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FHA, Fannie Mae, Freddie Mac, and the Great Recession

By WAYNE PASSMORE AND SHANE M. SHERLUND*

Did government mortgage programs mitigate the adverse economic effects of the financial crisis? We find that counties with greater participation in traditional government mortgage programs experienced less severe economic downturns during the Great Recession. In particular, counties with higher levels of participation in FHA, Fannie Mae, and Freddie Mac lending had relatively smaller increases in mortgage delinquency rates; smaller declines in purchase originations, home sales, home prices, and new automobile purchases; and smaller increases in unemployment rates. These results hold both in 2009 (soon after the peak of the financial crisis) and in 2014 (six years after the crisis). The persistence of better economic outcomes in these counties is consistent with a view that mortgage originators' access to a liquidity outlet (in this case, government-backed securitization) is key to maintaining credit flows and economic growth during financial turmoil.

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I. Introduction

Did traditional government mortgage programs do what they were designed to do, to mitigate the adverse economic effects of a financial crisis? This paper establishes that government mortgage programs did indeed lessen the economic downturn resulting from the financial crisis and promoted economic recovery afterward.

The U.S. 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) in 1970 and the Government National Mortgage Association (Ginnie Mae) in 1968. Green and Wachter (2005) provide more detailed information on the federal legislation that created mortgage programs from 1933 to 1989.[1]

Mortgage lending and the dramatic rise in mortgage delinquency rates has been cited as one major cause of the financial crisis. As shown in Figure 1, mortgage delinquency rates rose from under 2 percent during 2000-2006 to 8.5 percent in 2009. Coincident with the rise in default activity was a general pullback from mortgage lending, particularly away from the types of loans exhibiting the highest default rates (subprime and alt-A mortgages). After the onset of the financial crisis, aggregate mortgage lending fell from more than 6 million purchase originations per

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

year during 2004-2006 to around 3 million mortgages per year. As a result (and because the demand for housing also decreased), home sales declined from a pace of 7-8 million units per year during 2004-2006 to around 4.5 million units, and home prices fell by more than 25 percent, and new auto purchases declined from a pace of nearly 11 million vehicles per year during 2004-2006 to 7 million vehicles per year. The national unemployment rate increased from about 4.5 percent in 2006 to nearly 10 percent in 2009.

These employment losses were not shared evenly across industries. As shown in Figure 2, from the end of 2005 to the end of 2009, total employment in the U.S. declined by 4 percent, while construction employment declined nearly 25 percent. Even though construction employment comprised only 5.6 percent of total employment in 2005, construction-related employment losses accounted for over a third of total employment losses.

Nor were the employment losses spread evenly across states and counties. In California and Florida, total employment declined 7 to 10 percent from 2005 to 2009, while construction employment declined 40-45 percent. Furthermore, construction-related employment losses in these states accounted for around 40 percent of the total. Given the effects of lower construction activity, lower lending activity, the decline in wealth resulting from lower home prices, and lower spending on durable consumption, we posit that the direct and indirect effects on unemployment rates could be economically meaningful for many counties.

Drawing on a wide variation across counties in government mortgage program participation and economic outcomes during and after the financial crisis, we find a strong correlation between counties that participated more heavily in government mortgage programs and better economic outcomes, and, further, that these better outcomes can be attributed directly to greater program participation. In particular, counties with higher levels of FHA participation had smaller increases in unemployment rates; smaller declines in purchase originations, homes sales, and home prices; and smaller increases in mortgage delinquency rates. These results hold both in 2009 (immediately following the financial crisis) and in 2014 (six years after the crisis). To a lesser extent, counties with substantial participation in GSE programs (Fannie Mae and Freddie Mac) also had better economic outcomes. In contrast, counties more reliant on bank portfolio and private-label securitization for funding mortgage originations experienced larger changes.

We use generalized propensity score (GPS) methods to identify and estimate the effects of government mortgage programs on economic outcomes. We control for counties' abilities to select their level of program participation, or selection of treatment doses, based on pre-crisis county characteristics. In addition, we show that our results are robust to varying degrees of unobserved heterogeneity in counties' selection of treatment doses. These techniques have not been previously used to analyze the empirical effects of mortgage credit on real economic outcomes; we provide a comprehensive approach to applying these techniques in this area.

We proceed as follows. Section II discusses mortgage market structures and describes the data we use in our analysis. Section III summarizes the GPS methodology, which we use to identify the effects of the intensity of government mortgage program participation on county-level delinquency rates, purchase originations, home sales, home prices, new auto purchases, and unemployment rates. Section IV tests some of the underlying assumptions of the GPS methodology (the common support and balancing conditions). Sections V and VI discuss and summarize the estimated dose-response functions. These dose-response functions show that government mortgage programs can be effective at mitigating the effects of financial crisis on real economic activity. Sections VII and VIII discuss the policy implications of our results and conclude.

II. Mortgage Markets and Data

We segment the mortgage market into four methods of origination and financing: (1) government-guaranteed mortgages (Fannie Mae and Freddie Mac), (2) government-insured mortgages (FHA/VA), (3) private-label securitization (PLS), and (4) bank balance sheets (portfolios). The data are aggregated to the county level using data from the Home Mortgage Disclosure Act (HMDA), CoreLogic, and McDash Analytics.[2]

Fannie Mae and Freddie Mac are implicitly subsidized by the government (Acharya et al., 2011, Passmore et al., 2005, Passmore, 2005). On September 6, 2008, the Federal Housing Finance Agency placed Fannie Mae and Freddie Mac into conservatorship and the U.S. Department of the Treasury agreed to provide strong financial support for these entities, solidifying the perception of government support. Fannie Mae and Freddie Mac both remain under government conservatorship.[3] At the end of 2015, Fannie Mae and Freddie Mac guaranteed about $2.8 trillion and $1.7 trillion of MBS, respectively.

The FHA provides mortgage insurance for mortgages extended by FHA-approved lenders. FHA mortgages are typically securitized by Ginnie Mae or held in bank portfolios. Ginnie Mae mortgage-backed securities (MBS) carry the full faith and credit of the U.S. government. At the end of 2015, the FHA had about $1.3 trillion of insurance in force.

Private-label securitization (PLS) typically consists of mortgages deemed to be outside GSE parameters, either in terms of loan size—jumbo loans whose initial balances exceed the conforming loan limits—or in terms of underwriting—alt-A

[2] We make adjustments for differential data coverage across mortgage-market segments. For example, our data have nearly complete coverage of FHA and PLS lending, but incomplete coverage of GSE and portfolio lending.

[3] For a history of the GSEs' troubles, see Frame and White (2005) and Frame et al. (2015). For the current status of the GSEs, see CBO (2014).

loans whose income is not fully documented or subprime loans whose credit scores or loan-to-value ratios are too low or too high, respectively (Mayer et al., 2009). PLS activity accounted for about $700 billion of mortgages outstanding at the end of 2015.

Mortgages not securitized but held in bank portfolios often consist of very high credit quality mortgages and/or very low credit quality mortgages (Passmore and Sparks, 1996; Hancock and Passmore, 2011). Part of the motivation for these stricter underwriting standards is a desire to maintain the option to sell the mortgages to the government later, if needed. Part of the motivation for looser underwriting is to extend the mortgage market beyond those mortgages that could be securitized. Portfolio lending accounted for nearly $3.25 trillion at the end of 2015.

These four mortgage origination channels can be ranked by their government-backed financing and underwriting standards. FHA/VA uses government insurance and has the most generous underwriting standards. Fannie Mae and Freddie Mac have tighter underwriting standards than FHA/VA, and their government backing is more limited than FHA/VA. Although banks have government deposit insurance on some of their liabilities, they also have non-government-backed liabilities. In addition, their underwriting for fixed-rate mortgages typically follow either FHA or GSE underwriting standards, and is thus stricter than underwriting standards used by FHA, Fannie Mae, or Freddie Mac alone. PLS has no government backing and has the tightest underwriting standards, at least following the financial crisis. Before the crisis, of course, most PLS had notoriously loose underwriting standards.

As shown in Figure 3, the bulk of mortgage debt outstanding in the United States is held in bank portfolios or securitized by Fannie Mae or Freddie Mac. Private-label securitization grew rapidly leading up to the financial crisis, at the expense of FHA and GSE lending, but new PLS activity essentially ceased with the onset of the financial crisis (Mayer et al., 2009, Nadauld and Sherlund, 2013). FHA insured a relatively small portion of outstanding mortgage debt in 2005, but its share grew rapidly following the financial crisis.

A map of counties across the United States illustrates the wide variation in government involvement in mortgage lending prior to the financial crisis. The use of government mortgage programs (Figures 4A and 4B) appears to be concentrated away from the Coasts, dominating in the Midwest, Mountain West, Mississippi River Valley, and Appalachia. Most of California, South Florida, and the largest MSAs relied more heavily on private funding (Figures 4C and 4D).

Moreover, the empirical distributions of market shares further suggest significant variation in government mortgage program use across counties prior to the financial crisis (Figure 5). The bulk of GSE shares ranged from about 35 to 80 percent of originations in a county, while FHA shares ranged from 2 to 28 percent. The bulk of bank portfolio shares ranged from 4 to 27 percent, while PLS shares, even at its heyday prior to the financial crisis, ranged from 4 to 31 percent of mortgage originations in a county. Summary statistics are provided in Table 1.

Of course, the four market shares necessarily sum to 1, so Table 2 shows how the various market shares tend to co-vary with each other.[4] PLS and portfolio shares tend to decline as GSE or FHA shares increase, while GSE and FHA shares exhibit an inverse-U shape relationship with each other. Similarly, GSE and FHA shares tend to decline as PLS or portfolio shares increase, whereas PLS and portfolio funding exhibit more of a direct relationship with each other.

In addition to the mortgage market share data, we use county-level data from a variety of other sources (also summarized in Table 1). Mortgage delinquency rates, home sales, and home prices come from CoreLogic. New automobile purchase registration data comes from R.L. Polk. Unemployment rates come from the Bureau

[4] We use nonparametric kernel regression techniques to estimate these average shares.

of Labor Statistics. Median Equifax risk scores and the percentage of households with risk scores within risk score buckets 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 and salaries, exemptions, dividends and interest, and the percentage of returns within income buckets come from the IRS 2005 Statistics of Income data. The number of lenders and purchase originations are calculated from the Home Mortgage Disclosure Act (HMDA) data. Population, age, gender, race and ethnicity, poverty rate, and education statistics for 2005 come from the Census Bureau.

III. 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. Unlike the ideal natural experiment setting, in which treatment and control groups are clearly and randomly assigned, the intensity of GSE, FHA, PLS, portfolio market shares take on a continuum of values and can vary based on county characteristics. That is, a county's particular market share structure might not be independent of the same conditions that influence economic performance. Thus, we control for the propensity of a county to select its GSE, FHA, PLS, and portfolio market shares, conditional on economic fundamentals such as average income, home price appreciation, and the unemployment rate. The GSE, FHA, PLS, and portfolio market shares for each county can then be considered a random treatment once each county's underlying characteristics have been taken into account. We can then estimate the effect of the mortgage market shares on economic activity.

Propensity scoring has been used in other financial studies. For example, Casu et al. (2013) use propensity scoring to identify the effects of securitization on bank performance. They find that banks that securitize loans seem to have similar risk-adjusted returns as banks that do not securitize loans. Bharath et al. (2009) investigate lending relationships and loan contract terms. They use propensity scores to create a matched sample of firms with lender relationships and those without such relationships, and find that relationships yield a small but significant funding advantage for borrowers. Finally, Chemmanur et al. (2014) use propensity scores to assess and to rule out the possibility that corporate venture capital firms are simply better at selecting innovative projects. They find that corporate venture capital firms have a superior ability to nurture innovative ventures than independent venture capital firms. Our approach is similar in spirit to Rosenbaum and Rubin (1983) and most similar to Hirano and Imbens (2004). We use generalized propensity scores, in which the probability of a particular county receiving a particular dose or market share is a function of its pre-existing, underlying characteristics.

Our identification strategy relies on the variation in government involvement in mortgage markets across counties. Counties with significant government involvement are subject to liquidity, credit risk pricing, and underwriting standards that are set at the national level by FHA, Fannie Mae, and Freddie Mac. In contrast, counties with little government involvement are more likely subject to more local liquidity, 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 more likely correlated with local market conditions).

The extent of a county's participation in government mortgage programs can be characterized as a "treatment" administered by the government to augment the financial infrastructure and support homeownership in a county. We assume that each county's mortgage market structure changes only slowly over time, and reflects the characteristics of the population and economic conditions within each county. We therefore model county-level GSE, FHA, PLS, and portfolio market shares as a function of county characteristics during the 2004-2007 pre-crisis period. We use only counties for which we have complete data on home prices during our 2004-2014 observation period, resulting in 972 county-level observations.[5] Not surprisingly, as shown in Figure 6, the counties that remain are predominantly located in metropolitan areas. Moreover, these counties account for 85-90 percent of purchase originations and home sales and 82 percent of new auto purchases observed in the full data set.

We perform a set of first-stage regressions of the four treatment levels on county-level characteristics:

(1) $$t_i = \beta_0 + \beta_1 X_i + e_i,$$

where t_i is the market share, X_i the vector of observed county characteristics, and e_i is an error term. As the market shares necessarily sum to 1 for each county, we restrict the regression so that the sum of β_0 across the equations equals 1, and the sum of each element of β_1 across the equations equals 0. We also include state fixed effects.

We include pre-crisis, county-level measures of credit quality, income, population and demographics, economic fundamentals, housing affordability, market competition, and conforming loan limits in X_i. The credit quality measures consist of median risk scores, the proportion of the population with a credit report, and the proportion of reports with risk scores in several bins: <580, 580-619, 620-679, 680-739, 740-799, and 800+. Our income measures include average wages and salaries, average exemptions, average dividends and interest, and the proportion of returns with income in several bins: \$0-10K, \$10-25K, \$25-50K, \$50-

[5] Our initial, incomplete data set started with 3,141 counties. Missing or incomplete house price data accounts for the majority of the dropped observations.

75K, \$75-100K, and \$100K+. The population and demographic measures consist of total population, age proportion bins, gender proportion bins, race and ethnicity proportion bins, poverty rates, and education proportion bins. Our economic fundamentals include 12-month house price appreciation and the unemployment rate, while our housing affordability measure is the median home price over average income. Finally, the mortgage market competition measures consist of the total number of lenders reporting to HMDA in 2005 as well as the change from 1998, while the conforming loan limit measures consist of the difference between the median home price and the conforming loan limit and the proportion of home sales that occur at or below 125 percent the conforming loan limit.

As shown in Table 3, these measures do a decent job in explaining the variation in the four market shares, with *R*-squared values of 54 to 80 percent. Furthermore, credit scores, income, population and demographics, economic fundamentals, housing affordability, mortgage market competition, and conforming loan limits each contribute in ways that make sense across the equations. For instance, GSE shares tended to be larger with higher average incomes, while FHA and PLS shares tended to be lower. GSE and FHA shares tended to be higher when the proportion of home sales at or below 125 percent of the conforming loan limit was higher, while PLS and portfolio shares tended to be lower.

The generalized propensity score (GPS) estimates are then

$$r_i = \phi((t_i - \beta_0 - \beta_1 X_i)/\sigma), \tag{2}$$

where ϕ is the standard normal probability density function. The inclusion of the estimated GPS in our subsequent analysis accounts for the selection of counties into their particular treatment levels.

IV. Testing the Estimated GPS

The adequacy of the estimated GPS relies on two important assumptions: the common support condition and the balancing condition. The common support assumption assures that treated observations have similar untreated observations with which to compare. The balancing condition ensures that the covariates are orthogonal to the doses conditional on the GPS, so that differences in county characteristics do not implicitly bias our results. In other words, when we estimate the impact of mortgage market shares on real economic activity, we can be confident that the estimates causal effects are coming from changes in market shares as opposed to changes in the underlying characteristics of the counties. We explore each of these conditions next.

To assess the common support condition, we follow the approach of Hirano and Imbens (2004) and estimate the GPS for all counties at each quartile of treatment, and then compare these estimates across quartile groups. Observations that lie outside the support of the comparison group are dropped.[6] In each case, we compare observations with actual market shares within 25 percentiles of the assumed treatment (treated group) with those with actual market shares outside 25 percentiles of the assumed treatment level (control group). If a particular GPS estimate lies outside the support of its comparison group then we drop that observation. This procedure reduces the sample size to 916 counties for our GSE analysis (6.8 percent dropped), 879 counties for our FHA analysis (9.6 percent dropped), 837 counties for our PLS analysis (13.9 percent dropped), and 949

[6] For example, we estimate the GPS for each county assuming GSE market shares of 46.7, 54.3, and 61.3 percent—the 25th, 50th, and 75th percentiles. We then compare the GPS based on the 25th-percentile market share across two groups: those with actual GSE market shares below the 50th percentile and those with actual GSE market shares above the 50th percentile. Similarly, we compare the GPS based on the 75th-percentile market share across two groups: those with actual GSE markets shares above the 50th percentile and those with actual GSE market shares below the 50th percentile. Finally, we compare the GPS based on the 50th-percentile market share across two groups: those with actual GSE market shares between the 25th and 75th percentiles and those with actual GSE market shares below the 25th percentile or above the 75th percentile.

counties for our bank portfolio analysis (2.4 percent dropped). The remaining counties satisfy the common support condition, which ensures that each county has at least one counterpart to which it can be compared.

To test the balancing property, we also follow the approach of Hirano and Imbens (2004) and discretize market shares into three equal-sized groups and the estimates GPS into five equal-sized groups. We then test for the equality of covariate means across treatment groups, conditional on the GPS.[7] Adjusting for the GPS substantially improves the balance, reducing the magnitudes of the *t*-statistics reported in Tables 4A-4D. More generally, the GPS adjustment substantially reduces the magnitudes of the *t*-statistics—in fact, most are statistically insignificant once adjusted by the estimated GPS. Thus our estimated GPS balances the covariates in our sample. We therefore take some comfort in that we can isolate the pure effect of government involvement in the mortgage market on the economic variables of interest.

V. 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 on their pre-determined mortgage market structures and on their estimated GPS. The four subsequent periods we study are 2007:H2-2008 (early crisis period), 2009 (crisis period), 2010-2012 (early post-crisis period), and 2013-2014 (post-crisis period). The six economic outcomes of interest we evaluate include: (1) mortgage delinquency rates, (2) purchase

[7] For example, as shown in Table 4A, when we test the equality of average credit score medians for counties with GSE market shares of 49 percent or less against those with GSE market shares greater than 49 percent, counties with GSE market shares of 49 percent or less tend to have lower median credit scores than counties with GSE market shares above 49 percent (*t*-statistic of -10.4). Similarly, counties with GSE market shares above 59 percent tend to have higher median credit scores than counties with GSE market shares of 59 percent or less (*t*-statistic of 9.9). To adjust for the GPS, we compute the GPS for an assumed GSE market share of 43 percent (the median for counties with GSE market shares of 50 percent or less) for each county. For each GPS quintile, we compute the *t*-statistic for the equality of median credit scores across counties with GSE market shares of 49 percent or less versus those with GSE market shares greater than 49 percent, then compute the weighted average across GPS quintiles to arrive at the overall *t*-statistic.

originations, (3) home sales, (4) home prices, (5) new auto purchases, and (6) unemployment rates. We also consider the evolution of mortgage market shares. For each time period, mortgage delinquency rates, home prices, and unemployment rates are measured relative to their 2005 year-end values, while purchase originations, home sales, and new auto purchases are measured relative to their 2004-2007:H1 monthly averages.

We estimate the dose-response functions using nonparametric local-linear regression and weight by the estimated GPS to account for selection into treatment levels. In particular,

$$y_i = m(t_i, r_i) + e_i, \tag{3}$$

where y_i is the economic variable of interest, t_i is the treatment level or market share, r_i is the estimated GPS evaluated at the actual market share and the observed county characteristics, and m is an arbitrary nonparametric function.[8] We specify a Gaussian kernel and use a rule of thumb bandwidth throughout.[9]

VI. Graphical Dose-Response Functions

Graphical dose-response functions provide a convenient summary of the estimated dose-response functions. They show the expected value of the economic outcome conditional on a level of treatment and the estimated GPS. Confidence bands are generated from 2,500 bootstrap replications (with replacement), and are shown for 2009 and 2014; those for 2008 and 2012 are of similar size.

[8] We also explored estimating the dose-response functions using parametric functions with linear and higher-order polynomials of t_i and r_i ,as well as an unweighted multivariate local-linear regression of y_i on t_i and r_i. Our qualitative results remain the same.

[9] Using optimal, cross-validated bandwidths produces similar results, although a bit more "wiggly."

A. Mortgage Delinquencies

Overall, mortgage delinquency rates increased by a factor of about 4.5 from 2005 to 2009. Delinquency rates (Figure 7) rose the most in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending. This is consistent with the findings of Mian and Sufi (2009) and Mayer et al. (2009), who all attribute higher delinquency rates and foreclosures to the use of private-label securitization and portfolio lending activity. By 2014, mortgage delinquency rates had declined, but still remained about twice as high as in 2005. The rise in delinquency rates remained the highest in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending.

In particular, by 2009 mortgage delinquency rates had risen by a factor of 16 in the lowest FHA-share counties compared to a factor of 3 in the highest FHA-share counties. Similarly, delinquency rates had risen by a factor of 12 in the lowest GSE-share counties compared to a factor of about 3.5 in the highest GSE-share counties. In contrast, by 2009 mortgage delinquency rates had increased by a factor of 3 in the lowest PLS-share counties, compared to a factor of 10 in the highest PLS-share counties; and had increased by a factor of about 3 in the lowest portfolio-share counties, compared to a factor of 18 in the highest portfolio-share counties.

B. Mortgage Market Shares

Given the large increases in delinquencies associated with PLS-funded originations, in particular, mortgage originators (and investors) moved away from private funding sources during and following the financial crisis—both in an absolute and a relative (market share) sense. As shown in Figure 8, PLS funding fell to essentially zero and portfolio shares declined somewhat, most notably for higher portfolio-share counties. FHA and GSE funding made up some of these losses: FHA shares increased notably across the board (FHA shares increased parallel to the 45-degree line), while GSE shares increased for lower GSE-share counties. Note that GSE shares ultimately declined among the higher GSE-share counties, likely reflecting increased guarantee fees and the increased FHA presence. Overall, 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 unchanged prices.

C. Purchase Originations

Overall, monthly purchase originations fell by about half from the 2004-2007:H1 period to 2009. Purchase originations (Figure 9) declined the most in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending. By 2014, purchase originations had increased slightly, but remained well below their levels in 2005. The decline in purchase originations remained the largest in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending.

In particular, by 2009 purchase originations had fallen by over 50 percent in the lowest FHA-share counties compared to about 40 percent in the highest FHA-share counties. Similarly, purchase originations had fallen by over 50 percent in the lowest GSE-share counties compared to 38 percent in the highest GSE-share counties. In contrast, by 2009 purchase originations had declined by 33 percent in the lowest PLS-share counties, compared to 55 percent in the highest PLS-share counties; and 36 percent in the lowest portfolio-share counties, compared to 54 percent in the highest portfolio-share counties.

D. Home Sales and Home Prices

Given the vital link between home financing and home sales, one might expect to find similar results for home sales. Overall, monthly home sales fell by about half from the 2004-2007:H1 period to 2009. Home sales (Figure 10) declined the most in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending. By 2014, home sales had increased slightly, but remained well below their levels in 2004-2007:H1. The decline in home sales remained the largest in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending.

In particular, by 2009 home sales had fallen by about 50 percent in the lowest FHA-share counties compared to about 35 percent in the highest FHA-share counties. Similarly, home sales had fallen by 46 percent in the lowest GSE-share counties compared to 35 percent in the highest GSE-share counties. In contrast, by 2009 home sales had declined by 26 percent in the lowest PLS-share counties, compared to over 50 percent in the highest PLS-share counties; and 32 percent in the lowest portfolio-share counties, compared to 46 percent in the highest portfolio-share counties.

Home prices, the primary store of wealth for many Americans, also exhibited stark differences across mortgage market structures. Home prices (Figure 11) declined the most in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending. By 2014, home prices had increased somewhat, but remained below their 2005 levels on average. The decline in home prices remained sizable in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending, while home price declines were largely erased in counties (if not somewhat higher) with the highest exposures to GSE or FHA lending and lowest exposures to PLS and portfolio lending.

In particular, by 2009 home prices had fallen by 22 percent in the lowest FHA-share counties compared to only 4 percent in the highest FHA-share counties. Similarly, home prices had fallen by 22 percent in the lowest GSE-share counties compared to only 4 percent in the highest GSE-share counties. In contrast, by 2009 home prices were essentially unchanged from 2005 in the lowest PLS-share counties, compared to having fallen 20 percent in the highest PLS-share counties; and essentially unchanged in the lowest portfolio-share counties, compared to having fallen 23 percent in the highest portfolio-share counties.

E. New Auto Purchases

Given the effects on home prices, it is natural to ask if there were any wealth effects on consumption, particularly of durable goods. To evaluate this, we consider new auto purchase registrations. Overall, new auto purchases fell about 40 percent from the 2004-2007:H1 period to 2009. New auto purchases (Figure 10) declined the most in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending. By 2014, new auto purchases had increased significantly, but remained below their levels in 2004-2007:H1. The decline in new auto purchases remained the largest in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending.

In particular, by 2009 new auto purchases had fallen by about 40 percent in the lowest FHA-share counties compared to about 30 percent in the highest FHA-share counties. Similarly, new auto purchases had fallen by 40 percent in the lowest GSE-share counties compared to 25 percent in the highest GSE-share counties. In contrast, by 2009 home sales had declined by 27 percent in the lowest PLS-share counties, compared to 43 percent in the highest PLS-share counties; and 28 percent in the lowest portfolio-share counties, compared to 44 percent in the highest portfolio-share.

F. Unemployment Rates

As we showed before, declines in construction employment comprised an outsized share of the overall declines in employment. Moreover, declines in real estate and real-estate finance employment likely added to employment declines. Declines in home prices decreased household wealth, which likely affected household saving and consumption decisions, such as automobile purchases, possibly leading to other types of employment losses. To explore this further, we evaluate the relationship between pre-crisis mortgage market shares and post-crisis unemployment rates.

Overall, unemployment rates increased from an about 5 percent in 2005 to almost 10 percent in 2009. Unemployment rates (Figure 12) increased the most in counties with the highest exposures to PLS or portfolio lending and lowest exposures to GSE or FHA lending. In particular, by 2009 unemployment rates had more than doubled in the lowest FHA-share counties compared to increasing by almost 70 percent in the highest FHA-share counties. Similarly, unemployment rates had increased by 93 percent in the lowest GSE-share counties compared to 72 percent in the highest GSE-share counties. In contrast, by 2009 unemployment rates had increased by 64 percent in the lowest PLS-share counties, compared to nearly doubling in the highest PLS-share counties; and 62 percent in the lowest portfolio-share counties, compared to more than doubling in the highest portfolio-share counties.

What is clear is that the financial crisis was a substantial shock which influenced all counties, but the effects were larger in counties with lower government involvement (higher private involvement) in mortgage markets prior to the shock. By the end of 2012, unemployment rates had fallen across the board, but remained

83 percent higher in low FHA-share counties—and 51 percent higher in high FHA-share counties—relative to before the crisis. For comparison, unemployment rates remained 43 percent higher in low PLS-share counties and 72 percent higher in high PLS-share counties. By the end of 2014, unemployment rates remained 34 and 21 percent higher than in 2005 for low and high FHA-share counties, respectively. For comparison, unemployment rates remained 18 percent higher in low PLS-share counties and 30 percent higher in high PLS-share counties.[10] Here, it is evident that the effects of the financial crisis still remain, and that those effects are larger for lower FHA- and GSE-share counties, and higher PLS- and portfolio-share counties.

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.[11,12]

[10] If we showed our charts in *levels*, rather than 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.

[11] The average treatment effect is commonly reported to characterize differences between treated and untreated groups. Here, our treatment is continuous, so the average treatment effect is the derivative of the dose-response function.

[12] In results not reported here, we compute Mantel-Haenszel (1959) test statistics and Rosenbaum bounds around those test statistics to assess the sensitivity of our results to unobserved heterogeneity. Our results are fairly robust to mild to moderate cases of unobserved heterogeneity. These results are available upon request from the authors.

VIII. Why Does Government Involvement Prior to the Crisis Speed a Recovery?

We find large economic effects across counties because of differences in participation in mortgage channels, even though such channels would likely have only small differences in mortgage rates or credit costs. Indeed, mortgage borrowers likely choose among mortgages across these different channels, creating competitive pressures that minimize the cost differences across channels. Since we have accounted for variations county market shares across both aggregate individual mortgage borrower characteristics and across country characteristics (e.g. home prices), it seems even more likely the share of mortgage originations flowing through a particular mortgage channel within a county does not reflect relative price differences. As we show above, after our first-stage regression, the shares of mortgages originated through a particular channel in a particular county become randomized.

As a result, the variation in economic outcomes across counties during the financial crisis should only reflect variations by what each mortgage channel provided lenders and/or borrowers during the financial crisis. The possible behavior of mortgage-related institutions during a financial crisis was rarely discussed, much less priced into mortgage rates, during the housing boom.

In particular, we would point to how the mortgage channels varied in their ability to provide mortgage originators liquidity, via securitization, during the prolonged period financial turmoil. The PLS channel shutdown down during the crisis and, to date, has not returned. The crisis revealed the inability of this channel to provide liquidity during financial turmoil, and it may be that this inability to persist during a crisis will remain a serious problem for PLS activity in the future.[13]

[13] Many observers have argued that without a credible legal framework for handling disputes related to mortgage defaults, private sector investors will remain unwilling to invest again (Goodman, 2015).

Similarly, the crisis revealed that the banking sector seems poorly suited to provide mortgage credit during a financial crisis and afterwards. Many banks moved from originating and financing mortgages to only originating mortgages and then securitizing them through government-backed mortgage channels.[14]

The mortgage channels that both prospered and created relative prosperity during the crisis were the securitization channels that had either implicit or explicit government-backing. Government backing of a mortgage securitization outlet for mortgage originators during a crisis may be a key ingredient for a quicker economy recovery during a prolonged financial crisis.[15]

IX. Conclusion

Do government mortgage programs mitigate the adverse economic effects of a financial crisis? Do they promote faster recovery? Drawing on the wide variation across counties in government mortgage program participation and economic outcomes during and after the financial crisis, we find a strong correlation between counties that participated more heavily in government-backed mortgage programs and better economic outcomes. Moreover, we find that these better outcomes can be attributed directly to greater participation in these government mortgage programs. In particular, counties with higher levels of participation in FHA, Fannie Mae, and Freddie Mac lending had smaller increases in delinquency rates; smaller declines in purchase originations, home sales, home prices, and new auto purchases; and smaller increase in unemployment rates. These results hold both in 2009 (right after the peak of the financial crisis) and in 2014 (six years after the

[14] Again, the legal framework for bearing the costs of default for both mortgage servicing and mortgage defaults seems partly responsible for the financial fragility of bank financing during and after a crisis.

[15] 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 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). And, of course, selling into the secondary market leads to adverse selection and other agency problems (Passmore and Sparks, 2000, Demarzo, 2005, Heuson et al., 2001).

crisis). The persistence of better outcomes in counties with heavy participation in government mortgage programs is consistent with a view that mortgage originators' access to a liquidity outlet (in this case, government-backed securitization) is key to maintaining credit flows and economic growth during financial turmoil.

REFERENCES

Acharya, Viral V., Matthew Richardson, Stijn Van Nieuwerburgh, and Lawrence J. White, 2011. Guaranteed to Fail: Fannie Mae, Freddie Mac and the Debacle of Mortgage Finance, Princeton and Oxford: Princeton University Press.

Allen, Franklin and Douglas Gale, 1998. "Optimal Financial Crisis," *Journal of Finance*, 53, 1245-1284.

Bharath, Sreedhar T., Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan, 2009. "Lending Relationships and Loan Contract Terms," *Review of Financial Studies,* 24(4), 1141-1203.

Casu, Barbara, Andrew Clare, Anna Sarkisyan, and Stephen Thomas, 2013. "Securitization and Bank Performance, *Journal of Money, Credit and Banking,* 45(8), 1617-1658.

Chemmanur, Thomas J., Elena Loutskina, and Xuan Tian, 2014. "Corporate Venture Capital, Value Creation, and Innovation," *Review of Financial Studies,* 27(8), 2434-2473.

Congressional Budget Office (CBO), 2014. "Transitioning to Alternative Structures for Housing Finance," http://www.cbo.gov/publication/49765.

DeMarzo, P., 2005. "The Pooling and Tranching of Securities: A Model of Informed Intermediation," *Review of Financial Studies*, 18(1), 1-35.

Frame, W. Scott, Andreas Fuster, Joseph Tracy, and James Vickery, 2015. "The Rescue of Fannie Mae and Freddie Mac," *Journal of Economic Perspectives*, 29(2), 25-52.

Frame, W. Scott, and Lawrence J. White, 2005. "Fussing and Fuming over Fannie and Freddie: How Much Smoke, How Much Fire?" *Journal of Economic Perspectives*, 19(2), 159-184.

Goodman, Laurie, 2015. "The Rebirth of Securitization: Where Is the Private-Label Mortgage Market," Housing Finance Policy Center, Urban Institute.

Green, Richard K., and Susan M. Wachter, 2005. "The American Mortgage in Historical and International Context," *Journal of Economic Perspectives*, 19(4), 93-114.

Hancock, Diana, and Wayne Passmore, 2011. "Catastrophic Mortgage Insurance and the Reform of Fannie Mae and Freddie Mac" In *The Future of Housing Finance: Restructuring the U.S. Residential Mortgage Market*, ed. Martin N. Baily. Washington, DC: Brookings Institution Press.

Heuson, Andrea, S. W. Passmore, and Roger Sparks, 2001. "Credit Scoring and Mortgage Securitization: Implications for Mortgage Rates and Credit Availability," *Journal of Real Estate Finance and Economics*, 23, 337-363.

Hirano, Keisuke, and Guido W. Imbens, 2004. "The Propensity Score with Continuous Treatments" In *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives*, eds. Andrew Gelman and Xiao-Li Meng. 73-84. West Sussex: John Wiley and Sons.

Holden, Steve, Austin Kelly, Douglas McManus, Therese Scharlemann, Ryan Singer, and John D. Worth, 2012. "The HAMP NPV Model: Development and Early Performance," *Real Estate Economics*.

Krishnamurthy, Arvind, 2010. "Amplification Mechanisms in Liquidity Crises," *American Economic Journal: Macroeconomics*, 2(3), 1-30.

Mantel, N., and W. Haenszel, 1959. "Statistical Aspects of the Analysis of Data from Retrospective Studies of Disease," *Journal of the National Cancer Institute*, 22, 719-748.

Mayer, Christopher, Karen Pence, and Shane M. Sherlund, 2009. "The Rise in Mortgage Defaults," *Journal of Economic Perspectives*, 23, 27-50.

Mian, Atif and Amir Sufi, 2009. "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis," *Quarterly Journal of Economics*, 124(4), 1449-1496.

Nadauld, Taylor, and Shane M. Sherlund, 2013. "The Impact of Securitization on the Expansion of Subprime Credit," *Journal of Financial Economics*, 107, 454-476.

Passmore, Wayne, 2005. "The GSE Implicit Subsidy and the Value of Government Ambiguity," *Real Estate Economics*, 33(3), 465-486.

Passmore, S. Wayne, Shane M. Sherlund, and Gillian Burgess, 2005. "The Effect of Housing Government-Sponsored Enterprises on Mortgage Rates," *Real Estate Economics*, 33(3), 427-463.

Passmore, S. Wayne, and Roger Sparks, 2000. "Automated Underwriting and the Profitability of Mortgage Securitization," *Real Estate Economics*, 28(2), 285-305.

Passmore, S.W. and R. Sparks, 1996, "Putting the Squeeze on a Market for Lemons: Government-Sponsored Mortgage Securitization," *Journal of Real Estate Finance and Economics*, vol. 96, no 13, 27-43.

Rosenbaum, P.R., and D.B. Rubin, 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika*, 70, 41-55.

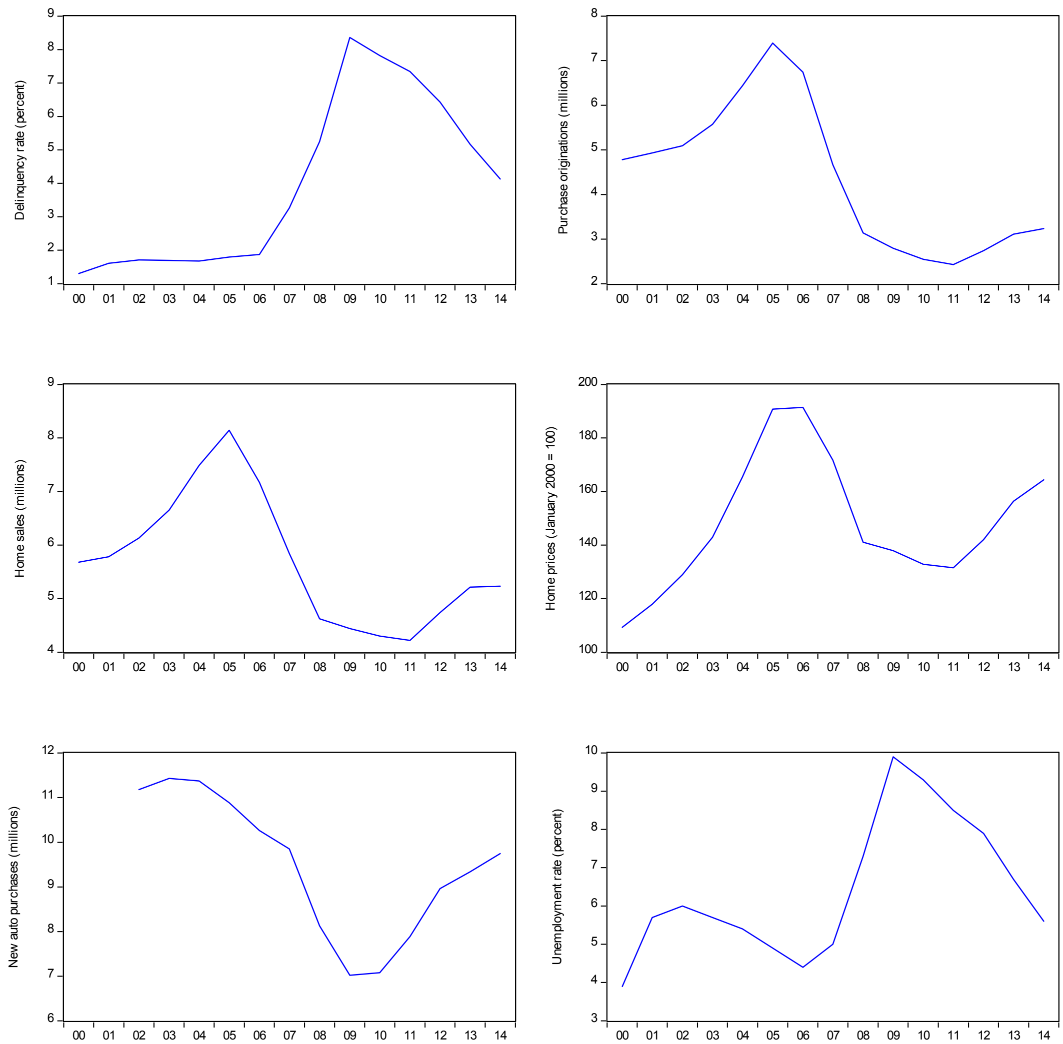

FIGURE 1. DELINQUENCY RATES, PURCHASE ORIGINATIONS, HOME SALES, HOME PRICES, NEW AUTO PURCHASES AND UNEMPLOYMENT RATES

Source: Delinquency rates, home sales, and home prices from CoreLogic. Purchase originations based on data from the Home Mortgage Disclosure Act (HMDA), CoreLogic, and McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc. New auto purchases from RL Polk. Unemployment rates from the Bureau of Labor Statistics.

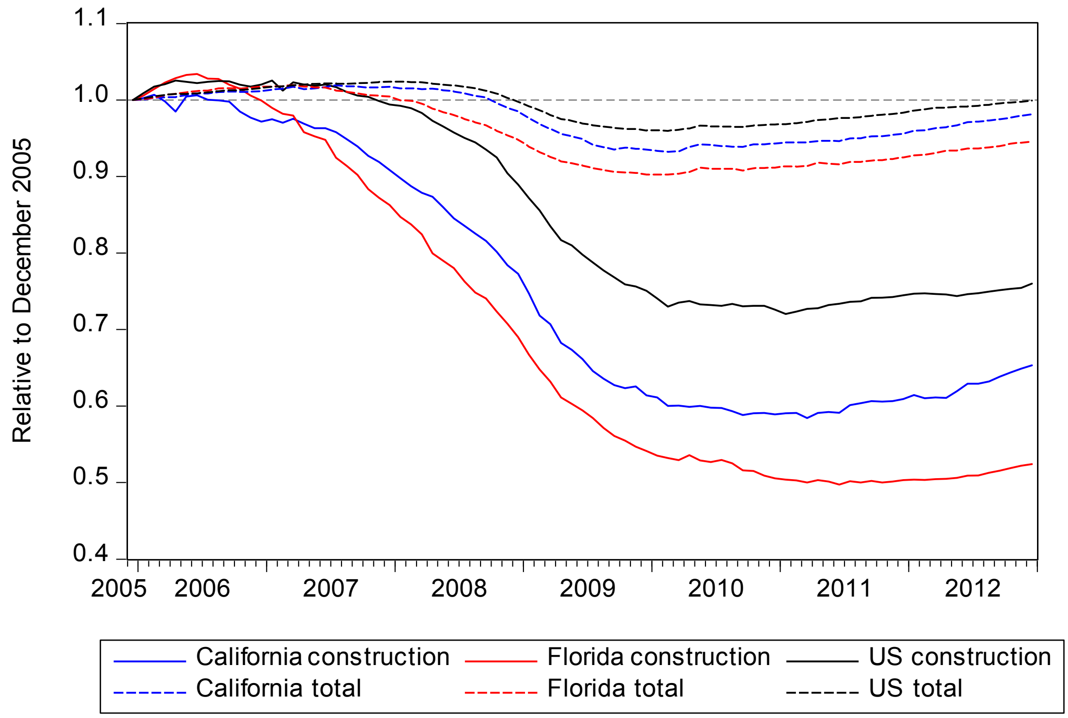

FIGURE 2. TOTAL AND CONSTRUCTION-RELATED EMPLOYMENT RELATIVE TO DECEMBER 2005

Source: Calculations based on data from Bureau of Labor Statistics.

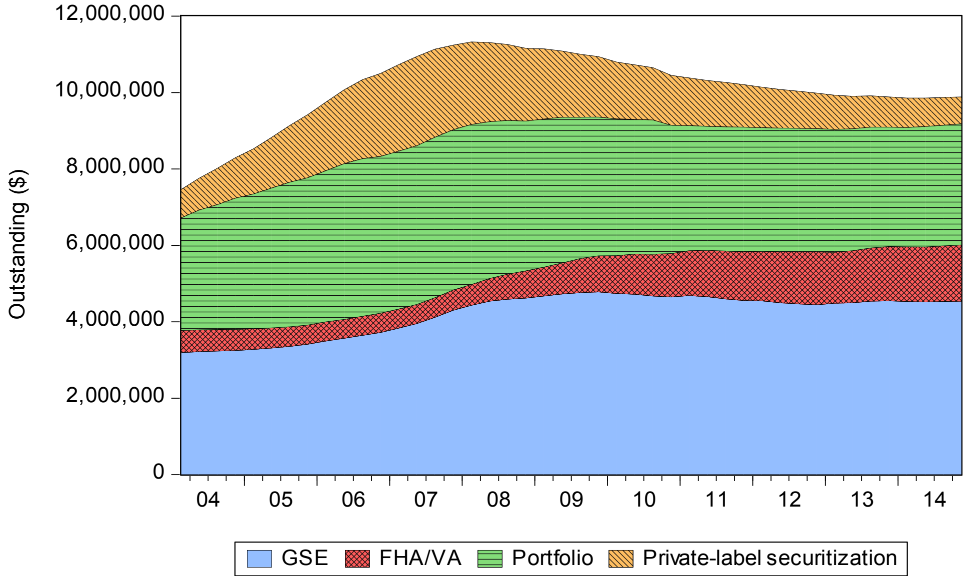

FIGURE 3. MORTGAGE DEBT OUTSTANDING

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

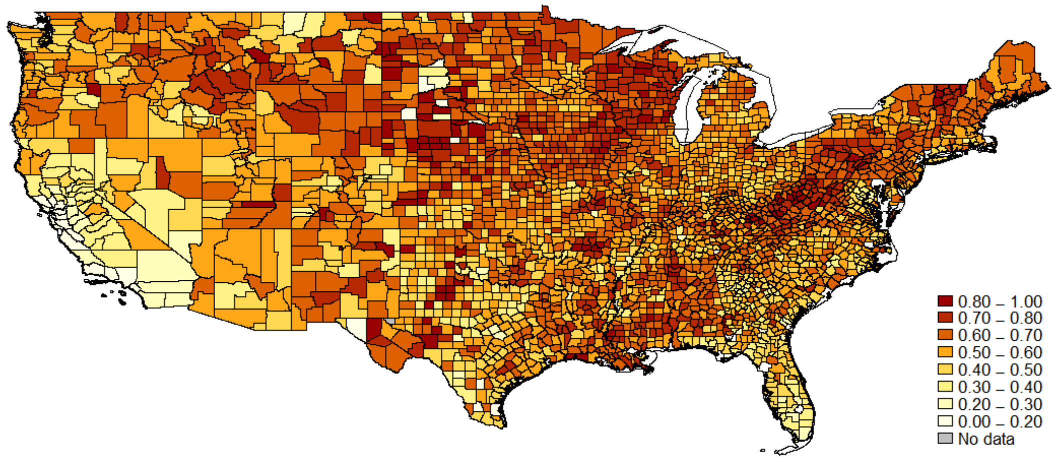

FIGURE 4A. GSE SHARES 2004-2007:H1

Source: Calculations based on data from the Home Mortgage Disclosure Act (HMDA), CoreLogic, and McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc.

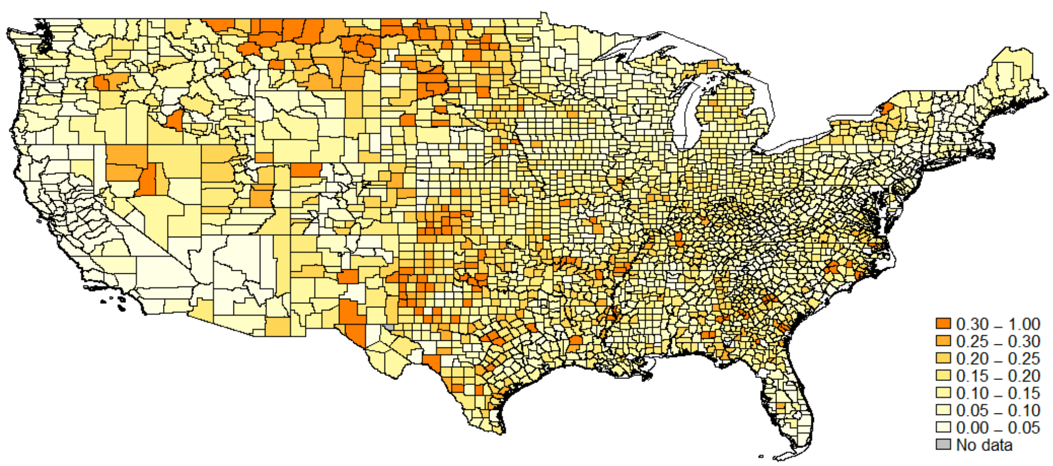

FIGURE 4B. FHA SHARES 2004-2007:H1

Source: Calculations based on data from the Home Mortgage Disclosure Act (HMDA), CoreLogic, and McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc.

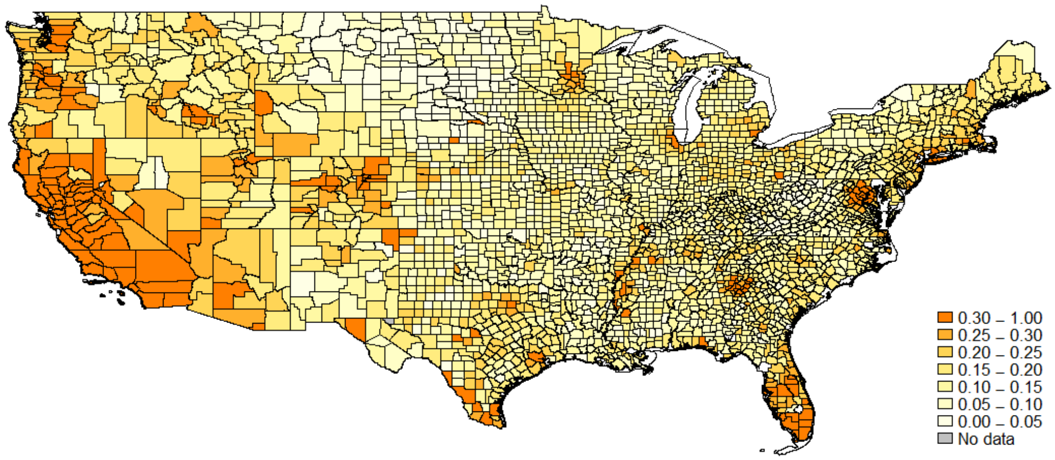

FIGURE 4C. PLS SHARES, 2004-2007:H1

Source: Calculations based on data from the Home Mortgage Disclosure Act (HMDA), CoreLogic, and McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc.

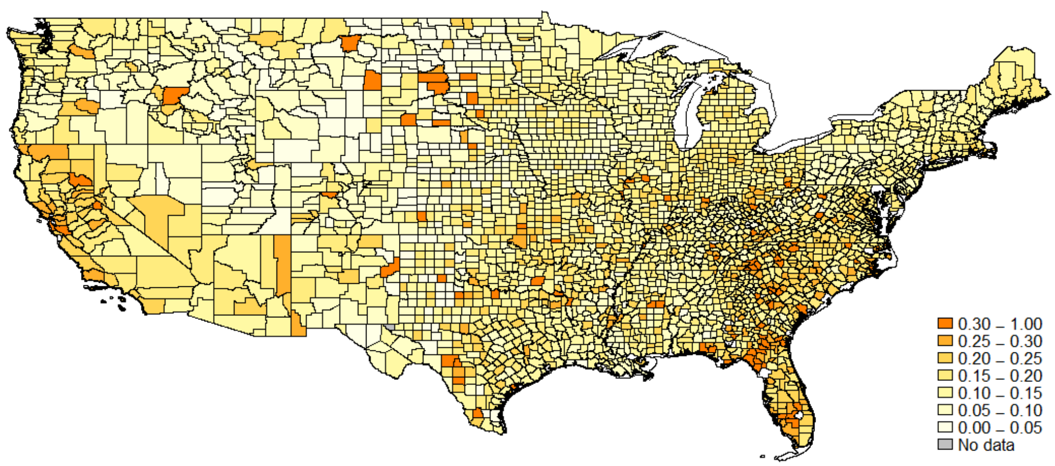

FIGURE 4D. PORTFOLIO SHARES, 2004-2007:H1

Source: Calculations based on data from the Home Mortgage Disclosure Act (HMDA), CoreLogic, and McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc.

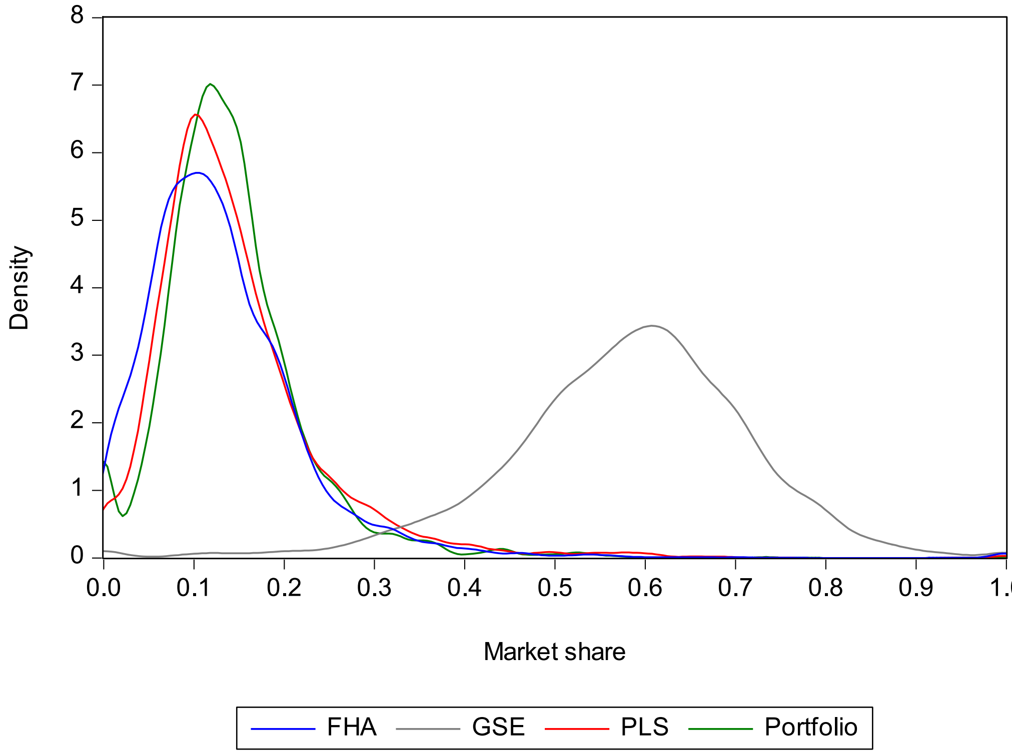

FIGURE 5. MORTGAGE MARKET SHARES, 2004-2007:H1

Source: Calculations based on data from the Home Mortgage Disclosure Act (HMDA), CoreLogic, and McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc.

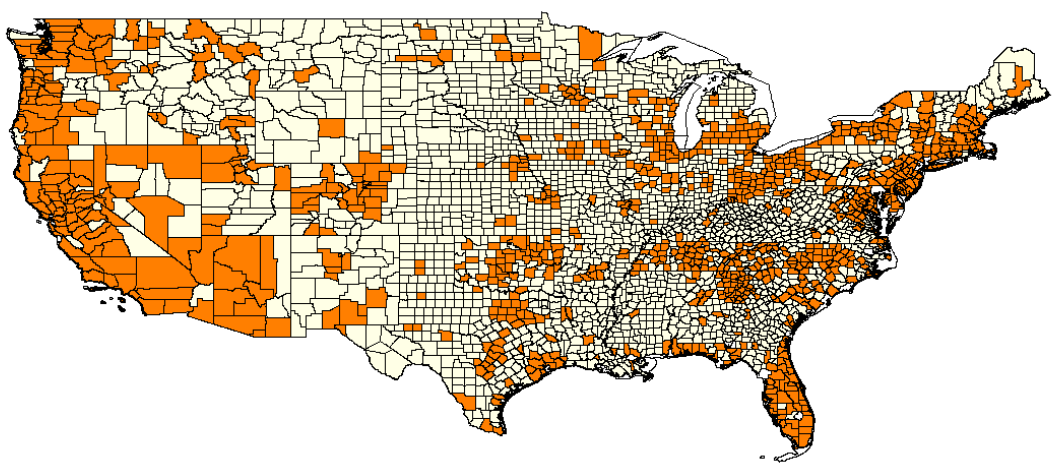

FIGURE 6. DATA COVERAGE

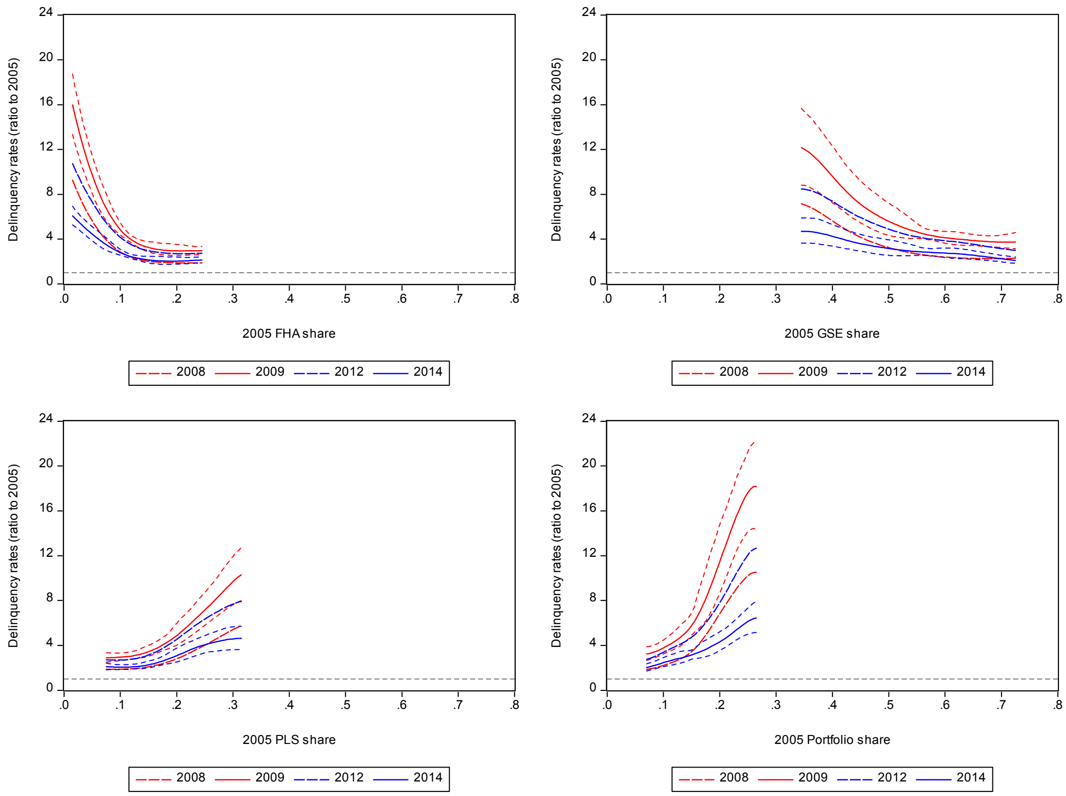

FIGURE 7. MORTGAGE DELINQUENCY RATE DOSE-RESPONSE FUNCTIONS

Note: Mortgage delinquency rates are measured relative to their December 2005 levels.

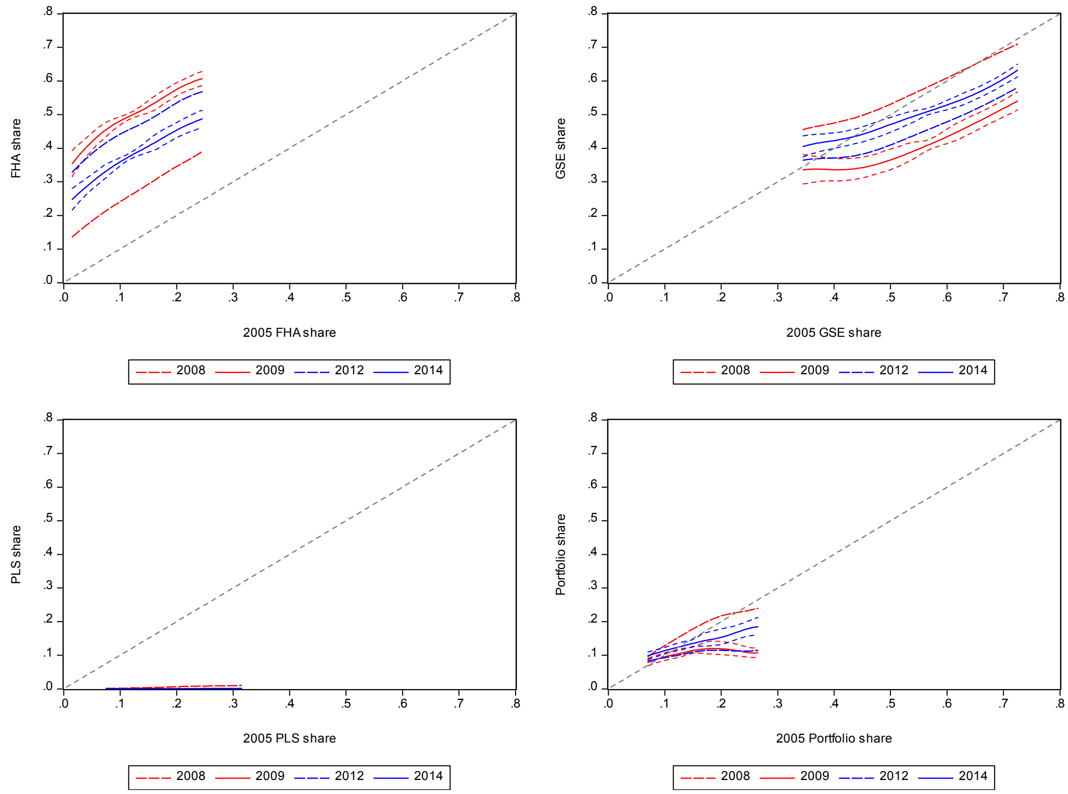

FIGURE 8. MARKET SHARE DOSE-RESPONSE FUNCTIONS

Note: Market shares are measured over 2004-2007:H1 (denoted 2005), 2007:H2-2008 (denoted 2008), 2009 (denoted 2009), 2010-2012 (denoted 2012), and 2013-2014 (denoted 2014).

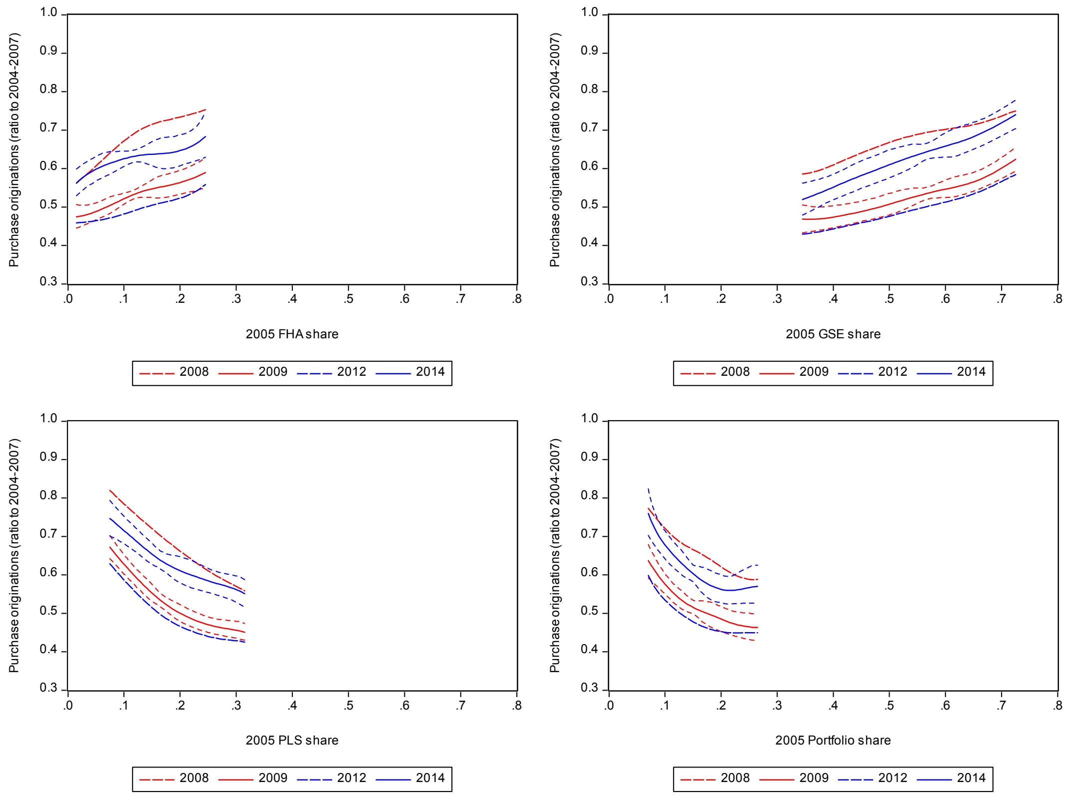

FIGURE 9. PURCHASE ORIGINATION DOSE-RESPONSE FUNCTIONS

Note: Purchase originations are measured relative to their 2004-2007:H1 levels.

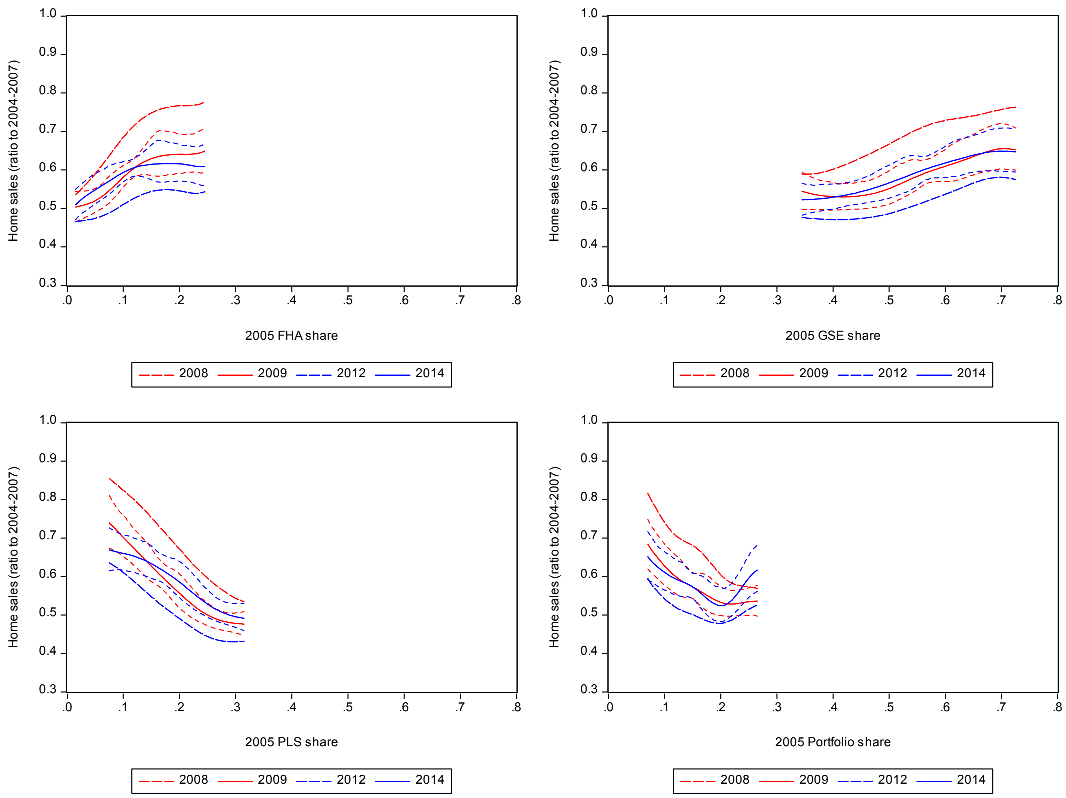

FIGURE 10. HOME SALES DOSE-RESPONSE FUNCTIONS

Note: Home sales are measured relative to their 2004-2007:H1 levels.

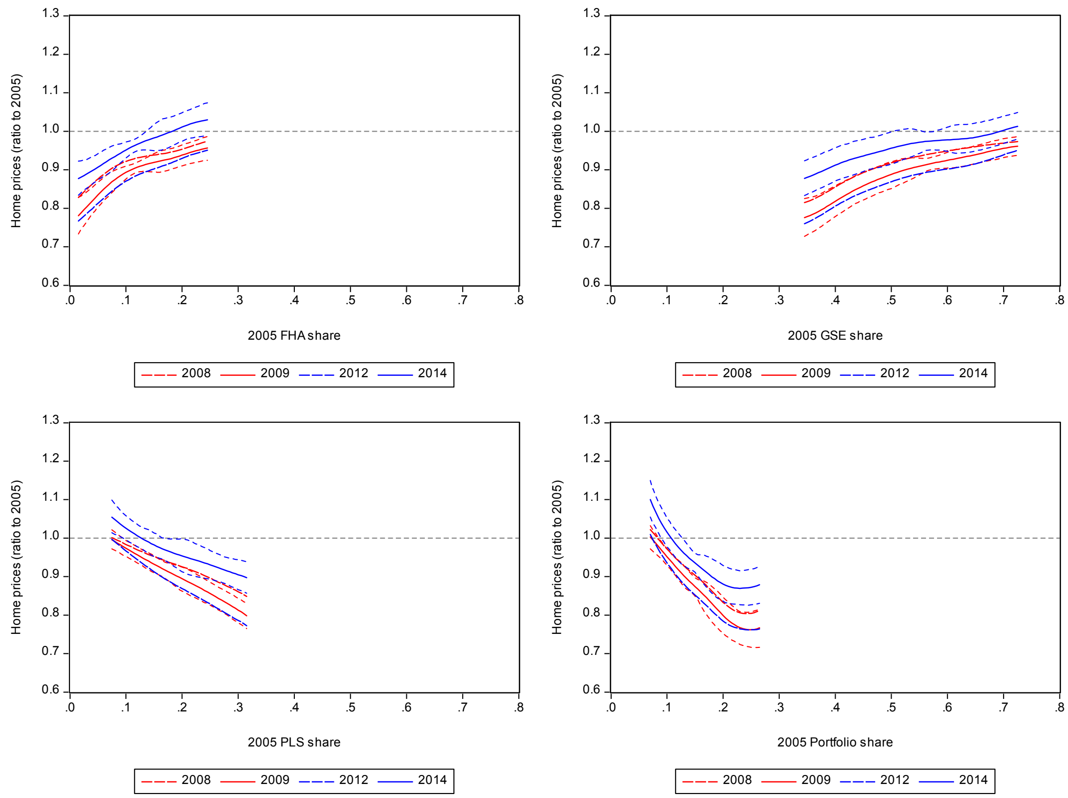

FIGURE 11. HOME PRICES DOSE-RESPONSE FUNCTIONS

Note: Home prices are measured relative to their December 2005 levels.

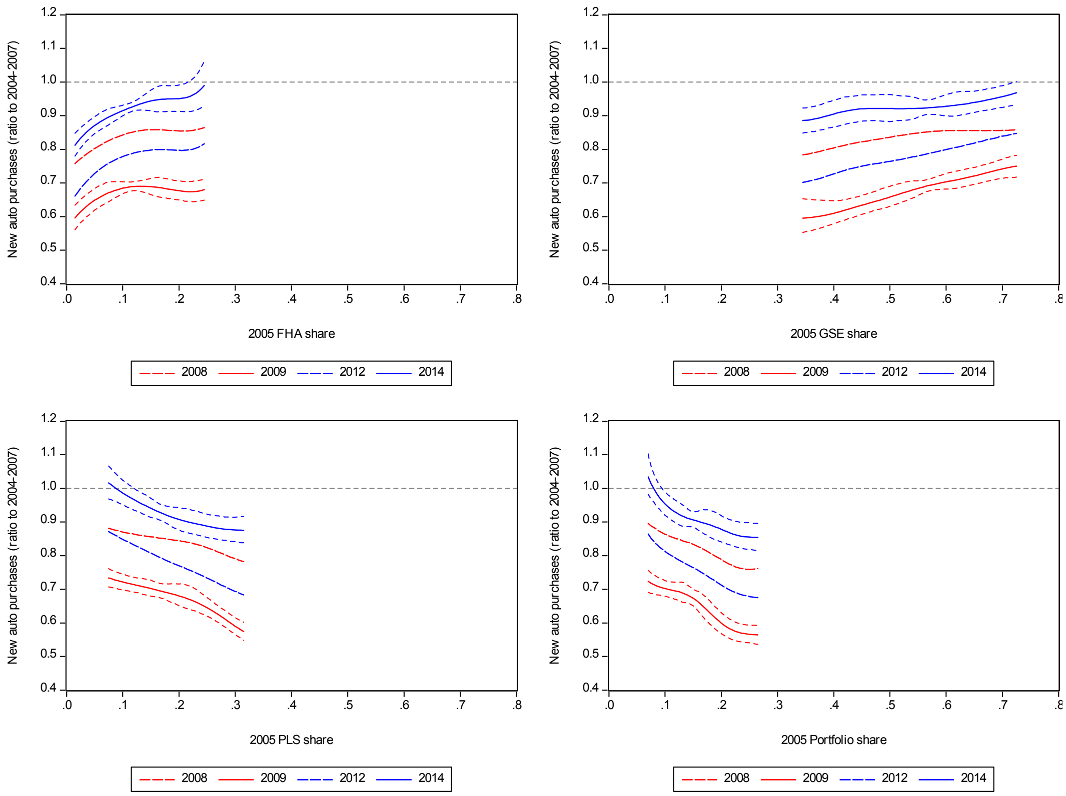

FIGURE 12. NEW AUTO PURCHASES DOSE-RESPONSE FUNCTIONS

Note: New auto purchases are measured relative to their 2004-2007:H1 levels.

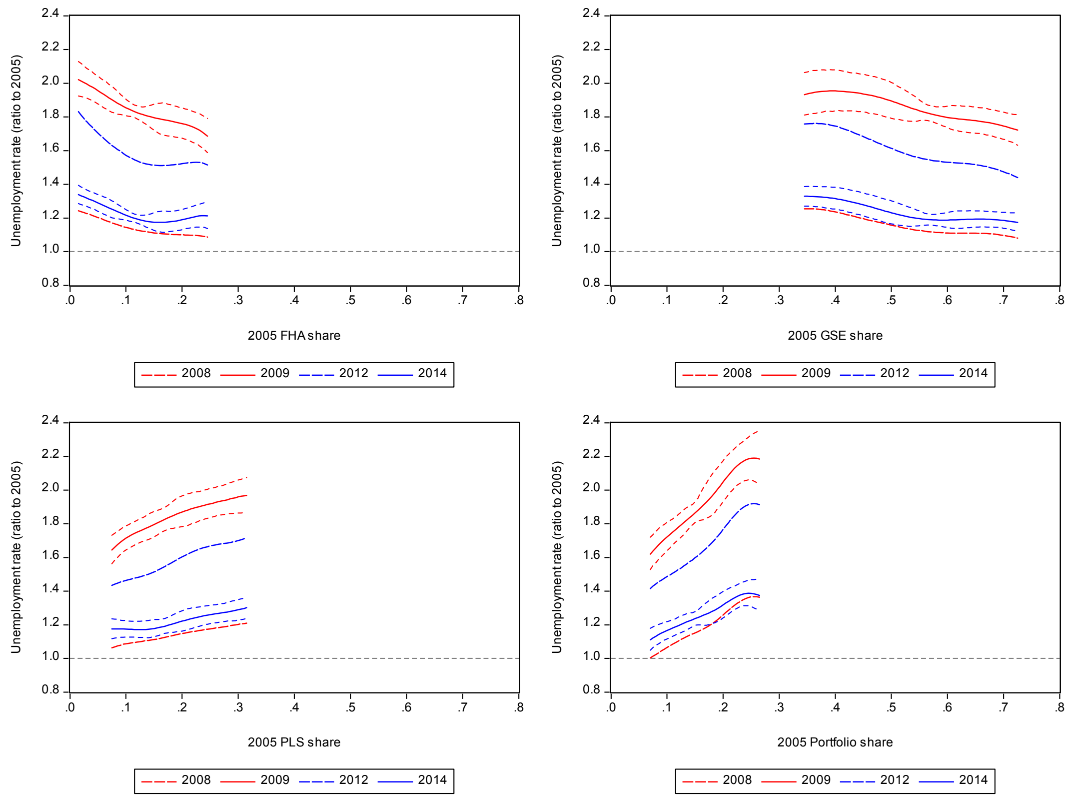

FIGURE 13. UNEMPLOYMENT RATE DOSE-RESPONSE FUNCTIONS

Note: Unemployment rates are measured relative to their December 2005 levels.

TABLE 1—SUMMARY STATISTICS

	Mean	Median	Std. Dev.	Minimum	Maximum
GSE share, 2004-2007:H1	.530	.543	.121	.090	.850
GSE share, 2007:H2-2008	.568	.575	.115	.159	.868
GSE share, 2009	.409	.395	.144	.044	.861
GSE share, 2010-2012	.449	.446	.126	.051	.866
GSE share, 2013-2014	.498	.508	.107	.098	.818
FHA share, 2004-2007:H1	.116	.107	.079	.0001	.633
FHA share, 2007:H2-2008	.253	.253	.103	.0001	.766
FHA share, 2009	.483	.494	.135	.004	.900
FHA share, 2010-2012	.445	.451	.133	.012	.889
FHA share, 2013-2014	.365	.362	.131	.001	.862
PLS share, 2004-2007:H1	.206	.185	.106	.015	.655
PLS share, 2007:H2-2008	.007	.004	.008	.000	.066
PLS share, 2009	.0004	.000	.001	.000	.014
PLS share, 2010-2012	.0003	.000	.001	.000	.020
PLS share, 2013-2014	.0007	.000	.002	.000	.033
Portfolio share, 2004-2007:H1	.148	.139	.058	.034	.572
Portfolio share, 2007:H2-2008	.172	.163	.064	.032	.494
Portfolio share, 2009	.107	.094	.060	.017	.486
Portfolio share, 2010-2012	.105	.096	.046	.021	.406
Portfolio share, 2013-2014	.136	.118	.078	.000	.704
Mortgage delinquency rate, 2005	1.974	1.650	1.995	0.100	42.540
Mortgage delinquency rate, 2008	4.292	3.790	2.333	0.460	19.110
Mortgage delinquency rate, 2009	6.861	6.165	3.479	1.070	29.040
Mortgage delinquency rate, 2012	5.910	5.260	3.084	0.470	20.890
Mortgage delinquency rate, 2014	4.123	3.695	2.254	0.440	15.910
Purchase originations, 2004-2007:H1	.409	.162	.785	.013	10.092
Purchase originations, 2007:H2-2008	.246	.109	.415	.009	4.665
Purchase originations, 2009	.202	.088	.371	.005	5.137
Purchase originations, 2010-2012	.186	.082	.338	.006	4.843
Purchase originations, 2013-2014	.233	.101	.402	.009	4.958
Home sales, 2004-2007:H1	.339	.099	.769	.010	10.609
Home sales, 2007:H2-2008	.184	.067	.352	.007	4.450
Home sales, 2009	.172	.057	.394	.006	5.934
Home sales, 2010-2012	.150	.049	.348	.007	5.294
Home sales, 2013-2014	.166	.056	.343	.006	4.523
Home prices, 2005	1.610	1.429	.446	.992	3.110
Home prices, 2008	1.436	1.402	.305	.653	2.610
Home prices, 2009	1.382	1.356	.276	.601	2.440
Home prices, 2012	1.355	1.345	.285	.578	2.578
Home prices, 2014	1.500	1.470	.339	.680	3.173
Median home prices, 2005	.191	.154	.110	.038	.760
Median home prices, 2008	.170	.150	.084	.021	.820
Median home prices, 2009	.166	.146	.082	.045	.740
Median home prices, 2012	.169	.150	.088	.038	1.100
Median home prices, 2014	.182	.155	.097	.035	1.000
New auto purchases, 2004-2007:H1	.773	.328	1.542	.030	27.406
New auto purchases, 2007:H2-2008	.624	.278	1.179	.024	19.348
New auto purchases, 2009	.504	.221	.902	.017	13.651
New auto purchases, 2010-2012	.567	.255	1.011	.019	15.423
New auto purchases, 2013-2104	.682	.302	1.292	.023	20.360

Notes: Purchase originations and market shares are based on data from the Home Mortgage Disclosure Act (HMDA), CoreLogic, and McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc. Mortgage delinquency rates measured (percent) at year end, purchase originations (thousands per month) over period, home sales (thousands per month) over period, home price indexes (1.000=January 2000) at year end, median home prices ($millions) at year end, and new auto purchases (thousands per month) over period.

TABLE 1—SUMMARY STATISTICS (CONTINUED)

	Mean	Median	Std. Dev.	Minimum	Maximum
Unemployment rate, 2005	5.119	4.900	1.458	2.300	16.100
Unemployment rate, 2008	5.821	5.600	1.831	2.100	22.400
Unemployment rate, 2009	9.329	8.900	2.756	2.900	27.900
Unemployment rate, 2012	8.027	7.800	2.407	1.600	27.200
Unemployment rate, 2014	6.179	6.000	1.904	1.500	25.200
Median Equifax risk score[1]	702.5	708	32.5	601	782
Equifax risk scores < 580	.187	.179	.063	.043	.419
Equifax risk scores 580-619	.098	.098	.022	.027	.173
Equifax risk scores 620-679	.148	.148	.016	.084	.222
Equifax risk scores 680-739	.168	.168	.018	.108	.235
Equifax risk scores 740-799	.260	.261	.045	.118	.386
Equifax risk scores 800+	.139	.137	.046	.031	.319
Population with credit reports	.780	.782	.053	.565	.952
Average wages and salaries	37.738	35.491	9.520	20.317	80.122
Average exemptions	2.178	2.170	.152	1.598	2.813
Average dividends and interest	2.075	1.791	1.223	.419	12.006
Income < $10K	.189	.189	.022	.105	.293
Income $10-25K	.244	.246	.044	.087	.427
Income $25-50K	.250	.252	.024	.134	.333
Income $50-75K	.142	.142	.018	.067	.206
Income $75-100K	.081	.079	.020	.031	.141
Income $100K+	.094	.081	.048	.026	.349
Poverty rate	.127	.124	.049	.025	.407
House price appreciation, 2005	11.047	8.950	8.551	-7.170	45.340
Median house price / Average income	5.047	4.088	2.592	1.264	22.411
Median house price – 2005 CLL	-.169	-.206	.110	-.321	.400
Home sales le 125% CLL	.899	.988	.176	.000	1.000
No. HMDA lenders, 2005	.290	.253	.149	.054	1.005
No. HMDA lenders, 1998	.214	.186	.109	.034	.814
Census county population	.252	.107	.509	.010	9.786
Ages < 20	.276	.275	.030	.130	.394
Ages 20-29	.131	.124	.034	.067	.330
Ages 30-39	.131	.130	.017	.082	.213
Ages 40-49	.153	.153	.015	.094	.226
Ages 50-59	.132	.132	.016	.071	.200
Ages 60-69	.085	.082	.020	.043	.220
Ages 70+	.092	.090	.027	.023	.251
Female	.506	.508	.014	.362	.544
White	.770	.815	.172	.039	.979
African American	.089	.042	.114	.001	.666
American Indian	.011	.003	.032	.001	.449
Asian	.022	.011	.035	.001	.442
Other	.017	.013	.020	.001	.336
Hispanic	.091	.047	.119	.005	.952
High school or less	.502	.508	.109	.146	.788
Some college	.282	.280	.048	.156	.428
Bachelor's degree or higher	.216	.193	.092	.056	.605

[1] Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Note: Unemployment rates (percent) at year end; average wages and salaries, exemptions, and dividends and interest measured ($thousands) during 2005; house price appreciation (percent) during 2005; median house prices and average income during 2005; median house prices relative to 2005 conforming loan limit of $359,650 ($millions); proportion of home sales under 125-percent of the 2005 conforming loan limit; number of lenders reporting to HMDA (thousands) during 2005 and 1998; population (millions) in 2005; and Equifax risk score, age, gender, race and ethnicity, income proportions, poverty rate, and education during 2005.

TABLE 2—EMPIRICAL MARKET SHARES, 2004-2007:H1

	Market Shares		
Panel A. GSE Market Share	FHA	PLS	Portfolio
10	0	61	30
20	8	48	25
30	12	37	21
40	14	28	18
50	13	21	15
60	11	16	13
70	8	12	10
80	5	7	8
Panel B. FHA Market Share	GSE	PLS	Portfolio
0	32	43	24
10	57	19	14
20	49	17	14
30	45	12	13
40	40	9	12
50	29	10	10
60	22	9	8
Panel C. PLS Market Share	GSE	FHA	Portfolio
0	71	16	13
10	61	16	13
20	54	12	14
30	46	8	13
40	37	5	18
50	27	2	21
60	15	1	24
Panel D. Portfolio Market Share	GSE	FHA	PLS
0	74	19	7
10	59	13	17
20	45	9	26
30	35	5	29
40	33	6	22
50	23	5	22

Source: Calculations based on data from the Home Mortgage Disclosure Act, CoreLogic, and McDash Analytics, LLC, a wholly owned subsidiary of Lender Processing Services, Inc.

TABLE 3—FIRST-STAGE GPS RESULTS

	GSE		FHA		PLS		Portfolio	
Constant	4.488	**	-.814		-5.013	**	2.369	
Median Equifax risk score[1]	-1.122	**	.541	*	.606	**	-.026	
Pct. Equifax risk scores < 580	-.927	**	.261		.232		.434	**
Pct. Equifax risk scores 580-619	-.288		.471	*	-.147		-.036	
Pct. Equifax risk scores 620-679	-.977	**	.494	**	.232		.251	
Pct. Equifax risk scores 680-739	.141		-.361	**	.097		.123	
Pct. Equifax risk scores 740-799	.900	**	-.433	**	-.394	**	-.072	
Pct. with credit reports	-.188	**	.112	**	.131	**	-.054	
Average wages and salaries	.275	**	-.161	**	-.163	**	.049	
Average exemptions	-.079		-.031		.265	**	-.156	**
Average dividends and interest	.002		-.018	**	.003		.013	*
Pct. income < $10K	-.305		-.134		1.467	**	-1.029	**
Pct. income $10-25K	.290		.262		1.021	**	-1.573	**
Pct. income $25-50K	-.761	**	-.409		2.110	**	-.940	**
Pct. income $50-75K	-.761	*	.882	**	1.745	**	-1.867	**
Pct. income $75-100K	.691		-.626		2.065	**	-2.131	**
Poverty rate	.440	**	-.601	**	.230	**	-.068	
House price appreciation, 2005	.030		-.054	**	.042	*	-.018	
Median house price / average income	.028	**	-.018	**	-.010	**	.001	
Unemployment rate, 2005	-.006	**	-.005	**	.007	**	.004	**
Median house price – CLL	-.001	**	.000	**	.001	**	.000	
Pct. home sales le 125 CLL	.096	**	.018		-.034	**	-.080	**
No. HMDA lenders, 2005	-.038	**	-.078	**	.082	**	.034	**
No. HMDA lenders, 2005 – 1998	.000	**	.000	**	.000	**	.000	**
Census county population	.011	**	.017	**	-.012	**	-.016	**
Pct. ages < 20	.239		.237		-.700	**	.223	
Pct. ages 20-29	.971	**	.305		-1.074	**	-.202	
Pct. ages 30-39	.325		-.253		-.470	**	.399	**
Pct. ages 40-49	.614	*	1.338	**	-1.378	**	-.573	*
Pct. ages 50-59	1.560	**	-1.905	**	.483	*	-.138	
Pct. ages 60-69	1.302	**	.750	**	-3.127	**	1.075	**
Pct. female	1.333	**	-.538	**	-.211		-.584	**
Pct. African American	-.128	**	.085	**	.077	**	-.035	
Pct. American Indian	.061		.028		-.116	**	.027	
Pct. Asian	-.022		-.172	**	.121		.072	
Pct. Other	-.167		.273	**	-.010		-.096	
Pct. Hispanic	-.116	**	.050	**	.117	**	-.052	**
Pct. high school or less	.008		-.115	**	.032		.075	**
Pct. some college	-.364	**	.177	**	.136	**	.052	
No. obs.	972		972		972		972	
R-squared	.705		.662		.803		.541	

[1] Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

** Significant at the 5-percent level.

* Significant at the 10-percent level.

TABLE 4A—COVARIATE BALANCING FOR FHA SHARES

	Unadjusted			Adjusted for GPS		
	0-33rd	33-66th	66-100th	0-33rd	33-66th	66-100th
Equifax risk score[1]	10.5	.2	-10.3	1.5	-.7	-1.2
Pct. Equifax risk scores < 580	-11.2	.9	9.7	-1.8	1.1	1.2
Pct. Equifax risk scores 580-619	-10.1	.7	9.9	-1.6	1.1	1.2
Pct. Equifax risk scores 620-679	-6.5	-1.0	8.2	-.7	.0	1.3
Pct. Equifax risk scores 680-739	7.9	-2.9	-5.0	1.1	-1.5	-.9
Pct. Equifax risk scores 740-799	7.3	1.0	-8.3	.9	-.3	-.9
Pct. with credit reports	3.0	.3	-3.7	.9	-.2	-.1
Average wages and salaries	5.1	.3	-7.4	.5	-.3	-2.0
Average exemptions	-6.0	.9	6.1	-1.6	1.0	.5
Average dividends and interest	13.2	-1.4	-13.8	2.2	-.9	-2.6
Pct. income < $10K	-2.9	.5	2.3	-.3	.6	.5
Pct. income $10-25K	-4.4	-1.1	6.0	-.2	.1	.0
Pct. income $25-50K	-2.6	-1.1	3.7	.1	-.3	.6
Pct. income $50-75K	1.3	1.7	-3.0	-.3	.3	-.3
Pct. income $75-100K	5.3	.7	-7.0	.2	-.3	-1.5
Poverty rate	-5.3	.6	4.9	-1.0	.6	1.0
House price appreciation, 2005	9.6	-4.2	-6.3	1.7	-1.7	-1.1
Median house price / Average income	15.7	-8.4	-13.0	3.1	-3.5	-2.9
Unemployment rate, 2005	-2.5	1.9	1.0	-.4	.3	.7
Median house price – CLL	17.0	-7.7	-15.6	3.3	-3.4	-4.3
Pct. home sales le 125 CLL	-9.5	4.6	8.1	-1.6	1.4	1.4
No. HMDA lenders, 2005	11.1	-.4	-11.4	1.6	-.9	-2.6
No. HMDA lenders, 2005 – 1998	10.3	-3.6	-10.2	1.8	-1.9	-3.2
Census county population	5.7	.1	-6.8	.7	-.5	-1.8
Pct. ages < 20	-5.6	.8	5.8	-1.2	.6	.3
Pct. ages 20-29	-1.5	.0	1.7	.5	-.1	-.3
Pct. ages 30-39	-.2	.4	-.1	.0	-.1	-1.2
Pct. ages 40-49	1.7	.1	-2.2	-.2	-.3	-.2
Pct. ages 50-59	4.4	-.1	-5.1	.2	-.4	.2
Pct. ages 60-69	3.0	-1.3	-2.8	.5	-.4	.4
Pct. female	.1	1.0	-1.2	.1	.1	.0
Pct. African American	-2.5	.7	1.7	-.2	.2	-.1
Pct. American Indian	-.8	-1.9	2.2	-.8	.0	.7
Pct. Asian	7.1	-4.8	-7.5	1.9	-2.0	-3.2
Pct. Other	1.8	-2.5	-.6	.2	-.7	-.1
Pct. Hispanic	3.5	-3.8	-.1	.6	-1.4	-.2
Pct. high school or less	-9.0	2.2	7.2	-1.7	1.2	1.7
Pct. some college	2.0	-1.1	-1.0	.7	-.3	-.6

[1] Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Note: 33rd and 66th percentiles for 2005 FHA share: 7.6 and 14.0 percent.

TABLE 4B—COVARIATE BALANCING FOR GSE SHARES

	Unadjusted			Adjusted for GPS		
	0-33rd	33-66th	66-100th	0-33rd	33-66th	66-100th
Equifax risk score[1]	-10.6	1.7	10.7	-2.1	.4	1.7
Pct. Equifax risk scores < 580	9.5	-.3	-9.9	1.9	-.2	-1.6
Pct. Equifax risk scores 580-619	11.2	-.8	-10.3	3.1	-.7	-1.7
Pct. Equifax risk scores 620-679	9.0	-.3	-8.6	1.9	-.2	-1.7
Pct. Equifax risk scores 680-739	-3.7	-1.6	5.5	-1.2	-.4	.8
Pct. Equifax risk scores 740-799	-12.7	.4	12.5	-2.7	.2	2.2
Pct. with credit reports	-1.0	.5	.6	.1	-.5	.5
Average wages and salaries	-2.6	.4	2.1	-1.5	.1	.2
Average exemptions	.1	2.4	-2.6	-.6	1.0	-.8
Average dividends and interest	-3.6	.0	4.4	-1.1	.0	1.0
Pct. income < $10K	-5.0	1.6	4.1	-.8	.9	1.4
Pct. income $10-25K	5.7	-.6	-5.3	1.7	-.1	-.7
Pct. income $25-50K	7.9	-.8	-7.8	2.3	-.5	-2.4
Pct. income $50-75K	-4.1	.3	4.3	-1.2	-.3	.5
Pct. income $75-100K	-3.9	.1	3.7	-1.7	-.1	.6
Poverty rate	3.8	-.2	-3.6	1.2	.2	-.4
House price appreciation, 2005	6.6	-2.4	-5.7	.7	-.6	-.9
Median house price / Average income	6.6	-2.8	-5.4	.6	-.9	-.5
Unemployment rate, 2005	1.9	2.7	-5.1	1.0	1.2	-1.2
Median house price – CLL	5.2	-2.3	-4.1	.2	-.9	-.6
Pct. home sales le 125 CLL	-2.9	.7	2.6	.2	.2	-.3
No. HMDA lenders, 2005	6.3	-1.1	-5.7	1.1	-.7	-1.3
No. HMDA lenders, 2005 – 1998	7.0	-4.8	-4.9	1.5	-2.1	-.7
Census county population	3.3	.7	-4.6	.5	.4	-1.5
Pct. ages < 20	2.8	1.4	-4.7	.1	.8	-1.5
Pct. ages 20-29	1.6	-2.1	.3	-.1	-.1	.4
Pct. ages 30-39	4.9	-1.1	-4.5	.6	-.4	.2
Pct. ages 40-49	-2.3	.1	2.0	-.8	-.4	.2
Pct. ages 50-59	-5.3	1.6	3.8	-.9	.2	.9
Pct. ages 60-69	-1.4	.3	1.2	.3	-.3	.6
Pct. female	-1.7	1.2	.8	.3	.2	.3
Pct. African American	6.6	-.2	-8.6	1.0	.1	-1.9
Pct. American Indian	.8	.0	-1.0	.6	-.1	.1
Pct. Asian	2.0	.7	-3.4	-.2	.8	-1.0
Pct. Other	2.7	.3	-4.4	.7	.2	-1.9
Pct. Hispanic	7.2	-1.5	-9.4	1.2	.0	-2.6
Pct. high school or less	2.0	.1	-2.0	1.5	-.2	-.4
Pct. some college	1.7	.5	-2.4	-.3	.4	-.6

[1] Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Note: 33rd and 66th percentiles for 2005 GSE share: 49.4 and 59.0 percent.

TABLE 4C—COVARIATE BALANCING FOR PLS SHARES

	Unadjusted			Adjusted for GPS		
	0-33rd	33-66th	66-100th	0-33rd	33-66th	66-100th
Equifax risk score[1]	1.1	-.9	-.3	-.1	.0	-.2
Pct. Equifax risk scores < 580	-1.8	2.1	-.3	-.2	.4	.1
Pct. Equifax risk scores 580-619	-.9	.3	.7	.0	-.1	.5
Pct. Equifax risk scores 620-679	.8	-1.8	.9	.6	-.7	.1
Pct. Equifax risk scores 680-739	3.8	-3.5	-.3	1.1	-1.0	-.2
Pct. Equifax risk scores 740-799	3.6	-1.1	-2.7	.6	-.3	-.7
Pct. with credit reports	-5.3	4.4	.9	-2.4	1.9	.6
Average wages and salaries	-5.6	-.1	4.8	-1.2	-.1	.6
Average exemptions	.9	-1.1	.2	1.4	-.6	-.6
Average dividends and interest	-3.7	-.3	3.4	-1.7	.2	.7
Pct. income < $10K	5.1	1.8	-6.7	.2	1.0	-1.3
Pct. income $10-25K	2.7	.3	-2.7	.5	1.0	-1.3
Pct. income $25-50K	-1.3	-1.4	2.5	.2	-1.1	1.4
Pct. income $50-75K	-1.7	-.5	2.0	-.1	-.4	.1
Pct. income $75-100K	-5.1	.0	4.5	-.9	.0	.4
Poverty rate	2.7	.2	-2.6	.0	.3	-.4
House price appreciation, 2005	-6.9	-1.9	7.3	-1.6	.2	1.3
Median house price / Average income	-9.4	-3.0	10.0	-1.6	-.5	2.1
Unemployment rate, 2005	-3.1	2.7	.2	-.9	1.2	.3
Median house price – CLL	-12.5	-3.1	11.9	-2.6	-.5	2.4
Pct. home sales le 125 CLL	2.0	2.5	-4.2	-.1	.7	-1.3
No. HMDA lenders, 2005	-16.4	2.1	12.9	-4.8	1.1	1.9
No. HMDA lenders, 2005 – 1998	-9.1	-2.0	8.6	-2.9	.1	.6
Census county population	-9.4	1.8	6.0	-3.2	1.0	.4
Pct. ages < 20	-2.0	-.8	2.3	.7	-.5	.2
Pct. ages 20-29	3.4	-2.2	-2.0	1.0	-1.1	-.2
Pct. ages 30-39	-5.4	-.4	4.7	-.4	-.5	.7
Pct. ages 40-49	-4.1	1.1	2.7	-.5	.4	.2
Pct. ages 50-59	-2.1	2.9	-.6	-1.4	1.4	-.1
Pct. ages 60-69	.9	1.0	-1.8	-.7	.7	-.2
Pct. female	-1.9	3.5	-1.2	-1.5	1.5	.0
Pct. African American	-5.9	1.7	3.1	-.5	.4	.4
Pct. American Indian	2.7	-1.6	-1.2	.4	.1	-.6
Pct. Asian	-3.6	-3.1	5.2	-1.0	-.5	.7
Pct. Other	2.4	-2.4	-.7	.7	-.3	-.6
Pct. Hispanic	-5.6	-2.5	6.1	-.9	-.2	.8
Pct. high school or less	3.8	1.5	-5.1	.6	.2	-.6
Pct. some college	-2.7	-1.7	4.1	.3	-.4	.1

[1] Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Note: 33rd and 66th percentiles for 2005 PLS share: 14.6 and 22.3 percent.

TABLE 4D—COVARIATE BALANCING FOR PORTFOLIO SHARES

	Unadjusted			Adjusted for GPS		
	0-33rd	33-66th	66-100th	0-33rd	33-66th	66-100th
Equifax risk score[1]	6.0	-1.0	-4.7	.8	-.4	-.5
Pct. Equifax risk scores < 580	-6.3	1.5	4.4	-1.0	.6	.6
Pct. Equifax risk scores 580-619	-5.8	1.1	4.6	-.7	.5	.4
Pct. Equifax risk scores 620-679	-2.7	.7	2.1	-.2	.4	.1
Pct. Equifax risk scores 680-739	2.8	-.8	-1.9	.5	-.1	-.3
Pct. Equifax risk scores 740-799	7.0	-1.2	5.9	1.3	-.6	-1.0
Pct. with credit reports	-1.9	-1.2	2.8	-.1	-.8	.9
Average wages and salaries	1.4	1.3	-2.6	-1.0	.3	-.5
Average exemptions	2.7	1.0	-3.5	.5	.3	-1.5
Average dividends and interest	-.6	-1.8	2.0	-.5	-.7	.9
Pct. income < $10K	1.9	1.1	-2.9	.8	.6	-.9
Pct. income $10-25K	-4.0	-.3	4.4	-.1	.2	.7
Pct. income $25-50K	-6.3	-.6	6.5	-1.4	-.3	1.8
Pct. income $50-75K	4.9	-.1	-5.0	.5	-.5	-.8
Pct. income $75-100K	3.3	.5	-4.0	-.1	-.1	-.8
Poverty rate	-2.3	.4	1.9	-.1	.5	.0
House price appreciation, 2005	-5.3	-3.5	7.3	-.5	-1.1	1.6
Median house price / Average income	-8.6	-4.3	9.6	-1.7	-1.1	2.4
Unemployment rate, 2005	-5.2	1.7	2.6	-1.2	1.0	.4
Median house price – CLL	-7.6	-3.6	7.9	-2.3	-1.0	2.1
Pct. home sales le 125 CLL	8.5	4.2	-8.9	2.0	1.1	-2.5
No. HMDA lenders, 2005	-6.3	1.2	4.6	-2.8	.5	1.1
No. HMDA lenders, 2005 – 1998	-7.2	-2.6	6.8	-2.7	-.9	1.6
Census county population	-2.9	1.9	.8	-2.1	.7	.4
Pct. ages < 20	3.2	2.0	-5.0	.0	.7	-1.7
Pct. ages 20-29	3.8	-.8	-3.4	.6	-.2	-.5
Pct. ages 30-39	-3.0	2.3	.6	-1.7	.9	.0
Pct. ages 40-49	-.9	2.4	-1.3	-.8	.7	-.5
Pct. ages 50-59	-2.2	-.7	2.9	.0	-.3	.8
Pct. ages 60-69	-5.4	-1.8	6.0	.1	-.4	1.3
Pct. Female	-1.5	1.8	-.4	-.6	.5	.0
Pct. African American	-6.3	.4	4.8	-1.7	.1	1.1
Pct. American Indian	-1.2	.0	.9	.1	.1	.1
Pct. Asian	-4.2	.1	2.8	-2.6	.3	.8
Pct. Other	-2.8	-.9	2.3	-1.0	-.5	1.1
Pct. Hispanic	-2.0	.3	1.7	-.8	.6	.1
Pct. high school or less	-4.4	.8	3.4	-.3	.5	.4
Pct. some college	4.7	-1.3	-3.2	1.2	-.9	-.6

[1] Equifax risk scores aggregated from the FRBNY Consumer Credit Panel / Equifax data.

Note: 33rd and 66th percentiles for 2005 portfolio share: 12.0 and 15.6 percent.