# What Did Lenders Know? House Price Increases and Previously Rejected Mortgages

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*We examine whether the incidence of originated mortgages that had been previously denied by a different lender predicts house price increases in the United States from 2004-2006. Since these "Rebound" mortgages had been denied by a previous lender, it suggests that there was information available to lenders that the mortgages were excessively risky. We find that the incidence of Rebound mortgages was highest in Nevada, Florida, Arizona, and California. These four states had the highest default rates immediately after the housing market fell. In addition, the incidence of Rebounds predicts larger house price increases across major metropolitan statistical areas.*

## INTRODUCTION

There are a number of theories about why house prices rose dramatically and then collapsed in the United States. These theories fall into two broad categories. The first attributes the run-up in house prices to market forces. This group includes the possibility that a glut of credit from newly emergent economies lowered borrowing costs on mortgages, causing house prices to rise. A second theory is that the liquidity the Federal Reserve infused into the U.S. economy following the terrorist attacks on September 11, 2001, and the ensuing growth in the economy could have contributed to the house price run-up. The collapse in house prices is explained by some as simply the bursting of a "bubble" while others point to economic shocks and market forces.

A second set of theories, which we shall refer to as "excess mortgage credit" theories, point to an excessive supply of mortgage credit, where the ultimate suppliers of credit were not sufficiently compensated for the risk of the mortgages, based on current market information available to the originator. This could have been the result of a reduction in screening by mortgage originators for some reason, or originators could have been responding to some kind of pressure or incentive to originate excessively risky mortgages. In either case, originators chose to ignore information about the borrower, or reduced screening below the level called for given the potential risk of the loan. This in turn caused the ultimate suppliers of capital for the mortgages to receive an interest rate on the loans that did not reflect the risk of the loan.

We examine whether excess mortgage credit theories explain the run-up in house prices. We define excessive mortgage credit to be an instance where the interest rate on mortgages failed to compensate the suppliers of capital for the mortgages for risk, given information available to the originator. Not all relevant information is known about a borrower. However, the risk that comes from less than full information should be priced into the interest rate of a typical mortgage. When interest rates on mortgages fail to compensate the suppliers of credit in a systematic way, given information available to lenders, excessive credit has occurred.

We use a variable called Rebound as a measure of excess mortgage credit. A Rebound is a mortgage loan that was previously denied by a different lender. Since the borrower was previously denied, this suggests that there is information available to the lender that the borrower is insufficiently worthy of credit. In this way, rather than trying to construct a measure of creditworthiness, we let other lenders tell us if there is adverse information about the borrower indicating that they are not worthy of credit. DiLellio and Forsyth (2014) found that Rebounds predict income falsification on mortgage applications.

Our paper is most closely related to Mian and Sufi (2009). They find that areas with high latent demand, as measured by the previous fraction of loan denials in a zip code, had higher house price increases and subsequently, increased defaults. Their conclusion was that the cause was moral hazard on the part of originators who sold off their mortgages, a flood of international capital, and the bundling of collateralized mortgage obligations into tranches, which allowed deep pocketed institutions to hold the highest rated tranches.

We take a similar approach in focusing on previous denials. However, Mian and Sufi look at an earlier time period, and measure the fraction of loans denied in a zip code. We look at loans where the borrower had been recently denied for the same property. Therefore, our measure includes information on what data the lender had access to about the borrower. Rather than consider latent demand, we consider in a more direct way whether there was excessive mortgage credit.

In addition to Mian and Sufi (2009), a number of other papers point to securitization as a cause for the high incidence of mortgage defaults. Rajan, Seru, and Vig (2010) found a reduced reliance on soft information, which the originator can screen for, and an increased reliance on hard information. Keys, Mukherjee, Seru, and Vig (2010), found that at a credit score of just above 620, default rates jumped. They point out that a credit score of 620 is a “rule of thumb” cut-off point for securitizers to purchase mortgages. Nadauld and Sherlund (2011) also blamed securitization for reduced screening. Piskorski, Seru, and Witkin (2015) showed that securitizers misrepresented information about the underlying mortgages that they bundled and sold. Specifically, the occupancy status and presence of a second lien were falsified. Purnanandam (2010) discusses how a reduction in the incentive to collect soft information occurs when loans are sold off, and finds that lenders that sold more mortgages had higher defaults. He interprets this to mean that these lenders could not sell these mortgages when house prices began to fall. These papers focus on an excessive supply of credit coming from securitizers, and some of the papers attempt to estimate if the loans were sufficiently compensated for risk. However, in our approach, we use other lenders, who rejected the borrower, to answer this question.

Another strand of literature focuses on governance and fraud problems. If the managers or the owners of a lender were able to pay out large portions of loan proceeds to themselves, their incentive to promote sound underwriting practices is reduced. They may be motivated to engage in deceptive practices themselves. Piskorski et al. (2015) is an example of this further down the chain from loan origination. Ben David (2011) found that seller down-payment schemes, where the seller “gives the down-payment” to the borrower, (thus allowing the bank to misrepresent that the down-payment has come from the borrower) contributed to the increase in house prices. Garmaise (2015) found that the frequency of reported assets on mortgage applications are higher just above multiples of $100,000 than just below, suggesting that borrowers were “picking” assets values to report. Carillo (2013) found evidence of fraud for housing schemes, where the house price is inflated, and default is almost immediate after the mortgage is originated. (These schemes require a side payment from the seller to the buyer.) DiLellio and Forsyth (2014) found that clusters of reported income at certain levels (suggesting purposefully picked income numbers), are higher for incomes above the jumbo loan cut-off point than below, where the greater documentation requirements of Fannie Mae and Freddie Mac (the GSEs) suppressed income falsification. Jumbo loans are ineligible for sale to the GSEs. Mian and Sufi (2015) found that in areas where reported income on mortgage applications outstrips area income, as independently reported to the IRS, higher mortgage fraud and higher default rates occur. Many of these papers focus on fraud that the lender had to be aware of. This is similar to our paper, which also focuses on situations with adverse information available to lenders. However, in our paper this adverse information may or may not involve fraud or borrower misrepresentation. We take it a step further and link adverse information about borrowers to house price increases. Ben David also took this step, but only for the specific instance of seller down-payment schemes.

Another strand of the literature considers whether legal or regulatory pressure caused lenders to originate excessively risky loans. Bostic, Mehran, Paulson, and Saidenberg (2005) found that banks that had higher originations of low and moderate income loans were more likely to acquire another bank within a year. They attribute this to the Community Reinvestment Investment Act (CRA), which requires that banks that want to merge or expand show that they are serving "community needs." Serving community needs involves lending to low-income borrowers. Agarwal, Benmelech, Bergman, and Seru (2012) found that banks made loans with greater risk around CRA examination dates. DiLellio and Forsyth (2015) found that regulatory pressure on the GSEs to make loans in "underserved areas," caused them to buy securitized mortgages with falsified income from these areas because they were not allowed by regulators to purchase the mortgages directly. Underserved areas were defined through regulation, and were based in part on a low-income requirement. Since regulatory pressure could cause lenders to originate mortgages that they would not otherwise consider to be sufficiently compensated for risk, regulatory pressure could also be associated with excess credit. However, while this approach may involve showing that there were adverse consequences, such as higher default rates, it does not examine whether lenders knew if the loans were sufficiently compensated for risk at the time the loan was originated.

Our paper contributes to the literature by using the Rebound variable to examine whether excessive credit contributed to the house price run-up. It can be argued that lenders had no way of knowing that house prices would not continue to rise. Therefore, based on information that they had at the time, the loans that they originated were compensated for risk. However, the Rebound variable indicates that a lender had information that the borrower was not credit worthy since the borrower had been denied at a different lender. Therefore, we link the origination of mortgages, where the originator had information that the mortgages did not sufficiently compensate the suppliers of capital for risk, to the run-up in house prices. DiLellio and Forsyth (2014) also used Rebound. However, they focused on whether Rebounds predicted income falsification, and did not consider house prices. Forsyth and Crawford (2015) predicted the incidence of Rebound loans. They found evidence that the GSEs had a lower incidence of Rebounds in loans they directly purchased. However, they found evidence that the GSEs were purchasing Rebound loans from securitizers that were from underserved areas. In our paper, we look at whether Rebounds were associated with rising house prices.

## THE DATA

We collected data, as compiled under the Home Mortgage Disclosure Act (HMDA) from 2004 to 2006. These years are associated with the run-up in house prices. The HMDA requires most residential mortgage lenders to report, and these data cover most United States mortgage applications. We restricted our analysis to applications for home purchases only and eliminated rental and vacation properties. We only included mortgages secured by a first or subordinate lien. Multi-family units were removed. Lastly, we eliminated observations that were not mortgage originations, such as when mortgages were purchased, preapproval requests were denied, and preapproval requests were approved but not accepted.

Our Rebound variable indicates that a mortgage loan for the same property had been previously rejected by a different lender. We started by identifying mortgage applications that had a matching application that had been denied at a different mortgage lender within the same year, based on matching census tract, loan amount, and sex, race, and ethnicity of the applicant and co-applicant. Sometimes, there was more than one matching loan application at the accepting institution, or denied loan application at a different institution. The matching applications and denied loan applications were then separately numbered. If an application had a larger number than the maximum number for the denied applications, it was not labeled a Rebound. However, a denied application could have been matched with another accepting lender, since a denied loan could have resulted in more than one loan application at different lenders. After Rebounds were identified, only accepted applications were kept, rather than all applications.

We used the HPI (House Price Index reported by the Federal Housing Finance Agency.) The HPI is broadly measured, weighted, and based on repeat-sales, so that it measures average price changes in repeat sales or refinancings on the same properties. It indexes house price changes within large MSAs, among other geographic areas. We were able to match 91 MSAs from the HPI with MSAs in the HMDA data for 2004 to 2006. House price ratios were constructed, that were equal to the current end-of-year index value for an MSA, divided by the previous end-of-year value. Ratios were constructed for non-seasonally adjusted data, and seasonally adjusted data.

## EMPIRICAL ANALYSIS

Table 1 provides summary statistics for Rebound by sample year, and for all years. Over the entire sample period there are 11,037,114 accepted mortgage applications in the matched MSAs. Rebounds occur in 5.8% of accepted mortgages. The incidence of Rebound increases each year from 3.7% in 2004 to 7.3% in 2006, corresponding to the run-up in house prices.

**TABLE 1**
**REBOUND SUMMARY STATISTICS**

| Years | Observations | Mean |
|---|---|---|
| All Years | 11,037,114 | .058 |
| 2004 | 3,490,306 | .037 |
| 2005 | 3,943,323 | .063 |
| 2006 | 3,603,485 | .073 |

*Note.* An individual mortgage loan is one observation.

Before turning to house prices, it is instructive to look further into where and when Rebounds occurred. Table 2 reports an OLS regression where Rebound is the dependent variable. The explanatory variables are an intercept, binary variables for 2005 and 2006, with 2004 as the null variable, and state binary variables, where Alabama is the null variable. Not all states are represented because the matched MSAs do not cover every state.

Similar to the summary statistics in Table 1, Rebounds are 2.5% higher in 2005 and 3.6% higher in 2006. Some states are associated with a higher incidence of Rebound, while others have a lower incidence. However, it is interesting to look at the states with the highest incidence. Nevada has the largest coefficient at .05562, followed by Florida with .04720, California with .04453, and Arizona with a coefficient of .04436. According to Mullins (2008), and Zibel (2008), Nevada, Florida, California, and Arizona had the highest incidence of mortgage defaults immediately after the financial crisis.

These results support that Rebounds are related to default risk. However, there are several potential transmission channels. The most direct channel is that Rebound loans have very high risk since they were previously denied by a lender. However, Rebound loans alone cannot account for the default rates seen after house prices collapsed, since many loans that were not Rebounds defaulted as well. Another possibility is that Rebounds are associated with lenders supplying excess credit in a more general way in certain geographic areas. These areas then experienced house price increases that were unsustainable as defaults began to appear. We now turn to this possibility.

**TABLE 2**
**REBOUND RELATIONSHIP WITH YEARS AND STATES**

| Variable | Coefficient | Variable | Coefficient | Variable | Coefficient |
|---|---|---|---|---|---|
| Intercept | 0.01619 | IA | -0.01226 | NC | -0.00193 |
| | (18.01)*** | | (-3.96)*** | | (-1.94)* |
| 2005 | 0.02480 | KS | -0.00977 | OH | -0.00187 |
| | (145.12)*** | | (-8.31)*** | | (-1.93)* |
| 2006 | 0.03584 | KY | -0.00116 | OK | -0.00954 |
| | (205.07)*** | | (-0.95) | | (-8.54)*** |
| AZ | 0.04436 | LA | -0.00232 | OR | 0.00804 |
| | (46.71)*** | | (-1.99)** | | (7.33)*** |
| AR | -0.00951 | MD | 0.00363 | PA | -0.01162 |
| | (-6.41)*** | | (3.65)*** | | (-11.83)*** |
| CA | 0.04453 | MA | -0.00171 | RI | 0.00575 |
| | (48.93)*** | | (-1.59) | | (4.27)*** |
| CO | 0.01592 | MI | 0.02767 | SC | 0.00003 |
| | (15.94)*** | | (25.27)*** | | (0.03) |
| CT | 0.00853 | MN | 0.00071 | TN | 0.01495 |
| | (8.05)*** | | (0.70) | | (14.67)*** |
| DE | -0.01491 | MS | 0.01545 | TX | 0.02618 |
| | (-9.38)*** | | (7.70)*** | | (28.48)*** |
| DC | -0.00382 | MO | 0.00919 | UT | 0.03926 |
| | (-2.57)** | | (8.97)*** | | (33.09)*** |
| FL | 0.04720 | NE | -0.01634 | VA | -0.00160 |
| | (51.19)*** | | (-11.45)*** | | (-1.67)* |
| GA | 0.02890 | NV | 0.05562 | WA | 0.00970 |
| | (30.20)*** | | (54.44)*** | | (9.86)*** |
| ID | 0.04144 | NJ | -0.00583 | WV | -0.01213 |
| | (31.00)*** | | (-5.59)*** | | (-3.43)*** |
| IL | 0.02054 | NM | -0.00264 | WI | -0.00731 |
| | (21.86)*** | | (-2.05)** | | (-6.27)*** |
| IN | 0.01431 | NY | 0.00417 | | |
| | (13.54)*** | | (4.19)*** | | |
| Adjusted $R^2$ | .0114 | | | | |
| Observations | 11,037,114 | | | | |

*Note*. This is an OLS regression. The dependent variable is Rebound. Data include 2004-2006. An individual observation is an individual mortgage that was originated. T statistics are in parentheses. "***", "**", and "*" denote significance at the 1%, 5%, and 10% level respectively.

We calculated the fraction of Rebound loans for each MSA, by year. We then matched these data with our two house price ratios (seasonally adjusted and unadjusted,) for each MSA-year. Table 3 reports summary statistics. Over three years, data were available for 91 observations (MSAs) per year, for a total of 273 observations. Over the entire sample, house prices increased on average by 8.6% on an annual basis. Non-seasonally adjusted house prices increased by 11.0% (11.1% seasonally adjusted) in 2004, by 11.5% (11.6%) in 2005, and by 3.1% (3.2%) in 2006. House prices peaked and began to soften in 2006, as reflected in the data. On average, Rebounds were 3.3% of a typical MSA's mortgage loans in 2004, rose to 5.2% in 2005, and continued to rise to 6.0% in 2006. The average for the entire time period was 4.8%.

**TABLE 3**
**SUMMARY STATISTICS**

| | All Years | | | 2004 | | 2005 | | 2006 | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | N | Mean | Std. | N | Mean | N | Mean | N | Mean |
| House Price Ratio *(Non-Seasonally Adjusted)* | 273 | 1.086 | 0.085 | 91 | 1.110 | 91 | 1.115 | 91 | 1.031 |
| House Price Ratio *(Seasonally Adjusted)* | 273 | 1.086 | 0.085 | 91 | 1.111 | 91 | 1.116 | 91 | 1.032 |
| Fraction Rebounds in MSA | 273 | 0.048 | 0.028 | 91 | 0.033 | 91 | 0.052 | 91 | 0.060 |

*Note.* An MSA in a single year is one observation.

In Table 4 we examine whether Rebounds predict both seasonally unadjusted and seasonally adjusted house price increases. The intercept indicates that absent other variables, non-seasonally adjusted house prices rose by 9.41% per year (9.49% for seasonally adjusted prices.) The coefficient for 2005 Indicator is insignificant. However, the 2006 Indicator coefficient is -9.22% (-9.18%) and is significant at the 1% level. Absent other effects, house prices softened in 2006.

Fraction Rebounds in MSA has a positive coefficient of .4961 for non-seasonally adjusted housing prices (.4805 for seasonally adjusted prices.) The coefficients are significant at the 1% level. In MSAs with more Rebounds, house prices significantly rose. As previously seen in Table 3, in 2006 the mean fraction of Rebounds was 6%. If we multiply this by the non-seasonally adjusted coefficient for Rebounds of .4961, the presence of an average number of Rebounds in an MSA accounts for a 3.0% increase in house prices in 2006. The average increase in non-seasonally adjusted house prices in 2006 was 3.1%. By themselves, Rebounds account for almost the entire increase in house prices in 2006. A similar calculation for 2005 shows that Rebounds alone account for 22.4% of house price increases in 2005. Of course, Rebounds by themselves cannot be expected to account for house price increases since Rebounds were not a large fraction of mortgage loans. However, to the extent that they reflect pervasive excessive credit in an area, their ability to explain house price increases becomes more economically plausible.

## CONCLUSION

We used a variable called "Rebound." This variable indicates that a borrower that received a mortgage had previously been denied by a different lender. This variable is of interest because it indicates that adverse information was available to the lender that the borrower posed excessive risk. Therefore, Rebound can be considered a measure of "excess credit," where the originator knew that the mortgage did not compensate the suppliers of capital for the risk of the mortgage. (Some theories of the house price run-up rely on originator knowledge that the loan was not compensated for risk, while others do not.) We then link the incidence of Rebound to the house price run-up.

**TABLE 4**
**THE RELATIONSHIP BETWEEN HOUSE PRICE INCREASES AND REBOUND**

| | Non-Seasonally Adjusted | Seasonally Adjusted |
|---|---|---|
| Variable | Coefficient | Coefficient |
| Intercept | 1.0941 | 1.0949 |
| | (111.99)*** | (111.92)*** |
| 2005 Indicator | -0.0047 | -0.0043 |
| | (-0.40) | (-0.37) |
| 2006 Indicator | -0.0922 | -0.0918 |
| | (-7.61)*** | (-7.56)*** |
| Fraction Rebounds in MSA | 0.4961 | 0.4805 |
| | (2.81)*** | (2.72)*** |
| Adjusted $R^2$ | 0.2186 | 0.2172 |
| Observations | 273 | 273 |

*Note.* This is an OLS regression where an MSA-year is an observation. The dependent variable is the ratio of the current year house price index to the previous year house price index. Data include 2004-2006. T statistics are in parentheses. "***" denotes significance at the 1% level.

We found that the highest incidences of Rebound are associated with Nevada, Florida, Arizona, and California. These states had the highest default rates on mortgages soon after housing prices collapsed. We also calculated the fraction of Rebounds for MSAs and matched these data with an index of house prices. Between 2004 and 2006, we found that the effect of Rebound on non-seasonally adjusted house prices is .4961, and is statistically significant at the 1% level. Multiplying this coefficient by the mean number of Rebounds in 2006 implies an annual increase in housing prices of 3.0%. This represents nearly the entire increase in house prices in 2006 for sample MSAs. A similar calculation shows that Rebounds alone account for 22.4% of the 2005 increase in house prices. These results are for areas with an average incidence of Rebounds. For areas with an incidence of Rebound that is above the mean, the effect will be stronger.

The Rebound variable could be expected to only capture a fraction of loans where investors were not compensated for risk. It could easily be the case that many insufficiently compensated loans were made without having been rejected elsewhere. Nevertheless, a large fraction of house price increases are explained by Rebound, suggesting that lenders had information that the mortgages they were originating did not compensate investors for risk, and that these lenders contributed significantly to the house price run-up in the United States.

## REFERENCES

Agarwal, S., Benmelech, E., Bergman, N., & Seru, A. (2012). Did the community reinvestment act (CRA) lead to risky lending? Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w18609

Ben-David, I. (2011). Financial constraints and inflated home prices during the real-estate boom, *American Economic Journal: Applied Economics, 3*(3), 55-78.

Bostic, R. W., Paulson, A. L., Mehran, H., & Saidenberg, M. (2005). Regulatory incentives and consolidation: The case of commercial bank mergers and the Community Reinvestment Act, *Advances in Economic Analysis & Policy, 5*(1).

Carrillo, P. (2013). Testing for fraud in the residential mortgage market: How much did early-payment-defaults overpay for housing? *Journal of Real Estate Finance and Economics, 47*, 36-64.

DiLellio, J., & Forsyth, J. (2014). Government-sponsored enterprises and income falsification on mortgage applications, *International Journal of Business, Accounting, and Finance, 8*(1).

DiLellio, J., & Forsyth, J. (2015). Income falsification on mortgage applications during the housing bubble, Pepperdine University: working paper.

Forsyth, J., & Crawford, P. (2015). Was there a Regulatory Approval Market for Mortgages? Pepperdine University: working paper.

Garmaise, M. (2015). Borrower misreporting and loan performance. *Journal of Finance, 70*(1).

Keys, B., Mukherjee, T., Seru, A., & Vig, V. (2010). Did securitization lead to lax screening? Evidence from subprime loans, *Quarterly Journal of Economics, 125*(1).

Mian, A., & Sufi, A. (2009). The consequences of mortgage credit expansion: evidence from the U.S. mortgage default crisis, *The Quarterly Journal of Economics, 124*(4).

Mian, A., & Sufi, A. (2015). Fraudulent income overstatement on mortgage applications during the credit expansion of 2002 to 2005. Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w20947.

Mullins, L. (2008, May 14). Ten worst foreclosure states. *U.S. News and World Report*.

Piskorski, T., Seru, A., & Witkin, J. (2015). Asset quality misrepresentation by financial intermediaries: Evidence from RMBS market, *Journal of Finance,* forthcoming.

Purnanandam, A. (2010). Originate-to-distribute model and the subprime mortgage crisis, *The Review of Finance and Statistics, 24*, 1881-1915.

Rajan U., Seru, A., & Vig, V. (2015). The failure of models that predict failure: Distance, incentives and defaults, *Journal of Financial Economics, 115*(2) 237-260.

Zibel, A. (2008, December 11). Foreclosure activities drops to June levels. *Associated Press*.

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