liquid because it is more easily

[9] For a history of the GSEs' troubles, see Frame and White (2005), and Frame *et al.* (forthcoming). For the current status of the GSEs, see CBO, 2014.
[10] Of course, selling into the secondary market leads to adverse selection and other agency problems (Passmore and Sparks, 2000, Demarzo, 2005, etc.).
[11] Hancock and Passmore (2011), Heuson, Passmore, and Sparks (2001).

traded among investors. As a result, financial institutions can operate with more leverage and savers can build more optimal portfolios; these outcomes can enhance economic growth, particularly after a financial crisis. This process, however, depends on the creditability among investors of the mortgage credit risk certification process. After the most recent financial crisis, credit monitors, such as credit rating agencies, were in disrepute, and only the government was able to provide a meaningful guarantee for the securitization of mortgage assets.

Just as only the government may be able to provide a meaningful guarantee for securitization after a financial crisis, only the government may be able to price credit risk without significant risk-premiums after a financial crisis. Private market participants may have a distribution of views on the appropriate credit risk premiums to charge for various types of borrowers and properties, and may be particularly risk-averse after a crisis. However, if the government sets a fee for insurance and covers the costs of default to the lender once the lender has paid the fee, then the government effectively caps the price of credit risk.

The government's circumvention of market-based credit risk premiums takes place through government guarantees or government-backed securitization. Private-sector investors purchase securities backed by FHA, Fannie Mae, and Freddie Mac without considering credit risk because explicit or implicit government guarantees provide timely payment of principal and interest and protect investors from default.[12] Investors who have become risk averse after a crisis will purchase the security rather than finance a mortgage by buying the equity or debt of mortgage originators.

When the government provides lower mortgage rates and looser underwriting standards, households are more likely to take out mortgage loans and make home purchases (Mian and Sufi, 2009). Home purchases can have an effect on house prices and household consumption (Stein, 1995, Campbell and Cocco, 2007, Mian and Sufi, 2011), and housing wealth can influence macroeconomic activity (Mian, Rao, and Sufi, 2013).

Despite providing lower mortgage costs, in aggregate, government-backed insurance programs

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[12] GSE and FHA mortgage insurance premiums vary somewhat by risk, but not greatly (FHFA, 2012). As a result, risk premiums can vary significantly for any individual mortgage. In addition, the market's calculation of risks and the government's calculation of risk can vary substantially, depending on the objective of the government. If the government is pricing "through the business cycle" for macroprudential reasons, or to "increase credit availability" to meet social objectives, the capital held by the government for covering credit losses can vary significantly from the capital needed to meet market expectations of profitability (Hancock and Passmore, 2015).

appear to be negatively correlated with home sales during the past decade. The share of government involvement in the mortgage market decreased during the economic boom during 2004 through 2006, and then increased since financial crisis. The level of home purchases moved in the opposite directions (Figure 2). This aggregate movement hides the fact that mortgage loan and housing purchases declined during the crisis, and remained low afterwards. We now turn to disentangling this relationship government mortgage insurance programs and economic activity.

3. Data and Estimation Results

We make two contributions in this paper. First, we establish the importance of government mortgage insurance programs during the financial crisis and the ensuing economic recovery. Second, we illustrate the use of generalized propensity scores (GPS) in the identification and estimation of these effects.

We characterize the mortgage market by four methods of origination and financing: (1) FHA/Ginnie Mae; (2) private mortgage originators/Fannie Mae/Freddie Mac; (3) banks; and (4) private-market origination and securitization (frequently referred to as private-label securities or PLS).[13] These data are aggregated to the county level using data from McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc., and data from CoreLogic, and include adjustments to account for differential data coverage across mortgage market segments.

A map of counties across the United States illustrates the wide variation in government shares of mortgage lending (Figure 3) prior to the financial crisis (2004-2007). The use of government mortgage insurance programs is concentrated in the Northeast and the Upper-Midwest. The South and California are less likely to have a large proportion of mortgage origination flow into government-backed programs. Moreover, the frequency distributions (Figure 4) further suggest significant variation in the utilization of government programs by county prior to the financial crisis. GSE securitization ranges from approximately 25 percent to 75 percent of the proportion of originations in a county. Use of the FHA is much lower ranging from close to zero to 35 percent. The share of mortgage originations flowing into bank portfolios ranges from 6

[13] The FHA/VA channel may or may not include mortgages securitized by Ginnie Mae.

percent to 33 percent. PLS, even at its heyday prior to the financial crisis, accounted for a relatively small proportion of the flow of mortgage originations from a county, ranging from 8 percent to 45 percent.

The extent of a county's participation in government-sponsored mortgage programs can be characterized as a "treatment" administered by the government to augment the financial infrastructure in a county. Table 1 shows nonparametric estimates of the empirical "doses" in our data set, i.e. the proportion of mortgage originations flowing through each origination channel. Rather than selecting arbitrary "buckets" to use for averaging treatments across counties, we use nonparametric kernel regression techniques to estimate these average treatment levels. Given a level of GSE treatment, we calculate the average treatment level across counties for FHA, PLS and portfolio market shares by giving greater weight to those counties that have more similar levels of GSE treatment and lesser weight to those counties that have different levels of GSE treatment. These average treatment levels are useful in interpreting the co-movement in GSE, FHA, PLS, and portfolio "treatments."

A. Estimation of the Generalized Propensity Score

Ultimately, we want to estimate how the intensity of GSE, FHA, PLS, and portfolio exposures influence the state of the real economy. However, the use of such securitization outlets and the prevalence of bank portfolio alternatives may not be independent from the same conditions that create relatively high economic performance in a county. Thus, we want to control for the "propensity" of particular counties to select into various GSE, FHA, PLS, and portfolio treatments, conditional on economic fundamentals such as average incomes, house prices, and unemployment rates. By controlling for counties' propensities to select into GSE, FHA, PLS, and portfolio treatments, we can directly estimate the effect of financing alternatives on economic activity within a county.

Propensity scoring has been used in other financial studies. For example, Casu, Clare, Sarkisyan, and Thomas (2013) use propensity scoring to identify the effects of securitization on bank performance, and find that banks that securitize loans and banks that do not, seem to have similar risk-adjusted returns once the underlying propensity to securitize is adjusted. Bharath, Dahiya, Saunders, and Srinivasan (2009) investigate lending relationships and loan contract terms. They use propensity scores to create a "matched" sample of firms with lender relationships and firms without such relationships, and find that relationships yield a small but significant funding advantage for borrowers. Finally, Chemmanur, Loutskina, and Tian (2014) find that corporate venture capital firms have a superior ability to nurture innovative ventures than independent venture capital firms. They use propensity scores to assess and, to the extent possible, rule out the possibility that corporate venture capital firms are simply better at selecting innovative projects.

Our approach is similar in spirit to Rosenbaum and Rubin (1983). In particular, as in Hirano and Imbens (2004), we use generalized propensity scores (GPS), where the probability of a county being "treated" with different levels of mortgage-type exposure is a function of its underlying characteristics. In other words, the GSE, FHA, PLS, and portfolio market shares for each county can be considered as a random treatment once each county's underlying characteristics have been taken into account. Hirano and Imbens show that, under relatively weak conditions, "systematic 'selection' into levels of the treatment based on unobservable characteristics not captured by observable ones" can be ruled out (Flores, Flores-Lagunes, Gonzalez, and Neuman, 2012).[14]

Our identification strategy relies on the variation in government involvement in mortgage markets across counties. Counties with significant government involvement are subject to credit risk pricing and underwriting standards that are set at a national level. In contrast, counties with little government involvement are more likely subject to local credit risk pricing and underwriting standards, as set by local banks, thrifts, mortgage banks, and private-sector mortgage securitization conduits (whose underwriting standards may or may not be set at the national level, and whose underwriting standards are likely more responsive to current market conditions).

We assume each county contains a set of mortgage financing structures that changes only slowly over time and reflects the economic characteristics of the population that lives in those counties. As the securitization outlets are provided by national entities, their relative usage in a county therefore reflects county characteristics. Thus, we model the extent of banks' participation in securitization outlets on the basis of observed census characteristics that are unrelated to the

[14] This technique is similar to a difference-in-difference approach, where the pre-treatment covariates define sub-samples, and then for each subsample, we estimate the "average dose function." The continuous form of the first-state regression, however, allows the simultaneously adjustment by many covariates.

availability of the securitization outlets.

In addition to the mortgage market share data described above, the county-level data we use come from a variety of other sources. Median Equifax risk scores and the percentage of households with risk scores below certain thresholds are aggregated from the FRBNY Consumer Credit Panel / Equifax data. These data contain credit records for 5 percent of U.S. households with credit files as of 2005:Q4. Information on tax returns, including wages, salaries, exemptions, dividends, interest, and adjusted gross income come from the IRS 2005 Statistics of Income data. House prices, home sales, mortgage delinquency rates, and foreclosure completions come from CoreLogic HPI and MarketTrends data. House prices and delinquency rates are measured as of December 2005, 2008, 2009, 2012, and 2014. Home sales and foreclosure completions are measured as the monthly averages during January 2004 to June 2007, July 2007 to December 2008, January to December 2009, January 2010 to December 2012, and January 2013 to December 2014. The number of lenders come from the 1998 and 2005 HMDA data. Unemployment rates come from the Bureau of Labor Statistics. As with house prices, these are measured as of year-end 2005, 2008, 2009, 2012, and 2014.

We begin by modeling the county-level GSE, FHA, PLS, and portfolio shares of mortgage originations as a function of county characteristics during the 2004-2007 benchmark period. We use only counties that have complete data on house prices and home sales during our sample period (2004-2014), resulting in 861 county-level observations (out of 3,137 counties in our initial data set).[15] As shown in Figure 5, the counties that remain are predominantly located in large metropolitan areas. Moreover, these counties account for about 85-95 percent of mortgage purchase originations, home sales, and mortgage delinquencies and foreclosures in our full sample.

We perform a set of regressions of the four treatment levels (which we assume to be log-normally distributed) on county-level characteristics (including credit scores, average income measures, several house price measures, unemployment rates, and mortgage market structures in 2005):

$$\ln T_i | X_i \sim N(\beta_0 + \beta_1' X_i, \sigma^2),$$

where T_i is the level of treatment and X_i is a vector of observed county characteristics. As shown

[15] Most of the dropped observations are because of missing house price data.

in Table 2, county-level wealth, income, employment, credit ratings, house price growth, and the level of house prices each play important roles in determining how counties finance their mortgage markets. The GPS estimates are then

$$\hat{R}_i = \phi\left(\frac{\ln T_i - \hat{\beta}_0 - \hat{\beta}_1' X_i}{\hat{\sigma}^2}\right),$$

where ϕ is the standard normal probability density function and $\hat{R}_i$ is the estimated GPS.

B. Testing the GPS

The adequacy of the GPS relies on two important checks: the common support condition and the balancing condition. The common support (or overlap) assumption assures that "treated" observations have similar "untreated" observations with which to compare. The balancing property ensures that the covariates are orthogonal to discretized levels of treatment conditional on the GPS, so that differences in county characteristics do not implicitly bias our results. We address each of these conditions next.

To assess the common support condition, we estimate the GPS for all counties at each quartile for each treatment, then compare these estimates across treatment groups. Observations that lie outside the support of its comparison group are dropped. For example, based on our preliminary regression we estimate the GPS for each county assuming GSE treatment levels of 47.6, 54.4, and 61.4 percent, representing the 25th, 50th, and 75th percentiles of GSE treatment, respectively. We then compare the estimated GPS assuming a 25th-percentile GSE treatment across two groups: those with actual GSE treatment levels at or below the median treatment level, and those with actual GSE treatment levels above the median treatment level. Similarly, we compare the estimated GPS assuming a 75th-percentile GSE treatment across the same groups (at or below median treatment and above median treatment). Finally, we compare the estimated GPS assuming a 50th-percentile GSE treatment across the following two groups: those with actual GSE treatment levels above the 25th-percentile treatment and less than the 75th-percentile treatment, and those with actual GSE treatment levels below the 25th-percentile treatment or above the 75th-percentile treatment. In each case, we compare observations within 25 percentiles of the assumed treatment with all other observations. If a particular GPS estimate lies outside the support of its comparison group, we drop that observation. This procedure reduces the sample size to 764 counties (11.3 percent dropped) for our GSE analysis, 652 counties (24.3 percent dropped) for our FHA analysis, 706 counties (18.0 percent dropped) for our PLS analysis, and 785 counties (8.8 percent dropped) for our portfolio analysis. The remaining counties satisfy the common support condition, which ensures that each county has a similar observation with which to compare.

The second crucial assumption behind propensity scoring is that conditional on the propensity score, the set of covariates is orthogonal to the level of treatment,

$$X_i \perp 1\{T_i = t\} | R(t, X_i).$$

In other words, the GPS balances the county characteristics across treatment levels. This helps ensure that, when we assess the impact of mortgage market treatments on real economic activity, the estimated causal effects are coming from changes in the treatment levels as opposed to changes in the underlying characteristics of the counties. To test the balancing property, we follow the procedure of Hirano and Imbens (2004) and discretize both the level of treatment (into three groups) and the GPS (into five groups). We then test for the equality of covariate means across treatment groups holding GPS "neighborhoods" fixed.

As shown in Table 3, we split each treatment level into three groups of roughly equal size. We then test the equality of credit score means for counties with GSE treatment levels of 50 percent or less versus those with GSE treatment levels of more than 50 percent—counties with GSE market shares of 50 percent or less tend to have lower median credit scores than counties with GSE market shares above 50 percent (*t*-statistic of -12.2). Similarly, counties with GSE market shares above 60 percent tend to have higher median credit scores than counties with GSE market shares of 60 percent or less (*t*-statistic of 12.7). To adjust for the estimated GPS, we compute the GPS for an assumed GSE treatment level of 45 percent (the median treatment for counties with GSE treatment levels of 50 percent or less) for each county, i.e., $r(45, X_i)$. For each GPS quintile, we compute the *t*-statistic for the equality of the median credit score across counties with GSE treatment of 50 percent or less versus the counties with GSE treatment of greater than 50 percent. As shown, adjusting for the GPS improves the balance of median credit scores significantly, reducing the magnitude of the t-statistic from 12.2 and 12.7 to 2.4 and 2.1.

Broadly speaking, the GPS adjustment reduces the magnitudes of the *t*-statistics. In fact, most *t*-statistics are statistically insignificant once adjusted by the GPS. Thus, our GPS balances our sample in the sense that conditioning on the values of the GPS, the means/medians of the county characteristics (or, in the above example, the median credit score) are similar for low treatment (that is, low government involvement) and high treatment (that is, high government involvement) counties. Therefore, as we consider the response of economic activity to additional government involvement in mortgage originations, we have controlled for differences in county characteristics that might be related to the treatment and the economic outcome. We therefore take some comfort that in our results because we have isolated the pure effect of government involvement in the mortgage market on the economic variable of interest.

C. Estimation of the Dose Response Functions

Now that we have verified the common support and balancing conditions, we regress the economic outcomes of four periods: July 2007 to December 2008 (early crisis), January to December 2009 (crisis), January 2010 to December 2012 (early post-crisis), and January 2013-December 2014 (post-crisis) on their pre-determined mortgage market structures and on their GPS (i.e., the probability of observing that market structure during the 2004-2007 benchmark period). We focus on six outcomes of interest that describe the economic state of the county: unemployment rates, total home sales, home prices, delinquency rates, and completed foreclosures. All of these outcomes are measured as a ratio relative to their values during the 2004-2007 benchmark period.

We estimate the "dose-response" functions using ordinary least squares (OLS), where the probability of observing a particular treatment level is, of course, an implicit function of the treatment level itself. In other words,

$$y_i = \beta_0 + \beta_1 t_i + \beta_2 \widehat{R_i} + \beta_3 \widehat{R_i}^2 + \varepsilon_i$$

where y_i is the variable of interest (e.g. unemployment, home sales, etc.), t_i is the treatment received (e.g. the GSE proportion of mortgage originations in the county), and $\widehat{R_i}$ is the GPS evaluated at the level of treatment received and the observed county characteristics.[16] Throughout our analysis, all standard errors and confidence bands are generated from 1,000 bootstrap replications (with replacement).

D. Dose Response Functions

Graphical dose-response functions provide a convenient summary of the estimated dose-response functions. They show the expected value of the outcome variable conditional on a level of treatment and the GPS. We also calculate average treatment effects as the derivative of the dose-response functions; the average treatment effect coming from an increase in treatment is the average rate of change of the dose response function over a particular interval.

Our first set of results describe the dose-response functions for the unemployment rate (Figure 6). Here we see a clear downward trend in how much unemployment rates changed, relative to 2005, for counties with higher levels of GSE securitization for both the crisis and post-crisis periods. Similarly, there is a distinct downward trend for counties that made more use of the FHA. By the end of 2008, unemployment rates had increased by 26 percent in counties that had low FHA shares in 2005, relative to a 4 percent increase in unemployment rates in counties that had high FHA shares in 2005. By the end of 2009, unemployment rates had increased by 106 and 58 percent for the same groups of counties. What is clear is that the financial crisis was a substantial shock which influenced all counties, but had larger effects in counties with lower government involvement in mortgage markets prior to the shock. By the end of 2012, unemployment rates had fallen across the board, but remained 79 percent higher in low FHA-share counties—and 49 percent higher in high FHA-share counties—relative to before the crisis. By the end of 2014, unemployment rates remained 30 and 19 percent higher than in 2005 for the same groups of counties.[17] Here, it is evident that the effects of the financial crisis still remain, and that

[16] We also explored estimating the dose-response functions using nonparametric techniques, including local-linear regressions and weighted local-linear regressions. Our qualitative results remain the same.

[17] If we showed our charts in *levels*, rather than benchmarked relative to 2005, the interpretation of our results might be even stronger. The results for GSE, PLS and portfolio channels are similar, but for FHA, the effects are more dramatic. Prior to the crisis, counties with higher FHA shares tended to also have higher unemployment rates. During the crisis, however, this relationship flipped: Counties with higher pre-crisis FHA shares tended to have lower unemployment rates. By 2014, counties with higher pre-crisis FHA shares again tended to have higher unemployment rates, restoring the pre-crisis relationship.

those effects are larger for lower FHA- and GSE-share counties.

In contrast, counties that were more reliant on either PLS or bank portfolios in 2004-2007 experienced larger increases in their unemployment rates. By the end of 2008, unemployment rates had increased by 7 percent in counties that had low PLS shares in 2005, relative to a 25 percent increase in unemployment rates in counties that had high PLS shares in 2005. By the end of 2009, unemployment rates had increased by 69 and 106 percent for the same groups of counties. Again, the financial crisis influenced all counties, but had larger effects in counties with higher private funding use prior to the shock. By the end of 2012, unemployment rates had fallen across the board, but remained 45 percent higher in low PLS-share counties—and 76 percent higher in high PLS-share counties—relative to before the crisis. By the end of 2014, unemployment rates remained 17 and 31 percent higher than in 2005 for the same groups of counties. The effects of the financial crisis are still apparent across counties, but the effects are larger for higher PLS- and portfolio-share counties.

Similar qualitative patterns hold for home sales and home prices (Figures 7 and 8). Greater exposure to GSE or FHA activity during the pre-crisis period tended to be associated with smaller declines in home sales and house prices both during and after the financial crisis relative to 2005. During the height of the financial crisis, home sales had declined over 50 percent in low FHA-share counties (compared to only 17 percent in high FHA-share counties), while home prices had declined 14 percent in low-FHA share counties (compared to actually *rising* 5 percent in high FHA-share counties). In contrast, greater exposure to PLS or portfolio lending tended to be associated with larger declines in home sales and house prices. By 2009, home sales had declined 24 percent in low PLS-share counties (compared to nearly 50 percent in high PLS-share counties), while home prices had risen 4 percent in low-PLS share counties (compared to declining 18 percent in high PLS-share counties).

Delinquency rates and foreclosure completions (Figures 9 and 10) tended to rise the most in counties with high exposure to PLS or portfolio lending and/or low exposure to GSE or FHA lending. This is consistent with the findings of Mian and Sufi (year), Keys (year), and Mayer, Pence, and Sherlund (2009), who all attribute higher delinquency rates and foreclosures to the use of private-label securitization and portfolio lending activity. In particular, by 2009 delinquency rates had risen about 650 percent in low FHA-share counties (compared to 77 percent in high

FHA-share counties), while foreclosure completions had risen about 430 percent in low-FHA share counties (compared to rising 150 percent in high FHA-share counties). In contrast, by 2009 delinquency rates were essentially unchanged in low PLS-share counties (compared to rising nearly 850 percent in high PLS-share counties), while foreclosures had risen 22 percent in low-PLS share counties (compared to increasing about 425 percent in high PLS-share counties).

To explore how county-level mortgage markets might have affected real economic outcomes, we next explore how the market shares of our four channels moved during and subsequent to the financial crisis. Figure 11 shows the estimated dose-response functions for market shares at several points in time as a function of 2005 market shares. Between 2005 and 2008, GSE and portfolio shares remained stable, as their respective dose-response functions stayed near the 45-degree line. PLS shares, however, moved toward zero as the securitization market collapsed. FHA shares moved higher, presumably picking up at least some of the slack. As the financial crisis deepened, by 2009 even GSE and portfolio shares had declined, while FHA shares increased further. By 2014, FHA shares had declined slightly from their 2009-2012 levels but remained above their 2005 levels; GSE and portfolio shares increased slightly while remaining below their 2005 levels. PLS shares remained near zero.

This is the primary mechanism through which we expect FHA and GSE lending to provide positive economic impetus during a financial crisis. When other sources of mortgage financing become less available, either because of higher credit risk, higher liquidity premiums, or because of tighter underwriting standards, FHA and GSE lending (broadly speaking) remains available at roughly unchanging prices. The declines in lending activity were most pronounced in counties that relied most heavily on PLS or portfolio lending. As a result, economic activity in those counties declined, either because credit become less available or because lenders had to divert attention to securing alternative forms of financing. FHA shares increased during the financial crisis and remained high afterward—for low FHA-share and high FHA-share counties alike—providing access to mortgage credit and lessening the effects of the financial crisis on demand for housing, aggregate demand in general, and, as a result, on the labor market.

Overall, our results suggest that counties more reliant on some form of government funding for mortgages were more insulated from the financial crisis; the effects of the (negative) liquidity and funding shocks had smaller economic impacts on counties that utilized government mortgage more heavily prior to the financial crisis. Counties that relied on private sources of funding, however, experienced greater effects from the initial liquidity and funding shocks: even higher unemployment rates, even lower home sales, and even lower home prices. These effects were still apparent in 2014, though the effects of the initial shocks had decayed substantially.

As shown in Tables 4-5, the average treatment effects (the derivative the dose-response functions) differ quite substantially from their naïve OLS counterparts over significant portions of the treatment distributions. For example, Table 4 reports that, according to a naïve OLS regression, increasing the PLS market share in 2005 from 14 to 18 percent would be associated with home sales nearly 1-1/2 percent lower in 2009. But our estimated dose-response functions suggest that the true effect could be much larger, nearly 5-1/2 percent lower, suggesting that counties more reliant on PLS funding likely have selected into that source of financing because of higher house prices and home sales. This county selection bias illustrates the importance of our GPS correction for the likelihood of counties to select into treatment levels.

E. Sensitivity Analysis Using Rosenbaum Bounds

We next explore the possibility that counties select into treatment doses based on unobserved factors. Suppose county treatments are chosen such that $\ln T_i|X_i \sim N(\beta_1' X_i + \gamma u_i)$, where X_i are the observed characteristics and u_i is an unobserved variable. If there is no bias resulting from the omission of the unobserved factor, then $\gamma = 0$ and $\ln T_i|X_i \sim F(\beta_1' X_i)$ as assumed above. However, if there is a hidden bias, then two counties with the same X_i will have different probabilities of receiving treatment. That is, after controlling for observable county characteristics, two given counties might still differ in their odds of treatment by a factor of e^{γ} because of unobserved factors affecting selection into different treatments.

Similar to Aakvik (2001), we use Mantel-Haenszel (1959) test statistics, Q_{MH}, to compare the number of successful treated counties with the same expected number given that the true effect is zero. Rosenbaum (1995) shows that the Q_{MH} test statistic is bounded by Q_{MH}^{+} and Q_{MH}^{-}, which are both distributed chi-squared with one degree of freedom. If Q_{MH}^{+} to Q_{MH}^{-} is statistically different from zero, that is evidence against the null hypothesis that the estimated treatment effects are sensitive to unobserved selection bias.

The test statistics and test-statistic ranges in Table 6 show that our results are fairly robust to unobserved selection bias. For example, the effect of 2004-2007 GSE market shares on 2014 unemployment rates is robust to differences of as much as 25 percent in terms of unobserved county characteristics. But in some cases (such as the effect of 2004-2007 FHA market shares on 2014 unemployment rates), our results are not as robust. It is important to note that this sensitivity analysis simply shows how unobserved factors might bias our results; it unfortunately does not speak to the presence of these biases nor their magnitudes. Furthermore, given the results shown below, one must think of a compelling case for an unobserved or omitted factor to influence the results. Broadly speaking, unobserved factors are unlikely to influence many of our results unless the unobserved bias is very extreme.

4. Conclusion

Do government programs that provide greater liquidity, along with underwriting standards that are less onerous than the private sector, promote faster economic recovery? We empirically test this proposition in US mortgage markets and find that they did. In particular, counties with high levels of participation from government-sponsored enterprises and FHA had relatively lower unemployment rates, higher home sales, higher home prices, lower mortgage delinquency rates, and less foreclosure activity, both in 2009 (right after the peak of the financial crisis) and in 2014 (six years after the crisis) than did counties with lower levels of participation. The persistence of better outcomes in counties with heavy participation in federal government programs is consistent with a view that lower government liquidity premiums, lower government credit-risk premiums, and looser government mortgage-underwriting standards may yield higher private-sector economic activity after a financial crisis.

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Table 1: Empirical Doses (Nonparametric Estimates)

	Conditional Expectation					Conditional Expectation		
GSE Dose	FHA	PLS	Portfolio		FHA Dose	GSE	PLS	Portfolio
24	15.8	33.7	26.5		4	60.0	19.7	16.4
28	15.0	32.0	25.1		8	58.0	18.8	15.2
32	14.2	30.2	23.6		12	55.7	17.8	14.5
36	13.6	28.2	22.2		16	53.2	16.7	14.1
40	13.2	26.2	20.6		20	50.7	15.5	13.7
44	12.9	24.1	19.0		24	48.2	14.4	13.4
48	12.5	22.0	17.5		28	45.7	13.3	13.0
52	11.9	20.1	16.0		32	43.3	12.1	12.6
56	11.1	18.3	14.6		36	40.9	11.0	12.1
60	10.0	16.8	13.3					
64	8.8	15.3	12.0					
68	7.5	13.8	10.7					
72	6.3	12.3	9.4					
76	5.2	10.8	8.1					
	Conditional Expectation					Conditional Expectation		
PLS Dose	GSE	FHA	Portfolio		Portfolio Dose	GSE	FHA	PLS
8	58.9	20.2	12.9		8	63.9	16.5	11.6
12	58.2	16.3	13.5		12	57.4	13.0	17.6
16	56.8	13.0	14.2		16	53.0	11.1	19.9
20	53.2	11.3	15.5		20	49.7	10.0	20.4
24	48.9	10.1	17.0		24	46.2	8.7	21.1
28	44.7	8.8	18.5		28	42.3	7.2	22.5
32	41.0	7.2	19.8		32	38.2	5.5	24.3
36	37.5	5.5	21.1					
40	34.1	3.6	22.3					

Table 2: GPS Results

	GSE	FHA	PLS	Portfolio
Constant	19.812** (5.988)	-44.831** (18.109)	-37.472** (9.173)	-26.081** (10.127)
Median Equifax risk score	-3.811** (0.855)	4.708* (2.586)	5.381** (1.310)	4.169** (1.446)
Wages and salaries	0.708** (0.078)	0.731** (0.237)	-0.452** (0.120)	-0.339** (0.133)
Exemptions	-0.593** (0.099)	0.963** (0.300)	0.561** (0.152)	-0.327* (0.168)
Dividends + interest	0.098** (0.020)	-0.361** (0.059)	-0.119** (0.030)	0.097** (0.033)
2005 HPA	0.422** (0.090)	0.379 (0.272)	0.094 (0.138)	0.150 (0.152)
HP/Income	0.095** (0.010)	-0.004 (0.031)	-0.060** (0.016)	-0.042** (0.017)
Unemp 2005	-0.010** (0.004)	-0.104** (0.013)	0.048** (0.007)	0.041** (0.007)
HP – CLL	-0.004** (0.001)	-0.006** (0.001)	0.003** (0.001)	0.002** (0.001)
# lenders 2005	-0.006 (0.034)	-0.312** (0.103)	0.500** (0.052)	0.500** (0.058)
# lenders 2005 – 1998	-0.001** (0.000)	-0.001* (0.000)	0.001 (0.001)	0.001 (0.001)
% Equifax risk scores le 620	-2.366** (0.500)	1.749 (1.512)	2.742** (0.766)	4.665** (0.846)
% Equifax risk scores le 680	-1.688** (0.531)	1.168 (1.606)	1.722** (0.813)	1.830** (0.898)
% Equifax risk scores le 740	1.140** (0.385)	-3.359** (1.165)	-0.190 (0.590)	1.421** (0.651)
% Equifax risk scores le 800	0.875** (0.377)	-3.734** (1.139)	-1.288** (0.577)	1.348** (0.637)
% sales le 125 CLL	0.384** (0.058)	1.030** (0.175)	-0.205** (0.089)	-0.725** (0.098)
County population	0.006 (0.010)	0.024 (0.032)	-0.076** (0.016)	-0.164** (0.018)
No. obs.	861	861	861	861
R-squared	.634	.815	.629	.514
R-squared with interactions	.835	.886	.749	.669
R-squared with interactions and state fixed effects	.867	.911	.805	.758

Standard errors in parentheses. ** and * denote statistical significance at the 5-, and 10-percent significance levels. Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Table 3A: Covariate Balancing for GSE Market Share

	Unadjusted			Adjusted for GPS		
	<=50	50-60	>60	<=50	50-60	>60
Equifax risk score	-12.2	0.8	12.7	-2.4	0.1	2.1
Wages and salaries	-6.5	1.5	4.2	-2.1	0.8	-0.1
Exemptions	1.0	2.4	-3.6	-0.1	1.1	-1.0
Dividends + interest	-6.3	-0.6	8.0	-1.1	-0.3	1.1
2005 HPA	3.3	-2.1	-1.6	1.0	-1.2	0.5
HP/Income	1.1	-1.0	-0.3	0.5	-0.2	0.1
Unemp 2005	4.1	1.4	-6.2	1.2	0.2	-0.3
HP – CLL	-1.3	-0.2	1.7	-0.4	0.2	0.0
# lenders 2005	-0.6	0.6	0.1	-0.5	0.2	-0.2
# lenders 2005 – 1998	2.9	-2.5	-1.3	0.8	-0.8	0.0
% Equifax risk scores le 620	12.4	-0.5	-12.8	2.6	-0.1	-2.2
% Equifax risk scores le 680	6.2	0.1	-6.0	1.2	0.3	-0.6
% Equifax risk scores le 740	-4.3	0.2	4.5	-1.0	-0.2	0.1
% Equifax risk scores le 800	-12.5	0.7	12.3	-2.7	0.2	1.9
% sales le 125 CLL	-1.0	-0.1	1.1	-0.5	-0.1	0.5
County population	-1.3	1.1	0.3	-0.7	0.4	-0.2

Note: Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Table 3B: Covariate Balancing for FHA Market Share

	Unadjusted			Adjusted for GPS		
	<=7	7-14	>14	<=7	7-14	>14
Equifax risk score	8.2	0.3	-7.9	1.5	0.1	-1.1
Wages and salaries	6.8	-0.4	-8.5	1.8	-0.5	-2.6
Exemptions	-3.2	-1.1	4.6	-0.3	-0.5	0.4
Dividends + interest	9.8	-0.1	-9.4	1.5	0.5	-1.4
2005 HPA	5.5	-2.3	-4.2	0.6	-0.6	-0.1
HP/Income	9.0	-2.5	-8.0	0.9	-0.5	-0.7
Unemp 2005	-2.2	1.9	0.3	-0.1	0.6	-0.3
HP – CLL	13.1	-3.0	-12.0	2.2	-0.9	-2.1
# lenders 2005	9.1	1.5	-11.7	1.4	0.4	-2.3
# lenders 2005 – 1998	7.8	-1.6	-8.0	1.0	-0.5	-1.1
% Equifax risk scores le 620	-8.3	0.3	7.6	-1.4	0.1	1.1
% Equifax risk scores le 680	-4.5	-1.4	5.7	-1.3	-0.3	1.4
% Equifax risk scores le 740	5.0	-1.8	-3.0	0.7	-0.6	-0.5
% Equifax risk scores le 800	6.8	0.6	-6.9	1.6	0.1	-1.3
% sales le 125 CLL	-3.2	-1.3	5.6	-0.1	-1.0	1.7
County population	4.7	1.8	-7.5	0.6	0.5	-1.8

Note: Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Table 3C: Covariate Balancing for PLS Market Share

	Unadjusted			Adjusted for GPS		
	<=15	15-20	>20	<=15	15-20	>20
Equifax risk score	0.1	0.9	-0.9	-0.5	0.4	-0.8
Wages and salaries	-4.1	1.0	2.8	-1.2	0.5	-0.3
Exemptions	0.7	-0.8	0.2	0.6	-0.6	0.5
Dividends + interest	-1.5	-0.3	1.5	-0.7	0.2	-0.4
2005 HPA	-5.3	-1.6	6.0	-0.6	-0.5	1.0
HP/Income	-6.2	-2.4	7.2	-1.1	-0.8	0.6
Unemp 2005	-2.4	1.3	0.9	0.5	-0.0	0.7
HP – CLL	-8.9	-1.8	8.1	-2.2	-0.5	0.5
# lenders 2005	-9.5	-0.4	9.3	-1.5	-0.4	0.7
# lenders 2005 – 1998	-6.1	-3.1	7.0	-1.2	-1.2	1.0
% Equifax risk scores le 620	-0.2	-0.3	0.5	0.5	-0.2	0.7
% Equifax risk scores le 680	-0.5	-0.8	1.3	0.2	-0.4	0.6
% Equifax risk scores le 740	-1.0	-0.5	1.5	-0.7	-0.2	0.1
% Equifax risk scores le 800	2.0	0.6	-2.6	-0.3	0.5	-0.9
% sales le 125 CLL	2.7	1.1	-3.4	0.5	0.2	-0.0
County population	-5.9	-0.7	5.8	-1.4	-0.4	0.4

Note: Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Table 3D: Covariate Balancing for Portfolio Market Share

	Unadjusted			Adjusted for GPS		
	<=12	12-16	>16	<=12	12-16	>16
Equifax risk score	4.4	0.9	-5.1	0.6	0.7	-0.9
Wages and salaries	-0.1	1.0	-0.9	-0.6	0.2	-0.4
Exemptions	1.8	0.1	-1.7	0.4	-0.1	-0.2
Dividends + interest	-0.4	0.1	0.2	-0.4	0.3	-0.6
2005 HPA	-6.0	-2.8	7.2	-1.7	-1.1	1.2
HP/Income	-9.2	-1.8	8.4	-2.3	-0.7	0.9
Unemp 2005	-3.0	0.6	1.9	-0.0	0.0	0.2
HP – CLL	-8.2	-1.2	7.1	-2.6	-0.6	0.8
# lenders 2005	-7.8	1.3	5.7	-2.2	0.3	0.4
# lenders 2005 – 1998	-7.4	-2.6	6.8	-2.8	-1.1	1.1
% Equifax risk scores le 620	-4.7	-0.5	5.0	-0.5	-0.6	0.9
% Equifax risk scores le 680	-1.3	-1.0	2.2	-0.7	-0.4	0.8
% Equifax risk scores le 740	1.1	0.1	-1.2	0.1	0.2	-0.2
% Equifax risk scores le 800	5.7	0.8	-6.3	0.9	0.7	-1.1
% sales le 125 CLL	9.0	1.2	-7.0	3.1	0.4	-0.5
County population	-4.1	1.6	2.1	-1.5	0.5	0.0

Note: Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Table 4: 2009 Average Treatment Effects

	GSE 48 to 54	GSE 54 to 61	FHA 5 to 10	FHA 10 to 16
Unemployment rate	-.009	-.067	-.120	-.072
OLS	*-.039*	*-.045*	*-.072*	*-.086*
Home sales	.000	.011	.083	.055
OLS	*.000*	*.000*	*.046*	*.055*
Home prices	.014	.031	.023	.031
OLS	*.033*	*.038*	*.041*	*.050*
Delinquency rates	-.512	-1.019	-1.863	-.832
OLS	*-2.202*	*-2.569*	*-2.584*	*-3.101*
Foreclosures	-.046	-.393	-1.137	-.363
OLS	*-.709*	*-.828*	*-1.063*	*-1.276*
	PLS 14 to 18	PLS 18 to 23	Port 11 to 14	Port 14 to 18
Unemployment rate	.067	.074	.113	.060
OLS	*.050*	*.062*	*.066*	*.088*
Home sales	-.054	-.038	-.039	-.038
OLS	*-.016*	*-.020*	*-.026*	*-.034*
Home prices	-.047	-.033	-.058	-.032
OLS	*-.043*	*-.053*	*-.036*	*-.048*
Delinquency rates	1.840	1.628	2.285	1.944
OLS	*2.779*	*3.474*	2.340	*3.120*
Foreclosures	.846	.604	.971	.678
OLS	*1.051*	*1.314*	*.785*	*1.047*

Table 5: 2014 Average Treatment Effects

	GSE 48 to 54	GSE 54 to 61	FHA 5 to 10	FHA 10 to 16
Unemployment rate	-.016	-.017	-.055	-.014
OLS	*-.021*	*-.025*	*-.031*	*-.038*
Home sales	.024	.018	.055	.020
OLS	*.016*	*.019*	*.023*	*.028*
Home prices	.012	.020	.032	.022
OLS	*.022*	*.026*	*.031*	*.038*
Delinquency rates	-.082	-.202	-.947	-.296
OLS	*-.308*	*-.359*	*-.779*	*-.934*
Foreclosures	-.006	.012	-1.200	-.070
OLS	*-.024*	*-.029*	*-.333*	*-.400*

	PLS 14 to 18	PLS 18 to 23	Port 11 to 14	Port 14 to 18
Unemployment rate	.023	.032	.056	.035
OLS	*.026*	*.032*	*.030*	*.041*
Home sales	-.034	-.034	-.033	-.037
OLS	*-.019*	*-.024*	*-.023*	*-.031*
Home prices	-.029	-.023	-.053	-.023
OLS	*-.028*	*-.035*	*-.029*	*-.038*
Delinquency rates	1.890	1.840	.672	.601
OLS	*.526*	*.657*	*.571*	*.762*
Foreclosures	.292	.100	.404	.219
OLS	*.108*	*.135*	*.234*	*.312*

Table 6A: Sensitivity Analysis for $e^{\gamma} = 1.25$, $e^{\gamma} = 1.5$, and $e^{\gamma} = 2$

	χ^2 *for* $e^{\gamma} = 1$	χ^2 *bounds for* $e^{\gamma} = 1.25$	χ^2 *bounds for* $e^{\gamma} = 1.5$	χ^2 *bounds for* $e^{\gamma} = 2$
2009 Unemployment Rates				
GSE	6.15**	0.95—16.10	(0.07)—27.70	(4.87)—52.79
FHA	21.27**	10.68—36.10**	4.69—51.12**	0.19—80.77
PLS	11.32**	3.67—23.51*	0.53—36.76	(1.31)—64.14
Portfolio	29.87**	15.69—49.33**	7.45—68.92**	0.63—107.37
2014 Unemployment Rates				
GSE	14.11**	5.04—28.15**	1.01—43.22	(0.90)—74.07
FHA	3.52*	0.24—10.79	(0.42)—19.69	(5.99)—39.41
PLS	11.54**	3.82—23.77*	0.59—37.03	(1.20)—64.41
Portfolio	28.90**	14.99—48.09**	6.96—67.44**	0.50—105.49
2009 Home Sales				
GSE	0.01	(1.92)—2.62	(6.84)—8.12	(20.89)—23.11
FHA	43.42**	27.34—64.42**	16.89—84.67**	5.59—123.37**
PLS	35.66**	20.81—55.42**	11.59—74.82**	2.54—112.22
Portfolio	13.53**	4.84—26.99**	0.98—41.45	(0.85)—71.09
2014 Home Sales				
GSE	3.79*	0.22—11.88	(0.55)—21.86	(7.07)—44.08
FHA	11.68**	4.29—23.08**	0.93—35.30	(0.60)—60.40
PLS	22.27**	11.07—37.97**	4.78—53.94**	0.16—85.52
Portfolio	20.67**	9.59—36.53**	3.64—52.90*	0.00—85.55
2009 Home Prices				
GSE	7.52**	1.52—18.31	(0.00)—30.66	(3.83)—56.99
FHA	21.20**	10.59—36.07**	4.60—51.16**	0.16—80.94
PLS	42.55**	25.88—64.44**	15.27—85.71**	4.25—126.42**
Portfolio	75.22**	51.84—104.73**	35.92—132.59**	16.97—184.90**
2014 Home Prices				
GSE	1.86	(0.03)—8.43	(1.99)—17.34	(11.51)—38.11
FHA	15.19**	6.31—28.37**	1.89—42.17	(0.17)—70.04
PLS	13.91**	5.20—27.21**	1.19—41.38	(0.60)—70.25
Portfolio	41.05**	24.27—63.23**	13.79—84.98**	3.30—126.85*

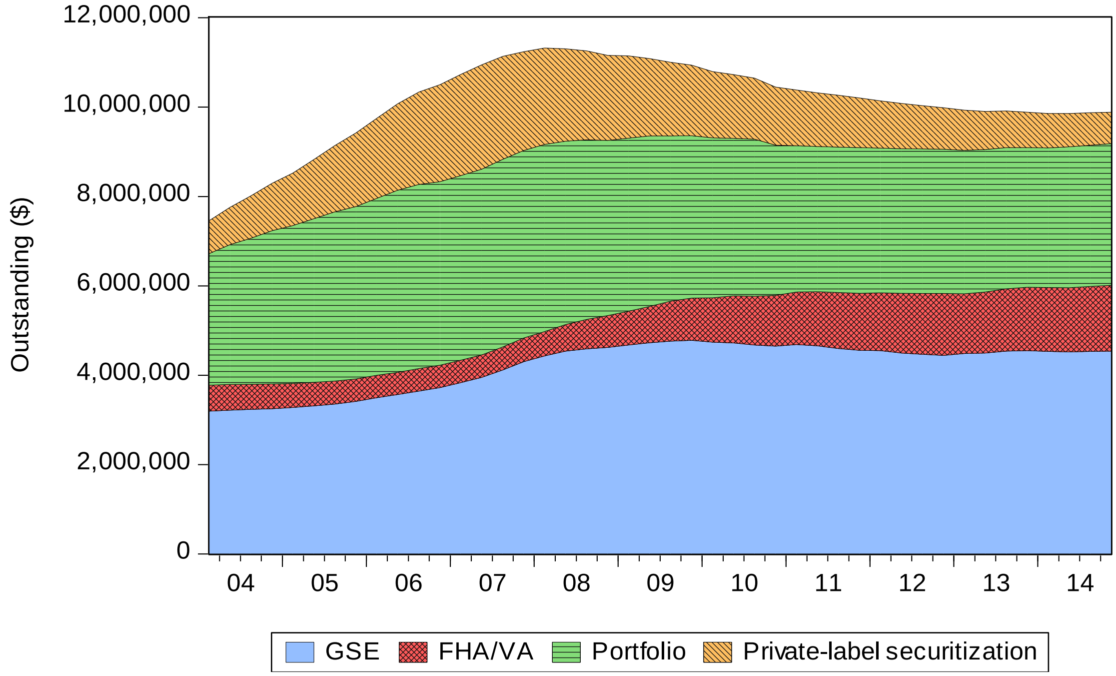
** and * denote statistical significance at the 5- and 10-percent significance levels.

Table 6B: Sensitivity Analysis for $e^{\gamma} = 1.25$, $e^{\gamma} = 1.5$, and $e^{\gamma} = 2$

	χ^2 *for* $e^{\gamma} = 1$	χ^2 *bounds for* $e^{\gamma} = 1.25$	χ^2 *bounds for* $e^{\gamma} = 1.5$	χ^2 *bounds for* $e^{\gamma} = 2$
2009 Delinquency Rates				
GSE	0.21	(0.86)—3.39	(4.25)—8.87	(14.93)—23.00
FHA	73.57**	55.01—96.94**	41.86—118.57**	25.21—158.88**
PLS	54.47**	36.71—77.27**	24.79—99.04**	10.93—140.57**
Portfolio	64.57**	44.24—90.50**	30.52—115.29**	14.31—162.69**
2014 Delinquency Rates				
GSE	0.01	(1.78)—2.29	(6.24)—7.18	(18.98)—20.61
FHA	25.91**	15.14—40.37**	8.47—54.66**	1.91—82.46
PLS	41.64**	26.12—61.95**	16.11—81.69**	5.31—119.71**
Portfolio	38.29**	22.59—59.13**	12.82—79.70**	3.07—119.73*
2009 Foreclosure Completions				
GSE	3.02*	0.11—10.04	(0.69)—18.86	(7.09)—38.75
FHA	18.90**	9.73—31.70**	4.46—44.67**	0.29—70.34
PLS	22.55**	11.45—38.04**	5.13—53.79**	0.26—85.05
Portfolio	42.12**	25.65—63.79**	15.21—85.05**	4.35—126.27**
2014 Foreclosure Completions				
GSE	0.35	(0.67)—4.00	(3.87)—9.97	(14.43)—25.06
FHA	7.61**	2.44—15.93	0.34—25.04	(0.93)—44.06
PLS	7.57**	2.00—16.99	0.10—27.54	(1.99)—49.87
Portfolio	9.00**	2.49—19.85	0.17—31.95	(2.02)—57.52

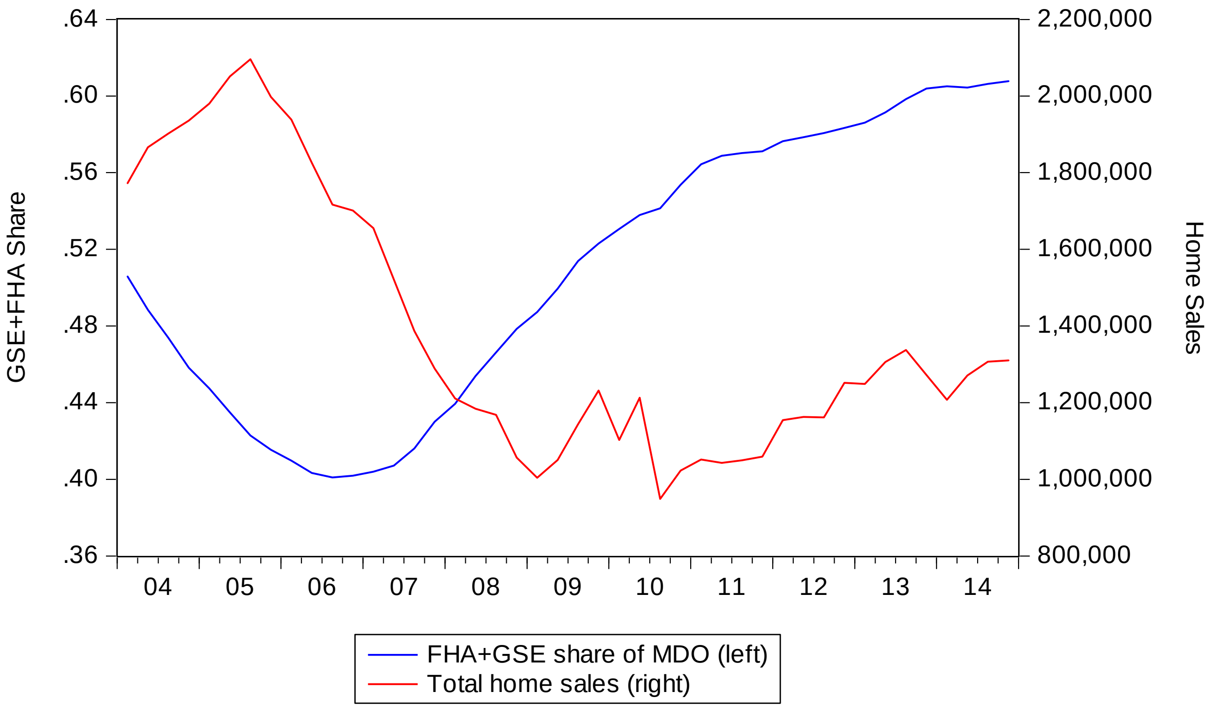
** and * denote statistical significance at the 5 and 10 percent significance levels.

Figure 1: Mortgage Debt Outstanding



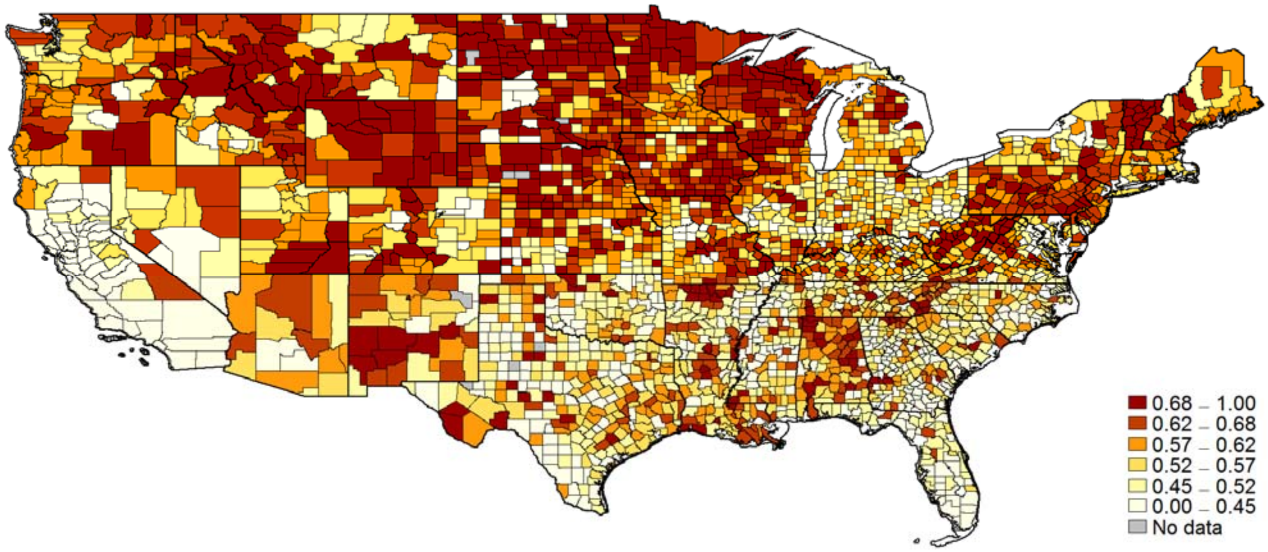
Source: Federal Reserve Board Financial Accounts of the United States.

Figure 2: Home Sales versus Government Share of Mortgage Debt Outstanding



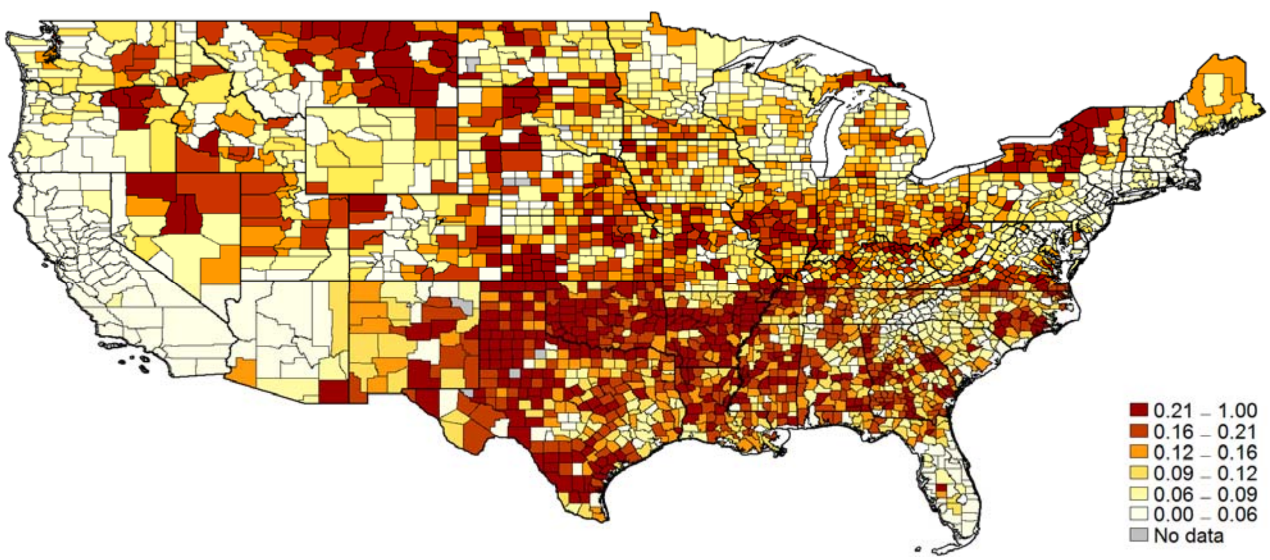
Source: Calculations based on data provided by McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc., and data provided by CoreLogic.

Figure 3A: GSE Lending in the United States



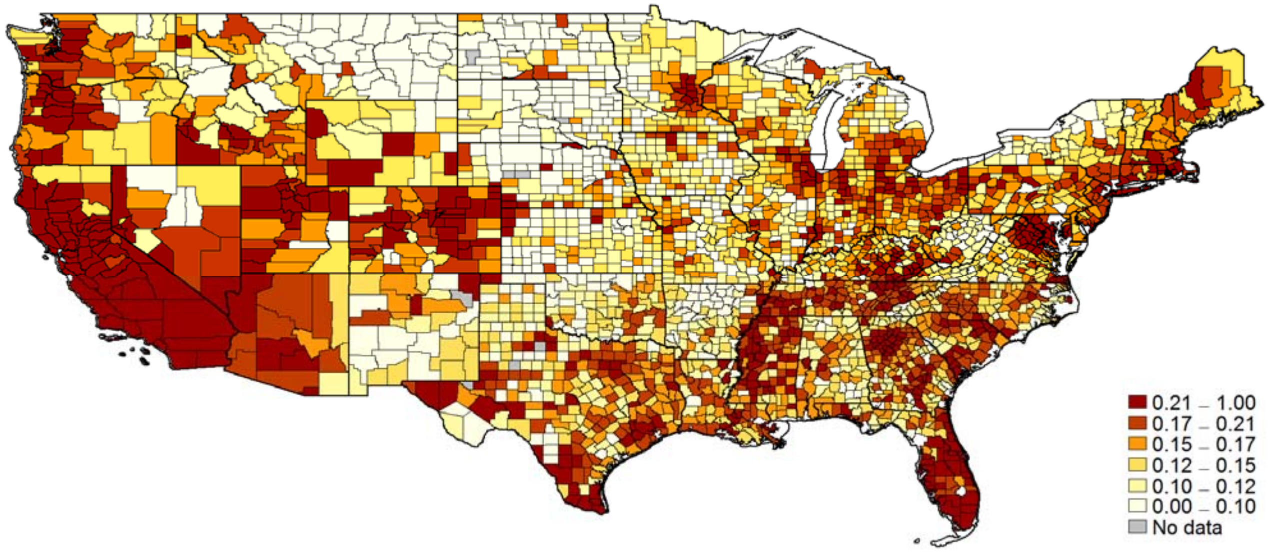
Source: Calculations based on data provided by McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc., and data provided by CoreLogic.

Figure 3B: FHA Lending in the United States



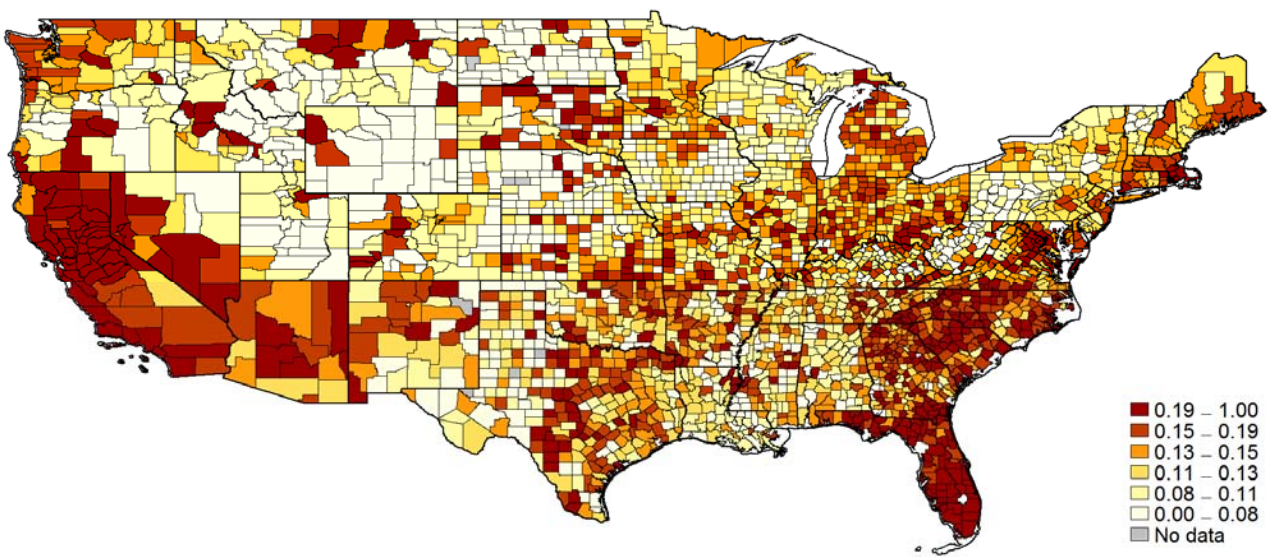
Source: Calculations based on data provided by McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc., and data provided by CoreLogic.

Figure 3C: PLS Lending in the United States



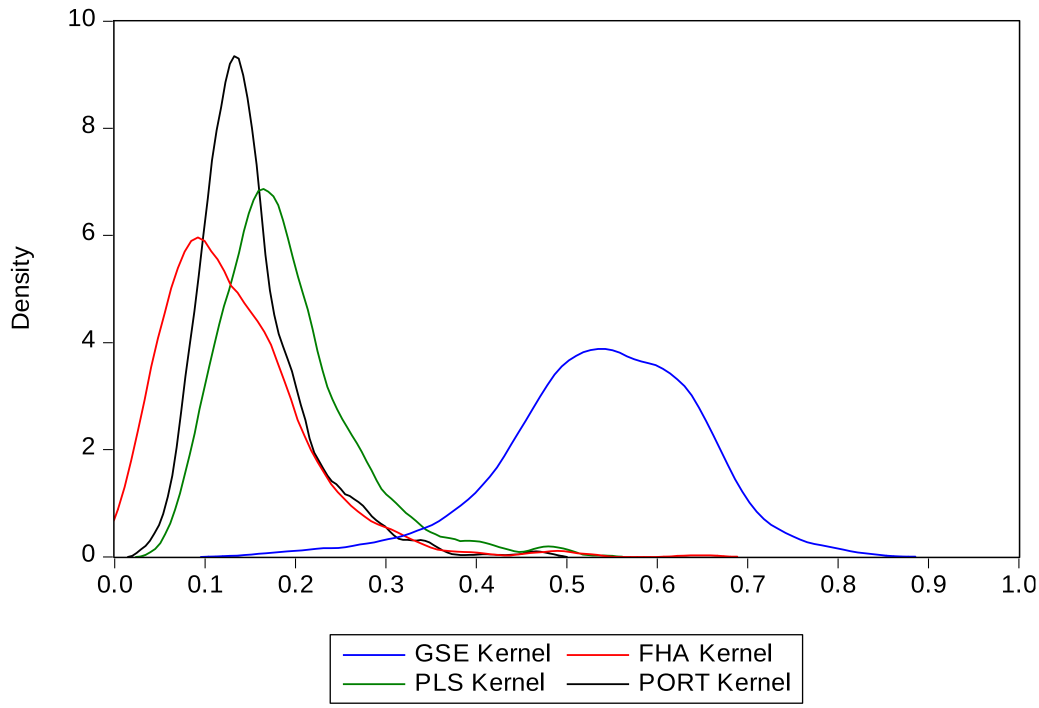
Source: Calculations based on data provided by McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc., and data provided by CoreLogic.

Figure 3D: Portfolio Lending in the United States



Source: Calculations based on data provided by McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc., and data provided by CoreLogic.

Figure 4: Mortgage Market Share Density Functions



Source: Calculations based on data provided by McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc., and data provided by CoreLogic.

Figure 5: Data Coverage

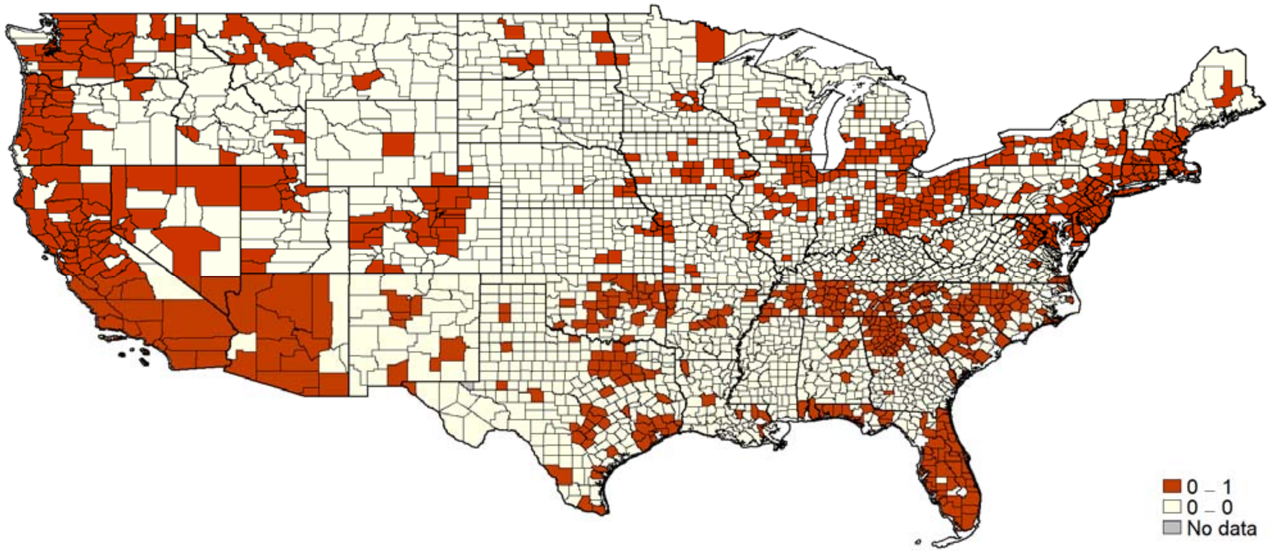


Figure 6: Unemployment Rate Dose-Response Functions

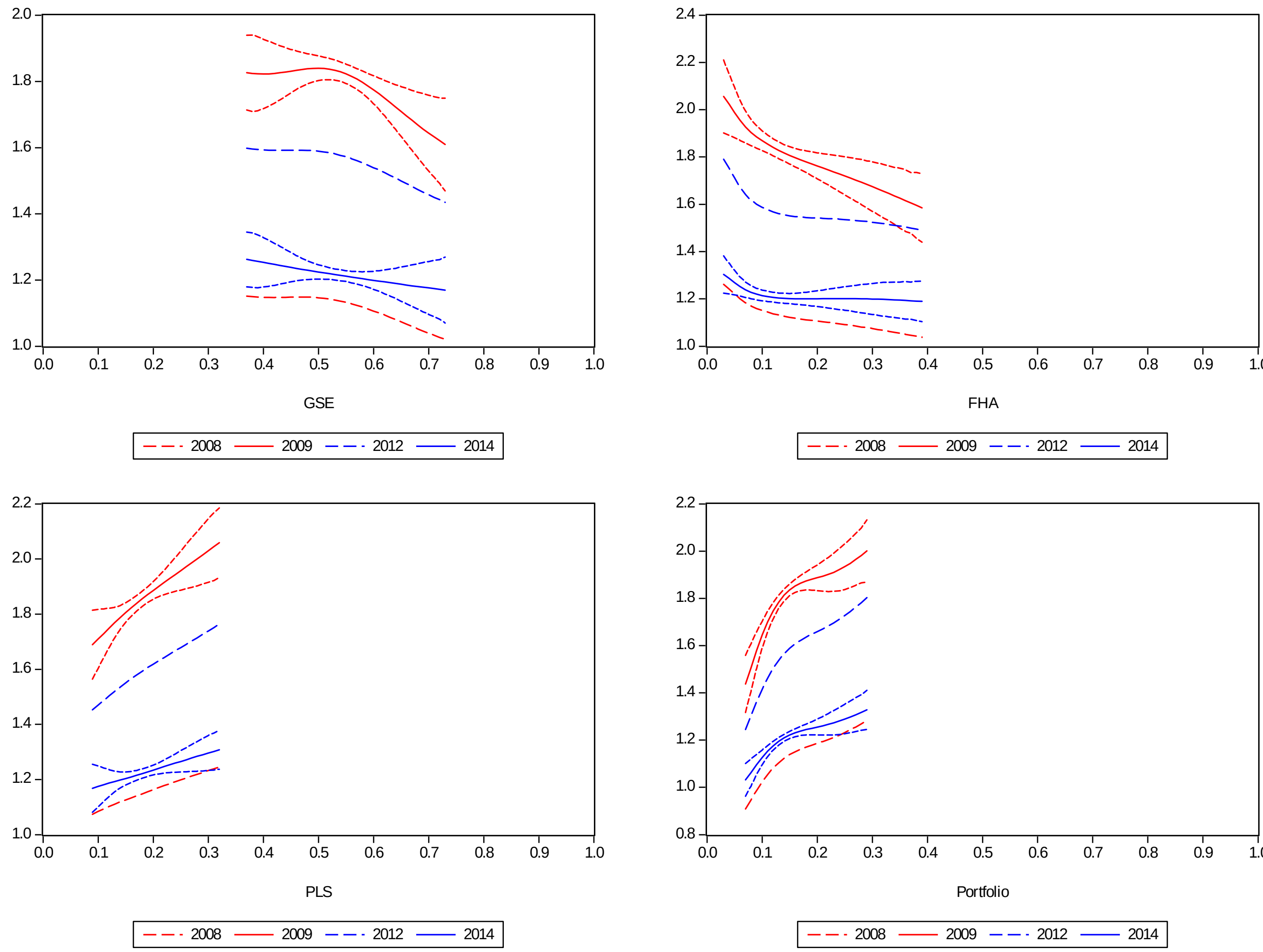


Figure 7: Home Sales Dose-Response Functions

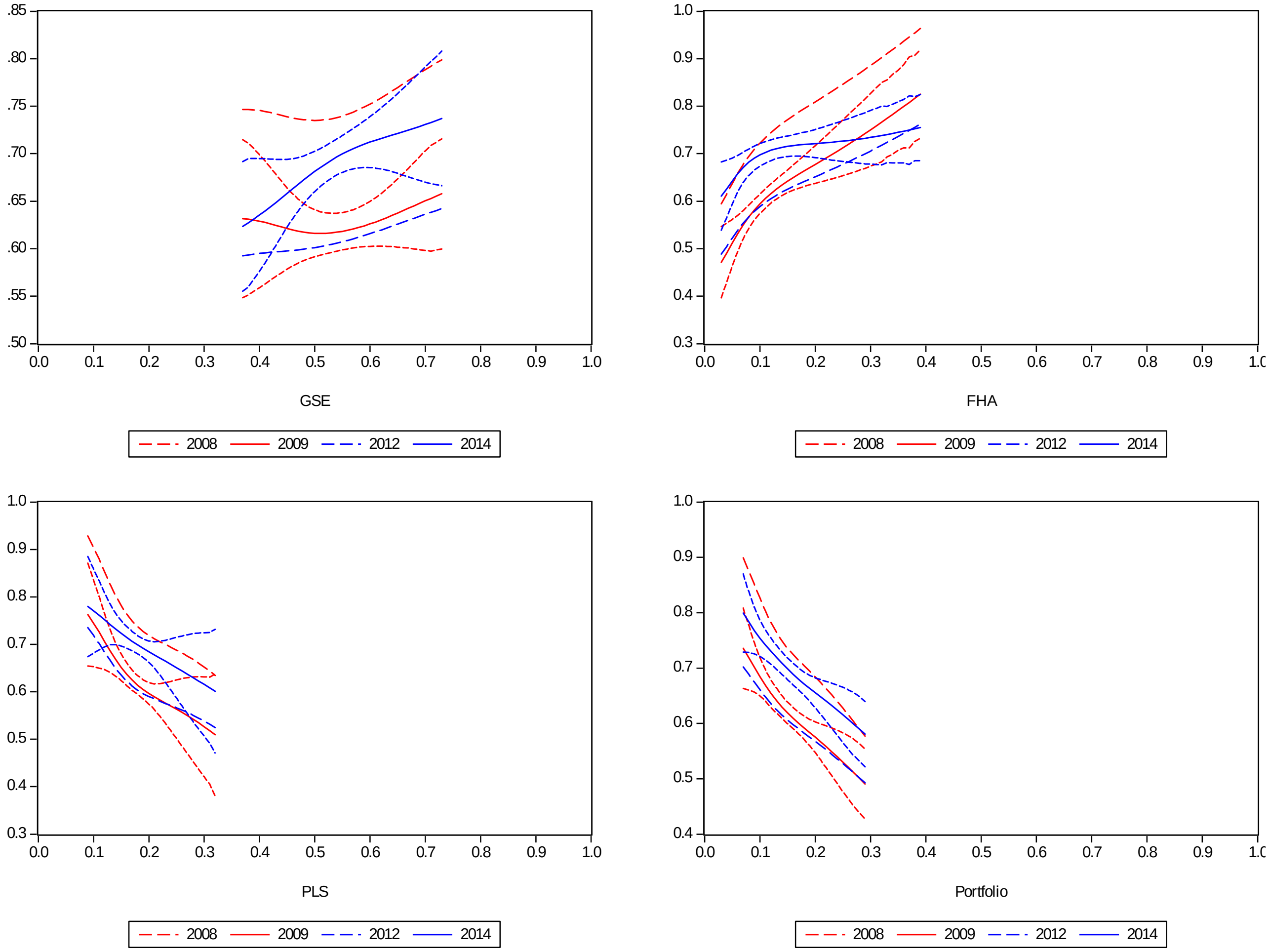


Figure 8: Home Prices Dose-Response Functions

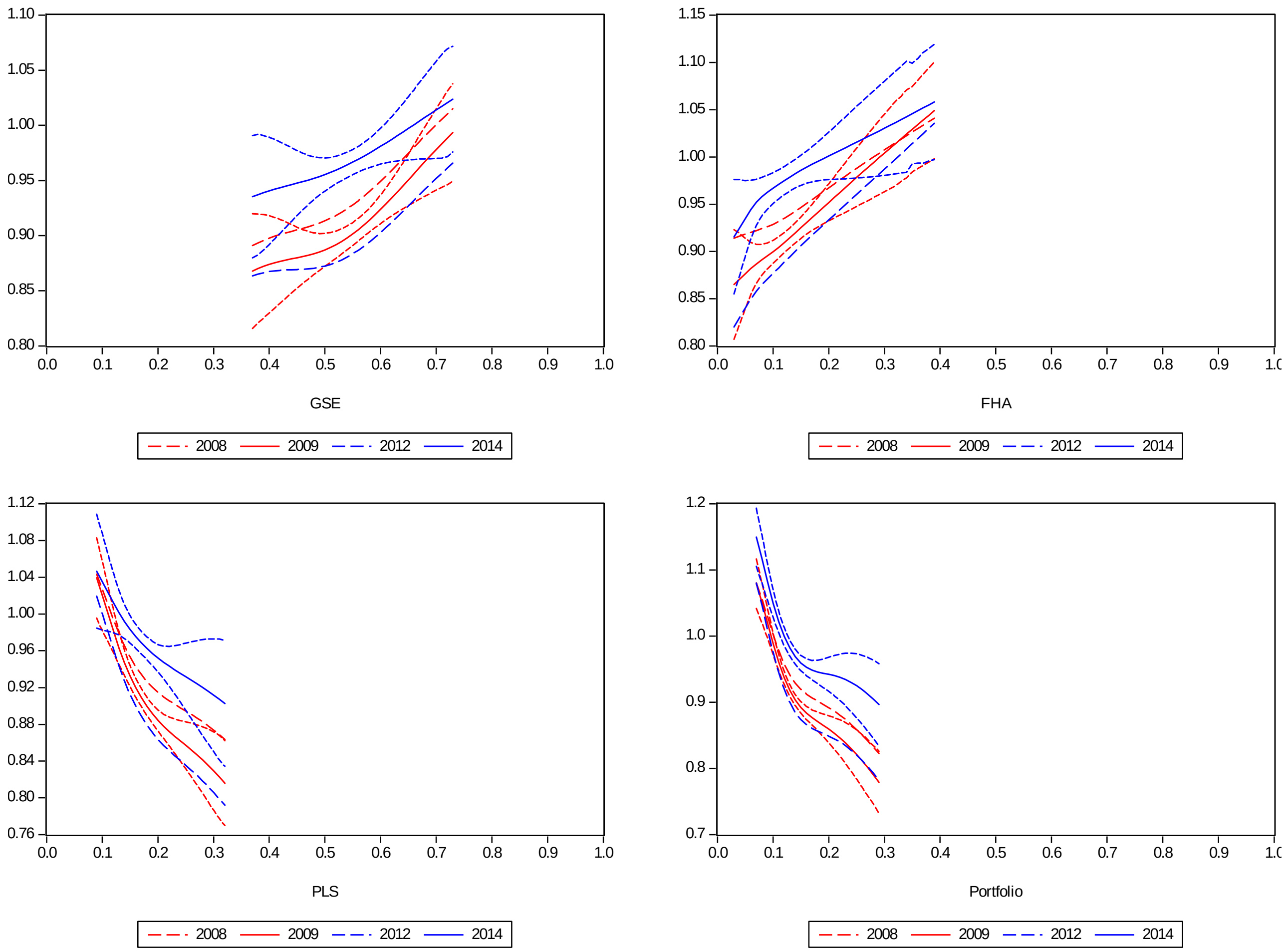


Figure 9: Delinquency Rate Dose-Response Functions

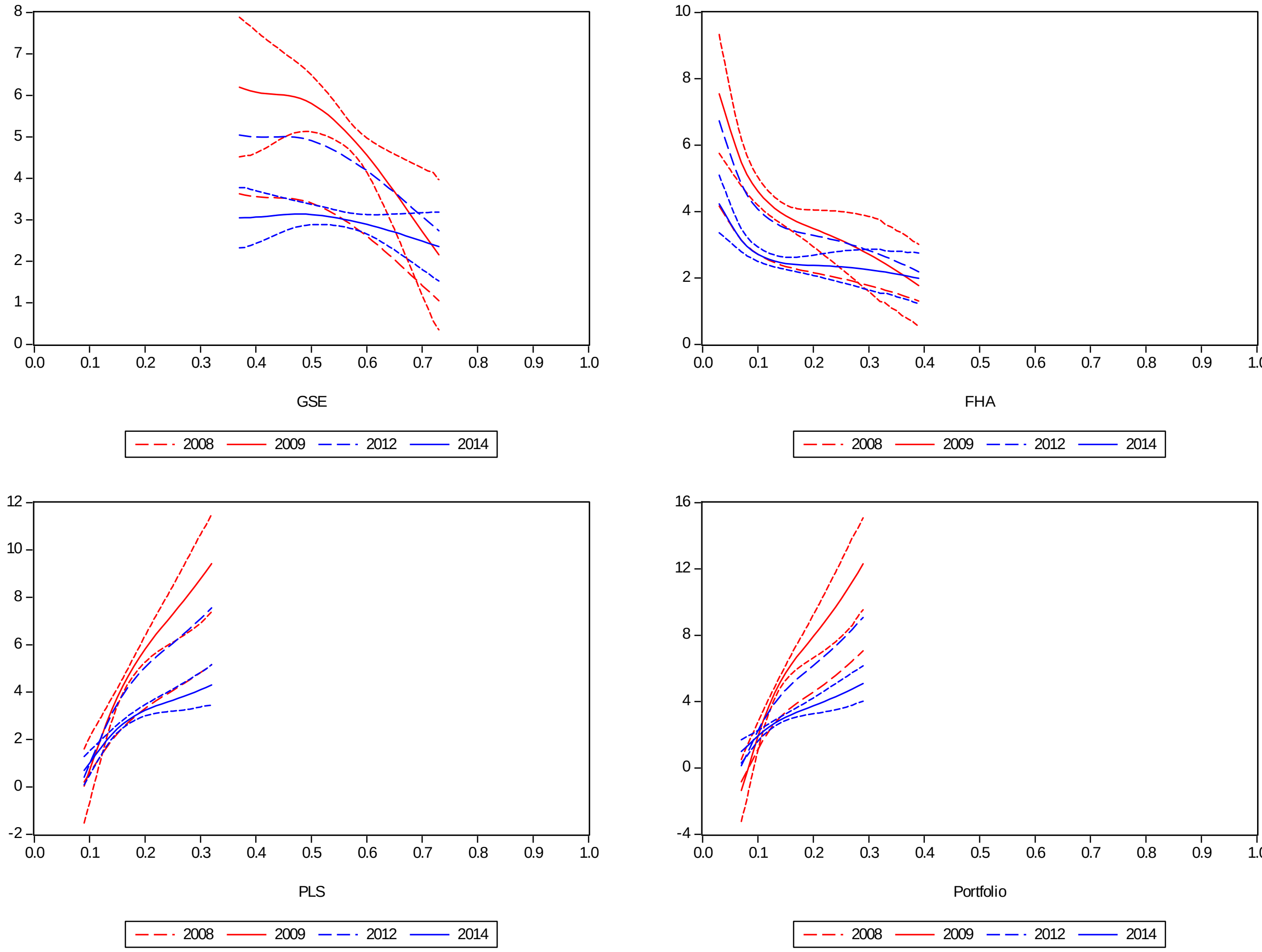


Figure 10: Foreclosure Completions Dose-Response Functions

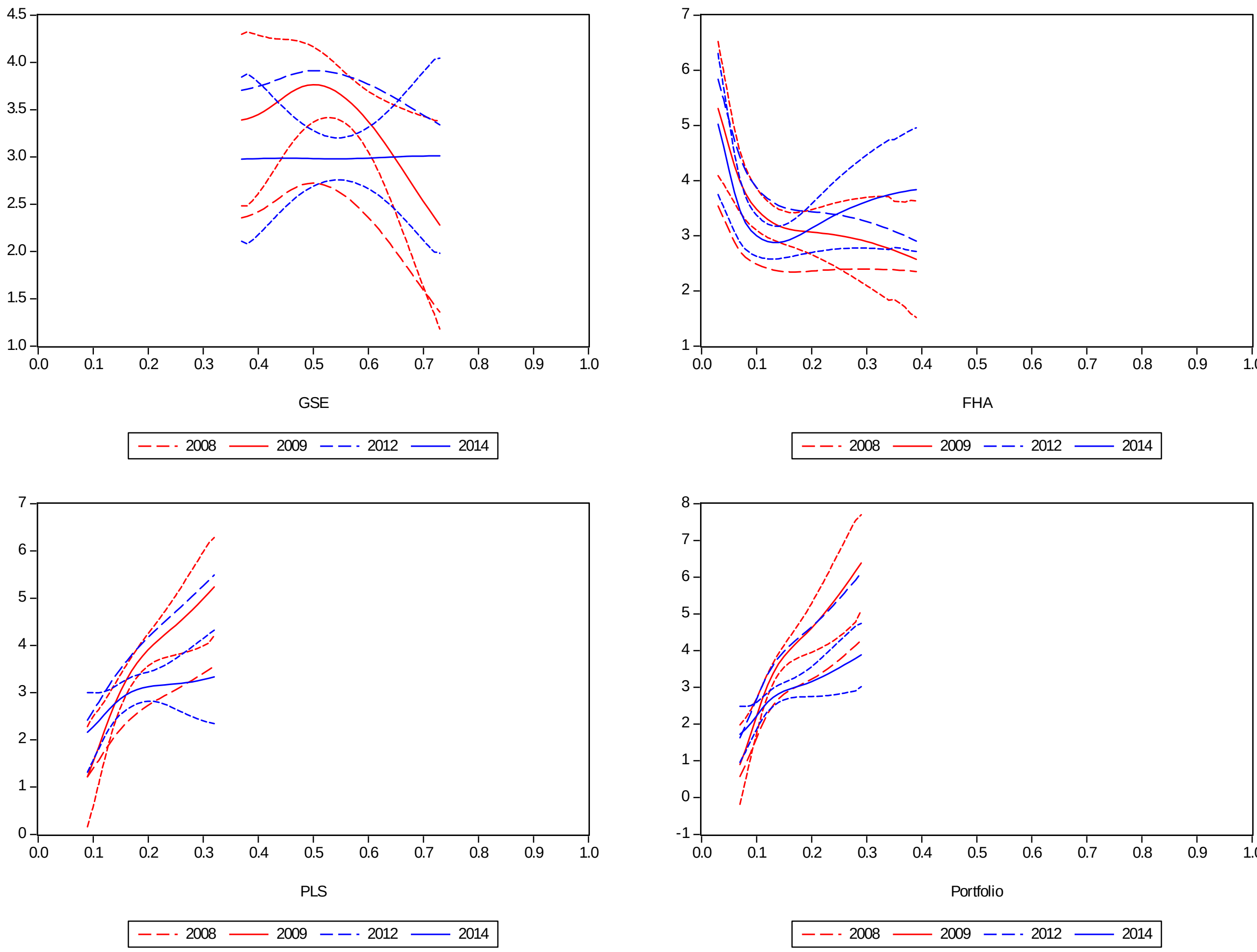


Figure 11: Market Share Dose-Response Functions