working paper

10 21R

Homeownership for the Long Run: An Analysis of Homeowner Subsidies

O. Emre Ergungor

FEDERAL RESERVE BANK OF CLEVELAND

Working Paper 10-21R February 2011*

Homeownership for the Long Run:
An Analysis of Homeowner Subsidies

O. Emre Ergungor

This paper examines the impact of interest-rate and down-payment subsidies on default rates and losses given default, and finds that down-payment subsidies create successful homeowners at a lower cost than interest-rate subsidies.

Keywords: mortgage default, interest rate subsidy, down-payment subsidy, housing-finance policy

JEL Codes: H53, I38, R31.

*This paper is a revised version of a paper that was posted in November 2010.

O. Emre Ergungor is a senior research economist at the Federal Reserve Bank of Cleveland. He can be reached at Federal Reserve Bank of Cleveland, Research Dept. P.O. Box 6387, Cleveland, OH 44101-1387; (216) 579-3004 (phone); (216) 579-3050 (fax); or ozgur.e.ergungor@clev.frb.org.

I. Introduction

The notion that homeownership contributes to social harmony and to individuals' happiness and welfare is deeply rooted in the American psyche. Consequently, encouraging, subsidizing, and protecting homeownership are deeply ingrained in public policy.

Under the assumption that we will continue to subsidize homeownership as a nation, this paper examines two broad classes of homebuyer subsidies that could be directed toward households with low-to-moderate income. More specifically, I focus on the effectiveness of the two main delivery mechanisms: interest-rate subsidies and down-payment assistance. Our current tax regime already provides an interest rate subsidy to homeowners through the mortgage interest deduction.[1] However, this type of subsidy is unavailable to most lower-income households who take the standard deduction (Glaeser and Shapiro, 2003).[2] My focus in this paper will be a hypothetical interest subsidy program that targets solely low-moderate income households.

Earlier comparative research on subsidies emphasized their impact on affordability rather than their sustainability. For example, the tenure-choice literature has found that many potential homebuyers are constrained by their lack of a sufficient down payment. Therefore, down-payment assistance is more effective than interest-rate subsidies in influencing home-purchase decisions, not just here in the U.S. but also abroad (Gobillon and le Blanc, 2008; Hegedüs et al., 2004; Quercia et al., 2000; also see Feldman, 2001 for a comprehensive review of the tenure-choice literature). However, following the recent crisis, attention shifted from the purchase decision to the sustainability of homeownership. On this front, two questions need to be addressed: First, what is the impact of each type of subsidy on loan performance in low-to-moderate-income (LMI) areas? Second, what is the cost of such subsidies to the taxpayer?

On the first question, I find that a to achieve the same reduction in default risk from a one basis-point decline in mortgage rates, LMI homebuyers would need a supplemental down payment of $32. For example, a 25 basis point mortgage rate subsidy is equivalent to an $800 supplemental

---

[1] Lower interest costs can also be achieved through FHA mortgage insurance funded by premiums paid by borrowers, although this does not constitute a subsidy if the insurance is properly priced.

[2] In 2007, tax payers reporting income below $50,000 (approximately the U.S. median income) received 4.1 percent of the subsidy's value, while those earning more than $100,000 received 73 percent of the subsidy (Ventry, 2009).

downpayment in that they both reduce default rates by 19 basis points. On the second question, I find that the total resources needed to enable all such borrowers to pay in an extra down payment are well below the cost of an interest-subsidy program over a 15-year period. In addition to lower costs, what makes the down-payment program attractive is that it would create a significantly larger number of new homebuyers compared to the interest-rate subsidy. Even after accounting for renters who become homeowners as a result of the downpayment subsidy, the cost of the down-payment program still trails that of the interest-subsidy program by more than 30 percent.

But why would one expect one type of program to be better than the other? The advantage of a down payment program is that it would provide higher homeowner equity. Genesove and Mayer (1997) show that equity makes sellers more flexible in pricing, and reduces the time a house stays on the market. For a homeowner who lacks any pricing flexibility because the mortgage exceeds the value of his home, the only way out of homeownership is to pay the difference to the lender or to let the lender take over the property with all the associated losses. Simply subsidizing the mortgage rate does not provide the same benefits as a down payment. A lower rate would surely make payments more affordable and lower the instance of defaults. However, it may not permit an exit from homeownership that precludes default during bad times.

The advantage of interest subsidies is that while every low-income homebuyer would receive down payment assistance at the time of the purchase, the benefit of a subsidized mortgage rate accumulates over time only to those who stay current on their mortgages; that is, the interest rate program is a contingent subsidy. Whether the greater benefit of the down payment program or the contingent nature of below-market interest rates dominates in the end is an empirical question, which is addressed in this paper.

As a final note, the cost of either subsidy to the taxpayer also depends on program parameters. Under the current housing finance policy, the interest-rate subsidy takes the form of a federal mortgage-interest tax deduction and its cost is fully borne by the taxpayer. A program that targets low-moderate income households could also be designed as a tax expenditure or it could be similar to USDA Section 502 direct loans, which are loans with subsidized payments to rural households. Down-payment assistance is provided at the local level through nonprofit organizations using a combination of public *and* private funds. In other words, while higher down payments do require larger resources at origination—compared to an interest subsidy disbursed over time—the full cost is not necessarily borne by the taxpayer.

The main contribution of this paper is that it offers a way to compare alternative subsidy delivery mechanisms if we choose to preserve homeownership as a housing policy goal. It is a first effort in addressing an important policy question with imperfect data. Consequently, the results come with many caveats reported in Section 5. The remainder of the paper evaluates the subsidies.

The questions of *whether* homeownership should be subsidized and, if so, by how much, are beyond the scope of this paper.

II. Data and Method

In this section, I examine how homeowner subsidies affect loan performance and how much they cost. The primary data source is the LPS Applied Analytics' loan-level mortgage-servicing data for loans originated in the 2002–04 period and tracked until December 2005. Two factors determine the choice of origination years. First, as Demyanyk and Van Hemert (2009) have documented, mortgage underwriting standards declined steadily over many years before the beginning of the crisis. After the mortgage market stabilizes, the terms and performance of the loans originated near the peak of the housing bubble are unlikely to be observed again. Based on this assertion, I exclude originations in the years 2005 and later. The second factor is data availability: The market coverage of servicing data is thin before 2003. Yet, given that the dataset is already limited to years 2004 and earlier by the first factor, I settle on 2002 through 2004 as my preferred origination years. The observation period ends in December 2005 to dissociate loan performance from the last hurrah and the bursting of the housing bubble and the effects of the financial crisis. Admittedly, it is impossible to completely disentangle the effect of the crisis on loan performance and determine how the loans would have behaved in a "normal" market. I will discuss this issue in greater detail in the next section.

There are 5,782,120 first-lien, home-purchase mortgages for owner-occupied properties in the sample. Keeping in mind that the cost of any program is a major issue, I restrict the availability of subsidies to zip codes with median family incomes that are below the national median ($55,832), loan amounts below the FHA limit for low-price markets in 2005 ($172,632), and home values below the median home value in 2005 ($211,700). Obviously, these are subjective limits and not intended as a policy recommendation. With these restrictions, there are 2,776,072 loans in the sample.

II.a. Method

The LPS Applied Analytics dataset contains information on loan characteristics at the time of origination as well as during the life of the loan (see table 1). Using these characteristics, the estimation strategy involves predicting the probability and timing of default over a 15-year period if interest rates are subsidized by 0.25, 0.50, 075 or 1 percentage point for LMI borrowers. Then, I estimate the amount of down-payment assistance that would produce the same default pattern as an interest-rate reduction. Given that both types of subsidies have the same default pattern, the second stage of the analysis involves estimating the net cost of the subsidies, taking into account not just the money that has to be spent but also the savings from lower losses.

Loans disappear from the sample for three reasons: loan default, prepayment, or the servicer's sale of servicing rights. I investigate default and prepayment with a gamma hazard model.[3] In the loan-default model, the hazard is defined as a delinquency period of 90 days or more. Prepayments and loans that are sold or outlast the observation period are treated as censored observations. In the prepayment model, the prepayment is the hazard; defaults and other loans are treated as censored observations. Both models have the form

$$\log T_i = \beta_1 x_{1i} + \ldots + \beta_k x_{ki} + \sigma \varepsilon_i \tag{1}$$

where T_i is the hazard time from origination and the x's are the covariates defined in table 1. Table 2 presents the sample statistics.

To estimate model (1) and predict the prepayment and default probabilities of the subsidized loans in the sample for each month, I split the sample into two groups, one for the estimation and one for the predictions. The estimation subsample consists of a randomly chosen one-third of all the loans, and the prediction subsample consists of the remainder.[4]

[3] Data reject a proportional hazard assumption. The gamma model provides the best fit compared to other distributions as measured by the log-likelihood.
[4] Results are robust to differences in the way the sample is split for estimation and prediction.

The subsidies are introduced to the prediction sample, either by reducing the loans' interest rate (0.25, 0.5, 0.75 or 1 percent) or by keeping the interest rate at its original level but reducing the origination amount by a supplemental down payment that generates a default profile equivalent to that of the interest-rate subsidy. After the predicted default and prepayment probabilities are determined in each month, a random draw from a uniform distribution—with support over [0,1]—is used to determine whether a loan is prepaid, is in default, or survived the period. The prepayment and default behavior of the loans is predicted for 180 periods (through the end of 2017), using their original characteristics as well as the subsidized loan terms. In a market that appreciated at its historic rate before the housing boom (the average of the 1980–2000 period), there was usually enough equity in the house after 180 periods to allow defaults without any loss to the lender. Each sample is simulated 100 times to obtain a distribution of outcomes.

As mentioned earlier, events after December 2005 are excluded from the estimation sample. Default rates show a sharp increase in 2007 and 2008 for all origination-year cohorts. Survival models of any distributional form provide an extremely poor fit to the data. For example, predicted default rates in 2008 are about 6 percentage points above the actual default rates in the data. Note that the purpose of this paper is not to make accurate predictions about default rates in a crisis but to predict the effect of subsidies on default rates in a more "normal" market. So by ending the observation period in December 2005, I partly undo the impact of the crisis. Using this method, predicted default rates in 2008 are 1 percentage point below actual defaults.

The data presents some unique challenges. The first is the large number of missing observations in some critical variables, which creates sample-selection issues. Missing values in borrowers' debt-to-income ratios, credit histories, and completeness of loan documentation are of primary concern because of the obvious relationship between these variables and the loan's survival probability. I deal with this problem by including an inverse Mill's ratio for each of the three variables as a covariate. Each inverse Mill's ratio, $\hat{\lambda}_Y$, is estimated from the following probit model, where Y is an indicator dummy for a missing debt-to-income ratio, a missing credit history, or missing information on loan documentation.

$$\Phi^{-1}\left(\Pr(Y)\right) = \mathbf{X}\boldsymbol{\beta}_{\mathbf{Y}} + \varepsilon_Y \tag{2}$$

For the sake of brevity, I do not present these results, but I calculate the inverse Mill's ratio as

$$\hat{\lambda}_Y = \phi(\mathbf{X}\hat{\boldsymbol{\beta}}_{\mathbf{Y}}) \Big/ \left(1 - \Phi(\mathbf{X}\hat{\boldsymbol{\beta}}_{\mathbf{Y}})\right) \tag{3}$$

Proper identification requires finding instruments correlated with the missing observations but uncorrelated with the error term in the hazard model. Unfortunately, all variables in the LPS Applied Analytics dataset are chosen to capture factors that are relevant for the hazard rates. Consequently, I have to rely on functional form for identification.

A univariate analysis of the data reveals that, on average, observations with a missing debt-to-income ratio have smaller loan sizes, are less likely to have prepayment penalties or negative amortization, and are more likely to have a balloon payment than observations with valid data. Those with incomplete documentation have higher loan-to-value ratios and loan amounts but a lower likelihood of having a prepayment penalty, balloon payment, or negative amortization. Those with missing FICO scores are smaller in size and shorter in maturity. They are less likely to have a prepayment penalty or negative amortization but more likely to have a balloon payment. It is likely that these missing values are caused by a particular servicer's not reporting these variables; unfortunately, servicer identity is not available in the LPS Applied Analytics dataset. $\mathbf{X_Y}$ includes the variables stated above for each Y.

A second data challenge is the need to create a mortgage-rate history for every loan. The amount of the interest-rate subsidy in each month depends on the outstanding loan amount, which, in turn, depends on the history of mortgage rates. In the actual data, the rate history ends when the loan is prepaid or defaults. However, in the simulations, a subsidized loan is likely to survive beyond its actual survival time. This does not pose any problem for fixed-rate mortgages, but the series must be recreated for adjustable-rate mortgages using the base rate (such as COFI, COSI, prime rate, T-bill rate, LIBOR, etc.) and the mark-up, both provided in the LPS data. Observations with missing base-rate type are deleted. If the markup is missing, the observation is deleted unless the loan went through at least one rate reset and the markup can be deduced from the latest rate and the base rate. Forward-looking base rates are assumed to remain constant at their last actual rate. In other words, all mortgage rates are treated as fixed going forward.

After accounting for all the missing data, there are 258,656 observations in the estimation sample and 517,311 observations in the prediction sample.

Determining the default and prepayment paths of the loans in the prediction sample is the first stage of the analysis. The second stage is estimating the costs associated with the subsidies. The direct costs of interest subsidies and down-payment assistance are straightforward to calculate, given that the loan characteristics and the number of borrowers are known. The challenge is the estimation of the subsidies' effect on loss in case of default. For that purpose, home values at default could be calculated using the appraisal value at origination, modified by the appreciation/depreciation rate of the Case-Shiller Home Price Index during the life of the loan in the state where the property is located. Moreover, the price received by the lender when the property is sold may be discounted by an additional 25 percent because the property is real-estate-owned, and it takes a long time to sell a property in a down market (Pennington-Cross, 2006, Campbell et al., 2010). The difference between the discounted price and the outstanding loan amount is the gain/loss to the lender. Unfortunately, this strategy confirms that the housing bubble masked potential losses from default, as one might expect. For example, there would have been no losses to lenders from mortgages defaulting in 2006, in the sense that home values were greater than the amount owed in almost all defaulting loans. To undo the effect of the housing bubble, I take the average state-level monthly appreciation rate in the 1980–2001 period and assume that this rate remains constant over time.

There are also many effects of the crisis that I cannot disentangle from the mortgage performance. For example, interest rates declined to historically low levels following the severe recession, and adjustable-rate-mortgage borrowers benefited from the lower rates. What the rates would have been in the absence of the crisis is not an issue I deal with in this paper.

As a final note, recall that the simulations are based on 517,311 loans totaling $54 billion. This is a miniscule number relative to the overall size of the market. The total size of the market (as reported by LPS Applied Analytics), including all loans with missing information, is $290.5 billion. Furthermore, the LPS data captures only about one-third of the actual loans originated. For example, it reports $114 billion in purchase loans originated in the second quarter of 2003 (including loans of all sizes in the entire country). In comparison, the Mortgage Bankers Association reports $344 billion in purchase originations in that same quarter. To capture the total market size, I assume that the loans missing from the sample are similar to those in the sample. Then, I augment my cost and loss calculations for each loan with a multiplier that reflects the true size of the origination market in the month of the loan's origination relative to the size of loan originations in my sample in that month. With this technique, I estimate that there would have been 11 million participants in the assistance programs in the 2002-2004 period, with $1.1 trillion in total lending. As mentioned earlier, the participation numbers are likely to be lower if the programs can be tailored more narrowly to the low-moderate income group than my sample allows.

Details about the multiplier are in Appendix A. All costs reported in the next section are the augmented numbers. The dollar amounts are in *constant dollars,* assuming a 2 percent inflation rate.

III. Results

Table 3 shows the coefficient estimates for the default and prepayment models, where the sign of the coefficient indicates the impact on survival probability. The coefficients of the default model have the expected sign. Higher interest rates, higher loan amounts (keeping appraisal value constant), lower FICO scores, adjustable interest rates, interest-only loans, lack of full documentation, and lower appraisal values are associated with lower survival rates. Similarly, prepayments are more likely if interest rates are high or variable, FICO scores are low, loan amount and debt-to-income ratios are high, and the loan is fully documented. Negative amortization loans, interest-only loans, and loans with prepayment penalties are less likely to prepay.

Because the ultimate motive of supplemental down payments and interest subsidies is assumed to be the creation of sustainable homeownership, cost comparisons should be made after insuring that the outcomes are equivalent in terms of sustainability. In other words, long-term default outcomes must be the same. By equating the predicted December 2017 default rates in the interest- and down-payment-assisted pools, I find that a 1 basis point interest-rate subsidy is equivalent to a $32 supplement to down payments. Figure 1 shows the cumulative default pattern of the subsidized loans for different types and at different levels of the subsidy. The 180-month cumulative default rate is 11.5 percent in the unsubsidized pool, 11.3, 11.1, 10.9, and 10.7

percent in the $800, $1,600, $2,400, and $3,200 supplemental down payment pools, respectively. The change in default rate from an additional $3,200 down payment represents 83,374 households exiting the default state by becoming successful or prepaying. The next step is to calculate how much it costs to reduce defaults through interest rate or down payment assistance.

The supplemental down payment required is the number of originations times the necessary amount per borrower. The cost of the interest-rate subsidy depends on how long the subsidized loans survive before being prepaid or going into default.[5] Therefore, it is determined by the prepayment and default paths generated by the simulations (figures 1 and 2). Figure 3 shows how the cost of each program varies at four different levels of assistance. Their ratio indicates that the cost of the interest-rate subsidy relative to the down payment assistance increases at higher levels of subsidy. To see why, one needs to recall the relative advantages of each type of subsidy. As we have discussed, the advantage of down payment assistance is that defaults are more sensitive to down payments than to interest rates. The advantage of the interest rate subsidy is that it is a contingent subsidy. However, as we increase the level of the interest rate subsidy, not only the cost per individual goes up but fewer of them default as well; in other words more people receive a larger subsidy. Therefore, the cost grows more rapidly.

The two types of subsidy also differ in the loss suffered in the event of default. Because the loan amounts are smaller, down-payment-assisted loans will suffer smaller losses at the time of default. The loan amounts at default come from the simulations. Figure 4 shows the loss profiles in two subsidized samples: 0.50 percent, 1 percent and their respective down payment programs. At 0.5 percent, the losses in the interest-subsidy sample reach $5 billion, whereas the losses in the down-payment-assisted sample add up to $4.6 billion. Both compare favorably to losses of $5.6 billion that would occur in the absence of any assistance. If the interest subsidy is set at 1 percent, the losses are $4.5 billion and $3.8 billion in the interest and down payment pools, respectively. One must subtract the savings coming from reduced losses from the gross cost of the assistance programs when calculating the net costs. For example, the $3,200 down payment assistance costs $35 billion and it saves $1.8 billion, or around 5 percent. The net cost is close to $33 billion. The cost of the $1,600 down payment program would be a net $16 billion rather than the gross of $17 billion.

[5] The interest subsidy ends if the borrower refinances. It is assumed not to transfer to the new loan.

At this point, down-payment assistance seems like the lower-cost program. However, in addition to reducing defaults, the subsidies also incentivize renters to buy their homes. Using the estimates of Linneman et al. (1997), a 1-percent interest-rate subsidy creates a 0.07-percent increase in the homeownership rate, which translates to 73,836 new homeowners. The $3,200 down-payment assistance reduces the average loan-to-value ratio by 3.1 percent and creates a 0.51-percent increase in homeownership rate or 541,627 new buyers. Assuming that the default and prepayment profiles, as well as the loss rates, for these new buyers will be identical to those for existing borrowers, the new buyers use up $297 million in interest subsidies or $1.6 billion in down-payment assistance. However, despite the large addition of new buyers, the down-payment program still needs 34 percent less resources.

III.b. Robustness Check

As mentioned earlier, Demyanyk and Van Hemert (2009) have documented that mortgage underwriting standards declined steadily over many years before the beginning of the crisis. While I tried to eliminate most poorly underwritten loans by excluding originations after 2004, there may still be some loans, which may be deemed too risky to originate in the future. I define these loans as loans with LTV and debt-to-income (DTI) ratios in the 99th percentile of the sample; i.e., greater than 102 percent LTV and 67 percent DTI. To examine what the interest rate – down payment trade-off would look like in the absence of such extreme loans, I repeat the analysis after deleting those observations.

I find that the down payment assistance looks more attractive when the extreme observations are eliminated. The trade-off improves from $32 to $30 for each basis point mortgage rate decline. The improvement is mostly due to the declining sensitivity of defaults to interest rates in the absence of potentially poorly underwritten loans. The regression results and the cost analysis are omitted from the paper for the sake of brevity but are available up on request.

Another factor that may have a significant impact on the results is the potential for nonlinear relationships in the data. For example, the effects from downpayments might be close to linear because monthly payment is proportional to loan size, while effects coming from interest rates might be nonlinear because monthly payment is not proportional to interest rates. A one percent decline in interest rates would have a much less significant effect on monthly payments at higher interest rates. To capture this nonlinearity, I repeat the analysis by replacing *Int.Rate* with log(1+*Int.Rate*). The regression results and the cost analysis are omitted from the paper but two findings are worth mentioning. First, the logged interest rate model provides a significantly poorer fit to the data based on a comparison of log-likelihoods. Second, the mortgage rate – downpayment trade-off deteriorates to $47.50 per basis point. Despite this deterioration, the downpayment program is still five percent cheaper than the mortgage subsidy program. However, the second finding is suspect given the first finding. An alternative specification that uses *Int.Rate* and its square also provides a poorer fit.

IV. Policy Implications

Two policy issues arise from this analysis. The first is whether or not we want to spend tens of billions of dollars to increase sustainability (or reduce defaults) by a fraction of a percentage point (the largest subsidy we considered, 1% - $3,200, reduces defaults by 0.75 percent). Assuming that this question is answered in the affirmative, the second issue is the funding options for the subsidies. As mentioned earlier, interest subsidies are currently funded through tax expenditures, but programs for down-payment assistance are funded through a mixture of public and private resources. I will assume that this structure will continue. In other words, interest-rate subsidies will continue to be paid entirely with tax money, while down-payment subsidies can be enhanced through private contributions. This is a sensible assumption, given the voluntary nature of private contributions. Interest-rate subsidies are disbursed over the life of the mortgage (although few mortgages are still alive after 15 years). Any private source would have trouble committing itself for such an extended period.

One complication of down-payment assistance is that it adds to the homebuyer's equity, so it could potentially be borrowed against by the homebuyer and spent on consumption instead of being a source of stability. There are ways to get around this problem—for example, by granting the assistance program a silent second lien on the property that is "talkative" enough to warn off home-equity-line-of-credit lenders but expires automatically if the homeowner stays in the house for a previously specified period.

It is also worth noting that the down-payment supplement does not have to be entirely in "assistance" form. There are promising savings programs targeting LMI households such as individual development accounts (IDAs). These are savings accounts established with local financial institutions and managed by community organizations in the name of an LMI individual in order to encourage saving toward starting a business, paying for education or job training, or buying a home. IDA programs typically provide $1 to $3 in matching funds for every dollar saved by an individual participant. The matching funds come from public and private sources; the federal Assets for Independence program requires IDA sponsors to raise private funds to match the federal money. The match comes with some strings attached. For example, participants must save for a minimum length of time before they can withdraw their savings without losing the matching funds. They must also get training in financial literacy before they can use the money. More information about account features, participant characteristics, and findings from pilot programs can be found in Schreiner and Sherraden (2007).

There is some evidence that IDAs encourage new savings, but the existing experimental designs are too weak to prove that the saving rate does indeed increase. Schreiner and Sherraden report that IDA participants in the American Dream Demonstration pilot program saved *on average* $558 over the life of the program (varied regionally, with a maximum of 4.5 years); this comes to a little more than $1,000 if matching *private* funds are included. But the authors also recognize that it is not clear how much of those savings came from the cannibalization of other savings accounts, such as retirement accounts.

Still, if the numbers are reliable in terms of the actual additional savings they can create, such a savings program could potentially shave $11 billion (11 million borrowers at $1,000 each) from the cost of the down-payment program.

V. Caveats

This paper's findings come with many warnings attached. First, as mentioned earlier, the housing boom and bust most likely reduced the occurrence of defaults—as well as the severity of losses in default—and increased the occurrence of prepayments. Even though my analysis left out most of the home price boom and bust, their impact will still be felt indirectly through the path followed by mortgage rates, for example. Therefore, the loss estimates should be interpreted with caution.

Second, program costs can be significantly reduced by limiting the subsidies to first-time homebuyers. People who managed to buy their first home can most likely buy their next without assistance. However, first-time-buyer information is not available in the dataset, so alternative cost analysis is not available.

Third, forecasting the default and prepayment paths of mortgages 15 years into the future, using three years' worth of observed data, can be a stretch. Yet the choice is unavoidable, given the data problems described earlier.

Finally, unlike down-payment assistance, which is disbursed at the time of purchase, the interest-rate subsidy is disbursed over the life of the loan; i.e., it has higher duration. Consequently, its present value is very sensitive to the choice of discount rate. Recall that the calculations so far assumed a discount rate of 2 percent. At 4 percent discount rate, the net cost of the subsidy programs drops by about 4.4 percent. Still, the decline is not sufficient to close the gap between the two programs.

VI. Conclusion

There is clear evidence that many low-to-moderate-income homebuyers are wealth-constrained; therefore, a dollar spent in down-payment subsidies is more successful at creating new homebuyers than a dollar spent in interest-rate subsidies. However, the recent crisis raised the important questions of whether these new homebuyers can actually remain homeowners in the long run and how much it costs to create successful new homeowners. This paper is an attempt at answering those questions.

I find that a dollar spent on interest-rate subsidies is not only less effective at encouraging homeownership than down-payment subsidies, but also less effective at reducing defaults. While the cost estimates of this paper can be improved upon with better data over time, the findings still suggest that down-payment programs have a pronounced edge over policies that target interest costs.

References

Campbell, J.Y., S. Giglio, and P. Pathak, 2010, "Forced sales and House prices," *American Economic Review* (forthcoming).

Demyanyk, Y., and O. Van Hemert, 2009, "Understanding the subprime mortgage crisis," *Review of Financial Studies* (forthcoming).

Feldman, R.J., 2002, "Mortgage rates, homeownership rates, and government-sponsored enterprises," *The Region: 2001 Annual Report Essay*, Federal Reserve Bank of Minneapolis.

Glaeser, E.L., and J.M. Shapiro, 2003, "The Benefits of the Home Mortgage Interest Deduction," *Tax Policy and the Economy* 17, pp. 37-82.

Genesove, D. and C.J. Mayer, 1997, Equity and time to sale in the real estate market, *American Economic Review* 87, pp. 255-269

Gobillon, L., and D. le Blanc, 2008, "Economic effects of upfront subsidies to ownership: The case of the Prêt à Taux Zéro in France," *Journal of Housing Economics* 17, pp. 1–33.

Hegedüs, J., N. Rogozhina, E. Somogyi, R. Struyk, and A. Tumanov, 2004, "Potential effects of subsidy programmes on housing affordability: The cases of Budapest and Moscow," *European Journal of Housing Policy* 4, pp. 151–184.

Linneman, P., I.F. Megbolugbe, S.M. Wachter, and M. Cho, 1997, "Do borrowing constraints change U.S. homeownership rates?" *Journal of Housing Economics* 6, pp. 318–33.

Pennington-Cross, A.N., 2006, "The value of foreclosed property," *Journal of Real Estate Research* 28, pp. 193–214.

Quercia, R.G., G.W. McCarthy, and S.M. Wachter, 2003, "The impacts of affordable lending efforts on homeownership rates," *Journal of Housing Economics* 12, pp. 29−59.

Schreiner, M. and M. Sherraden, 2007, *Can the poor save? Saving and asset building in individual development accounts*. Transaction Publishers, Piscataway, NJ.

Ventry Jr., D.J., 2009,"The accidental deduction: A history and critique of the tax subsidy for mortgage interest," *UC Davis Legal Studies Research Paper Series #196*, (November)

Table 1 – List of Covariates

Variable	Definition
Int.Rate	The interest rate on the loan at origination
FICO	Borrower's FICO score at origination
IO	Interest-only loan indicator
Fixed	Fixed-rate loan indicator
Prepay	Prepayment penalty indicator
Negam	Negative amortization indicator
Full.Doc	Fully documented loan indicator
LogAppraisal	Natural log of the appraisal value
DTI.Ratio	Borrower's debt-to-income ratio at origination
Term	The term of the loan
Single.Fam	Single family home indicator
LogOrig	Natural log of the loan amount at origination
Convent	Conventional loan indicator
Appreciate	Home price appreciation in the state in 1980–2000
LogIncome	Median income of the zip code in 2000
35 MONTH DUMMIES	A dummy that equals one in the month the loan was originated
51 STATE DUMMIES	A dummy for each state where loans were originated

Table 2 – Summary Statistics (Selected Variables) (775,968 observations)

Variable	Mean	Std Dev	Median	Minimum	Maximum
Int.Rate	6.09	0.94	6	1	16.13
FICO	689	69	691	300	966
Appreciate	1.48	0.54	1.36	0.57	3.93
IO	0.02	0.15	0	0	1
Fixed	0.81	0.39	1	0	1
Prepay	0.13	0.33	0	0	1
Negam	0.04	0.20	0	0	1
LTV	86.24	13.35	89.89	0.01	192.28
Full.Doc	0.72	0.45	1	0	1
Appraisal	122,775	40,789	123,000	3,000	211,700
LogAppraisal	11.65	0.38	11.72	8.01	12.26
DTI.Ratio	33.07	13.10	33	1	99
Term	29.02	3.70	30	0.5	80
Single.Fam	0.77	0.42	1	0	1
Orig	104,385	34,549	104,500	3000	172,632
LogOrig	11.49	0.39	11.56	8.01	12.06
Convent	0.67	0.47	1	0	1
Income	40,124	8,301	40,000	3,750	55,821
LogIncome	10.58	0.22	10.60	8.23	10.93

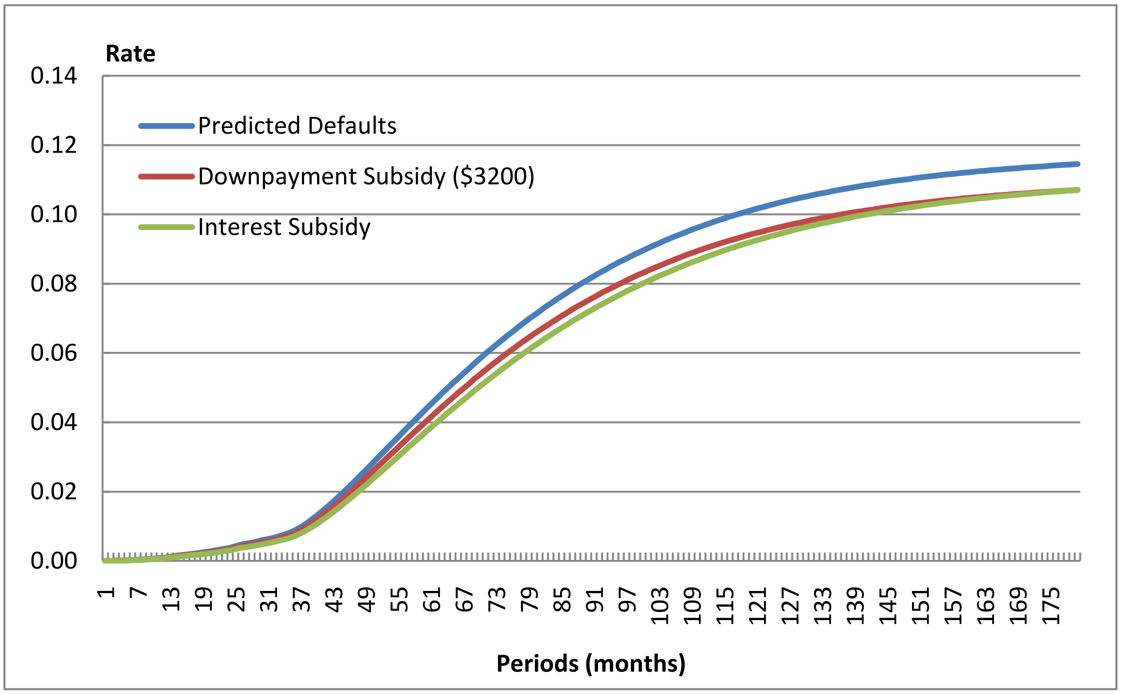
Table 3 – Hazard Regressions

	Default Model		Prepayment Model	
	Estimate	Chi-Sqr	Estimate	Chi-Sqr
Int.Rate	-0.112	278.3*	-0.068	1094.3*
FICO	0.006	2114.7*	0.001	392.7*
Appreciate	-0.223	1.1	2.519	2163.4*
IO	0.071	1.2	-0.072	45.8*
Fixed	0.185	78.5*	0.229	2072.9*
Prepay	0.057	2.2	-0.012	1.1
Negam	-0.752	217.7*	-0.057	18.9*
Full.Doc	-0.095	37.8*	0.079	467.1*
LogAppraisal	1.559	454.9*	-0.023	4.4
DTI.Ratio	-0.003	34.7*	-0.002	168.4*
Term	-0.006	3.6	-0.001	4.1
Single.Fam	-0.045	6.4	0.010	6.5
LogOrig	-1.492	411.9*	-0.120	119.4*
Convent	0.006	0.1	-0.040	87.4*
LogIncome	0.234	54.2*	-0.042	26.5*
State and origination month dummies	Included		Included	
Mill's Ratio	Included		Included	
σ	0.93		0.61	
δ	0.40		0.14	

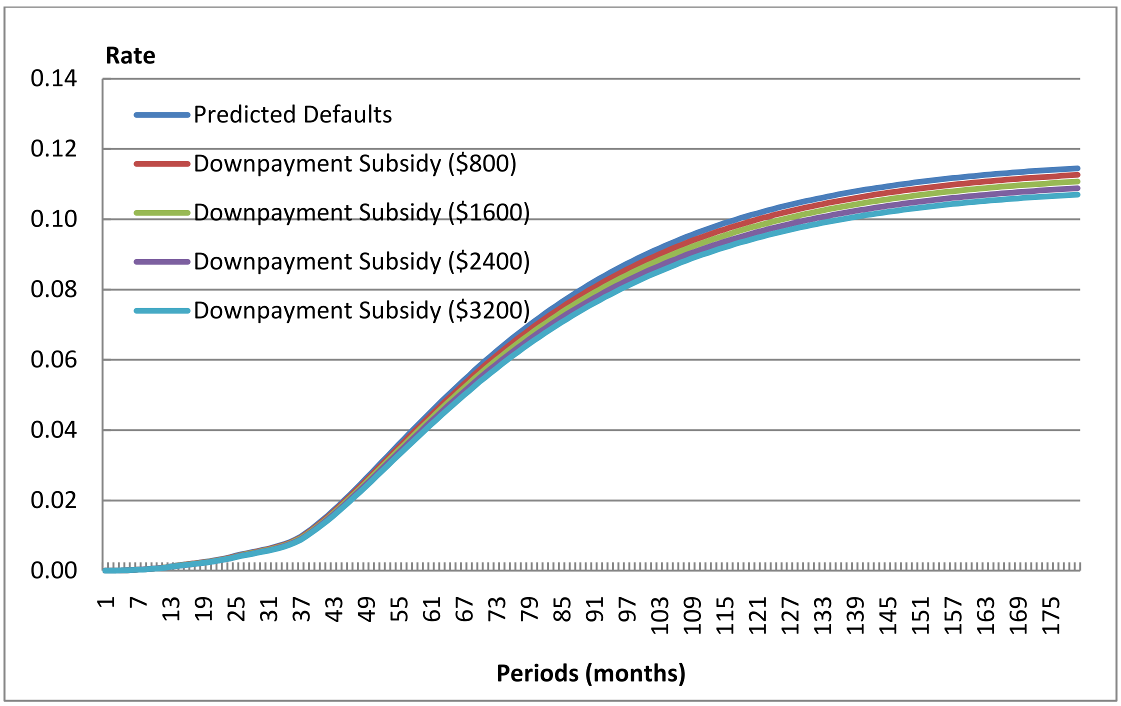
No intercept.

* Significant at 1 percent.

Figure 1 – Estimated cumulative default rates of original and subsidized loans

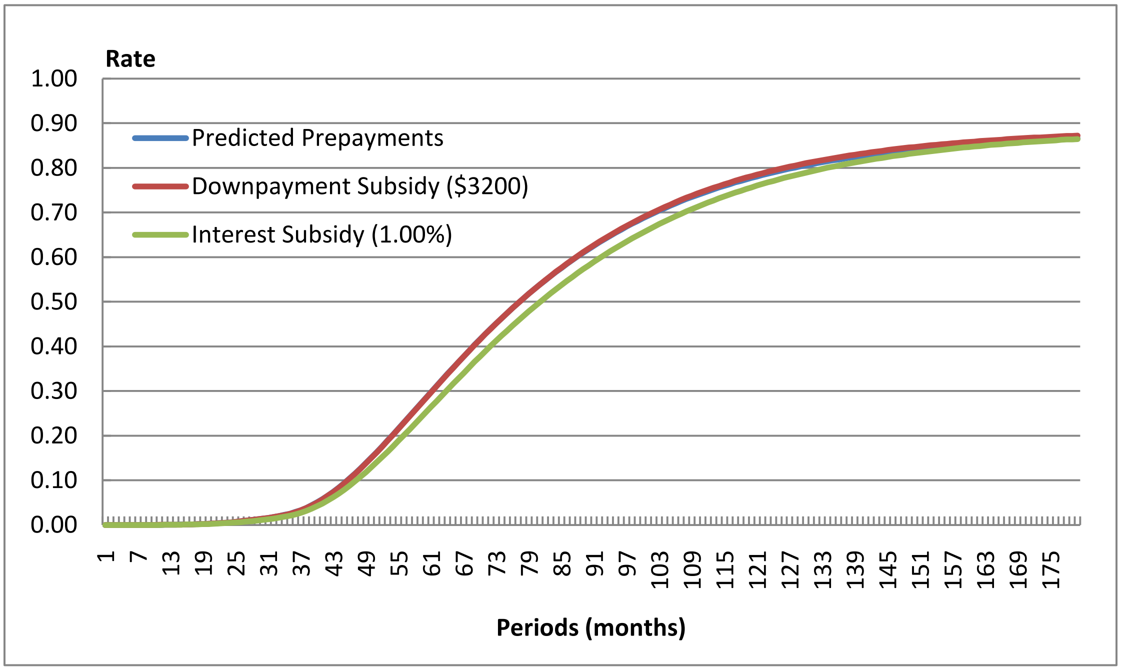


a. 1 percent interest vs. $3,200 down payment subsidy

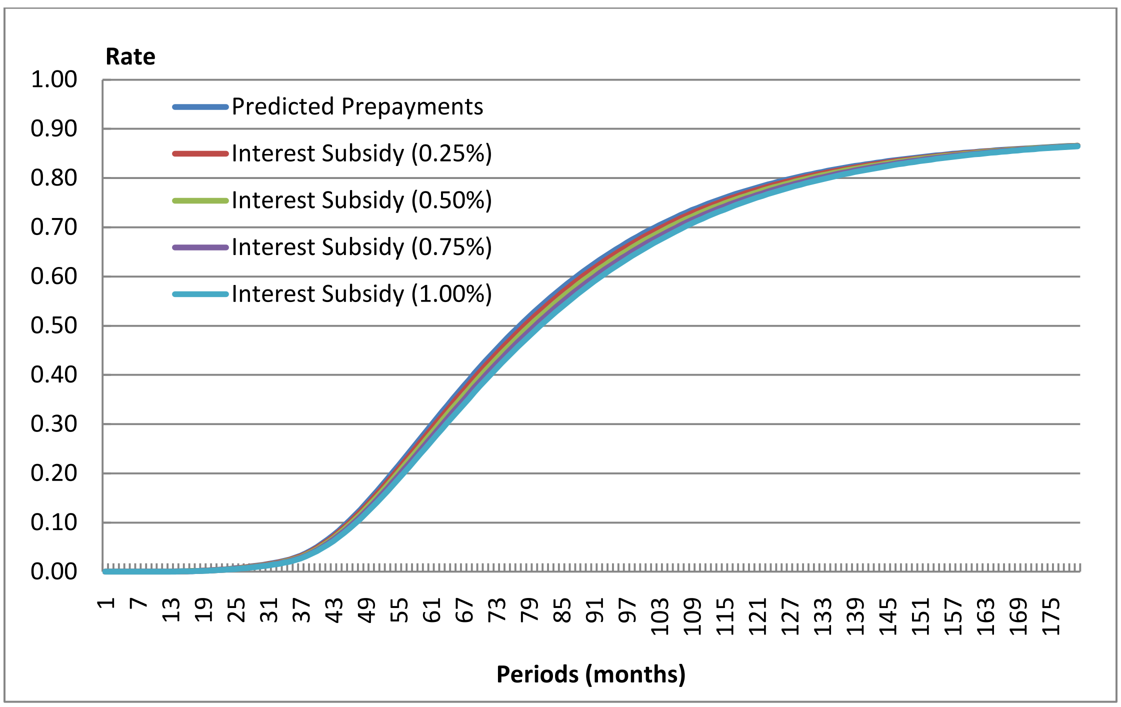


b. The sensitivity to down payment subsidies

Figure 2 – Estimated cumulative prepayment rates of original and subsidized loans



a. 1 percent interest vs. $3,200 down payment assistance



b. The sensitivity to down payment subsidies

Figure 3 – Cost of the Assistance Programs

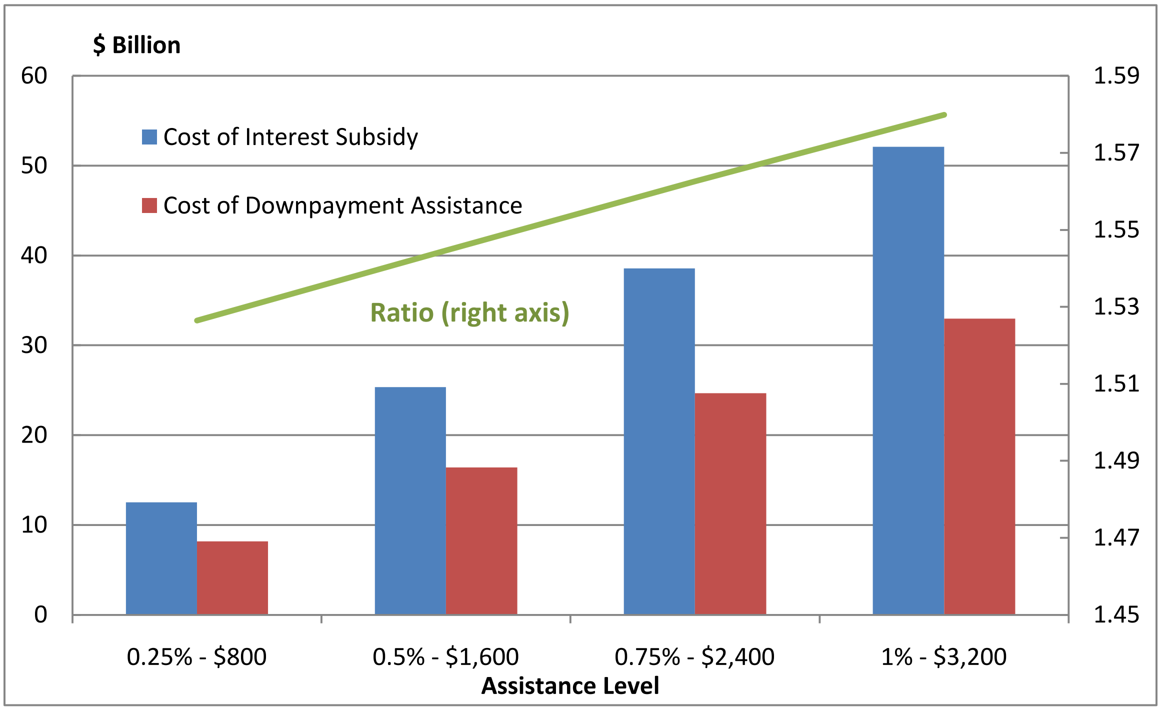
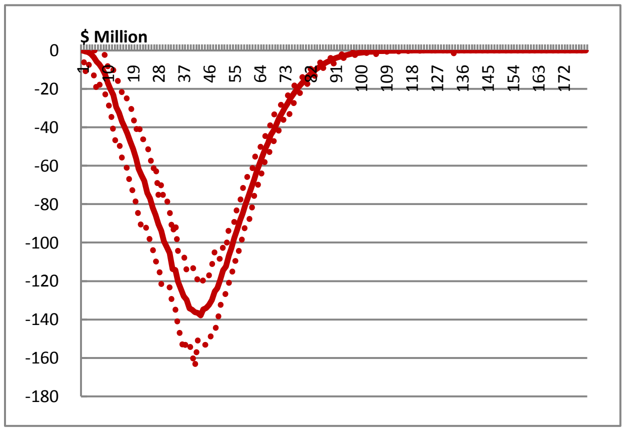
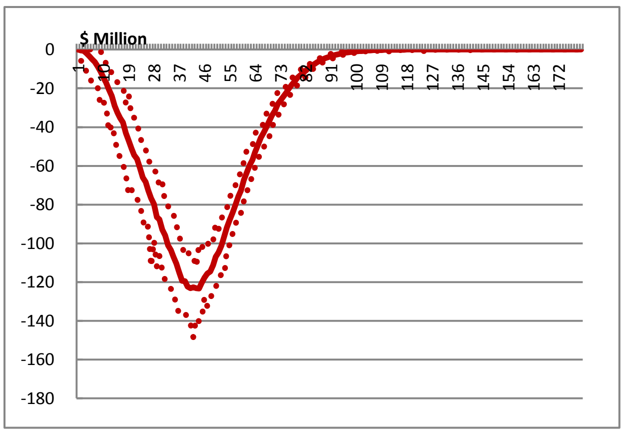
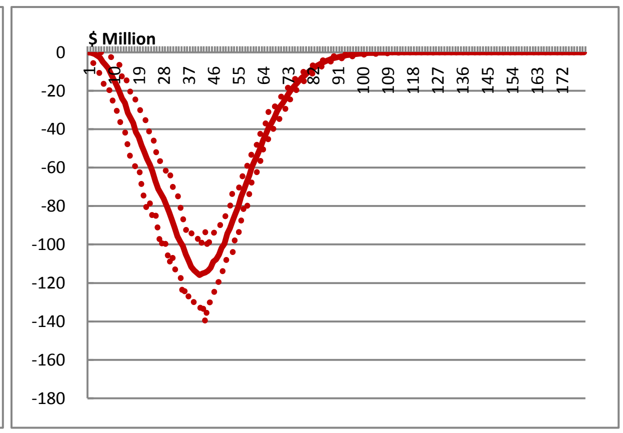


Figure 4 – Expected lender losses in foreclosure (present value)



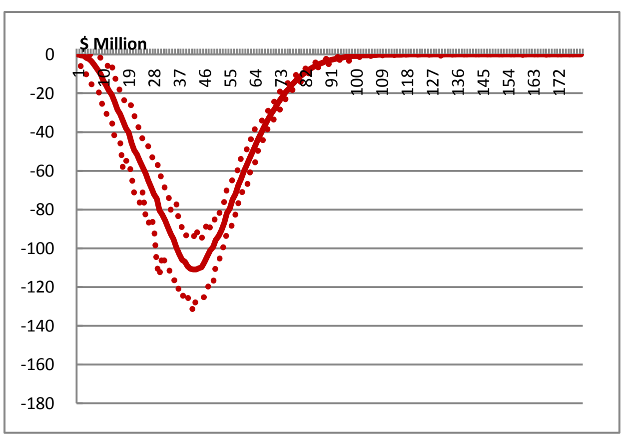
a. No Subsidy

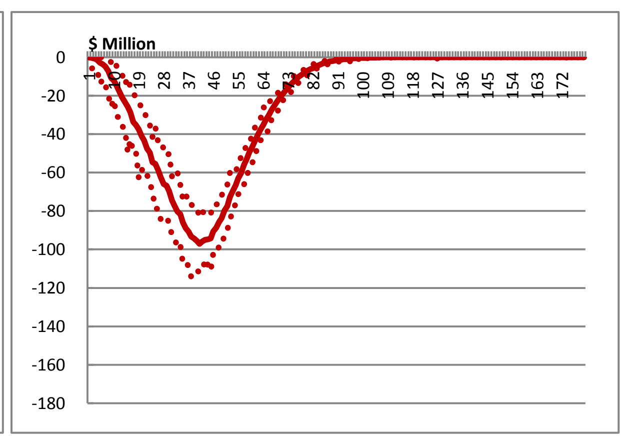




b. 0.5 Percent Interest-rate Subsidy

c. $1,600 Down Payment Assistance





The dashed lines indicate the minimum and maximum losses in each period.

d. 1 Percent Interest-rate Subsidy

e. $3,200 Down Payment Assistance

Appendix A – Market Multipliers

The calculations for the monthly multipliers are shown in Table A.1. For example, according to Mortgage Bankers Association (MBA), there were $217 Billion in purchase-mortgage originations in the first quarter of 2002 (column **(5)**). In the same period, LPS reports $18 Billion in purchase loans **(4)**. MBA does not report monthly origination numbers. However, assuming that monthly originations in MBA are proportional to those in LPS **(3)**, one can estimate the monthly originations in MBA **(6)**.

The next step is to calculate the amount of loans to low-moderate income (LMI) households that will be subject to the new subsidy proposal. Recall that these are loans in zip codes with median family incomes below the national median ($55,832), loan amounts below the FHA limit for low-price markets in 2005 ($172,632), and home values below the median home value in 2005 ($211,700). LPS reports $2 Billion worth of such loans originated in January 2002, $3 Billion in February, etc. **(7)**. The low-moderate income originations in January are 50 percent of the total originations in LPS in that month **(8)**; February LMI originations are 49 percent of the total originations. If the same ratios apply to MBA, then one would expect $28 Billion in total LMI originations in January and $35 Billion in February **(9)**.

Because I lose a large number of observations to missing data, the sample I use to estimate the cost of each type of subsidy and the mortgage losses in each pool is also very small. Out of the $2 Billion in LMI originations in LPS in January, my sample contains only $0.168 Billion worth of loans **(10)**. Similarly, the February sample contains $0.369 Billion. Therefore, I estimate that the actual market is 169.48 times the size of my sample in January and 94.87 times in February, etc. **(11)**. The cost and loss estimate for each loan is augmented by the multiplier of its origination month to estimate the full cost of the subsidies.

Table A.1. – Monthly Multipliers – All columns except (1), (2), (8), and (11) are in $Billions.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Year	**Month**	**LPS Originations**	**LPS Quarterly Total**	**MBA Originations**	**MBA Expanded**	**LPS LMI Originations**	**LPS LMI / LPS Total**	**MBA LMI Estimate**	**LPS LMI Used in Analysis**	**Multiplier**
2002	1	5			57	2	0.50	28	0.168	169.48
	2	6			71	3	0.49	35	0.369	94.87
	3	7	18	217	89	4	0.48	43	0.471	90.79
	4	7			85	3	0.47	40	0.491	80.90
	5	9			107	4	0.46	50	0.605	82.26
	6	10	27	315	123	5	0.44	54	0.696	77.15
	7	13			85	5	0.42	36	0.847	42.29
	8	16			108	7	0.40	43	0.994	43.22
	9	17	46	302	110	7	0.39	43	0.977	44.30
	10	21			90	8	0.37	34	1.141	29.60
	11	19			84	7	0.36	31	1.095	27.89
	12	21	61	263	89	7	0.35	31	1.158	26.68
2003	1	15			55	5	0.34	19	0.491	37.70
	2	20			74	7	0.34	25	1.046	23.82
	3	28	63	230	102	9	0.31	32	1.237	25.77
	4	32			97	10	0.31	30	1.512	19.77
	5	37			113	11	0.30	34	1.728	19.48
	6	44	114	344	135	12	0.27	36	1.891	19.18
	7	45			144	12	0.27	39	1.901	20.31
	8	42			135	12	0.28	37	1.887	19.67
	9	33	120	384	106	10	0.30	32	1.802	17.51
	10	33			114	10	0.30	34	1.582	21.51
	11	28			97	8	0.29	28	1.683	16.45
	12	32	93	322	111	8	0.26	29	1.839	15.82

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Year	**Month**	**LPS Originations**	**LPS Quarterly Total**	**MBA Originations**	**MBA Expanded**	**LPS LMI Originations**	**LPS LMI / LPS Total**	**MBA LMI Estimate**	**LPS LMI Used in Analysis**	**Multiplier**
2004	1	18			51	5	0.26	13	0.842	15.97
	2	29			82	8	0.26	21	1.574	13.53
	3	42	89	251	118	10	0.24	28	2.174	13.02
	4	46			119	11	0.23	28	2.231	12.42
	5	47			121	11	0.23	28	2.379	11.69
	6	54	147	379	138	12	0.22	31	2.561	12.03
	7	50			125	11	0.23	28	2.884	9.87
	8	50			125	11	0.22	28	2.554	10.83
	9	45	144	362	112	10	0.22	24	2.324	10.51
	10	45			106	10	0.21	23	2.198	10.35
	11	43			102	9	0.21	21	2.104	10.06
	12	46	134	317	109	9	0.20	22	1.262	17.48