Thy Neighbor’s Mortgage: Does Living in a Subprime Neighborhood Impact Your Probability of Default?∗

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1 Introduction

During the current decade, the U.S. housing market experienced two interrelated events. First, the U.S. experienced a housing market bubble in the early 2000’s that started to decline in 2006 and burst in the latter half of 2007.\footnote{See for example, Glaeser, Gyourk and Saks (2005) and Leamer (2007) for discussions of house price bubbles.} Second, during this same period, the use of alternative (or hybrid) mortgage products escalated.\footnote{See for example, Mian and Sufi (2008) and Leamer (2007) for a discussion of the role of credit expansion and the mortgage default crisis.} These products were designed to help borrowers in markets experiencing significant price appreciation. However, they were often marketed to borrowers with relatively poor credit histories as well. As a result, these mortgages became known as subprime mortgages since they did not meet the underwriting criteria of the housing government sponsored enterprizes (GSEs).

Since these mortgages were designed to provide borrowers with payment affordability during a period of rapidly rising housing values, the most common subprime mortgages had adjustable rate features and many had provisions for negative amortization of principle thus providing borrowers with low initial payments. The general belief was that rapidly rising home values would allow borrowers to refinance prior to the impact of the negative amortization feature. Of course, many did not foresee the softening of the U.S. housing market eliminating the ability to refinance. Thus, the default rate on subprime mortgages has increased dramatically and current estimates indicate that rising subprime defaults may add over 500,000 homes to the housing supply.\footnote{See, Louis, B. “Rising Subprime Mortgage Defaults Add to Unsold Homes Inventory”, Bloomberg.com (http://www.bloomberg.com/apps/news?pid=20601087&refer=home&sid=aC9LdDcv4.Wc)}

One interesting feature of these alternative mortgage designs, particularly subprime mortgages, is that they tend to be clustered in metropolitan areas that experienced significant house price increases. For example, Maricopa County (Phoenix, Scottsdale, Mesa and surrounding communities) had one of the most explosive rates in housing prices during the 2004-2006 time period (see Figure 1) with the Case Shiller house price index growing from an index value of 100.00 for...
January 2000 to a peak of 227.42 in June 2006, indicating that house prices over
doubled in price. Hence, Maricopa County represents an excellent laboratory
for studying the relationship between house price growth and the mortgage
products used to finance home purchases.

To demonstrate the extent of subprime concentration, Figures 2 and 3 show
the total mortgage origination activity and subprime origination activity for
the Phoenix metropolitan area by zip code between 2000 and 2007. The fig-
ures clearly indicate a spatial pattern of mortgage activity. However, to gain a
better perspective on subprime clustering, Figure 4 shows the concentration of
subprime mortgages by zip code. Not surprisingly, the highest concentration of
subprime activity (as a percent of all loan originations) occurs in the urban inner
city as opposed to the urban-rural periphery. In fact, between 2004 and 2006,
the areas with the highest volume of subprime loan origination were in new-
build locations (Southeast, West and North) but as a percentage of all loans,
the lower-income neighborhoods of Phoenix (downtown, older homes along the
interstates going West and North from the downtown) had the highest concen-
tration of subprime activity. Interestingly, interest-only (IO) ARMs are located
in the highest price areas of Maricopa County (Scottsdale, Paradise Valley and
Ahwatukee), but far less than in the high subprime concentration zip codes.

If subprime lending is correlated with poor underwriting standards, then the
clustering of subprime mortgages may cause a spillover effect in terms of default.
A number of studies have documented that the most common outcome of default
(foreclosure) is a negative spillover onto the value of surrounding properties and
for direct cost estimates of foreclosures on cities and neighborhoods, Immergluck and Smith
(2006) and Lin, Rosenblatt, and Yao (2008) for evidence of the effect on property prices.}
For example, Lin, Rosenblatt, and Yao (2008) document that
a foreclosure depresses property prices in the surrounding neighborhood by up
to 8.7 percent.

But do the spillover effects from subprime defaults imply that subprime
borrowers in neighborhoods (or zipcodes) that are clustered together have a
higher probability of default? That is, once we control for loan characteristics,
house price changes and alternative loan products, do subprime borrowers in neighborhoods with higher concentrations of subprime borrowers have a greater likelihood of default? That is the question that we wish to explore in this paper.

Our paper is organized as follows. Section 2 develops a theoretical setup to demonstrate the default cascade resulting from subprime origination in a neighborhood. Section 3 describes the empirical method and section 4 discusses the data. Section 5 describes the results of our empirical analysis and section 6 concludes.

2 Theoretical Setup

The theoretical setup for a default cascade is straightforward. First, we assume that homeowners follow the wealth maximizing decisions underlying modern mortgage option pricing models. That is, we assume that borrowers only default when the value of the underlying property is less than the present value of the mortgage debt. Second, we assume that homeowners observe noisy private signals about the value of their property. The noisy signal comes in two forms: high ($H$) or low ($L$). A high signal implies that the property market may be appreciating and the homeowner updates her property valuation accordingly. Examples of high signals include frequent sales in the neighborhood, short sale times on the market, favorable news reports about the neighborhood, etc. Conversely, a low signal implies that the property market may be depreciating. Examples of low signals include longer observed time on the market, more property for sale with fewer actual sales, foreclosure sales, evidence that houses are being abandoned, news reports about crime in the neighborhood, etc. As noisy low signals are observed, the homeowner updates her property valuation estimate downward. As the frequency of noisy low signals increase, the lower the homeowner’s estimate of property value becomes. Assuming the homeowner rationally applies the default boundary condition prior to each mortgage payment due date, the perceived decline in property value may result in an optimal default situation.
The problem is that the individual homeowner’s default decision depends upon her individual loan-to-value ratio, which is private information. However, if she defaults and the lender sells the property at foreclosure, the foreclosure sale becomes a public signal of a declining property market. That is, the remaining homeowners must assume that property values have declined from the time that the homeowner originated her mortgage, otherwise she would not have defaulted.

Since mortgage default decisions convey signals to neighboring homeowners about the direction of changes in property values, one homeowner’s decision to default may start a default cascade by causing the remaining homeowners to reevaluate their property values downward, perhaps to a level triggering an optimal default decision on their part. However, an initial default does not imply that a default cascade will occur. Recall that each homeowner evaluates the property value signal in light of the present value of their mortgage debt. Thus, a default cascade will most likely occur in neighborhoods where the majority of the homeowners have high loan-to-value ratios.

To illustrate, consider a neighborhood with 4 houses. At $t = 0$ each household observes a noisy private signal regarding the value of their house (assume that the probability of a high or low signal is 0.5). Further, assume that household $a$ has a high LTV ratio and all the other homeowners have low LTV ratios. If homeowner $a$ receives a low signal, she evaluates her default option value and decides to default at $t = 1$. At $t = 1$ the remaining households receive a private signal and observe $a$’s default. Although the remaining households observe the strong low signal resulting from $a$’s default, none of the remaining homeowners default at $t = 2$ since they have low LTV ratios and the payoff from defaulting is negative (even if their signals were $L, L$). Thus, the default cascade never materializes.

Now, consider an identical neighborhood where all the homeowners have high (but not equal) LTV ratios. Again, we assume that at each period the homeowners receive a private noisy signal of the change in property value. At $t = 0$, one of the four households who received the low signal determines that
default is optimal. At $t = 1$ all households receive a new private signal plus they observe the default of household $a$. Thus, the remaining households now have three signals to consider: the initial signal from $t = 0$, the new signal, and the observed default. Consider household $b$ who received the following private signals: $H, H$. This household has two private signals indicating property values are appreciating and thus discounts the observed default signal. Thus, $b$ does not default at $t = 2$. Household $c$’s private signals were $H, L$. In this case, the two private signals should cancel out, however, the observed default causes $c$ to place greater weight on the second signal and thus believes that property values are falling. Thus, $c$ defaults at $t = 2$. Lastly, $d$’s private signals were $L, L$. Although the first $L$ signal was insufficient to cause a default at $t = 1$, the combination of $L, L$ plus the observed default reinforce the perception of falling property values and thus $d$ defaults. In this case, we observe a default cascade as the default at $t = 1$ reinforces the $L$ signals received by the remaining households at $t = 1$.

Based on this simplistic example, we address the following research questions: Do borrowers in neighborhoods with higher concentrations of subprime mortgages (as a percentage of total mortgage origination volume) experience larger than average default rates?

## 3 Empirical Method

To test the default cascade hypothesis, we focus on individual mortgages to explore the impact of the concentration of subprime mortgages in a neighborhood on the probability that a specific mortgage will default.

We collect individual loan performance data, zip-code level mortgage concentration measures, and zip-code level repeat sales index house price changes. Using this information, we then estimate a proportional hazard rate model for borrower default conditional on the borrower’s risk at origination (as measured by their FICO score) and loan-to-value ratio. We also include a variety of control variables that identify the type of loan originated (i.e. low documentation,
We also include a set of zip-code level concentration variables that capture the percentage of loans outstanding in the borrower’s zip code at the time of origination that reflect various high-risk characteristics (i.e., the percentage of loans that are low documentation, no documentation, adjustable-rate, hybrid, interest-only, etc.). Thus, by examining these concentration variables, we are able to identify the impact that higher concentrations of risky loans have on the odds of borrower default.

4 Data

4.1 Mortgage Data

Our data come from the ABS data series of the LoanPerformance Corporation (LPC), Incorporated. This data series contains a large set of loan-level information describing the characteristics of the subprime loans that have been securitized in the private label market. The LoanPerformance Corporation indicates that the data covers 61 percent of the outstanding subprime market. We focus on the 461,729 mortgages contained in the LPC database that were originated from January 2000 through December 2007 in Maricopa County, Arizona.

The LPC data contains complete information on mortgage types. For example, LPC classifies mortgages as Subprime, Alt-A, or Prime and identifies whether the loan was originated with full documentation (Full Doc), partial or low documentation (Low Doc), or no documentation (No Doc) of borrower income and assets. In addition, LPC identifies whether the mortgage was a fixed-rate (FRM) or adjustable-rate (ARM) product. Furthermore, for ARM mortgages, LPC notes whether the mortgage is a traditional ARM or a hybrid-ARM. In terms of borrower characteristics, the LPC data indicates whether the mortgage was originated as a refinance and whether the borrower also cashed out equity at refinancing (cashout refinance). We also make use of information concerning the presence of prepayment penalties on the mortgage and whether
the loan was originated for a condominium or to an investor.

Since the LPC data covers primarily non-prime mortgages, we merge the LPC data with the Home Mortgage Disclosure Act (HMDA) database to determine the overall volume of mortgage origination activity in Maricopa County. Thus, using HMDA to determine the number of mortgages originated in zip-code $i$ at month $t$, we calculate concentration measures of outstanding loans by product type for each zip-code and month. Furthermore, based on the loan-level payment performance behavior of these loans, we calculate average default rates for each of the 109 individual zip codes from January 2000 to December 2008. We define defaults as 90+ days past due, in foreclosure, real estate owned, or in bankruptcy and alive in the prior time period (current or 89 days or less delinquent).

4.2 House Price Data

The housing data consists of only single-family houses that sold in Maricopa County, Arizona between January 1989 and September 2007. The data was acquired from Ion Data. We use this data to create a repeat sales index by zip code. In order to be included in the repeat sales index, the following criteria had to be met: a) all sales must be between unrelated parties, b) it must not be the sale of a new house, c) the period between sales should be at least six months, d) the price of a house must be greater than $5,000 and e) appreciation or depreciation must be no more than up 80 percent or down 60 percent per year.

The repeat sales indices were created using a three-step process:

Step 1: Qualitative variables were formed based on the starting quarter/month and the ending quarter/month and frequency. The number of qualitative variables equals the number of observations in the index. For example, the monthly index starting January 2000 and ending April 2008 has 88 qualitative variables. Thus, if a house was sold in January of 2007, then the dummy variable for that month would be a 1, the previous sale month will get a value of -1, and the
others receive a value of 0 for that sale.

Step 2: After assigning the dummy variable, we estimate a pooled weighted OLS regression (of all the observations), weighted by the gap between the current sale and previous sale.

Step 3: The coefficients obtained from the regression are then based to 100 from the first period which gives the house price index (HPI).

Our repeat sales indices are constructed following Case and Shiller (1987) in order to correct for heteroskedasticity found in the original repeat sales indices. Within each quarter and for each zip code, we divide home sales into three groups: high, medium and low. We then select the average price within each bucket to represent higher, medium and lower price houses in that zip code. The purpose of this approach is to examine whether the defaults are a function of higher, medium, or lower price homes in each zip code.

4.3 Statistical Summary

Consistent with the exponential growth in the subprime market between 2000 and 2006, Figure 5 shows that the number of subprime originations in Phoenix climbed from 10,653 in 2000 to a peak in 2005 of 145,333 loans. After 2005, the loan origination activity fell dramatically and by 2008 no new subprime mortgages were originated in Phoenix. Over this same interval, the Phoenix housing market experienced a significant increase in house values. The Case Shiller Index for Phoenix rose from a 100.00 in January 2000 to a peak of 227.42 in June 2006 then declines (see Figure 1). In fact, the index growth for Phoenix was far faster than the rest of the country (as measured by the Case Shiller Composite Index of 20 cities during the 2004-2005 period. Consistent with the option pricing view that mortgage default results from declines in house values relative to mortgage value, Figure 5 also shows the dramatic increase in the annual default rate starting in 2005. The number of defaults in increased dramatically over the 2000-2007 period with 2,220 defaults in 2000 rising to 13,870 in 2006. The surge in defaults occurred in 2005 when the incidents rose
from 3,876 on 2004 to 11,443 in 2005.

Figure 6 shows the concentration of mortgage type originated in Phoenix between 2000 and 2007. As the subprime market grew over this period, the proportion of fixed rate mortgages declined from over 50 percent of origination volume in 2000 to 36 percent in 2004 (and continued to stay in the 30 percent to low 40 percent range.) While the market share of fixed-rate mortgages declined, the proportion of adjustable rate mortgages increased from 46 percent in 2000 to 66 percent in 2004. Traditional ARM market share declined from 46 percent in 2000 to 16 percent in 2007. Figure 6 also shows that the percentage of full documentation (Full Doc) loans declined from 74 percent in 2000 to 42 percent in 2007. These loans were replaced with low and no documentation loans. Low Doc loans comprised 22 percent of market share in 2000 rising to 55 percent in 2007 while No Doc loans comprised only 1.1 percent in 2000 and had increased to 3.3 percent in 2005. Finally, Figure 6 shows that mortgage refinance activity generally tracked changes in mortgage interest rates with a sharp decline in 2004 coinciding with an increase in interest rates during that year.

As noted above, by merging the LPC data with total origination activity reported in HMDA, we are able to calculate zip-code level concentration measures of subprime activity. Table 1 reports the overall and yearly average zip-code concentration by mortgage classification. For example, we see the rise and fall of subprime activity between 2000 and 2007, noting that the average concentration of subprime origination activity rose from from 4.5 percent in 2000 to 12 percent in 2005 and then declined to 5.3 percent in 2007.

Figures 7 and 8 show the average yearly house price change for zip-codes at the bottom and top of the subprime concentration. The figures reveal that house price appreciation was higher in the lower priced housing market during the accelerating bubble years (2003 and 2004) in zip codes with the highest concentration of subprime activity (Figure 8). In contrast, Figure 7 reveals that the lower priced housing market in zip-codes with the lowest concentration of subprime activity had the lowest level of house price appreciation. Thus, it appears that subprime origination activity is correlated with house price appreciation.
suggesting that access to credit played a role in fueling the housing bubble in Phoenix.

5 Results

In this section, we analyze individual borrower defaults to determine whether higher concentrations of subprime and alternative mortgages in neighborhoods are a risk factor associated with default. We estimate a proportional hazard rate model for borrower default conditional on the borrower’s risk at origination (as measured by their FICO score and loan-to-value ratio), the type of loan originated (i.e. low documentation, no documentation, adjustable-rate, hybrid, interest-only, etc.), and a set of zip-code level concentration variables that capture the percentage of loans outstanding in the borrower’s zip code at the time of origination that reflect various high-risk characteristics ((i.e. the percentage of loans that are low documentation, no documentation, adjustable-rate, hybrid, interest-only, etc.). Table 2 reports the estimated coefficients from this proportional hazard model.

Consistent with previous studies of borrower default, we find that borrower credit score at origination is inversely related to default risk. That is, higher FICO scores are correlated with lower probabilities of default. We also see that higher loan-to-value ratios are associated with higher risk of defaults.

Turning to the impact of mortgage type, we find that subprime mortgages are 1.3 times more likely to default, all else being equal, than prime mortgages. Furthermore, borrowers that originated loans with either low or no documentation are 1.8 and 2.4 times more likely to default than borrowers that provide documentation of their incomes and assets. Not surprisingly, we find that borrowers who originated a mortgage in order to refinance an existing mortgage are less likely to default while the presence of a prepayment penalty raises the odds of default by 12 percent.

Much discussion in the popular press has blamed the use of adjustable-rate
mortgages for the current default crisis. However, the estimated coefficient indicating an ARM mortgage is negative and significant indicating that ARMs have a significantly lower default rate than fixed-rate mortgages. However, borrowers who selected hybrid-ARMs (the product most associated with higher risk subprime borrowers) have significantly higher default rates than fixed-rate borrowers. In fact, the odds ratio for hybrid-ARMs indicates that these mortgages have default rates that are twice as high as fixed-rate mortgages. Finally, we also observe that non-owner occupied mortgages and mortgages with junior liens have significantly higher default rates than traditional first-lien, owner-occupied mortgages.

To examine the impact of house price changes on default, we include the lagged monthly house price return for the three house price levels (low-, mid-, and high-tier markets). Overall, the results indicate that default probability is not sensitive to the current return on housing.

Turning to the measures of mortgage activity in the surrounding area, we find that default risk is highly correlated with mortgage origination activity, albeit in some surprising ways. First, we note that the negative and significant coefficient on subprime concentration indicates that borrower risk actually decreases as the percentage of subprime mortgage in the zip-code increases. This is in stark contrast with the estimated coefficient indicating that the risk of default is highly correlated with whether the loan is a subprime mortgage. One explanation for this result is apparent in Figure 8 where we see that zip-codes with the highest subprime concentration had the highest yearly price appreciation in 2003 and 2004 (the peak subprime boom years). This suggests that subprime origination activity was a credit supply phenomena that led to rising house prices in those areas during the periods when these mortgages were being most utilized.

We also see that the risk of default decreases as the concentration of ARMs increases. However, the concentration of hybrid-ARMs is positively related to default risk with each percentage increase in hybrid-ARM concentration raising the odds of default by 3.5 percent. Not surprisingly, the presence of low doc and no doc borrowers in an area does significantly increase the odds of default,
with a one percent increase in no doc concentration raising the odds of default by 10 percent. Consistent with previous studies that foreclosure sales impact surrounding property values, we find that a 1 percent increase in the percentage of foreclosed homes in a zip-code increases the odds of default by 3.8 percent.

6 Conclusions

In this paper, we examine the relationship between default and subprime mortgage concentration on a local rather than national level. Subprime mortgages are not evenly distributed over urban areas (in this case, Phoenix Arizona). Rather, we find that subprime mortgages are more highly concentrated in certain zip codes. In the case of Phoenix, these concentrations are found around the Central Business District and other lower-income neighborhoods.

As we would expect, individual borrower risk characteristics play a significant role in explaining the probability of borrower default. For example, borrower credit quality and loan-to-value ratios are important determinants of mortgage risk. Furthermore, individual loans that were classified as ‘subprime’ or ‘Alt-A’ mortgages were significantly riskier than loans to traditional, prime borrowers. Furthermore, our analysis shows that increases in the local foreclosure rate (using the concentration of foreclosures in the zip-code as a proxy) raises the probability of borrower default. None of these results are surprising.

However, our analysis does reveal that after controlling for individual borrower risk characteristics and foreclosures in the area, the concentration of subprime lending in the neighborhood does not increase the risk of borrower default. In fact, we find the opposite. As a result, it does not appear that extending credit to subprime borrowers in general increased the probability of borrower default. Our analysis suggests that subprime lending is a credit supply effect that led to rising house prices in those areas. However, we do find that higher concentrations of the more aggressive mortgage products (hybrid-ARMS and no or low documentation loans) did increase the probability of borrower default.
References


Table 1: Mean Neighborhood Characteristics by Origination Cohort

<table>
<thead>
<tr>
<th></th>
<th>ALL</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Zipcode Concentration</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>of Investor-owned Loans</td>
<td>2.005</td>
<td>0.549</td>
<td>0.369</td>
<td>0.766</td>
<td>1.861</td>
<td>2.350</td>
<td>2.700</td>
<td>1.692</td>
<td>1.193</td>
</tr>
<tr>
<td>of No-doc Loans</td>
<td>0.461</td>
<td>0.081</td>
<td>0.141</td>
<td>0.227</td>
<td>0.421</td>
<td>0.442</td>
<td>0.602</td>
<td>0.482</td>
<td>0.247</td>
</tr>
<tr>
<td>of Foreclosed properties (lag 3 months)</td>
<td>0.162</td>
<td>0.110</td>
<td>0.158</td>
<td>0.290</td>
<td>0.256</td>
<td>0.129</td>
<td>0.104</td>
<td>0.180</td>
<td>0.311</td>
</tr>
</tbody>
</table>
### Table 2: Hazard Rate Regression Analysis of the Probability of Default

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Std. Error Ratio</th>
<th>$\chi^2$</th>
<th>P-value</th>
<th>Hazard Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age of loan (in months)</td>
<td>-0.4777</td>
<td>0.00725</td>
<td>4.574</td>
<td>4338.453</td>
<td>&lt; 0.0001</td>
<td>0.62</td>
</tr>
<tr>
<td>Age Square</td>
<td>0.0034</td>
<td>7.27E-05</td>
<td>5.08</td>
<td>2176.673</td>
<td>&lt; 0.0001</td>
<td>1.003</td>
</tr>
</tbody>
</table>

**Borrower and Loan Characteristics:**

- **FICO (origination):** -0.0080 0.000139 2.107 3362.374 < 0.0001 0.992
- **LTV (origination):** 0.0229 0.000839 2.376 742.1798 < 0.0001 1.023
- **Subprime (0,1):** 0.2908 0.02253 1.898 166.6664 < 0.0001 1.338
- **Low Documentation (0,1):** 0.6032 0.01163 1.695 2690.315 < 0.0001 1.828
- **No Documentation (0,1):** 0.8585 0.03415 1.59 632.1471 < 0.0001 2.36
- **Refinance (0,1):** -0.3738 0.0133 1.868 790.0927 < 0.0001 0.688
- **Prepayment Penalty (0,1):** 0.1172 0.0187 2.118 39.2418 < 0.0001 1.124
- **Adjustable Rate Mortgage (0,1):** -0.5927 0.01398 1.601 1795.947 < 0.0001 0.553
- **Hybrid ARM (0,1):** 0.7765 0.01783 1.781 1896.706 < 0.0001 2.174
- **Condominium (0,1):** -0.2601 0.02136 1.426 148.2349 < 0.0001 0.771
- **Investor Occupancy (0,1):** 0.1137 0.01859 1.639 37.3853 < 0.0001 1.12
- **Lien > 1 (0,1):** 0.4981 0.02848 2.2 305.9645 < 0.0001 1.646
- **Monthly House Price Return - Low Price Range:** 0.0045 0.00289 0.704 2.3869 0.1224 1.004
- **Monthly House Price Return - Mid Price Range:** -0.0149 0.02196 0.831 0.4598 0.4977 0.985
- **Monthly House Price Return - High Price Range:** 0.0045 0.03838 1.118 0.0136 0.9071 1.004

**Zip-code Concentration Measures:**

- **Percent of Subprime loans concentrated in zipcode:** -0.0413 0.0038 2.137 118.44 < 0.0001 0.96
- **Percent of ARM loans concentrated in zipcode:** -0.1186 0.00714 2.575 276.361 < 0.0001 0.888
- **Percent of Hybrid ARMs concentrated in zipcode:** 0.0345 0.01002 2.725 11.8363 < 0.0001 1.035
- **Percent of investor occupancy concentrated in zipcode:** -0.1023 0.00562 2.144 331.6191 < 0.0001 0.903
- **Percent of No Doc loans concentrated in zipcode:** 0.0949 0.01565 3.844 36.7958 < 0.0001 1.1
- **Percent of Low Doc loans concentrated in zipcode:** 0.0868 0.00387 2.456 501.4186 < 0.0001 1.091
- **Percent of Cashout Refinance concentrated in zipcode:** 0.0752 0.00474 2.892 252.1689 < 0.0001 1.078
- **Percent of loans with Prepayment Penalty concentrated in zipcode:** 0.0353 0.00506 2.277 48.7251 < 0.0001 1.036
- **Percent of Foreclosed Homes concentrated in zipcode:** 0.0373 0.00851 2.066 1916.401 < 0.0001 1.036

**-2 Log Likelihood (Restricted):** 3004001
**-2 Log Likelihood (Unrestricted):** 2748474.3
**Pseudo $R^2$:** 8.51%

Note: This table reports the maximum-likelihood parameter estimates for the proportional hazard rate model of loan default probability. The dependent variable is a dummy variable equal to 1 if the loan defaulted (90-days delinquent) and 0 otherwise. The zip-code concentration variables capture the percentage of loans outstanding in the loan’s zip-code at loan origination.
Figure 1: SP/Case-Shiller Home Price Indices // January 2000 to January 2009 Year-Over-Year Price Change
Figure 2:
Figure 3:
Figure 4:
Figure 5: Subprime Mortgage Origination Volume and Default Rates for Phoenix, AZ// January 2000 to December 2007
Figure 6: Characteristics of Subprime Mortgage Origination Activity for Phoenix, AZ// January 2000 to December 2007
Figure 7: Year-over-year House Price Index Change for zip-codes in the 1st quintile of subprime concentration for Phoenix, AZ// January 2000 to December 2007
Figure 8: Year-over-year House Price Index Change for zip-codes in the 5th quintile of subprime concentration for Phoenix, AZ// January 2000 to December 2007