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

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Abstract

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The United Sates government has a long history of involvement in mortgage finance. During the 1930's, 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 grew in size and scope, and the government also introduced additional programs as well (e.g. the Federal Home Loan Mortgage Corporation, or Freddie Mac, and the Government National Mortgage Association, or Ginnie Mae). An analysis and timeline of the federal legislation that created mortgage programs from 1933 to 1989 are provided in Green and Wachter (2005).[2]

During the most recent financial crisis, most of the government focus concerning mortgage finance was on mortgage debt relief and mortgage refinancing 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, and 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 housing programs created during the Great Depression were taken as background fixtures during the Great Recession. The Great Recession, however, provides us an opportunity to empirically assess the importance of the Great Depression housing programs. Most of these programs were created with the objective of limiting the damage to households during the Great Depression and speeding the economic recovery. Did they perform this role during the Great Recession?

The traditional channel for how a financial crisis can affect the real economy is that the crisis raise the cost of financial intermediation and lower the value of borrower collateral, causing banks to raise rates and decrease credit availability (Bernanke, 1983, Bernanke and Gertler, 1989). Supposedly, these traditional housing recovery programs stabilize and moderate the cost of credit for certain types of loans, allowing an economic recovery to proceed more quickly. In addition, the designers of the government mortgage housing programs during the Great Depression hoped to limit the economic contraction created by tightening bank underwriting standards mainly by

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

extending mortgages under less onerous underwriting standards (Rose, 2011).[3]

Here, we focus on mortgage insurance programs and, in particular, the FHA and the government-sponsored enterprises (GSEs), Fannie Mae and Freddie Mac. Providing government guarantees for the performance of financial assets has well-known moral hazard problems (add citations). However, one advantage of such policies is that they can be targeted to bad states of world. Indeed, well-targeted government insurance programs have the potential to mitigate crisis in the mortgage markets (Hancock and Passmore, 2011). In contrast, “Implementing a blunt policy such as carry more liquidity/reduce leverage/reduce asset positions into all states of the world may be prohibitively costly since it distorts private sector actions in non-crisis states, and those states be the more likely ones” (Krishnamurthy, 2010).

The Great Recession provides an opportunity empirically test the proposition that government mortgage insurance programs mitigated the crisis and enhanced the economic recovery from 2009 to 2014. We proceed as follows: Section 1 describes the FHA, Fannie Mae, and Freddie Mac. Section 2 describes the data, the empirical technique, and the results. We discuss the results and conclude in section 4.

1. FHA, Fannie Mae, and Freddie Mac and Economic Activity

The FHA provides mortgage insurance for mortgages extended by FHA approved lenders. At the end of fiscal year 2014 (September 30, 2013), the FHA had $1.1 trillion of insurance-in-force.[4] FHA mortgages are securitized by Ginnie Mae or held in the portfolios of banks. Ginnie Mae securities trade with the full faith and credit of the United States government.

Fannie Mae and Freddie Mac are government-sponsored enterprises (GSEs) that purchase mortgages either to hold in portfolio or to create mortgage-backed securities (MBS) to sell to investors. Almost all mortgages securitized by the GSEs are 30-year, fixed-rate mortgages.[5] As of

[3] 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.

[4] A full review of the FHA’s finances can be found at http://portal.hud.gov/hudportal/documents/huddoc?id=AR2014MMIFwdRpt.pdf.

[5] 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

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.[6]

Fannie Mae and Freddie Mac are implicitly subsidized by the government (Acharya, et. al., 2011, Burgess, Sherlund and Passmore 2005, and Passmore, 2005). On September 6, 2008 FHFA 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.[7]

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 to secondary market participant. Most mortgages that are sold, 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.[8] The relative cost and ease of the securitization determines which method of mortgage finance dominates.[9]

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 crashed, with 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 the mortgages it insures remain a smaller part of the aggregate mortgage holdings.

Government-backed mortgage insurance programs can influence the costs of mortgage financing directly by "capping" the price of credit risk. Private market participants have views on

Fannie Mae during the Great Depression (Green and Wachter, 2005).

[6] 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.

[7] 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.

[8] Of course, selling into the secondary market leads to adverse selection and other agency problems (Passmore and Sparks, Demazio, etc.).

[9] Hancock and Passmore (2011), Heuson, Passmore and Sparks (2001).

the appropriate credit risk premiums to charge for various types of borrowers and properties. 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 caps the market's perception of the distribution of credit risk premiums.

The government's circumventing of market-based credit risk premiums takes place through government securitization. As mentioned above, private sector investors purchase securities backed by FHA, Fannie Mae and Freddie Mac without considering credit risk because of explicit or implicit government guarantees.

The tighter the government's effective cap on credit risk premiums embedded in mortgages, the lower the mortgage rate for most mortgages, all other things equal. Finally, the tighter the cap, the added impetus for households to take 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, and Mian and Sufi, 2011), and housing wealth can influence the macroeconomic activity (Mian, Rao, and Sufi, 2013).

GSE and FHA mortgage insurance premiums vary somewhat by risk, but not by much (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). .

In aggregate, government-backed insurance programs seem to be negatively correlated with home sales during the past decade. The share of government involvement in the mortgage market decreased during the boom and increased since financial crisis, while the level of home purchases has moved in the opposite directions (figure 2). But this aggregate movement hides the fact the mortgage loan and housing purchases collapsed during the crisis, and remained low afterwards. We now turn to disentangling this relationship government mortgage insurance programs and economic activity.

2. Data and Methodology

We make two contributions in this paper. One, we establish the importance of government mortgage insurance programs during the financial crisis and economic recovery. Two, we illustrate the use of a generalized propensity score in the identification and estimation of these effects.

A map of counties across the United States illustrates the wide variation in government shares of mortgage lending (figure 3). The use of government mortgage insurance programs is concentrated in the Northeast and Upper-Midwest part of the country, where as the South and California are less likely to have a large proportion of mortgage origination flow into government-backed programs.

The frequency distributions shown in figure 4 also suggest significant variation in the county distributions of government program use. GSE securitization typical ranges from nearly 25 percent to over 75 percent of the proportion of originations in a county, where use of the FHA is much lower, ranging from close to zero to over 35 percent (top two panels). The share of mortgage originations flowing into bank portfolios ranges from 6 percent to 33 percent (bottom left). Private-label securitization (PLS), even at their 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 just under 45 percent (bottom right).

We characterize the mortgage market structure of a county by four mortgage origination channels: the proportion of mortgages that flow in bank portfolio (portfolio share,) the proportion that are securitized by PLS (PLS share), the proportion that are securitized by Fannie Mae or Freddie Mac (GSE share), and the proportion that are insured by the FHA or VA share (FHA/VA share). The last group may or may not be securitized by Ginnie Mae.

Table 1 shows the empirical doses, that is, the average doses apparent in our data set. Rather than selecting arbitrary “buckets” to use for averaging treatments across counties, we use a kernel regression to estimate average treatment levels. That is, given a level of GSE treatment, we calculate the average treatment level for FHA, PLS and portfolio market shares by giving greater weight to counties that are more similar to level of GSE treatment and lesser weight to those counties that have a different levels of GSE treatment. These are useful in interpreting the co-movement in GSE, FHA, PLS, and portfolio treatments.

We want to estimate the effect of the intensity of usage of GSE, FHA, PLS, and portfolio exposures on the state of the real economy in across counties. 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 use or select into various treatments, conditional on economic fundamentals such as high or low incomes, or high or low house prices, so we can directly estimate the effect of financing alternatives on economic activity in 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 on securitization on bank performance, and find that banks that securitize loans have similar risk-adjusted returns to banks that do not once the underlying propensity to securitize is adjusted across bank securitizers and non-securitizers. Bharath, Dahiya, Saunders and Srinivasan (2009) investigate lending relationships and loan contract terms. They use propensity scores to create a "matched" sampled 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) compare corporate venture capital to independent venture capital, and judge that the former has a superior ability to nurture ventures that are innovated. They use propensity scores to assess and, to the extent possible, rule out the possibility that corporate venture capital are simply better at selecting innovate projects.

Our approach is similar in spirit to Rosenbaum and Rubin (1983). In particular, as in Hirano and Imbens (2004), we use a generalized propensity score (GPS), where the probability of a county being "treated" by different levels of securitization usage is a function of country's underlying characteristics or "covariates". In other words, the market shares of GSE, FHA, PLS, and portfolio-funded mortgages for each county can be considered a random treatment across counties once a county's underlying characteristics, which influence a variety of mortgage market structure characteristics like deposits flows and costs, and demand for mortgages, 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).[10]

[10] This technique is similar to a difference-indifference approach, where the pre-treatment covariates could be used

We begin by separately modeling the county-level GSE, FHA, PLS and portfolio market shares of mortgage originations as a function of county characteristics during a benchmark period. We pick the pre-crisis period January 2004 to June 2007, and use data that is available at a monthly frequency. We use only counties that have complete data on house prices and home sales, resulting in 862 county-level observations (out of 3,137 counties in our initial data set).[11] As shown in Figure 5, the counties that remain are predominantly located in large MSAs. Moreover, these counties account for about 85-95 percent of mortgage purchase originations, home sales, delinquencies, and foreclosures in our full sample.

We perform a set of preliminary regressions of the four treatment levels, which we assume to be log-normally distributed, on county-level characteristics, including median credit scores, average income measures, various house price measures, and unemployment rates 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. Our preliminary generalized propensity scores (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.

Two important checks on the adequacy of the GPS are the common support and balancing conditions. The common support 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 covariates do not 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 of every 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 county-level GPS at GSE treatment levels of 47.6, 54.4, and

to define sub-samples, and then for each subsample, we could estimate the "average dose function." The continuous form of the first-state regression, however, allows the simultaneously adjustment by many covariates.

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

61.4 percent, representing the 25th, 50th, and 75th percentiles of GSE treatment, respectively. Then we compare the GPS from the 25th percentile of GSE treatment across GSE treatment levels of [0,50] versus (50,100], the GPS from the 50th percentile of GSE treatment across treatment levels of [25,75] versus [0,25)U(75,100], and the GPS from the 75th percentile of GSE treatment across treatment levels of [50,100] versus [0,50). If a particular GPS estimate lies outside the support of its comparison group, we drop that observation. Across the three different treatment levels within each of the four treatments (GSE, FHA, PLS, portfolio), we drop a total of 48 observations that don't have sufficiently close comparisons in our continuous treatment analysis. These leaves our final sample of 814 counties that satisfy the common support condition.

Based on these 814 counties, we regress each market share against county characteristics that are likely to influence the mortgage market structure in the county (Table 1) to estimate the final GPS. Wealth, income, employment, credit ratings, house price growth, and the level of house prices each seem likely to determine the relative level securitization through each outlet and the likelihood of a bank keeping a loan in portfolio.

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

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

To test this 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 fixed GPS "neighborhoods."

As shown in Table 3, we split treatment levels into three groups of roughly equal size. For example, to 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, we compute the GPS for a GSE treatment level of 45 percent (the median for the group with 50 percent or less exposure) for all observations, $r(45, X_i)$. We then sort each of the observations into quintile groups defined by their estimated GPS. Then, conditional on the GPS quintile, we compute the *t*-statistic for the equality of credit score means across the group with GSE treatment of 50 percent or less versus the group with GSE treatment of greater than 50 percent. As shown, adjusting for GPS improves the balance of credit scores significantly, reducing the magnitude of the t-statistic from

11.2 to 2.3. The unadjusted version compares covariate means across groups unconditional of the GPS.

To elaborate on the example above, the unadjusted mean credit score for the three GSE treatment groups is 674, 687, and 700 respectively. Comparing the mean of the less than or equal 50^{th} percentile group (674) to the mean of the greater than or equal to 50^{th} percentile group (692) yields at t-statistic of -11.2. Clearly, the mean credit score of counties with more than 50 percent of their mortgage originations sold to the GSEs is significantly smaller than the mean credit score of a counties with more than 50 percent of their mortgage originations sold to GSEs.

We re-rank the counties in each of the three groups by their GPS where we assume the treatment for every county is the median treatment for counties receiving less than 50 percent GSE treatment(the group where 45 percent of the mortgages originated are sold to the GSEs). Taking the lowest quintile of GPS, the mean credit score for counties where less than 50 percent of their mortgage originations is sold to the GSEs is 687, whereas the mean credit score is 700 for the lower quintile of counties with more than 50 percent of their mortgages sold to the GSEs. We perform this calculation for each of the quintiles and then create a weighted-average (weighted by the number of counties within each group) of the means across the quintiles. The t-statistic for the difference in these means becomes -2.3 percent, a significant reduction. As shown in table 3, most of the t-statistics become insignificant after the GPS adjustment.

Thus, our approach balances our sample in the sense that conditioning on the values of the GPS, the means of the covariates (or, in the example, the 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 can control for differences in county characteristics that are related to the treatment. By using this approach, we can have confidence that we have isolated the pure effect of government involvement in the mortgage market on economic variable of interest.

Now that we have verified the common support and balancing conditions, we regress the economic outcomes of two periods: October 2008-December 2009 (crisis), and January 2013-December 2014 (post-crisis) on their pre-determined mortgage market structure and on the probability of observing that structure during the benchmark period. We focus on six outcomes of interest that describe the economic state of the county: unemployment rates, delinquency rates, completed foreclosures, total home sales, house prices, and mortgage purchase originations. All of these outcomes are measured relative to their values during the 2004-2007 benchmark period.

We estimate "dose-response" functions of counties' economic outcomes in response to a pre-determined level of various securitization outlets using several different methodologies. First, we estimate a parametric partial mean, in which the economic outcome is a linear function of the level of treatment and the probability of observing a particular treatment level. This is ordinary least squares, where the probability of observing a particular treatment level is, of course, an implicit function of the treatment level itself. In other words,

$$y_i = \beta_0 + \beta_1 t_i + \beta_2 \widehat{R}_i + \varepsilon_i$$

where y_i is the variable of interest (e.g. unemployment, home sales), t_i is the treatment received (e.g. the FHA proportion of mortgage originations in the county), and $\widehat{R}_i$ is the GPS evaluated at the level of treatment received and the observed covariates.

Second, we estimate a nonparametric partial mean, in which the economic outcome is an arbitrary function of the level of treatment and the probability of observing a particular treatment level. More precisely, we estimate a local-linear regression with weights depending upon a Gaussian kernel, k, and an optimally selected cross-validated bandwidth, b_n (Fan and Gijbels 1996),

$$w_i = k\left(\frac{t_i - t}{b_n}\right).$$

Finally, we estimate a nonparametric partial mean with inverse weighting, in which the economic outcome is an arbitrary function of only the level of treatment and is weighted inversely to its GPS value. In particular, we augment the kernel weighting with the inverse of the estimated GPS so that

$$w_i = k\left(\frac{t_i - t}{b_n}\right) / \hat{R}_i.$$

Hirano, Imbens, and Ridder (2003) show that this particular weighting can be used to identify the relevant dose-response function. Throughout our analysis, all standard errors and confidence bands are generated from 1,000 bootstrap replications (with replacement).

Dose-response function provide a convenient summary of these estimates. They show the expected value of the outcome variable conditional on a level of treatment and the GPS. Finally, we calculate average treatment effects as the derivative of the dose-response functions. That is, 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.

3. Results and Interpretations.

Our identification strategy relies on the variation in government involvement in mortgage markets across counties. Counties with significant government involvement are subject to underwriting standards that are set at a national level, whereas counties with little government involvement are subject to underwriting standard set by local banks, thrifts and mortgage banks, and by private-sector mortgage securitization conduits.

We envision each county containing a set of mortgage financing structures that change only slowly over time and reflect the economic characteristics of the population that live in those counties. As the securitization outlets are provided by national entities, their relative usage in a county 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 availability of the securitization outlets.

Our first set of results, those describing the dose-response functions for the unemployment rate, are summarized in in Figures 6. We can see a clear downward trend in unemployment 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 make more use of the FHA. In contrast, counties that were more reliant on either PLS or bank portfolios experienced higher levels of unemployment in both the crisis and post-crisis periods. During the financial crisis, the increase in the unemployment rate was over 20 percent higher in counties with the lowest levels of GSE securitization and 34 percent higher in counties with the lowest levels of FHA activity (relative to counties the highest levels of government involvement).

As shown in Figures 7 and 8, our results are quite robust to generalizations of the parametric model. Counties with higher government involvement are again estimated to have lower unemployment rates, whereas counties with higher levels of PLS/portfolio activity are estimated to have higher unemployment rates for both the nonparametric partial mean and a nonparametric partial mean with inverse weighting. Over the entire range of results, counties with low levels of GSE securitization activity had unemployment rates of 10 to 22 percent during the financial crisis, while counties with low levels of FHA activity had unemployment rates 26 to 35 percent higher.

Similar patterns hold for home sales and home prices (Figures 9 and 10). Greater exposure to GSE or FHA activity during the 2004-2007 period tended to be associated with greater home sales and higher house prices both during and after the financial crisis. The opposite holds for PLS and portfolio lending prior to the financial crisis: Home sales and house prices tend to fall more among counties with high exposures to PLS and portfolio lending.

As shown in Tables 4-5, the average treatment effects (that is, derivative the dose-response functions) are, on average, typically fairly similar to those coming out of a naïve OLS regression of the economic outcome on the treatment level. However, as is evident in the tables, some of the estimates differ quite substantially from their OLS counterparts over significant portions of the treatment distributions. For example, Table 5 reports that, according to a naïve OLS regression, increasing the PLS market share in 2005 from 14 to 18 percent would be associated with house sales nearly 11.6 percent lower. But our dose-response functions suggest that the true effect could be nearly twice as large, at over 3 percent. This shows the importance of correcting for the ability of counties to select into treatment levels and to adequately control for potential differences in county-level characteristics.

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Table 1: Empirical Doses

	Observed Average		
GSE Dose	**FHA**	**PLS**	**Portfolio**
12.9	0.7	51.4	35.1
16.4	4.4	47.9	31.3
20.3	7.4	44.7	27.6
24.4	10.7	38.6	26.3
29.1	14.4	32.5	24.0
33.1	12.0	31.6	23.2
37.4	12.7	27.8	22.1
41.2	14.1	24.6	20.1
45.1	14.3	22.0	18.6
48.6	14.1	20.0	17.3
52.2	13.1	19.0	15.8
55.9	11.7	18.2	14.2
59.8	10.0	17.2	13.0
63.2	8.7	15.9	12.1
66.3	7.7	14.5	11.5
70.0	7.0	12.7	10.2
74.3	6.4	11.2	8.1
78.0	5.3	10.1	6.6

	Observed Average		
FHA Dose	**GSE**	**PLS**	**Portfolio**
4.3	56.0	22.5	17.3
8.0	58.3	19.2	14.5
11.7	56.2	18.0	14.1
15.7	53.3	17.1	13.9
19.2	51.1	15.9	13.7
23.2	49.5	14.4	12.9
27.2	47.1	13.0	12.7
31.0	44.6	12.2	12.2
34.8	41.4	11.4	12.4
39.0	36.8	9.9	14.4
44.7	33.8	9.7	11.8
48.2	30.9	9.1	11.8
50.4	28.7	10.4	10.5

	Observed Average		
PLS Dose	**GSE**	**FHA**	**Portfolio**
9.8	59.5	18.0	12.6
12.8	57.9	15.5	13.9
16.1	57.0	12.3	14.5
19.5	55.0	10.8	14.7
23.3	52.0	8.9	15.8
27.2	48.5	6.7	17.7
31.1	44.1	5.7	19.1
35.1	39.0	4.8	21.1
39.6	35.5	2.3	22.7
44.0	29.9	1.8	24.3
48.5	21.5	0.6	29.3
50.5	19.1	0.4	30.0
54.3	15.3	0.3	30.2

	Observed Average		
Port Dose	**GSE**	**FHA**	**PLS**
6.1	68.7	12.5	12.7
9.0	61.2	14.5	15.2
12.2	57.2	13.1	17.4
15.5	53.8	11.6	19.1
19.4	47.9	9.9	22.8
23.5	43.8	5.6	27.0
27.5	40.4	3.8	28.3
31.6	33.9	3.5	31.0
35.4	34.0	1.7	28.9
39.3	22.1	1.4	37.2
44.2	31.0	4.7	20.1
47.5	33.1	4.4	15.0

Table 2: GPS Results

	GSE	FHA	PLS	Portfolio
Constant	-22.965**	15.363**	14.448**	28.499**
	(1.824)	(4.992)	(3.075)	(3.130)
Credit score	2.968**	-3.037**	-2.869**	-4.215**
	(.228)	(.684)	(.419)	(.471)
Wages and salaries	.387**	-.159	.350**	-.045
	(.092)	(.210)	(.129)	(.130)
Exemptions	-.279**	.909**	-.097	-.432**
	(.098)	(.265)	(.173)	(.161)
Dividends + interest	.061**	-.375**	-.075**	.106**
	(.020)	(.054)	(.031)	(.034)
2005 HPA	-.013	-.276	.682**	.528**
	(.103)	(.250)	(.132)	(.158)
HP/Income	.041**	-.144**	.021	.014
	(.015)	(.036)	(.020)	(.021)
Unemp 2005	-.010**	-.099**	.075**	.046**
	(.005)	(.014)	(.009)	(.011)
HP – CLL	-.002**	-.004**	.002**	.002**
	(.001)	(.001)	(.001)	(.001)
No. obs.	814	814	814	814
R-squared	.439	.748	.463	.325

Table 3: Covariate Balancing

GSE	Unadjusted			Adjusted for GPS		
	G<=50	50-60	G>60	G<=50	50-60	G>60
Credit score	-11.2	0.2	13.0	-2.3	-0.3	2.9
Wages and salaries	-5.4	1.3	3.6	-2.1	0.6	0.1
Exemptions	2.7	1.1	-4.4	0.3	0.7	-1.3
Dividends + interest	-5.9	-0.5	8.5	-1.2	-0.4	1.8
2005 HPA	4.8	-3.0	-2.6	1.5	-1.5	0.6
HP/Income	4.6	-3.8	-1.6	1.5	-1.4	1.5
Unemp 2005	3.7	1.8	-6.5	1.3	1.0	-1.4
HP – CLL	2.4	-2.8	-0.0	0.6	-0.9	1.2

FHA	Unadjusted			Adjusted for GPS		
	F<=7	7-14	F>14	F<=7	7-14	F>14
Credit score	13.1	-0.9	-11.2	4.5	-0.5	-2.2
Wages and salaries	6.5	0.8	-10.0	2.7	0.1	-3.2
Exemptions	-6.3	0.6	6.7	-1.8	0.4	1.0
Dividends + interest	15.0	-2.2	-14.0	5.1	-1.3	-3.3
2005 HPA	11.0	-3.9	-8.6	2.7	-0.9	-1.3
HP/Income	17.2	-7.7	-15.3	6.2	-2.6	-4.3
Unemp 2005	-3.8	1.9	2.3	-0.9	0.8	0.0
HP – CLL	19.6	-6.9	-18.6	7.3	-2.2	-6.7

PLS	Unadjusted			Adjusted for GPS		
	P<=15	15-20	P>20	P<=15	15-20	P>20
Credit score	1.5	-0.6	-0.8	-0.8	0.2	-0.2
Wages and salaries	-4.2	-0.5	4.2	-1.2	-0.2	0.6
Exemptions	0.2	-1.2	0.8	0.8	-0.6	0.4
Dividends + interest	-0.9	-1.3	1.8	-0.9	-0.4	0.1
2005 HPA	-8.0	-2.6	8.5	-1.1	-1.0	1.6
HP/Income	-9.1	-4.9	10.7	-1.4	-1.9	2.6
Unemp 2005	-4.1	1.7	1.9	0.1	0.7	0.8
HP – CLL	-11.4	-5.1	11.7	-2.8	-1.9	2.9

Portfolio	Unadjusted			Adjusted for GPS		
	R<=12	12-16	R>16	R<=12	12-16	R>16
Credit score	4.4	-0.3	-3.8	-0.2	0.2	-1.0
Wages and salaries	0.5	0.6	-1.1	-0.8	0.4	-0.3
Exemptions	2.0	1.0	-2.8	0.4	0.4	0.2
Dividends + interest	-0.9	-1.3	1.8	-0.5	-0.3	-0.7
2005 HPA	-6.8	-3.6	8.3	-0.8	-1.4	0.4
HP/Income	-10.0	-3.5	9.9	-2.7	-1.2	0.9
Unemp 2005	-4.2	2.3	1.4	-0.6	1.0	0.2
HP – CLL	-8.8	-2.7	8.2	-3.0	-0.8	0.8

Table 4: Average Treatment Effects (GSE and FHA Lending)

2009	**GSE** **48 to 54**	**GSE** **54 to 61**	**FHA** **5 to 10**	**FHA** **10 to 16**
Unemp. rate	-.040	-.060	-.085	-.086
OLS	-.*039*	-.*045*	-.*072*	-.*086*
Home sales	.003	.006	.067	.056
OLS	*.003*	*.004*	*.045*	*.054*
Home prices	.035	.033	.038	.048
OLS	*.033*	*.038*	*.041*	*.049*

Table 5: Average Treatment Effects for PLS and Portfolio Lending

2009	PLS 14 to 18	PLS 18 to 23	Port 11 to 14	Port 14 to 18
Unemp. rate	.066	.068	.099	.082
OLS	*.050*	*.062*	*.066*	*.088*
Home sales	-.031	-.022	-.041	-.034
OLS	*-.016*	*-.020*	*-.025*	*-.033*
Home prices	-.047	-.057	-.056	-.036
OLS	*-.042*	*-.053*	*-.036*	*-.048*

Figure 1: Mortgage Debt Outstanding

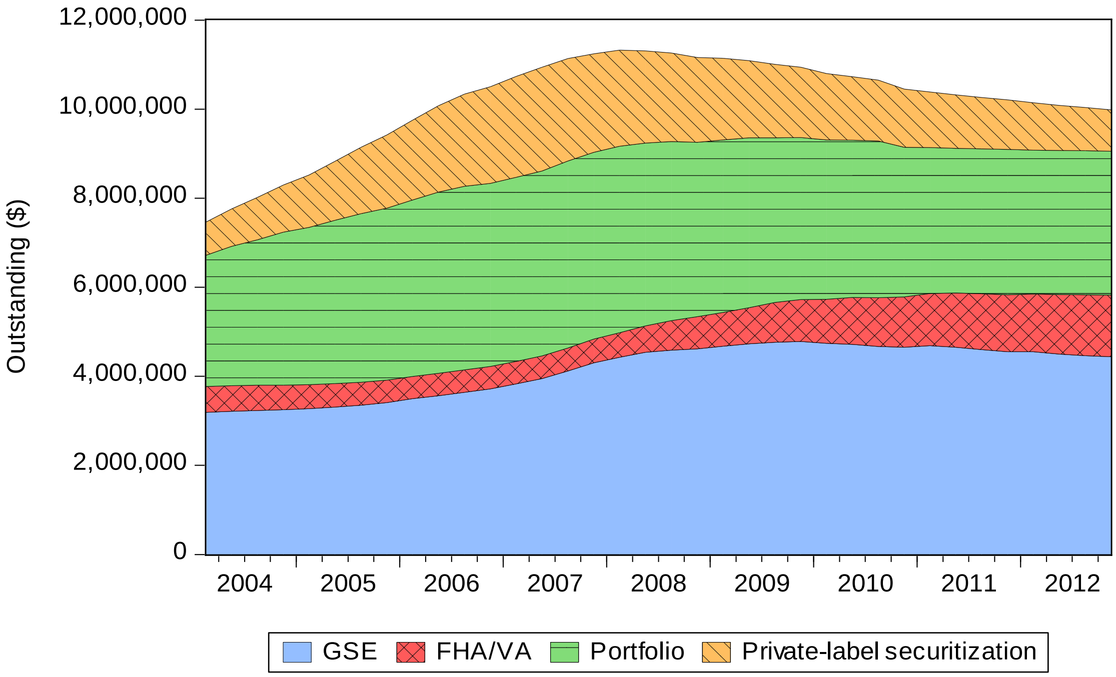

Figure 2: Home Sales versus Government Share of Mortgage Debt Outstanding

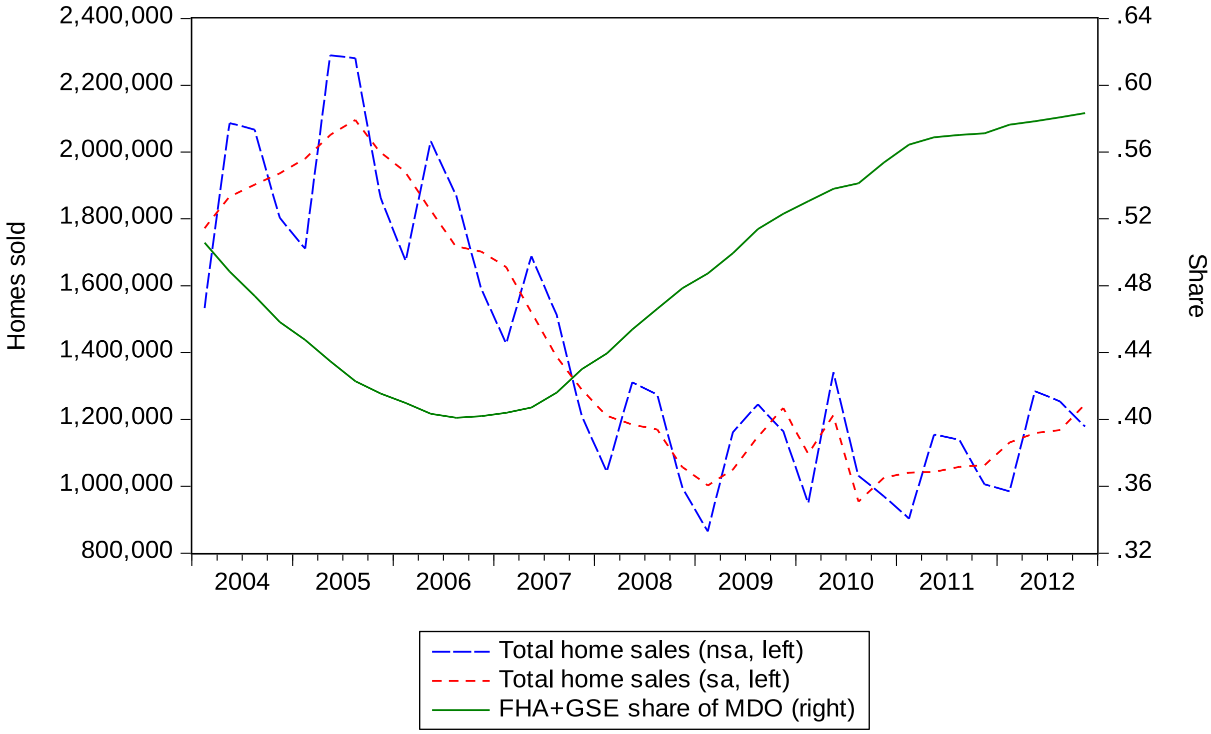

Figure 3: Government Lending in the United States

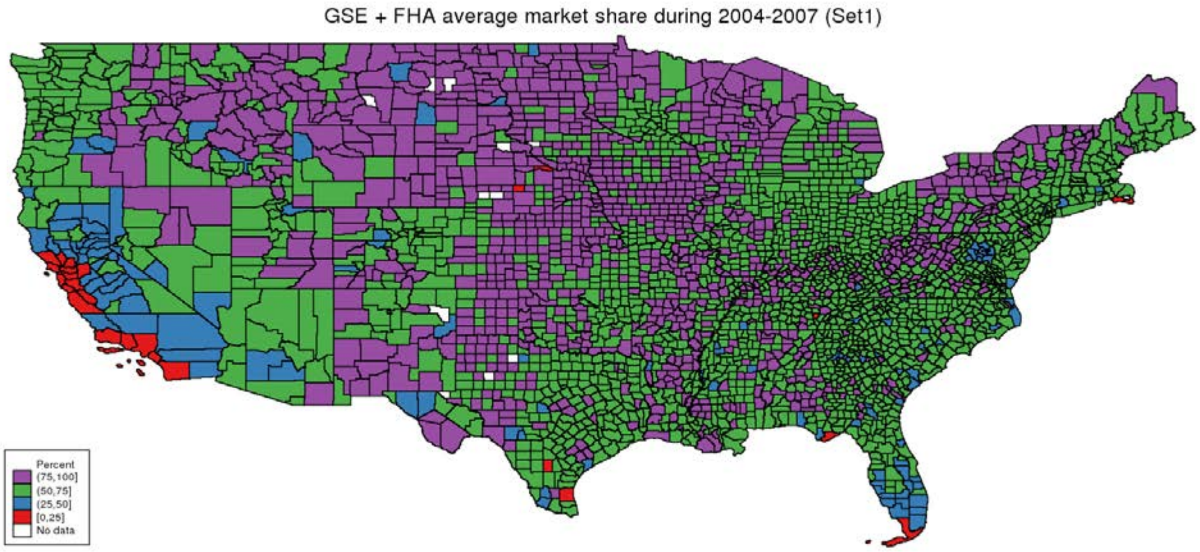

Figure 4: Mortgage Market Share Density Functions

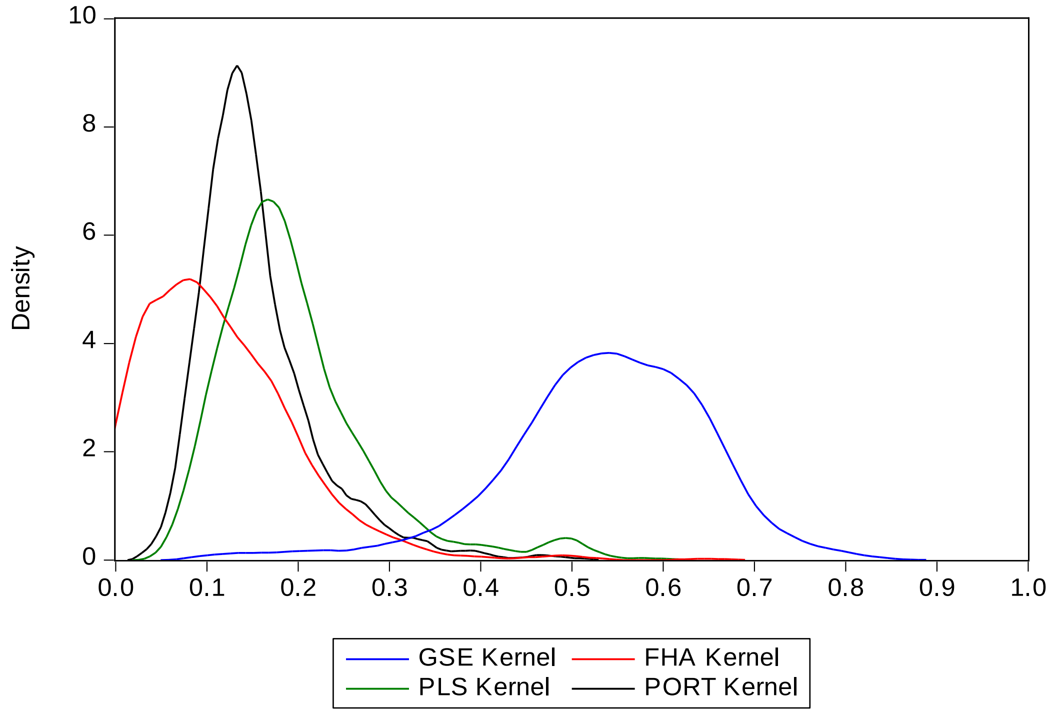

Figure 5: Data Coverage

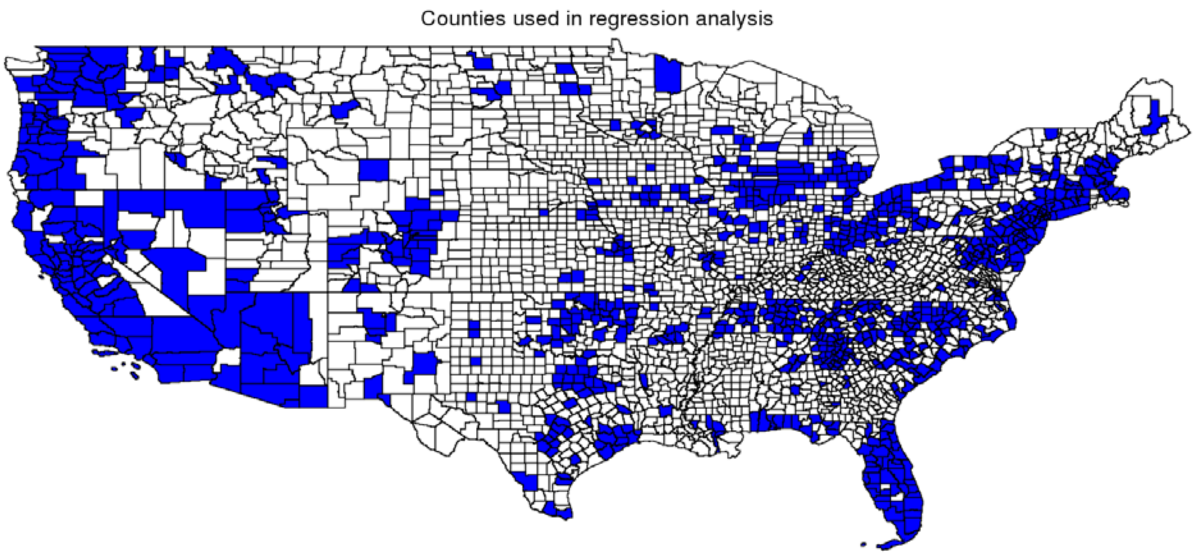

Figure 6: Unemployment Rate Dose-Response Function (Parametric Partial Mean)

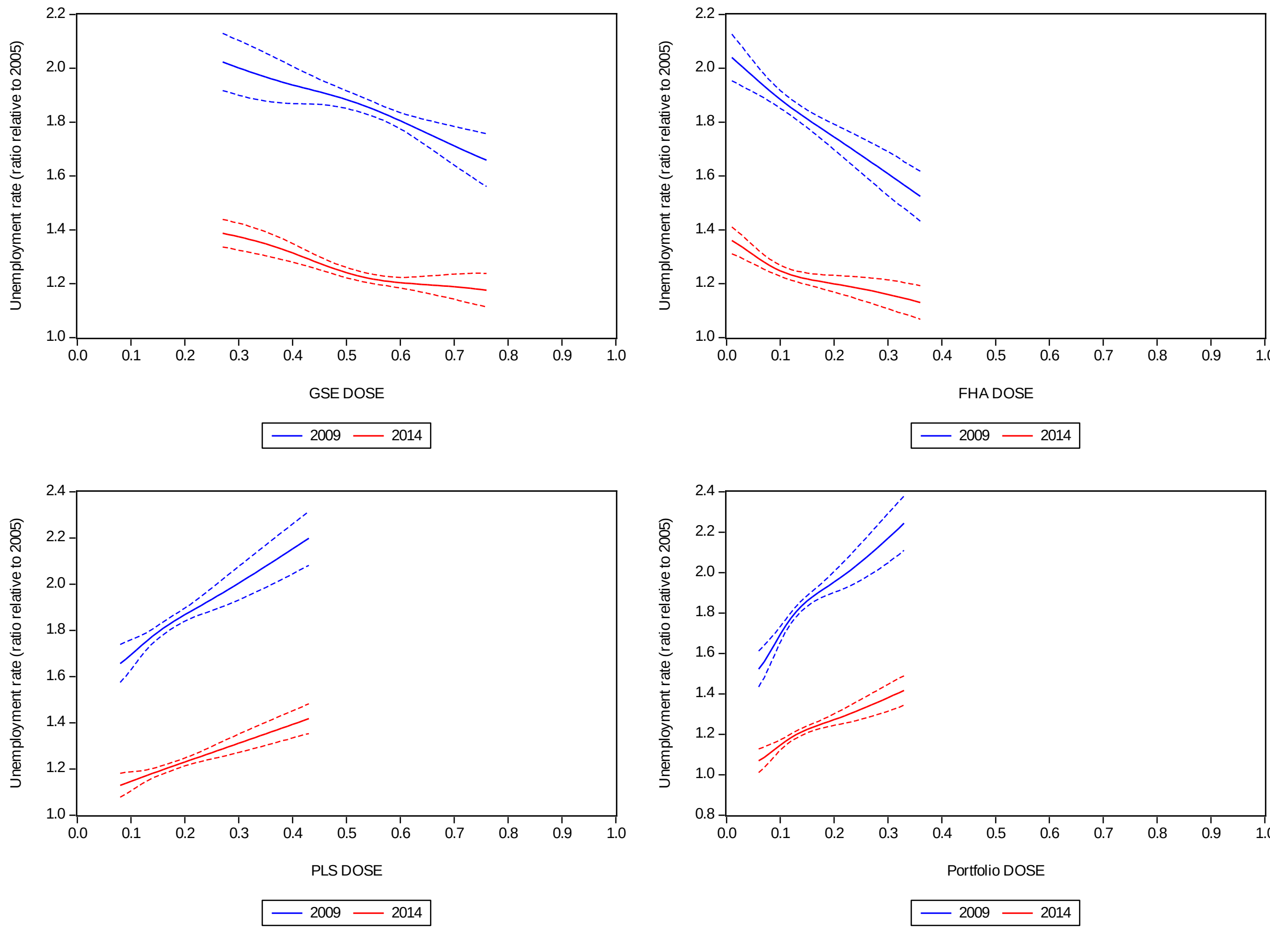

Figure 7: Unemployment Rate Dose-Response Function (Nonparametric Partial Mean)

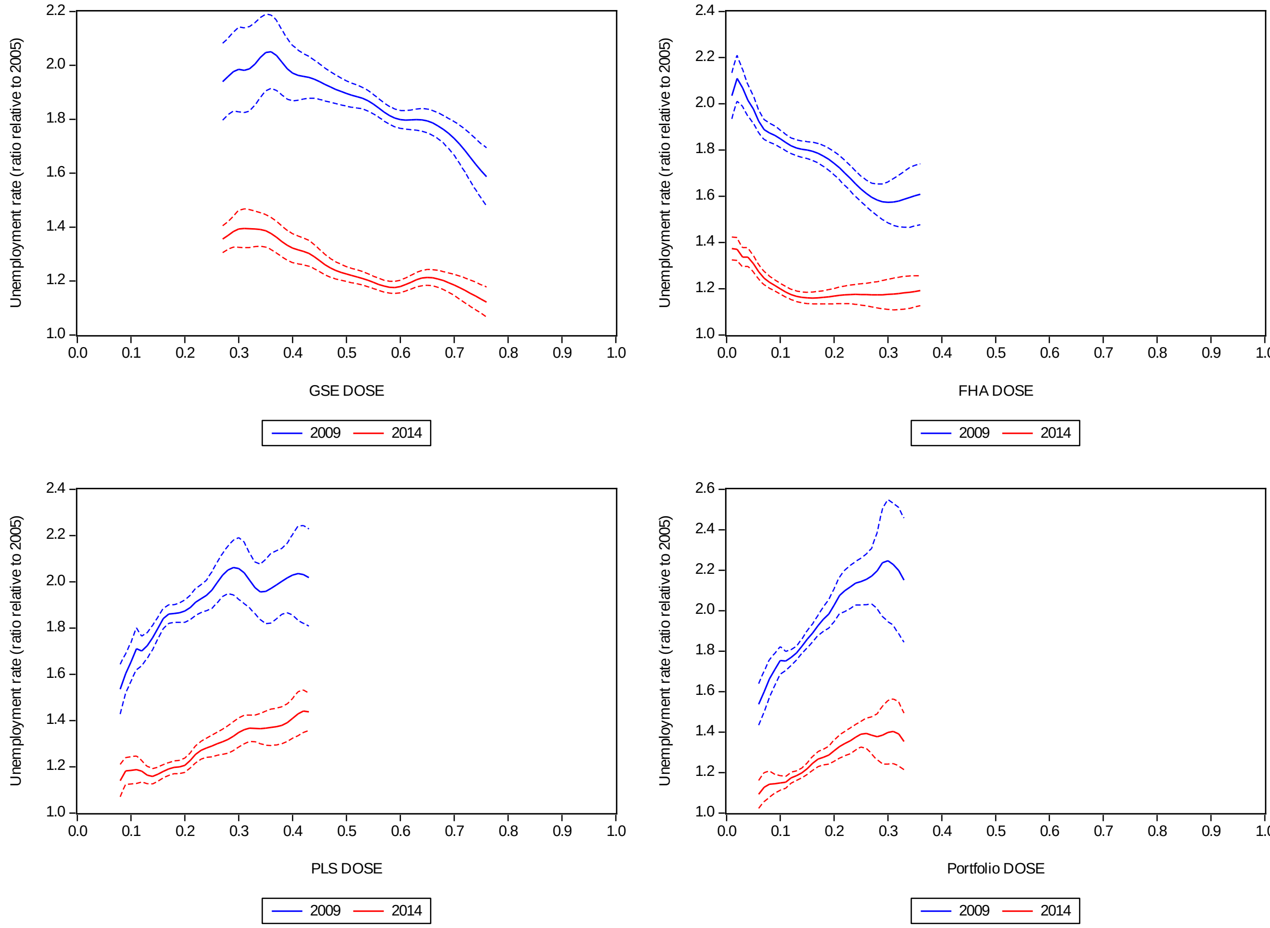

Figure 8: Unemployment Rate Dose-Response Function (Nonparametric Partial Mean with Inverse-GPS Weighting)

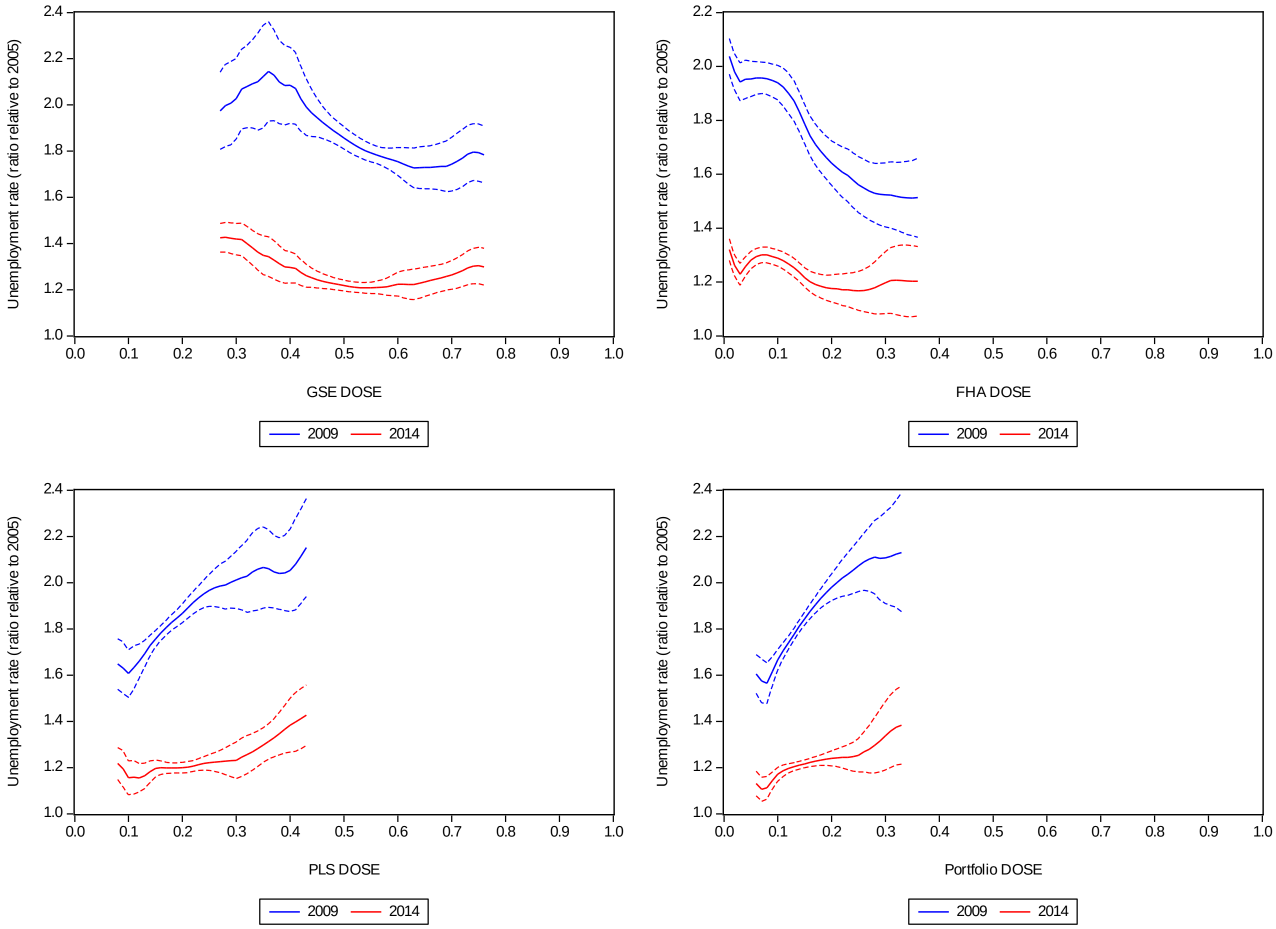

Figure 9: Home Sales Dose-Response Function (Parametric Partial Mean)

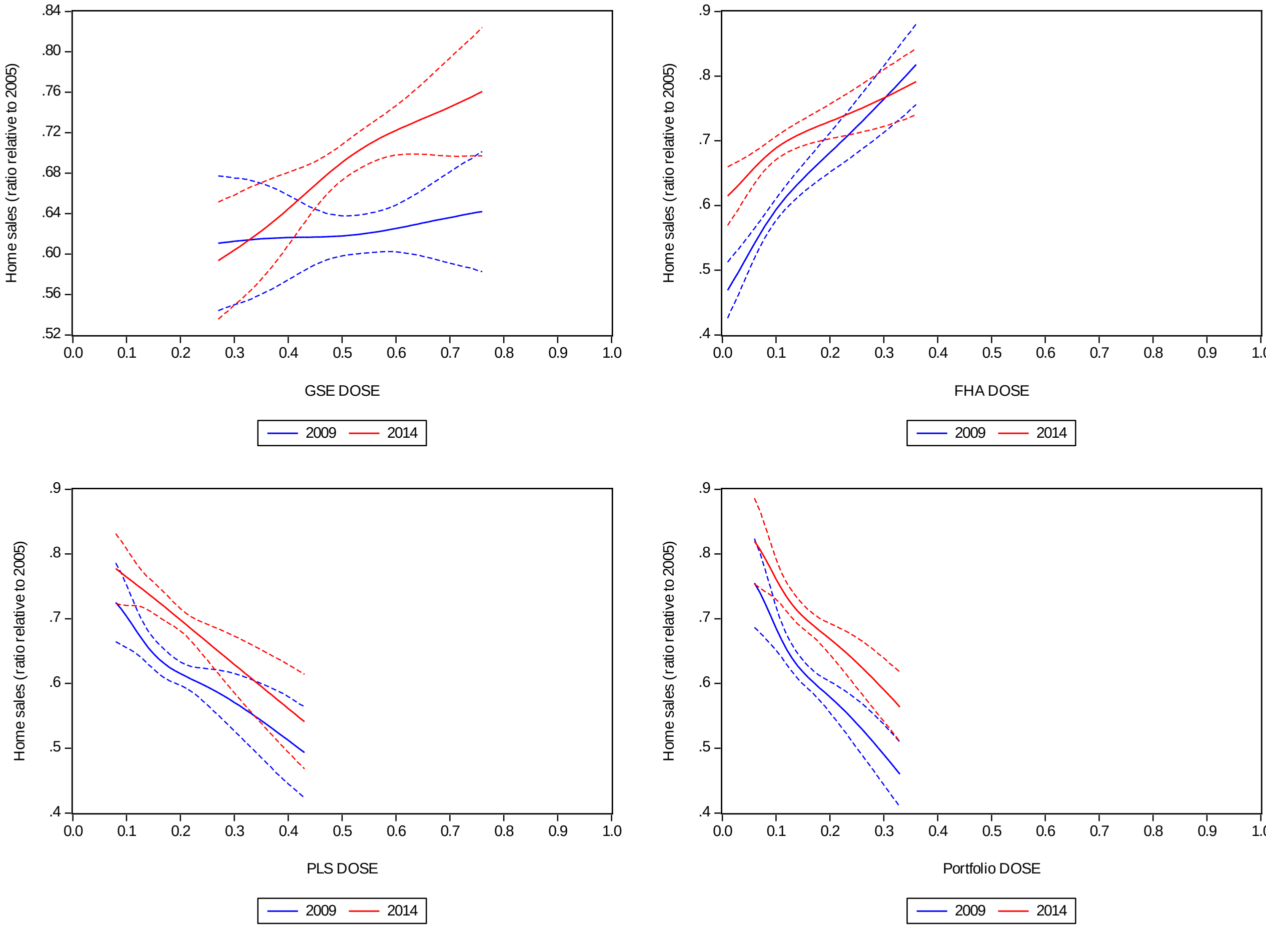

Figure 10: Home Prices Dose-Response Function (Parametric Partial Mean)