# Life without Foreclosures

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**Abstract**

What happens to the availability of home loans if the contracts no longer allow for foreclosures? Using a natural experiment that halted foreclosures of homes, we apply a difference-in-differences test using the loan supply of collateralized car loans as a counterfactual. We find a price effect of at least 42-80 basis points increase in loan rates. The supply effect, is much larger. Our baseline estimate is that lenders reject an additional 30% of applicants. We also find a more than 30% increase in probability of default after the law was enacted. Finally we document a steep jump in modification rates. The ratio of loan modifications go from less than 2% of the loans in default, to more than 16% after the moratorium. These modifications are favorable to the lenders as they offer not only higher duration but also lower rates. Our results on modifications provide new evidence to resolve the puzzle of why lenders do not modify loans: lenders are unwilling to weaked or erode the credibility of the threat of foreclosures that inhibits moral hazard in repayments.

Foreclosures are surely an unsightly proposition for lenders. Lenders risk the ire of both the popular press and the community, all for the outcome of being stuck with an asset whose value deteriorates sharply, if it has not already done so. Of course, newly houseless borrowers are generally not happy either. So why have foreclosures?

The simple answers are that beyond liquidation value providing the lender with some relief for the cost of default[1], lenders' threat of foreclosure should mitigate ex post moral hazard[2], and borrower's pledging of collateral should allow for ex ante sorting of types (Bester, 1985). With this in mind and a natural experiment in hand, we set out to test the importance of having a credible threat of foreclosures both ex ante in originations and ex post in modifications. Our evidence suggests that repayment moral hazard has a strong affect on supply decisions, both in the distribution of originations and in, perversely, in the failure of modifications.

Our work is most closely related to Adams, Einav, and Levin (2009), who study the supply reaction to the moral hazard and adverse selection lenders face ex ante in the subprime car loan market. We offer different insights specifically for the mortgage market and calculating the magnitude of how important the credible threat of foreclosure is for completing the market. In addition, we offer a new perspective on the failure of modifications in mortgages, an unresolved puzzle in current policy discussions.

In the U.S. because of recent events in the housing crisis, one thinks of ex post moral hazard as the failure of homeowners to upkeep houses when the potential for default rises (e.g., Campbell, Giglio and Pathek, 2012; others). But more generally, moral hazard *in repayments* occurs when the ability to default on or renegotiate the loan causes a borrower either to use cash for other consumption or saving activity rather than paying down the mortgage or to act with more risk in financial or labor income generation. Michelle White and Ethan Cohen-Cole (references forthcoming) study such behavior as it relates to decisions about making debt payment choices in financial duress, and find evidence that seemingly suboptimal debt decisions can occur because of other motives or constraints.

Our work also relates to the small literature on debt moratoria and foreclosure laws (Alston

[1] A small empirical literature examines the effect of collateral and liquidation value on household financial contracts Assuncao, Benmelech and Silva (2012) Benmelech, Garmaise and Moskowitz (2000).

[2] See, for example, Aghion and Bolton(1992), Dewatripont and Tirole (1994), Hart and Moore (1999); Hart (2001), Bolton and Scharfstein (1990), Eisfeldt and Rampini (2009), Bolton and Scharfstein (1996), Shleifer and Vishny (1992), Williamson (1988), Diamond (1991, 1993), Berglof and von Thadden (1994).

(1983), (1984), Pence (2006)). One of the challenges in answering questions of the importance of an institution like foreclosures is in isolating the causal price and supply effects from a foreclosure experiment from aggregate changes in the economy. Pence tackles this challenge by differencing loan supplier decisions across state lines with different laws to estimate the importance of foreclosures.

We exploit a 2010 moratorium of foreclosures in Greece and employ a micro-level data on all home and loan applications from one of the large banks in Greece to study life without foreclosures. Our empirical challenge is in the counterfactual exercise, both assessing supply and demand over time. We have to assert a counterfactual supply, understanding that bank capital was contracting and permanent income was declining in Greece in 2010. We do this by estimating hurdle rate changes for the bank in the collateralized car loan market. For demand, we first rely on the assumption that requested loan applications (many of which are rejected) reflect supply. We then show robustness by estimating housing consumption implied from car consumptions through engel curve transformation for zip code representative agents.

Our first finding is that the moratorium brought a large jump in delinquencies of existing loans, consistent with moral hazard at work. In the origination market, the foreclosure moratorium lead to a quite moderate increase in interest rates charged on loans (42-80 basis points) and a large reduction in the supply of home loans. A third to half of what would be pre-law approvals are rationed..

The distribution of these changes are important. The price increase is small and uniform across risk, in contrast to risk pricing of Adams, Einav and Levin (2009). New rationing does not occur primarily low risk types as in the original information signaling theories of Jaffee and Russell (1976), Stiglitz and Weiss (1981), and Bester (1985). It may be that the ability to come up with and risk downpayments is important. Indeed the loans after the moratorium have larger downpayments. But the evidence seems to point to ex post repayment moral hazard. Successful applicants after the law have higher incomes and smaller houses, consistent with the moral hazard concerns ex post in a number of theories and in the findings in Adams, Einav and Levin (2009). We then test whether the lender is successful in rationing those with higher default risk. We find this to be the case; delinquency rates are lower in the loans originated after the moratorium.

We offer one final contribution, perhaps our most timely commentary on current U.S. events. In a setup of financial duress, Barro (1976) shows how the possibility of a loan modification can be valuable to borrowers. On the flip side, lenders should want to modify loans if their valuations (e.g., because of foreclosure costs) are lower than that of the borrower. However, the empirical

reality coming out of the U.S. crisis finds that there have not been many loan modifications despite the efforts of the government to enhance such activity (Agarwal et.al, 2012). Prior literature has explored various channels that could explain the low levels of loan modifications, such as asymmetric information, securitization and servicer organization design (Piskorski, Seru and Vig,2010, Agarwal. et.al, 2011, Adelino, Gerardi and Willen, 2013, Agarwal et.al, 2013). We provide a new channel that can also impact renegotiations over and above the channels that have been explored so far, the lender's credible threat of foreclosure. The concern for long-run reputation effects may induce the creditor not to renegotiate if this is optimal ex-ante, even though it might be suboptimal ex-post. The foreclosure moratorium experiment is a clean test for whether lenders fail to modify loans because doing so may erode the credible threat of foreclosure that mitigates borrower moral hazard. We find that the institution of foreclosure *inhibits* modifications. The ratio of loan modifications go from less than 2% of the loans in default, to more than 15% after the moratorium. Furthermore, these modifications are favorable to borrowers as they offer not only higher duration but also lower rates.

The rest of the paper proceeds as follows. Section 1 describes the data and setting in Greece. Section 2 present default and modification findings before and after the moratorium. Section 3 describes the more challenging empirical task of estimating price and quantity effects in originations. Section 4 presents the origination main results, and section 5 presents the incidence of who is rationed and who experiences prices increase. Section 6 concludes.

# 1 Data and Setting

A word is in order concerning the role of homeownership in Greece. Mortgage contracts in Greece are quite similar to traditional contracts in the U.S.,with fixed or variable rates and median duration of 30 years. Home ownership is more prevalent in Greece than the U.S., and traditionally more important. About 80% of Greek households are homeowners. The housing market is quite sticky as people tend to buy their home and spend their lifetime without moving. This stickiness applies to prices as well, with the probable exception of island vacation property and commercial real estate in Athens. Greece did not exhibit a bubble in real estate prices (Hypostat (2009)); the Bank of Greece (2009) reports that the ratio of nominal house prices to rent ratio in 2009 was at the same levels as it was in 2002. That being said, prices are falling. The year 2010 witnessed a (transacted) house price decline of 4.5%, but the full scope of the decline has yet to be realized since a large

reduction in transactions has occurred since then.[3]

One other setting detail is important. In the United States, court-driven foreclosure is the centerpiece of the mortgage contract. In Greece, and more generally in Europe, foreclosures are not as common, and more resolution of delinquency is handled out of court. (Even in Spain, foreclosure rates in 2009 were less than 0.24% (Hypostat (2009)). The reason for out-of-court resolution is recourse on personal assets and sometimes on income streams (Jaffee (2011). According to the European Central Bank (2009) borrowers are "personal liable for any difference between the value of the property and the amount of the loan". Thus, the debt stays with households. In the US, a few States do permit recourse on other personal assets (Pence 2006). Ghent and Kudlyak (2009) show that this variation does affect loan contracting, even if recourse is scarcely exercised.

Our proprietary data come from a large bank in Greece. The bank provided us with the universe of application data for accepted and rejected home loan applications from 2006-2012, as well as the performance files of all mortgages during this period. The application dataset includes each applicant's characteristics, loan requests, loan terms, the collateral value, and the bank branch identifier. Our main borrower characteristics are the credit grade (risk score) and household income. When we apply our matching methodology, we follow Einav, Jenkins, and Levin (2012) by focusing on these two dimensions of loan applicant quality, income and credit risk. Other borrowers characteristic variables are occupation, employer type, the number of dependents, marital status, age and years in job. Loan request variables are the requested loan amount, requested loan duration, and the number of signors on the application. Loan terms for approved loans include the approved amount and duration, interest rate, and whether the rate is fixed or float. The performance files include payment and rate variables for all open mortgages.

Appendix Table 1 reports the summary statistics for all of these variables for home loans and for car loans. We have similar variables for car loan applications and home loan applications, except .the car loan applications do not include a credit grade variable, thus we have to re-engineer the credit risk variable from the other applicant characteristics variables. We describe in detail this re-engineering of the risk variable in Appendix A.

In 2010, the Greek government implemented two laws concurrently that jointly protected the home of Greeks borrowers from foreclosure and set up a process for an orderly claim on remaining personal asset through a personal bankruptcy restructuring. A little background on these laws

[3]The number of notarial acts on real estate declined by 13.9% in 2009 (Mitrakos, T., C. Akantziliotou and S. Panagiotou (2011))

may be helpful. In the aftermath of the crisis in US and the wake of the Greek crisis, popular pressure forced the government to take preventive measures to avoid the wave of foreclosures ongoing elsewhere. In July 2010, the Greek government introduced law No.3858/40 which suspended foreclosures on residencies for mortgage debt of 200,000 euros or less. At the same time, law N.3869/2010 {a personal bankruptcy law} was enacted, which protected from liquidation primary dwellings of a value up to 450,000 euros for a family with two children.[4] These limits are very high and cover most Greek dwellings. The law was set up to be continued on a renewal basis, with rhetoric suggesting that this process would be indefinite in the present state of the economy. The moratorium has been continuously extended on a semiannual basis and has been extended at least until the end of 2013.

We focus on a one-year span before and after the law was enacted, namely from June 2009 to June 2011. Table 1 reports summary statistics for home and car loans before and after the law. This simple first look at the data reveals much of where we are headed. First, the mean level of applicant household income increases significantly for both homes and cars. Second, the risk score increases (better credit risk people loans) in the post period in homes. Third, successful applicants in home loans face 1% higher interest rates and those in car loans face only 0.40% higher rates. Finally, approval rates in home loans fell from 0.635 approval to 0.277 approval. Car approvals only marginally fell, from 0.790 to 0.711 in approvals. These difference seems stark at first look. Of course we have to be more careful with supply and demand conditions than to just take these numbers at face value.[5]

## 2 Modification & Default Results

We begin by presenting evidence of the effect of the new law on existing contracts; namely on the performance of outstanding mortgages and then on modifications to restructure delinquent

[4]The limits start at 300,000 Euros for a single person, 350,000 Euros or a household and increases by 75,000 for each child. All individuals except merchants qualify. We looked (wishingly) for a discontinuity around the 250,000 euro value of a home, but we found nothing but smooth series.

[5]In Greece, similar to other European countries there is recourse on personal assets (but not on income streams). The foreclosure moratorium did not change the right of the lender of recourse on personal assets. Furthermore the new personal bankruptcy law (N.3869/2010) set a formal process for the borrowers to request protection under the bankruptcy law. The scope of the law is to mainly give protection to the dwellings of borrowers who were unable to fulfill their debt obligations, to complement the foreclosure law, while formalizing the process of setting up affordable repayment plans for lenders to enact recourse.

loans. Moral hazard in repayments arguments suggest that loan performance should deteriorate. Additionally, if the forelcosure moratorium increases moral hazard in repayments and if lenders think moral hazard increases when borrowers are near to default (resounding the risk shifting arguments in corporate finance), modifications should become more borrower friendly, and lenders should be more interested in modifying loans.

### 2.1 Loan Performance Findings

We acquired monthly data on the number of foreclosure auctions in greater Athens, representing about half of the population of Greece, from Lawnet, a major legal information service in Greece.[6] Unfortunately, these data are a mixture of business related auctions (auctionings of assets) and home auctions. We removed all items in this list which ended in the Greek equivalents of the words "company", "incorporated", "partners" and any other words that would suggest a business auction. Our remaining series is not fully cleaned of business records, however, in that many companies are identified in Greece without such markers, and Lawnet may not have recorded the full official name. Nevertheless, when we plot the counts of auctions (seasonally adjusted to remove holidays and summer vacations), the pattern is clear even with contamination.

Figure 1 shows that a dramatic and persistent drop in foreclosure counts occurred in May and June 2010. In particular, the pre-law average number of foreclosures was 396 per month. If we ignore the pre-law changes in May and June 2010, there were 415 foreclosures per month. After the law, this figure drops to 294, a decline of 121 per month, or 2,904 annually for all of Greece .Compared to the 3.75 million Greek households, of which 80 percent are homeowners, the count is only a 0.001 percentage point decrease in homeowners facing foreclosure. Another way to view this decline is relative to the number of home transactions occuring. In 2009, approximately 8,000 residential real estate transactions occurred (Bank of Greece). If one considers that the majority of homes at risk of foreclosure (those with low home equity) are homes bought within the prior 5 years, 40,000 homes may have been at risk. Of this, the decline in foreclosure risk is substantial (2,904/40,000 = 7.3%).

Next we look at the defaults of outstanding mortgages. We define a loan as becoming default if it becomes 90 days delinquent. Once a loan enters default it drops from further contributing to the

[6] LawNet is a law practice portal providing information on laws and legal transactions supporting legal research, due diligence, litigation and conveyancing. It is the authoritative source of legal information, with data directly provided by primary and secondary sources of law in Greece.http://www.lawnet.gr/yphresies.html.

estimation. We run a hazard rate estimation to represent the default hazard risk once removing the aging of the loan and time effects. The specification is the dynamic probit model of Shumway (1998) and Gross and Souleles (2002), which includes monthly time dummies to remove economic conditions and the 5th order polynomial in the aging of the loan maturity[7]:

$$Probit\left(default_{it}\right) = \sum_{t=2006qtr1}^{2011qtr4} \delta_t + \sum_{s=1}^{5} b_s \left(Aging_{it}\right)^{\wedge s} + \eta_{it}. \tag{1}$$

Table 2 columns 1 and 3 reports these result for home loans and car loans under this specification, estimating the time effects quarterly. The results are perhaps easier to visualize in figures; therefore Figures 2a and 2b plot these column results. Indeed in both cars and home, delinquency hazard rates are increasing over time. In home loans, however, we observe a discrete jump in default probability in the second quarter of 2010 which is the quarter the foreclosure moratorium was announced. Furthermore the default hazard probability for home loans stays at these higher levels for the remaining period.

In particular, we can loosen the specification above to include a polynomial in time rather than quarterly dummies, thus allowing us to include the post-law indicator. The indicator PostLaw in column 2 of Table 2 shows that the monthly default rate for home loans increased my 0.093 percentage points, which translates to an increase of 1.12 percentage points in the annual probability of default. This is a 30% increase in the probability of default for home loans relative to the pre-law period which had an annual probability of default of 3.7%. The cars had similar annual probability of default with home loans in the pre-law (3.6%), and the default pattern was increasing. However, the PostLaw indicator is insignificant; no post-law effect is discernible over and above the time pattern of increasing defaults, presumably due to the macroeconomy.

## 2.2 Modifications Findings

Thus far we have provided evidence that moral hazard in repayments seems to be at work. The theories that individuals can strategically choose to repay is evidenced by the fact that the introduction of the law reduced loan repayments by 30% in homes. As we motivated in the introduction, one of our main objectives is use our experiment to test the importance of the credible threat of foreclosure on modifications. In particular, it remains a puzzle why lenders do not modify more

[7]Shumway (1998) shows that this discrete duration model is equivalent to standard hazard rate functions. We implement this form for simplicity in conveying results.

loans, even with government monetary incentives, when borrowers have incentives to default. The prior literature has explored various channels that could explain the low levels of loan modifications, such as asymmetric information, securitization and servicer organization design (Piskorski, Seru and Vig,2010, Agarwal. et.al, 2011, Adelino, Gerardi and Willen, 2013, Agarwal et.al, 2013), but the magnitude of the non-modification puzzle remains largely unexplained.

We provide a new channel that can also impact renegotiations, the lender's credible threat of foreclosure. The concern for long-run reputation effects may induce the creditor not to renegotiate if this is optimal ex-ante, even though it might be suboptimal ex-post (Bester, 1994). Such a mechanism would be consistent with understanding Piskorski et al's finding that a set of large lender seem just never to modify, even under the HAMP program. This finding is also consistent with the re-default ideas in Adelino, Gerardi and Willen (2013), a point we explore later.

Figure 3 plots the ratio of mortgage restructurings to loans in default. We define a loan as *in default* if it is in the stock of delinquent accounts from 90 to 270 days past due. The plot shows a large jump in mortgage restructurings after the period the foreclosure moratorium was discussed and enacted. Mortgage restructurings were very stable and low before at less than 2% of delinquent loans. After the foreclosure moratorium more than 15% of delinquent loans are restructured. The graph provides clear evidence that taking away the lender's threat of foreclosure has a significant impact on inducing the lenders to modify.

A second point to explore is the terms of modification. As the moratorium changes the bargaining power in favor of the borrower, we should expect to see these modifications to lower the monthly payments for the lenders. Figure 4 plots the rate changes in restructurings from 2005-to 2012, while Figure 5 plots the changes in duration in restructurings. Before the debt moratorium, the duration extension was quite large, fluctuating around 10 years (120 months). The interest rate, however, did not change materially. It was seemingly a pretty good deal for borrowers.

After June 2010, modified loans began to have a drift up in the duration extension. Interest rates of modified loans actually decline. The average reduction was more than 16% of the old rate. The pattern suggests that the lender decided eventually to not give rate reductions, but rather to offer borrowers much longer extensions at the same rate. In any case, these results strongly support the idea that negotiation power shifted to the borrower. Thus the debt moratorium led not only to massively more modifications, but also on modifications that were more favorable to the borrowers. [8] The findings suggest that lenders dearly value the credible threat of foreclosure in preventing

[8] A point of concern might be that modifications are just repackaging of delinquent loans to re-age the risk for

repayment moral hazard, and that, perversely, the credible threat of foreclosure is an important consideration that inhibits lenders to renegotiate.

### 2.3 Re-Default Findings

Finally, we explore whether the modified loans redefault. Adelino, Gerardi, and Willen (2013) shows that in the U.S. market, borrowers may re-default, i.e., get into arrears again after a loan gets modified. Figure 6 plots the predicted monthly default probability of modified home loans averaged by quarter. As in the previous section, the default hazard is estimated using a dynamic probit model of default (Gross and Souleles, 2002). Consistent with the prior evidence from U.S., we observe that the modified loans have a more than 40% probability of re-default. One caveat is that our data end in the third of 2012, thus we can only observe a short period after the modifications.

## 3 Originations Methodology

The loss of the threat of foreclose has important implications to originations. Because borrowers are not exposed to recourse on their home equity, a lender would expect default rates to increase (as we have seen), as more moral hazard enters repayment behavior. We begin by laying out hurdle-rate, NPV calculations to set up our counterfactual of car loans for estimating the supply price reaction. What we are going to find, however, is that interest rate effects are modest, and quantity effects are massive. Thus, we then turn to the rationing literature started by Jaffee and Russell (1976) and Stiglitz and Weiss (1981), and in particular, Bester (1985) and Besanko and Thakor (1987), to understand the dimensions of rationing and to offer empirical insights on the role of collateral.

### 3.1 Pricing Methodology

In 2010 Greece, the supply of loans was contracting for reasons unrelated to the moratorium. In particular, as the bonds crisis spread, the solvency of Greek banks came into question, and the international interbank market for Greek banks closed. Captial requirements became generally binding for Greek financial institutions, and both capital and cash were in short supply. Greek banks reduced lending, which would have been accomplished by banks' increasing in the hurdle

bank capital requirement purposes. Our results that durations are extended and rates sometimes lowered suggest otherwise.

rate deemed acceptable for a prospective loan to approved, across all loan products.

A second macro economic reality in 2010 Greece was that Greek households' permanent income was declining, and income risk was increasing as the recession grew more severe. Thus, default and expected default were increasing.

To address these concerns, we use the change in the provision of collateralized car loans as a counterfactual for changes in supply of home loans had the law change not occurred. Conceptually, car loans make a reasonable candidate counterfactual: the collateralization aspect of cars loans in Greece is active with repossessions being frequently enforced. In addition, the liquidation depreciation of collateral value is about the same in cars as home loans (a -30% of value relative to user value).[9]

To be more explicit in our assumptions, we start by setting up the NPV calculation of a lender deciding on acceptable loan terms. Consider a borrower taking out a €1 loan today. The lender charges interest rate $i$ for $T$ periods and receives the annuity formula cash flow each period:

$$C = \frac{i}{\left(1 - \frac{1}{(1+i)^T}\right)}.$$

If the borrower can default on the payment each period with probability $p$ and if the lender discounts payments with a hurdle rate $r$, then the lender's net present value ($NPV$) is:

$$\begin{aligned} NPV &= \sum_{t=1}^{T} \frac{E\left[C_i\right]}{(1+r)^t} - 1 \\ &= \sum_{t=1}^{T} \frac{C(1-p)^t}{(1+r)^t} - 1. \end{aligned} \tag{2}$$

Applying the series rule and assuming the lender in a competitive market adjusts the interest rate $i$ such that $NPV = 0$, we have:

$$\frac{i(1-p)(1+i)^T}{((1+i)^T - 1)(p+r)} = 1. \tag{3}$$

In 2010, both default and hurdle rates were increasing in Greece with the macroeconomic conditions. This simple frame establishes how the bank would increase interest rates to reflect $dp$ (the change in the default probability) and $dr$ (the change in the hurdle rate). If we could solve equation (3) for $i = f(r, p; T)$, we would be interested in the total differentiation:

$$di = \frac{\partial f}{\partial r} dr + \frac{\partial f}{\partial p} dp \tag{4}$$

[9] Citations

We accomplish this by applying the Implicit Function Theorem to equation (3), to establish how the interest rate moves to incorporate changing macroeconomic conditions $(dr, dp)$.

$$\begin{aligned} di &= \frac{(p+r)\left((1+i)^T - 1 + i\left((1+i)^T - (1+T)\right)\right)}{i(1+i)[(1+i)^T - 1]} dr \\ &+ \frac{(p-1)(p+r)\left(-1 + (1+i)^T + i\left(-1(1+i)^T - T\right)\right)}{i(1+i)[(1+i)^T - 1](1+r)} dp. \end{aligned} \tag{5}$$

This simple derivation sets up the mean independence assumption, that the change in hurdle rate estimate in car loans applies to all loan products in the bank. Had there not been an increase in default probability in home loans caused by the law change, the interest rate in home loans would simply react to the hurdle rate change and the slight deterioration in default seen in the car loan market. To implement this, note that we observe the loan term parameters and ex ante default parameter $(i, T, p)$. We can impose and ex ante discount rate $r$; we assume $r = 0.10$, a standard corporate finance hurdle rate. Thus, if we had estimates of $\widehat{dp_{car}}$ and $\widehat{di}_{car}$, we can just calculate $\widehat{dr}_{car}$ using equation (5).

In the prior section, we estimated the change in the default rate for cars $dp_{car}$, an almost negligible, $\widehat{dp_{car}} = 0.0002$.We now estimate $di_{car}$ by setting up a matched differenced specification, whereby we ask what the change in interest rate is for the same profile of household.

In particular, we follow Einav, Jenkins, and Levin (2012) by matching applicants on two dimensions, household income and risk. We construct a 5 X 5 profiling of applicants, placing individuals in one of 25 cells, capturing quintiles of income crossed with quintiles of risk. To form the cells, we apply income and risk thresholds from the pre-law home loan applications to use a consistent weighting for all samples in the paper, pre- and post-law. We implement the matching by weighting the observations to line up with the pre-period sample in credit risk and income. Our matched difference estimate for cars is $\widehat{di}_{car} = \widehat{\mu}_{post}^{price\ effect}$, from the weighted estimating equation:

$$i_{car} = \mu_{car,post}^{price\ effect} + \alpha_{car,1} Risk + \alpha_{car,2} Income + \varepsilon. \tag{6}$$

In estimation, we condition on income and risk (linearly or non-parametrically) as well as weight the samples to match the 25 cells.

We then calculate $\widehat{dr}_{car}$ and $\widehat{di}_{home,counterfactual}$ from the estimates of $\widehat{dp_{car}}$ and $\widehat{di}_{car}$ using equation (5) and home loan terms observables. To be conservative, we can also set $dp_{car} = 0$, to force all the counterfactual interest rate change onto the hurdle rate.

To compare this counterfactual, we estimate the interest rate change in the matched framework for home loans:

$$i_{home} = \mu_{home,post}^{price\ effect} + \alpha_{home,1} Risk + \alpha_{home,2} Income + \varepsilon. \tag{7}$$

We take the matched difference estimate $\widehat{di}_{car} = \widehat{\mu}_{home,post}^{price\ effect}$ and compare:

$$\widehat{ddi}_{home}^{LawChange} = \widehat{di}_{car} - \widehat{di}_{home,counterfactual}.$$

In the results section, we show each of the pieces to not get lost in added complexities of hurdle rate versus raw interest rate comparison.

### 3.2 Rationing Methodology

As we learned in summary statistics, the lender does not adjust rates fully to price the added risk in originations; rather we see very large quantity supply effects. We can use this experiment to understand the extent to which rationing evolves in the way classic theories suggest and to speak to the role collateral plays ex ante by mitigating ex post moral hazard.

To make a counterfactual assumption, we apply a reduced form version of our prior arguments. Specifically, we assume that once we condition on the credit risk and income profiles of the borrowers, the change in acceptance probability in car loans would have approximated the change in acceptance probability of home loans had the foreclosure moratorium not been implemented. A few immediate points are important. First, the pre-period acceptance probabilities are almost identical in the two products, which is why we can compare levels-to-levels. Second, this assumption ignores the pricing effect we just estimated, but this should be conservative in that as the price of home loans goes up relative to that of car loans, fewer households complete a home loan application. (A technical note is that an applicant is generally given an idea of the rate to expect before the home loan application is completed.)

This second point segways into a third broader point: our demand estimation for home loans is likely to be understated. To the extent that Greek households knew the bank was contracting home loan supply because of the law, many would be discouraged from applying. (The process of picking a home and apply for a mortgage is costly.) Again, demand underestimation is going to bias down the size of rationing. Because we think this demand underestimation might be large, we will implement a consumption-based method later to show the potential magnitude of the underestimation.

Rationing entails two pieces: (i) how many applicants are rationed altogether, and (ii) how much rationing of house size occurs for those successful in taking out a home loan. These pieces

are econometrically endogenous in the sense that both the loan size for approved loans and the threshold for approval are potentially a function of the income and risk of the loan applicant. We are primarily interested in (i), so we begin with a simple probit model measuring the change in approval probability after the law, conditioned on risk and income and weighted so that the samples pre and post-law have the same distribution in the 5X5 cells of risk and income:

$$Probit(Approve_k) = \gamma_{k,1}Risk + \gamma_{k,2}Income + \mu^A_{k,,post} + \varepsilon^A_k, \text{ for } k = \{home, car\} \tag{8}$$

The unit of observation is an applicant, pooled across the pre- and post-periods. We suppress the applicant index. $k$ indexes whether the observation is a home or car loan applicant. Risk and income can enter as continuous variables or in nonparametric form to absorb more variation. We estimate home loans separately from car loans to absorb specific sensitivities between acceptance and risk or income. We also will incorporate requested amounts and durations for robustness. Our main focus is on the post-law period effect, $\mu^A_{k,post}$. In this simple form, we just compare: $\mu^A_{home,post} - \mu^A_{car,post}$.

A better model is the Heckman selection model to incorporate approval probabilities and the size of the loan given approval. A latent loan size, $L^*$, equation could be written:

$$L^* = \beta_0 REQUEST + \beta_{k,1}Risk + \beta_{k,2}Income + \mu^L_{k,post} + \varepsilon^L_k. \tag{9}$$

Latent loan size is a function of requested loan amount, income, and credit risk. Observed loan size $L$ equals latent loan size if the bank approves the loan:

$$L = \begin{cases} L^* \; if \; Approve = 1 \\ 0 \; if \; Approve = 0 \end{cases}. \tag{10}$$

Under bivariate normality, Heckman shows that one can think of the problem as estimating a probit of the *Approve* equation and then inserting an additional term, the non-approval hazard rate, into the loan size estimation.[10]

$$\begin{aligned} Probit(Approve) &= \gamma_{k,0}REQUEST + \gamma_{k,1}Risk + \gamma_{k,2}Income + \mu^A_{k,,post} + \varepsilon^A_k \\ L &= \beta_{k,0}REQUEST + \beta_{k,1}Risk + \beta_{k,2}Income + \mu^L_{k,post} + Non\text{-}ApprovalHazard + \varepsilon^L_k. \end{aligned} \tag{11}$$

Under our assumption that if two people show up for a car and home loan with the same risk profile, the proportion of loans rejected and the shrinking of the loan conditional on acceptance

[10] The non-approval hazard rate (the inverse Mills rate in Heckman's terminology) is $\frac{\phi(\cdot)}{\Phi(\cdot)}$, with $\phi(\cdot)$ denoting the standard normal density and $\Phi(\cdot)$ denoting the cumulative density.

would evolve in proportion to that in the car market if the law had not changed, the rationing difference estimators are:

$$\triangle\triangle \textit{ Acceptance Rationing} = \mu^{A}_{car,post} - \mu^{A}_{home,post} \tag{12}$$

$$\triangle\triangle \textit{ Loan Size Rationing} = \frac{\mu^{L}_{car,post}}{\overline{L}^{car}} - \frac{\mu^{L}_{home,post}}{\overline{L}^{home}}. \tag{13}$$

### 3.3 Adjusted Methodology: Engel Transmission from Car Consumption

The results from the prior methodology may be quite conservative due to demand underestimation. In this section, we put forth a method to estimate home loan demand directly. The method itself makes more assumptions. Our goal is not to prove the estimates in this section hold water under all storms of inquiry, but to put forth a second set of estimates for comparison and to understand just how conservative our main method might be. Our idea is to use car consumption as a way to isolate the permanent income shock to those showing up to make a durable consumption purchase.

Imagine that we had a dataset of all individuals, what car they hold ,and when they purchase a new car. Economists measure durable consumption with rental equivalences. In the case of cars, the depreciation on the car value is a good approximation. The standard rule (Kelly Blue Book) is that a car depreciates about 15% of beginning year value each year. (It is a declining balance depreciation in accounting terms.) We have a pretty good approximation of this. For a sufficient number of zip codes, we have a large enough number of applications for car loans within the zip code to form a panel of zip code representative agents.

Our implementation is as follows. We take all successful applications for cars for 2004-2009 and assume that represents a pool of individuals indicative of the zip code population. A few points to note are, first, that on average a Greek zip code has only 4000 households in it, compared to 20,000 in the United States, so the demographic will be more precise. Second, a car loan is typically 5 years. Third, a caveat is that we do not observe those who buy in cash (the rich) or who do not have a car, have a old car, or who buy on the low-end used car market (a poorer demographic on average).

With these notes in mind, we implement the Kelly Blue Book type measurement of car consumption as the average consumption of car value for this pool in 2009. In other words, we roll the people forward who bought cars post-2004. What we capture is along two dimensions: the mass of people buying cars in each year and the expense of the car they are buying.[11] We do the

[11] Implicitly, we are making the assumption, which is fine for Greece that the households do not move in and out

same for 2010 and 2011, rolling our start year forward one year. Of course, there is a bias in who shows up for a loan. But our idea is that this bias should be consistently applied in a zip code over time, except for capturing the permanent income demand shift in durables. Thus, the zip code difference in 2009 versus 2011 would represent the change in lumpy durable demand changes to car consumption.

Car consumption is not housing consumption. We can use an empirical Engel curve mapping to impose shifts in demand for cars on shifts in demand for housing. Figure 4 shows traditional Engel curves, plotting consumption *budget shares* on income for cars (panel A) and housing (panel B). We construct these pictures from the Consumer Expenditure Survey of the United States. Fortunately, the curvature of Engel curves across different goods has been found to look fairly similar across countries, only differing on the scale of income.

The budget share comparison of these figures allows us to mechanically translate the change in durable car consumption to the change in housing consumption for a zip code agent. We do this differing by income. Recall that we are working with representative zip code residents. Using data from the tax authority, we know the average household income for each of the 1457 zip codes in 2009. We thus assign a zip code to a point on the income distribution line.[12] Finally, we make the calculation of demand contraction in the post period using the car contraction and the deciles in the housing and car engel curve budget shares. We will use the percentage change by zip code to adjust the amount requested in 2009 to an estimated requested amount for 2011 using the engel transmission estimation.

# 4 Origination Results

## 4.1 Price Effects

Before running the price effect estimations, we make three adjustments to the interest rate data. First, we adjust all interest rates to be spread over euribor to be comparable over time. Second, we adjust fixed rates to a comparable float rate to pool the data, by adding in the premium changed (average in the month of application) for securing a fixed rate mortgage rather than a floating one. The majority of the sample are floating-rate mortgages. Finally, we adjust 20 and 40 year

of zip codes much. The population is stable.

[12] We assume that 10% of the tails of the income are censored due to using zip code averages rather than people. This is empirically supported (forthocming).

mortgages to be expressed in interest rates comparable to 30 year mortgages by subtracting out the discount or premium from the longer or shorter period, relevant at each month.

Table 4, column 1 reports a simple matched difference specification. Home interest rates increase by 119 basis points. In that specification, we weighted to match risk and income characteristics in the 5 X 5 cells pre-law. In columns 2-4, we add income and credit risk to the equation, linearly and then in quintiles and absorbing the full 25 buckets. The post law effect becomes marginally larger, up to 127 basis points. Columns 5 and 6 break this effect into floating and fixed rate effects. We find that the majority of the effect (about 100 basis points) comes from the floating market. Although we cannot reveal the counts of our data, what we see is that the bank adjusted rates in the float market and volume, which was predominantly in the float market ex ante, moved to a more balanced mix of float and fixed rate loans.

Columns 7 to 10 repeat the exercise for the car loan market. We find that care loan rates increased by only 16 basis points, at most, once controlling for risk income, and 6.7 basis points with no controls..

At the bottom of Table 4, we translate the car loan effect in rates into a home loan counterfactual, with the hurdle rate assumption made earlier in the text to incorporate the differing default and maturity structure of the car versus home loan market. The inputted parameters are that the car loan and home loan have, respectively, maturities of 5 and 30 years, with pre-period annual default of 3.6% and 3.7%, and pre-period rates of 6.9 + euribor and 2.48 + euribor. We impose a pre-period hurdle rate 0.10, a conventional rate.

Using equation (5), we can solve for the change in hurdle rate implied by the car loan estimate on post-law and then for the counterfactual estimate of home loan rates. These calculations are given in the last two rows of the table. Our counterfactual exercise suggests that of the 119-127 basis points of price increase post-law, the counterfactual accounts for a range of 34-82 points. Thus, under our hurdle rate assumption, the law caused the lender to increase the loan rates by 42-80 basis points. As a percent of the spread of 248 basis points over euribor, these might be substantive numbers. In our opinion, this increase in rates, although non-negligible, is quite moderate relative to the huge loss in collateral recourse the lender faced. The moderate effect in the internal margin suggests that the lenders might be adjusting on the external margin, which we investigate in the next section.

### 4.2 Rationing Effects

Table 5 presents the supply quantity effect of the law. One might posit that without foreclosure, one might expect complete market failure, as in Stiglitz-Weiss (1981). However, reasons exist why the market might not collapse. First, individuals still made downpayments on the mortgage, which would be at risk. Second recourse on other assets, including cosigner assets still existed. Third, relatedly, just because lenders could not seize assets would not render the borrower free of the obligation. In Greece, one market existed and until the loan was paid, the borrower would be blacklisted from other borrowing. Strategically defaulting may be appealing in the short term, but long-term consequences implied that normality would only come with repayment. Fourth, although the law was deemed to be "indefinite", indefinite would not imply forever. The bank would eventually have recourse on the loan. Fifth, political pressure might encourage the bank to continue lending. And finally, the lender itself need some liquidity in the mortgage market.

The first five columns of Table 5 estimate simple probits of loan acceptance, weighted to be a matched difference estimation, in the mortgage market. Loan acceptance pre-law (Table 2) was 0.635. Nearly two thirds of loans were accepted. Post-law, this figure drops by -0.318 to -0.377. Acceptances halve to a third of loans being accepted. The Heckman specification in column 7 finds a similar result. When controlling for requested amounts (demand), the Heckman specification finds that approval rate falls by -0.228. We conclude from this that loan supply rations a third to a half of demand. This is a large rationing. In terms of the loan size conditional on acceptance, we find that loan size conditional on acceptance declines by 5,511 euros (column 6 of Table 5). Approved loans are 78,257 euros smaller, even weighting the estimates to be matched in risk and income.

Table 6 presents the counterfactual car loan estimates akin to that in Table 5. We do not have requested amount data for approved loans that differs from approved amounts, so we run the parallel equations in Table 5 without requested amounts. We find that the approval rate drops by 0.08 to 0.09 in all specifications, including the Heckman. The baseline approval rate for cars was 0.79. Thus, as a percentage change, car loans only dropped 10 percent. Approved car loans are 2,092 euros smaller. Putting Tables 5 and 6 together, we see that the counterfactual does not come even close to the decline in loan supply for home loans.

Finally, we address the question of downward-biased demand. If the requested loans is not a good measure of demand in the post period because Greek households knew the bank was con-

tracting supply, *particularly for home loans,* many would be discouraged from applying.

As described in the methodology section, we offer robustness to the estimates in Table 5, by using an approach to estimate the decline in demand for housing consumption by car consumption of a representative agent in a zip code. We have 510 zip codes for which we can estimate the decline in monthly car payments. We turn this into a decline in demand in housing consumption by assigning zip codes (and their representative agent household) into income deciles that from the Greek tax authority. We use car consumption via the engel transmission to calculate a percentage change decline in housing consumption for each zip code.

Table 7 reports a first-pass at these estimation. We present a simple specification of the approved amount for a representative agent on requested amount. Column 1 reports that in the pre-period, 62.5 percent of requested loans were filled (this includes the rejected applications). Post-law change, the approved amounts declines by more than half (-34.1 percent), as we showed in the approval probits. When we replace the actual post-law requested amounts by the calculated requested amounts from the engel transmission, we find an almost identical answer. The same is true when we estimate approval rates (columns 5-8) rather than approval amounts.

# 5 Ex Ante Insights: The Role of Collateral

What defines households who are able to get loans in an environment in which foreclosure is not enforced? Insights in this line of thinking help us to understand the role that foreclosures are playing in the origination market.

We have seen that large-scale rationing occurs. We showed that price effect are moderate. In the modification section, we presented quite a bit of evidence that ex post moral hazard in repayments actually occurs and that lenders (or at least our lender) fears the erosion of the credibility of the foreclosure threat that mitigates strategic behavior on the part of the borrowers. If borrowers ex post had no incentive to pay, then the origination market would shut entirely. But recourse in our setting sets up a situation in which borrowers may act strategically when constrained or when they can get advantage vis-a-vis the lender, but have an incentive to pay eventually. Thus, we can try to say something more specific about what role collateral is actually serving ex ante.

Maybe it is worth pausing to think about the information stories starting from Jaffee and Russell (1976) and Stiglitz and Weiss (1981). In these models, a lender faces asymmetric information in knowing the good types from the bad and thus must price the loan at a rate that makes the loan

unattractive to good types. Market failure occurs. But, who are the *bad types* in household finance? Bad types are perhaps households whose current income is higher than permanent income or those with high expected income variance. Bester (1985) introduced collateral into this setting, offering the insight that when borrowers can signal their type with collateral choices, separation of types can eliminate market failure. Bad type borrowers identify themselves by selecting contracts that have lower collateral requirements and higher rates, while low-risk borrowers select contracts that have high collateral requirements and lower rates. If the foreclosure moratorium was partially unwinding Bester, we would have expected the interest rate to increase substantially, and the good types to fall out.

We showed that price increases are only quite moderate. Appendix Table 3 further shows that the price increase was uniform across risk and income quintiles. Moreover, Table 8 shows the after the moratorium, loans are given to higher income households. Those applying for loans ex post, in Table 2, also had higher income. Although the income sort does not imply that bad types drop out, these statistics suggest that lenders are very focused on ex post moral hazard. The lender wants good types ex post whose motive to act strategically in loan repayments when liquidity constrained is low. Higher interest rates may induce further moral hazard. If so, then lenders would want to keep rates low and ration away any borrowers and any loan contracts for which moral hazard in repayment may be large.

We find evidence suggestive along this line. Table 8 shows that loans originated after the moratorium are smaller, with higher loan-to-value ratios, and higher overall downpayments. Furthermore Table 9 shows that, with a very limited horizon, loan originated ex post have lower delinquency rates compared to 2009. To make this comparison, note that in aging (panel A), post law originated loans perform at least as well, generally. But post law loans are aging in worse economic conditions in Greece, which is transparent in the calendar time comparison in panel b.

Further work: Relationship sorts and Cosigners... Forthcoming:

Besanko and Thakor (1987) offer insights into what may mitigate information problems. First, when collateral is limited, the lender may use other metrics to sort high and low types into coarse risk classes. Within these buckets, rationing may still occur, but risk sorting with limited collateral helps complete the market. One mechanism to sort individuals may be relationships (e.g., Boot and Thakor (1994), Chakravarty and Scott (1999), Boot (2000)). Within a pool of borrowers, lenders may have a long-standing relationship with a borrower and be able to sort them out of the pool.

Agarwal, Chomsisengphet, Liu, and Souleles (2009) show that relationship customers have lower default rates. These borrowers may also may provide the lender with other income by way of other services.

The second additional insight of Besanko and Thakor is that the existence of a cosignor to increase the wealth endowment of low-risk types can eliminate the shortfall such that perfect sorting results. To the extent that rationing is imperfect, the lender may use other risk sorting measures to increase their ability to sort. Credit grade scoring, relationship strength, and cosignor wealth are three such metrics. We test these empirical predictions.

# 6 Conclusion

A natural experiment in Greece that halted foreclosures of homes allows us to study the effect both for new home loan originations as well as existing home loans repayment and modifications.

We first turn to originations. To address aggregate changes in the economy, we apply a difference-in-differences test using the loan supply of collateralized car loans as a counterfactual. We find that price effects are moderate. Lenders increase the interest rates by 42-80 basis points, adjusting to the heightened threat of strategic default. Rationing, however, is large, ranging from a third to half of the market and robust to alternative specification of demand. Second, looking into existing loans we find a more than 30% increase in probability of default after the foreclosure moratorium was enacted. Finally we document a steep jump in modification rates. The ratio of loan modifications go from less than 2% of the loans in default, to more than 15% after the moratorium. These modifications are favorable to the lenders as they offer not only higher duration but also lower rates.

More thoughts about implications to thinking in mortgage reform and to how the classic theories apply to households are forthcoming.

## 6.1 Appendix A: Risk Variable

For home loan applications, we observe the credit grade the application received. The credit grade is the bank's risk variable calculated automatically as the loan officer enters the application information into the IT system. The corporate office has a formula to grade the risk of the applicant, taking into account not only the applicant's demographics but also the requested loan amount. To

construct such a scoring, the bank periodically runs default models (discriminant analysis) to calibrate the sensitivity of default to demographics. The parameters of the credit grade remained stable throughout the period of analysis. Our car loan data does not include the credit grade risk variable. Thus, we construct it by backing into the loading on demographics and the loan-request to income variables. In particular, across households $i$ applying for primary homes, we regress:

$$\begin{aligned} \textit{credit grade}_i \quad = \quad & \alpha_1 Income_i + \alpha_2 Income_i^2 + \alpha_3 Age_i + \alpha_4 Age_i^2 + \alpha_5 Married_i + \alpha_6 Single_i \\ & + \alpha_7 Dependents_i + \alpha_8 Years\ in\ Job_i + \alpha_9 Homeowner_i + \\ & + \alpha_{10} LoanAmount + \alpha_{11} LoanDuration \\ & + Fixed\ Effects\ for\ Employer\ Type \text{ and } Occupation \\ & + Fixed\ Effects\ for\ Number\ of\ Applicants \text{ and } Branch\ Zipcode \end{aligned}$$

We use the year 2007 to do this estimation, prior to our period of study and the crisis in Greece. To make loan amount and loan duration comparable across different loan products, we first standardize these variables to a standard normal distribution. We estimate this equation and then take the $\alpha$ coefficients to calculate a new risk measure, $risk$, which is the projection on these coefficients for each of the applicants in the car and appliance applicant pool.

Panel A of Appendix Table 1 presents the socioeconomic statistics used in our risk profiling for primary home loans in 2007. The right hand side of Appendix Panel A reports the coefficients and standard errors for the regression above for primary homes. We achieve an R-Square of 0.395 in this regression. The correlation between $risk$ and the bank's original risk variable, *credit grade*, is 0.567.

Panel B of Appendix Table 1 reports the statistics for 2009-2011 used in our projection of the risk loading onto individuals applying for different loan products. The final row of the table presents the means and standard deviations of our projected $risk$ variable, and, for home loans, the original credit grade variable. The correlation in 2009-2011 remains nearly as high as it was in 2007.

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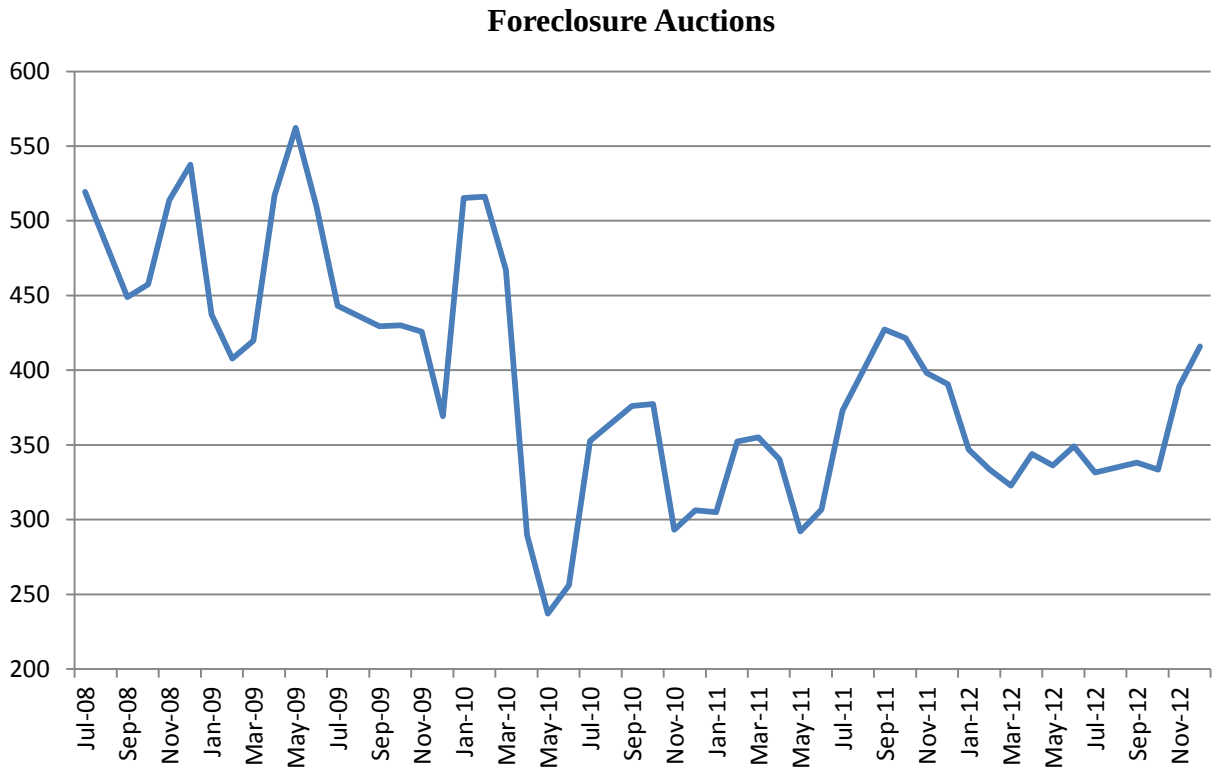


**Figure 1: Foreclosure Auctions**

This figure plots counts of foreclosures auctions in Greece the period July 2008 to November 2012. The data are seasonally adjusted to account for holidays and summer vacations. The data are acquired by Lawnet. The data Lawnet provided include a a mixture of business related auctions (auctionings of assets) and home auctions. We removed all items in this list which ended in the Greek equivalents of the words "company", "incorporated", "partners" and any other words that would suggest a business auction. Nevertheless, the remaining series is not fully cleaned of business records, however, in that many companies are identified in Greece without such markers or identified by the names of the owners, or Lawnet may not have recorded the full official name.

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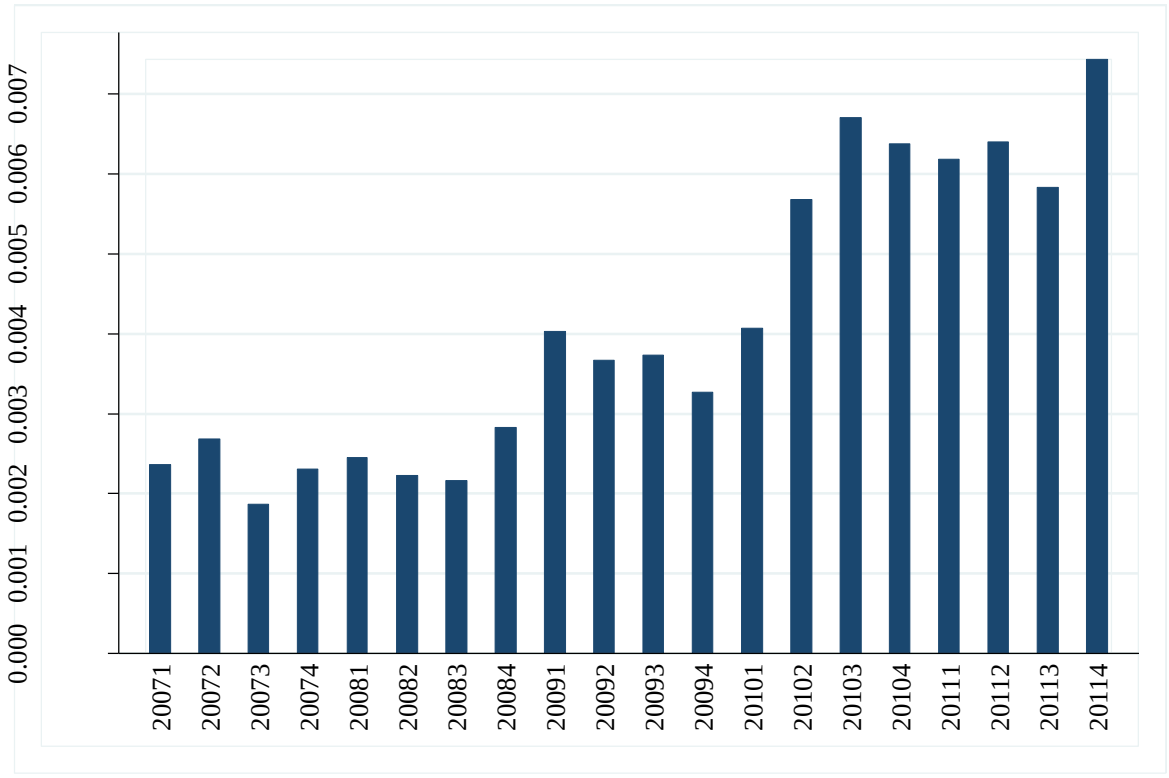


**Figure 2a: Predicted Default Probability for Home Loans**
This figure plots the predicted monthly default probability for home loans averaged by quarter. The default hazard is estimated using a dynamic probit model of default (Gross and Souleles, 2002).

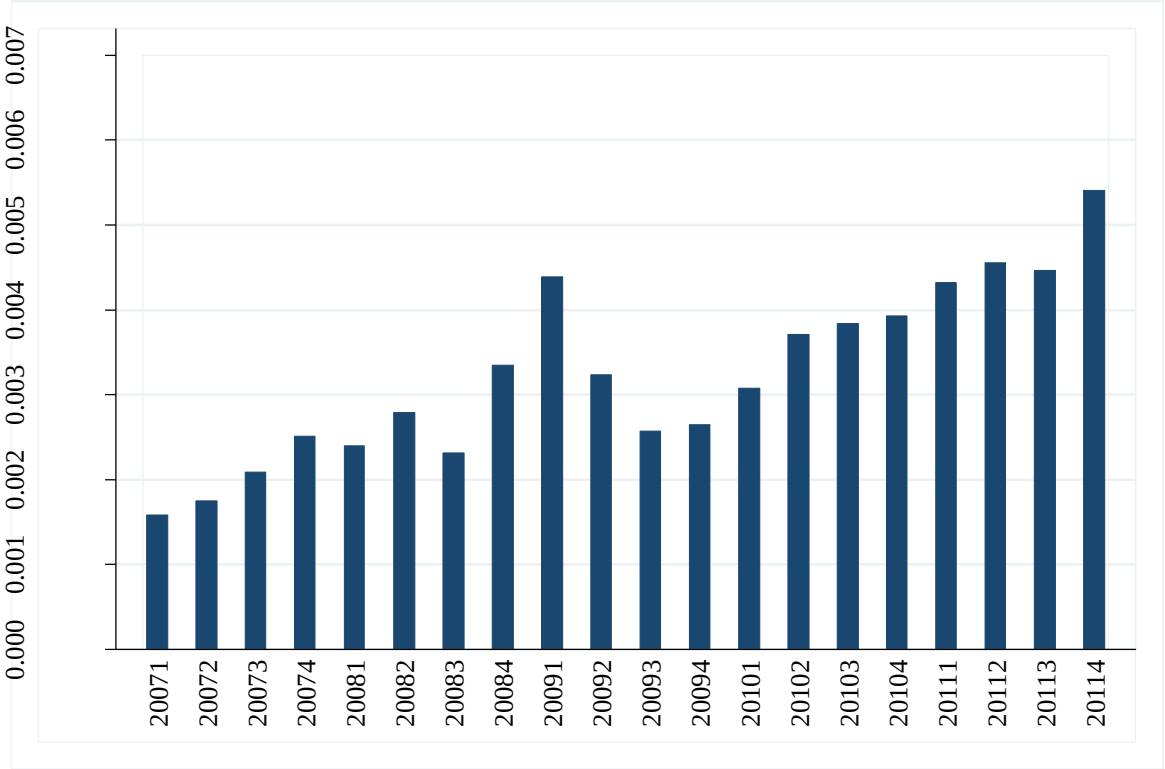


**Figure 2b: Predicted Default Probability for Car Loans**
This figure plots the predicted monthly default probability for home loans averaged by quarter. The default hazard is estimated using a dynamic probit model of default (Gross and Souleles, 2002).

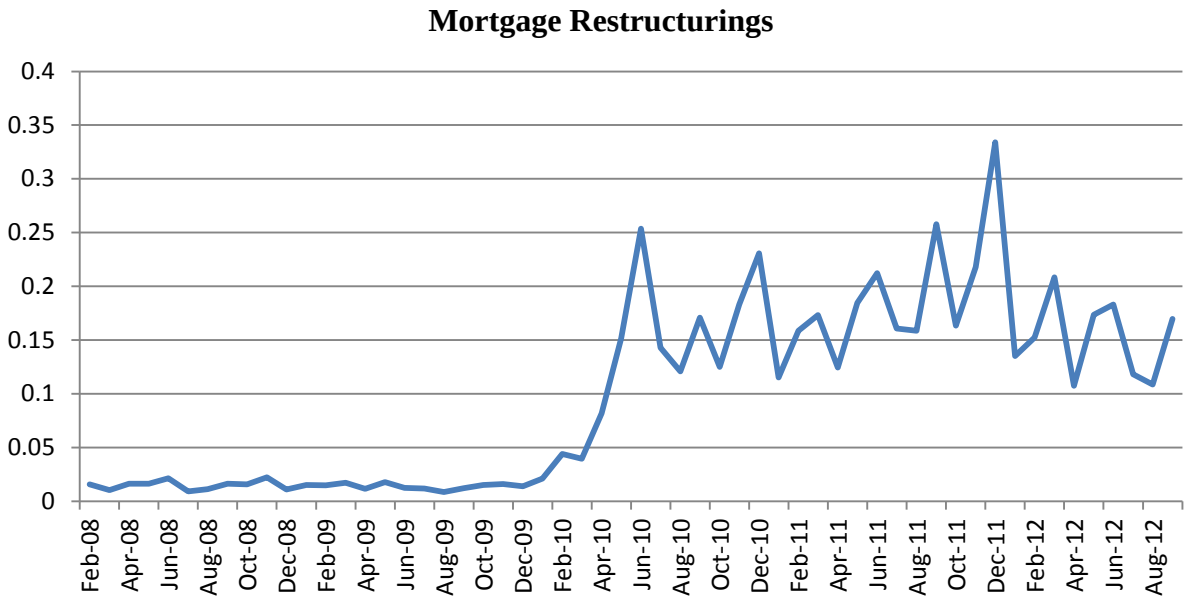


**Figure 3: Ratio of Mortgage Restructurings to Delinquent Mortgages**

The y-axis is the ratio of new mortgage restructurings to delinquent mortgages. Mortgage restructurings include mortgages that their duration or rate was modified. Delinquent mortgages are defined as the mortgages that are 90 to 270 days overdue.

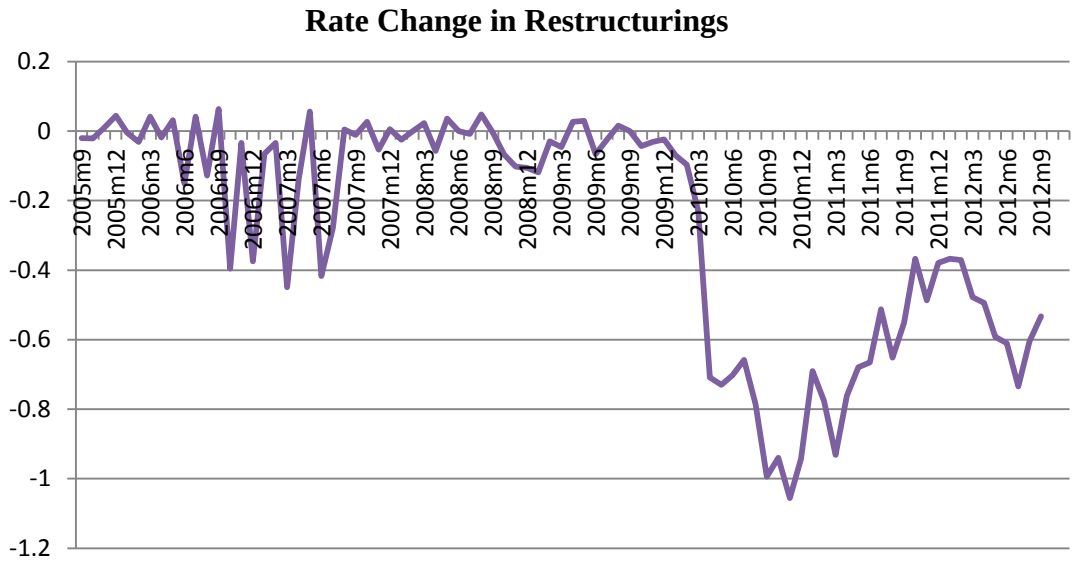


**Figure 4: Rate Change in Mortgage Restructurings**

The y-axis is the rate change in mortgage restructurings. The rate change is the difference between the new rate after the restructuring and the old rate before the restructuring. Mortgage restructurings include mortgages that their duration or rate was modified. The x-axis is the date of the restructuring.

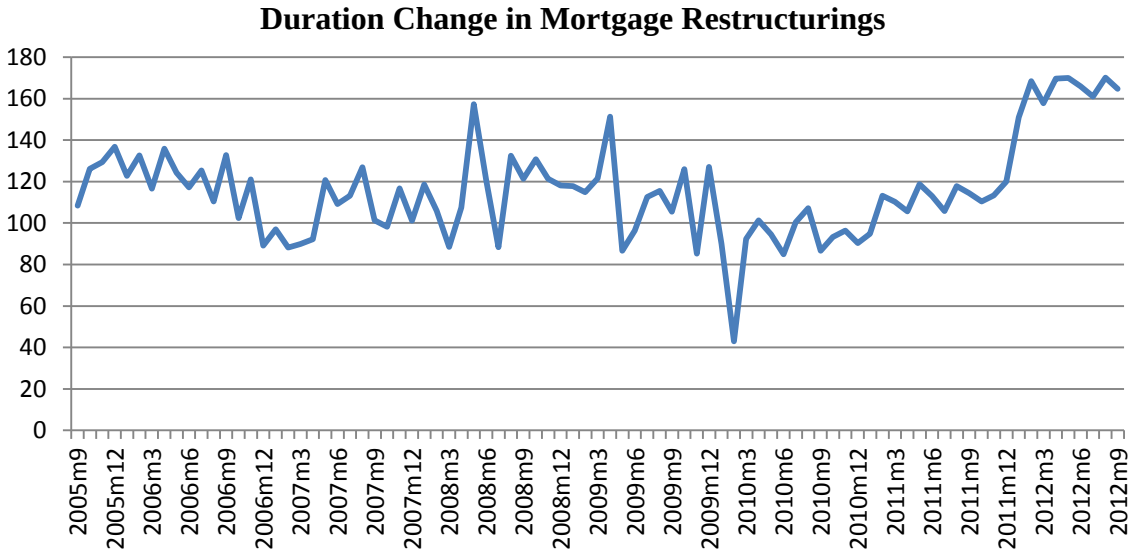


**Figure 5: Duration Change in Mortgage Restructurings**

The y-axis is the duration change in mortgage restructurings. The duration change is the difference between the new duration after the restructuring and the old duration before the restructuring. Mortgage restructurings include mortgages that their duration or rate was modified. The x-axis is the date of the restructuring.

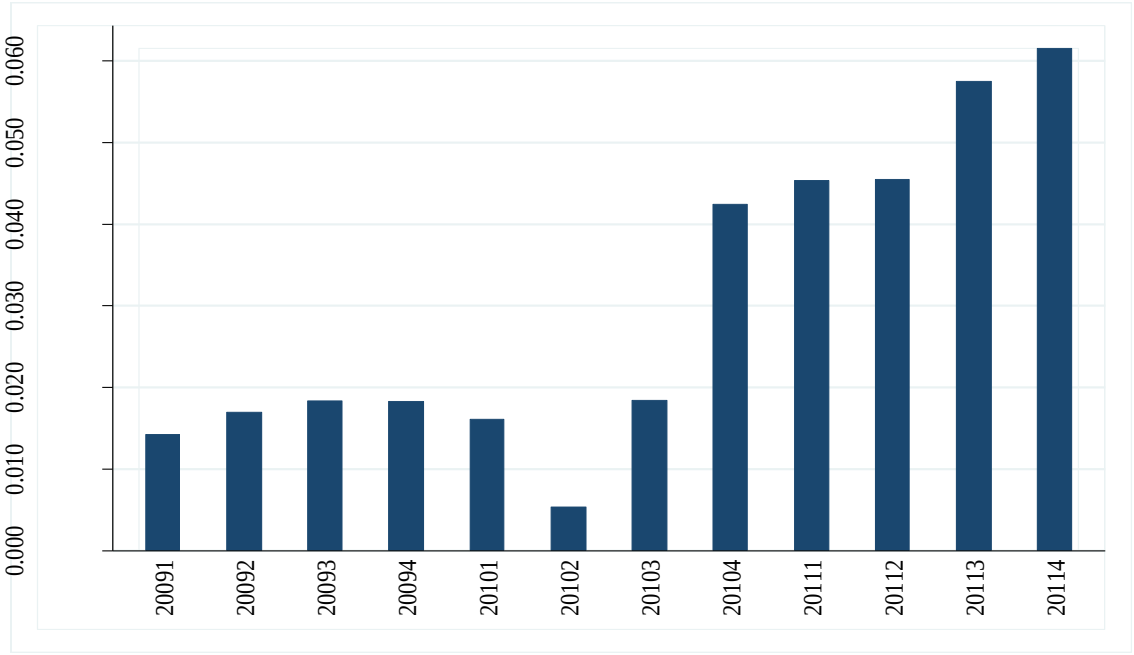


**Figure 6: Predicted Default Probability for Restructured Mortgages**
This figure plots the predicted monthly default probability for restructured home loans averaged by quarter. The default hazard is estimated using a dynamic probit model of default (Gross and Souleles, 2002).

**Table 1: Pre- and Post-Statistics of Risk, Acceptance, and Rate Spread**

Reported are the raw statistics (not after weighting to match income buckets) of household income, constructed risk, acceptance, and the interest rate spread over euribor by product and by period. An asterisk in the post period cell indicates that the difference is significant from the pre-period mean at the 5% confidence level.

Panel A: Pre-Law Period

| | Primary Homes | | Cars | |
|---|---|---|---|---|
| | Mean | StDev | Mean | StDev |
| HHIncome | 23,639 | 17,493 | 20,133 | 15,014 |
| Risk | 61.87 | 3.72 | 59.08 | 3.81 |
| Acceptance | 0.635 | 0.482 | 0.790 | 0.407 |
| Rate Spread | 2.26 | 0.83 | 6.99 | 2.40 |

Panel B: Post-Law Period

| | Primary Homes | | Cars | |
|---|---|---|---|---|
| | Mean | StDev | Mean | StDev |
| HHIncome | 26,031* | 18,600 | 21,889* | 16,958 |
| Risk | 62.52* | 3.62 | 59.14 | 3.84 |
| Acceptance | 0.301* | 0.447 | 0.711* | 0.453 |
| Rate Spread | 3.22* | 0.99 | 7.39* | 1.82 |

* Indicates a difference in means from the pre-period at the 5% confidence level or better.

**Table 2: Default Hazard for Home Loans and Car Loans**

The specification is a dynamic probit model (Gross and Souleles, 2002), which includes monthly time dummies to remove economic conditions and the 5th order polynomial in the aging of the loan maturity. Panel A presents the results for home loans, and Panel B for car loans. Columns 2 and 4 introduce the indicator Post-law for being after June 2010. Aging is a 5-th order polynomial of the loan account maturity. ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

| Panel A | **Homes** | | | | | | Panel B | **Cars** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | | | 2 | | | | 3 | | | 4 | |
| Aging | 0.00123 | (0.00003) | *** | 0.00123 | (0.000028) | *** | 0.00088 | (0.00006) | *** | 0.0008761 | (0.00006) | *** |
| Aging^2 | -0.00006 | (0.00000) | *** | -0.00006 | (0.000002) | *** | -0.00005 | (0.00000) | *** | -0.000049 | (0.00000) | *** |
| Aging^3 | 1.38E-06 | (0.00000) | *** | 1.38E-06 | (0.000000) | *** | 1.30E-06 | (0.00000) | *** | 1.29E-06 | (0.00000) | *** |
| Aging^4 | -1.38E-08 | (0.00000) | *** | -1.38E-08 | (0.000000) | *** | -1.57E-08 | (0.00000) | *** | -1.56E-08 | (0.00000) | *** |
| Aging^5 | 5.18E-11 | (0.00000) | *** | 5.19E-11 | (0.000000) | *** | 7.14E-11 | (0.00000) | *** | 7.10E-11 | (0.00000) | *** |
| Time | | | | 0.0009903 | (0.000114) | *** | | | | -0.00045 | (0.00046) | |
| Time^2 | | | | -0.00005 | (0.000005) | *** | | | | 0.00002 | (0.00002) | |
| Time^3 | | | | 1.12E-06 | (0.000000) | *** | | | | -3.48E-07 | (0.00000) | |
| Time^4 | | | | -1.03E-08 | (0.000000) | *** | | | | 2.18E-09 | (0.00000) | |
| Times^5 | | | | 3.49E-11 | (0.000000) | *** | | | | -4.12E-12 | (0.00000) | |
| PostLaw | | | | **0.00093** | (0.000091) | *** | | | | **0.000193** | (0.00020) | |
| 2005 qtr 2 | 0.00037 | -0.00015 | ** | | | | 0.00025 | (0.00102) | | | | |
| 2005 qtr 3 | 0.00204 | -0.00013 | *** | | | | -0.00010 | (0.00101) | | | | |
| 2005 qtr 4 | -0.00129 | -0.00016 | *** | | | | -0.00053 | (0.00101) | | | | |
| 2006 qtr 1 | -0.00116 | -0.00016 | *** | | | | 0.00118 | (0.00090) | | | | |
| 2006 qtr 2 | -0.00031 | -0.00016 | ** | | | | 0.00122 | (0.00089) | | | | |
| 2006 qtr 3 | 0.00039 | -0.00015 | *** | | | | 0.00109 | (0.00089) | | | | |
| 2006 qtr 4 | -0.00035 | -0.00016 | ** | | | | 0.00260 | (0.00084) | *** | | | |
| 2007 qtr 1 | -0.00049 | -0.00016 | *** | | | | 0.00245 | (0.00084) | *** | | | |
| 2007 qtr 2 | 0.00011 | -0.00015 | | | | | 0.00272 | (0.00083) | *** | | | |
| 2007 qtr 3 | -0.00123 | -0.00017 | *** | | | | 0.00326 | (0.00082) | *** | | | |
| 2007 qtr 4 | -0.00033 | -0.00015 | ** | | | | 0.00381 | (0.00081) | *** | | | |
| 2008 qtr 1 | -0.00008 | -0.00015 | | | | | 0.00367 | (0.00081) | *** | | | |
| 2008 qtr 2 | -0.00042 | -0.00015 | *** | | | | 0.00388 | (0.00080) | *** | | | |
| 2008 qtr 3 | -0.00051 | -0.00015 | *** | | | | 0.00352 | (0.00080) | *** | | | |
| 2008 qtr 4 | 0.00059 | -0.00014 | *** | | | | 0.00478 | (0.00079) | *** | | | |
| 2009 qtr 1 | 0.00201 | -0.00014 | *** | | | | 0.00565 | (0.00079) | *** | | | |
| 2009 qtr 2 | 0.00171 | -0.00014 | *** | | | | 0.00478 | (0.00079) | *** | | | |
| 2009 qtr 3 | 0.00188 | -0.00014 | *** | | | | 0.00417 | (0.00079) | *** | | | |
| 2009 qtr 4 | 0.00146 | -0.00014 | *** | | | | 0.00416 | (0.00079) | *** | | | |
| 2010 qtr 1 | 0.00241 | -0.00013 | *** | | | | 0.00450 | (0.00078) | *** | | | |
| **2010 qtr 2** | 0.00381 | -0.00013 | *** | | | | 0.00488 | (0.00078) | *** | | | |
| **2010 qtr 3** | 0.00454 | -0.00013 | *** | | | | 0.00480 | (0.00078) | *** | | | |
| **2010 qtr 4** | 0.00441 | -0.00013 | *** | | | | 0.00469 | (0.00078) | *** | | | |
| **2011 qtr 1** | 0.00439 | -0.00013 | *** | | | | 0.00485 | (0.00078) | *** | | | |
| **2011 qtr 2** | 0.00462 | -0.00013 | *** | | | | 0.00490 | (0.00078) | *** | | | |
| **2011 qtr 3** | 0.00434 | -0.00013 | *** | | | | 0.00477 | (0.00078) | *** | | | |
| **2011 qtr 4** | 0.00532 | -0.00013 | *** | | | | 0.00527 | (0.00078) | *** | | | |

**Table 4: Price Effects Estimation: Home and Car Loan Rates Around Law**

The dependent variable is the interest rate spread over euribor (in percentage points; i.e. 1%=1). The home loan rates (columns 1-6) are expressed in terms of floating 30 year mortgages. The car rates (columns 7-10) are all float and are expressed as 5-year loans. Post-law is a dummy for being after June 2010. The entire sample period is January 2009 to June 2011. Estimations are weighted least squares, weighted to the cross of the risk and income quintiles of applicants in the pre-law market. Robust standard errors are reported in parentheses. . ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The final row reports, for the car loan estimate columns, the counterfactual of home loan rates, as estimated by the change in car loan rates and tranformed into the home loan market through the hurdle rate formula given in the text.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Loan Market: | Homes | Homes | Homes | Homes | Homes | Homes | Cars | Cars | Cars | Cars |
| Rate Sample: | All with Spread Converted to Floating 30-Year Mortgage | | | | Fixed | Float | All with Spread Converted to 5-year Car Loan | | | |
| Post-Law | 1.187*** | 1.275*** | 1.247*** | 1.232*** | 0.114*** | 0.971*** | 0.0679** | 0.169*** | 0.163*** | 0.162*** |
| | [0.0329] | [0.0330] | [0.0329] | [0.0328] | [0.0403] | [0.0368] | [0.0345] | [0.0342] | [0.0343] | [0.0343] |
| Credit Risk Very Low | | | -- | | | | | | -- | |
| Credit Risk Low | | | -0.210*** | | | | | | 0.172*** | |
| | | | [0.0277] | | | | | | [0.0365] | |
| Credit Risk Middle | | | -0.357*** | | | | | | 0.105** | |
| | | | [0.0295] | | | | | | [0.0480] | |
| Credit Risk High | | | -0.659*** | | | | | | 0.0929* | |
| | | | [0.0292] | | | | | | [0.0513] | |
| Credit Risk Very High | | | -0.846*** | | | | | | -0.0403 | |
| | | | [0.0316] | | | | | | [0.0604] | |
| HHIncome Very Low | | | -- | | | | | | -- | |
| HHIncome Low | | | -0.190*** | | | | | | -0.323*** | |
| | | | [0.0304] | | | | | | [0.0396] | |
| HHIncome Middle | | | -0.0630** | | | | | | -0.699*** | |
| | | | [0.0310] | | | | | | [0.0396] | |
| HHIncome High | | | 0.0466 | | | | | | -0.829*** | |
| | | | [0.0314] | | | | | | [0.0425] | |
| HHIncome Very High | | | 0.384*** | | | | | | -0.908*** | |
| | | | [0.0326] | | | | | | [0.0480] | |
| Credit Risk | | -0.0104*** | | | | | | 0.0045*** | | |
| | | [0.00036] | | | | | | [0.00073] | | |
| HH Income | | 0.0050*** | | | | | | -0.0129*** | | |
| | | [0.00037] | | | | | | [0.00054] | | |
| Includes F.E. of 25 Income-Risk Buckets | | | | Yes | Yes | Yes | | | | Yes |
| R-squared | 0.083 | 0.129 | 0.139 | 0.145 | 0.056 | 0.241 | 0.001 | 0.017 | 0.018 | 0.018 |
| *Counterfactual Estimate: Translating Raw Rates from Cars to Home Loans* | | | | Hurdle (in percentage points): | | | 0.186 | 0.463 | 0.447 | 0.444 |
| | | | | Counterfactual Home Rate: | | | 0.342 | 0.849 | 0.819 | 0.814 |

**Table 5: Rationing Effects: Home Loans**

The dependent variable in columns 1-5 is home loan approval and estimations are probit. Columns 6 and 7 present Heckman estimations, in which the first column is the approval equation, and the second is the loan size condition on approval. Post-law is a dummy for being after June 2010. The entire sample period is January 2009 to June 2011. Estimations are weighted least squares, weighted to the cross of the risk and income quintiles of applicants in the pre-law market. Robust standard errors are reported in parentheses. . ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| Dependent Variable | (1) Probit | (2) Probit | (3) Probit | (4) Probit | (5) Probit | (6) Heckman | | (7) Heckman | |
|---|---|---|---|---|---|---|---|---|---|
| with Spread Converted to Float | | Approval | Approval | Approval | Fixed | Float | Loan Size | Approval | Loan Size |
| | *All Estimates Shown are Marginal Effects on the Probability of Approval or Loan Size* | | | | | | | | |
| Post-Law | -0.318*** | -0.383*** | -0.377*** | -0.377*** | -0.370*** | -0.228*** | 5,511*** | -0.351*** | -78,257*** |
| | [0.0064] | [0.0066] | [0.0063] | [0.0063] | [0.0064] | [0.0062] | [214.3] | [0.0061] | [1,538] |
| Credit Risk Very Low | | | -- | | | | | | |
| Credit Risk Low | | | 0.159*** | | | | | | |
| | | | [0.00743] | | | | | | |
| Credit Risk Middle | | | 0.217*** | | | | | | |
| | | | [0.00708] | | | | | | |
| Credit Risk High | | | 0.284*** | | | | | | |
| | | | [0.00665] | | | | | | |
| Credit Risk Very High | | | 0.341*** | | | | | | |
| | | | [0.00653] | | | | | | |
| HHIncome Very Low | | | -- | | | | | | |
| HHIncome Low | | | 0.0159* | | | | | | |
| | | | [0.00851] | | | | | | |
| HHIncome Middle | | | 0.0554*** | | | | | | |
| | | | [0.00843] | | | | | | |
| HHIncome High | | | 0.0612*** | | | | | | |
| | | | [0.00861] | | | | | | |
| HHIncome Very High | | | 0.0598*** | | | | | | |
| | | | [0.00913] | | | | | | |
| Credit Risk | | 0.0075*** | | | | -1.10e-06*** | -111.1*** | 0.0059*** | 1,089*** |
| | | [0.000167] | | | | [1.63e-07] | [4.232] | [0.00015] | [30.83] |
| HH Income | | 3.42E-10 | | | | 0.0047*** | 0.038*** | 2.60e-06*** | 0.790*** |
| | | [1.81e-07] | | | | [0.00015] | [0.0045] | [1.50e-07] | [0.0313] |
| Requested Amount | | | | | 3.58e-07*** | 8.82e-07*** | 0.970*** | | |
| | | | | | [5.30e-08] | [3.47e-08] | [0.0010] | | |
| Includes F.E. of 25 Income-Risk Buckets | | | | Yes | Yes | | | | |
| Pseudo R-Square | | | | | | | | | |

**Table 6: Rationing Effects: Car Loans**

The dependent variable in columns 1-3 is home loan approval and estimations are probit. Column 5 presents Heckman estimations, in which the first column is the approval equation, and the second is the loan size condition on approval. Post-law is a dummy for being after June 2010. The entire sample period is January 2009 to June 2011. Estimations are weighted least squares, weighted to the cross of the risk and income quintiles of applicants in the pre-law market. Robust standard errors are reported in parentheses. . ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | |
|---|---|---|---|---|---|---|
| | Probit | Probit | Probit | Probit | Heckman | |
| All with Spread Converted to Floatin | Approval | Approval | Approval | Approval | Fixed | Float |
| | *All Estimates Shown are Marginal Effects on the Probability of Approval or Loan Size* | | | | | |
| Post-Law | -0.0816*** | -0.0892*** | -0.0882*** | -0.0885*** | -0.0907*** | -2,092*** |
| | [0.00386] | [0.00404] | [0.00388] | [0.00388] | [0.00310] | [63.06] |
| Credit Risk Very Low | | | -- | | | |
| Credit Risk Low | | | 0.0254*** | | | |
| | | | [0.00342] | | | |
| Credit Risk Middle | | | 0.0385*** | | | |
| | | | [0.00411] | | | |
| Credit Risk High | | | 0.0527*** | | | |
| | | | [0.00498] | | | |
| Credit Risk Very High | | | 0.107*** | | | |
| | | | [0.00535] | | | |
| HHIncome Very Low | | | -- | | | |
| HHIncome Low | | | 0.0401*** | | | |
| | | | [0.00377] | | | |
| HHIncome Middle | | | 0.0541*** | | | |
| | | | [0.00380] | | | |
| HHIncome High | | | 0.0645*** | | | |
| | | | [0.00396] | | | |
| HHIncome Very High | | | 0.0598*** | | | |
| | | | [0.00455] | | | |
| Credit Risk | | 0.00163*** | | | 0.000618*** | -24.73*** |
| | | [9.93e-05] | | | [6.77e-05] | [1.432] |
| HH Income | | 1.46e-06*** | | | 2.77e-06*** | 0.114*** |
| | | [1.37e-07] | | | [8.15e-08] | [0.00182] |
| Includes F.E. of 25 Income-Risk Buckets | | | | Yes | | |
| Pseudo R-Square | | | | | | |

**Table 7: Home Loan Rationing using Engel-Adjusted Method for Demand**

The sample is representative agents for 510 zip codes, each with two observations, one before and one after the law. The dependent variable in columns 1-4 is the mean approved amount in the zip code. The dependent variable in columns 5-8 is the mean approval rate in the zip code. Requested amount is the actual zip code mean requested amount in the odd-number columns. In the even columns, the pre-period requested amount is actual and the post period is the actual pre-period requested amount times the engel decline in home consumption over the period. (See the text for description. Post-law is a dummy for being after June 2010. The entire sample period is January 2009 to June 2011. Robust standard errors are reported in parentheses. . ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent Variable | Approved Amount for Zip Code Agent | | | | Approval Rate within Zip Code | | | |
| Requested Definition: | rted to Float | Engel | Actual | Engel | Fixed | Float | Ln(Actual) | Ln(Engel) |
| Requested Amount | 0.625*** | 0.614*** | 0.622*** | 0.611*** | 0.0625*** | 0.0632*** | 0.0552** | 0.0563*** |
| | [0.0310] | [0.0292] | [0.0312] | [0.0291] | [0.0216] | [0.0205] | [0.0214] | [0.0201] |
| Requested Post-Law | -0.341*** | -0.304*** | -0.336*** | -0.298*** | -0.0289*** | -0.0284*** | -0.0286*** | -0.0281*** |
| | [0.0145] | [0.0182] | [0.0147] | [0.0183] | [0.000986] | [0.00115] | [0.00100] | [0.00116] |
| Credit Risk Very Low | | | -- | -- | | | -- | -- |
| Credit Risk Low | | | 2,161 | 2,196 | | | 0.0388*** | 0.0387*** |
| | | | [1,376] | [1,382] | | | [0.0145] | [0.0145] |
| Credit Risk Middle | | | 4,161*** | 4,351*** | | | 0.0461*** | 0.0461*** |
| | | | [1,433] | [1,432] | | | [0.0155] | [0.0155] |
| Credit Risk High | | | 5,180*** | 5,288*** | | | 0.0454*** | 0.0453*** |
| | | | [1,523] | [1,527] | | | [0.0154] | [0.0154] |
| Credit Risk Very High | | | 7,594*** | 7,754*** | | | 0.0872*** | 0.0874*** |
| | | | [1,693] | [1,707] | | | [0.0177] | [0.0177] |
| HHIncome Very Low | | | -- | -- | | | -- | -- |
| HHIncome Low | | | 4,040*** | 4,112*** | | | 0.0325** | 0.0323** |
| | | | [1,394] | [1,392] | | | [0.0149] | [0.0149] |
| HHIncome Middle | | | 3,064** | 3,024** | | | 0.0249 | 0.0244 |
| | | | [1,467] | [1,473] | | | [0.0161] | [0.0161] |
| HHIncome High | | | 4,433*** | 4,516*** | | | 0.0398** | 0.0393** |
| | | | [1,595] | [1,588] | | | [0.0170] | [0.0170] |
| HHIncome Very High | | | 2,976 | 2,968 | | | 0.0182 | 0.0171 |
| | | | [1,941] | [1,937] | | | [0.0191] | [0.0191] |
| Credit Risk | 380.2*** | 386.4*** | | | 0.00426*** | 0.00427*** | | |
| | [68.64] | [68.68] | | | [0.000688] | [0.000688] | | |
| HH Income | 0.133 | 0.133 | | | 2.20E-07 | 1.56E-07 | | |
| | [0.112] | [0.113] | | | [1.00e-06] | [1.00e-06] | | |
| Constant | -80,531*** | -80,708*** | -3,059 | -2,047 | -0.992*** | -1.001*** | -0.067 | -0.0796 |
| | [13,971] | [13,941] | [2,526] | [2,364] | [0.291] | [0.281] | [0.241] | [0.226] |
| Observations | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 |
| R-squared | 0.730 | 0.729 | 0.729 | 0.729 | 0.593 | 0.594 | 0.592 | 0.592 |

**Table 8: Which Households are Approved, Pre and Post Law**

The table presents the household income, home value, and loan-to-value of approved loans, pre and post law. Income and Home Value are in euros.

| | Mean | 25%ile | 50%ile | 75%ile |
|---|---|---|---|---|
| HH Income | | | | |
| Pre Law | 25,127 | 13,293 | 20,286 | 30,715 |
| Post Law | 29,837 | 15,448 | 24,235 | 37,650 |
| Home Value | | | | |
| Pre Law | 176,390 | 110,000 | 152,984 | 211,000 |
| Post Law | 165,116 | 100,000 | 146,000 | 203,390 |
| Loan-to-Value | | | | |
| Pre Law | 0.613 | 0.461 | 0.667 | 0.762 |
| Post Law | 0.541 | 0.370 | 0.552 | 0.714 |

## Table 9: Delinquency in Originations Pre and Post Law

Aging is the aging of account by month. Thus, the post-law aging accurs in a worse economic condition, as panel B shows. Delinquency is an indicator is the mortgage is over 90 days delinquent.

*Panel A*

| Aging | Pre-Law Delinquency | Post-Law Delinquency |
|---|---|---|
| 12 | | 0.0191 |
| 13 | | 0.0235 |
| 14 | | 0.0275 |
| 15 | | 0.0305 |
| 16 | | 0.0325 |
| 17 | | 0.0403 |
| 18 | | 0.0431 |
| 19 | | 0.0473 |
| 20 | | 0.0525 |
| 21 | 0.0632 | 0.0554 |
| 22 | 0.0802 | 0.0594 |
| 23 | 0.0837 | 0.0648 |
| 24 | 0.0885 | 0.0693 |
| 25 | 0.0956 | 0.0742 |
| 26 | 0.0943 | 0.0785 |
| 27 | 0.0986 | 0.0838 |
| 28 | 0.1002 | 0.0889 |
| 29 | 0.1043 | 0.0971 |
| 30 | 0.1053 | 0.1042 |
| 31 | 0.1085 | 0.1092 |
| 32 | 0.1123 | 0.1160 |
| 33 | 0.1184 | 0.1223 |
| 34 | 0.1219 | 0.1296 |
| 35 | 0.1317 | 0.1387 |
| 36 | 0.1422 | 0.1427 |

*Panel B*

| Time | Pre-Law Delinquency | Post-Law Delinquency |
|---|---|---|
| 201101 | 0.0886 | 0.0372 |
| 201102 | 0.0924 | 0.0386 |
| 201103 | 0.0936 | 0.0399 |
| 201104 | 0.0955 | 0.0421 |
| 201105 | 0.0990 | 0.0439 |
| 201106 | 0.0994 | 0.0440 |
| 201107 | 0.1012 | 0.0444 |
| 201108 | 0.1045 | 0.0474 |
| 201109 | 0.1046 | 0.0494 |
| 201110 | 0.1105 | 0.0544 |
| 201111 | 0.1163 | 0.0576 |
| 201112 | 0.1181 | 0.0592 |
| 201201 | 0.1283 | 0.0677 |
| 201202 | 0.1401 | 0.0735 |
| 201203 | 0.1480 | 0.0806 |
| 201204 | 0.1632 | 0.0908 |
| 201205 | 0.1666 | 0.0968 |
| 201206 | 0.1696 | 0.0984 |
| 201207 | 0.1751 | 0.1035 |
| 201208 | 0.1826 | 0.1075 |
| 201209 | 0.1876 | 0.1102 |

**Appnedix Table 1: Measuring Risk: Statistics and Estimates**

To construct the variable *risk*, we use the fact that we have an internal grade variable of the bank, but only for home loans. For the other loan products, we need to project risk onto the socio-economic variables used by the bank and take the loading projection. We use the year 2007 to construct the loading coefficients. Panel A presents the summary statisitcs for the 2007 primary home variables, excluding the fixed fixeds we include in the regression which are the number of applications, the employer type, occupation, and branch zip code. The right hand side of Panel A presents the projection estimation. Panel B reports the statistics for the projection variables and the calculated risk variable for each products for 2009. FOr the requested duration and requested amount, the projection is done on standardized versions of the variable to make it comparable. For the home products, Panel B also reports the correlation of the constructed risk variable with the actual risk variable, *internal grade.*

Panel A: 2007 Primary Home Statistics & Regression for Constructing Risk Projection

| | Primary Homes 2007 | | Dependant Variable: Internal Grade | |
|---|---|---|---|---|
| All with Spread Converted to Floa | | StDev | Fixed | Float |
| HHIncome | 22,960 | 16,848 | 0.775*** | (0.0266) |
| HHIncome^2 | | | -4.758*** | (0.2517) |
| Requested Duration (Months) | 281.8 | 113.0 | -9.425*** | (0.1877) |
| Requested Amount | 96,450 | 91,368 | 1.815*** | (0.1951) |
| Dependants | 0.67 | 1.00 | 0.365** | (0.1890) |
| Single | 0.21 | | 11.74*** | (0.7220) |
| Married | 0.70 | | 9.011*** | (0.6445) |
| Homeowner | 0.52 | | -10.39*** | (0.3844) |
| Age | 42.9 | 11.5 | 0.303*** | (0.1151) |
| Age^2 | | | -0.0041*** | (0.0013) |
| Years in Job | 9.61 | 8.67 | 0.202*** | (0.0247) |
| Additional Fixed Effects: Number of Applicants, Employer Type, Occupation, Branch Zip Code | | | R-Square | 0.395 |

Panel B: 2009-2011 Statistics for Varibles in Constructing Risk

| | Primary Homes | | Cars | | Second Homes | | Appliances | |
|---|---|---|---|---|---|---|---|---|
| | Mean | StDev | Mean | StDev | Mean | StDev | Mean | StDev |
| HHIncome | 24,151 | 17,762 | 20,460 | 15,410 | 33,961 | 25,701 | 18,480 | 12,707 |
| Requested Duration (Months) | 283 | 113 | 56 | 20 | 273 | 106 | 18 | 14 |
| Requested Amount | 93,614 | 73,053 | 12,176 | 6,539 | 97,659 | 102,788 | 998 | 1,117 |
| Dependants | 0.53 | 0.92 | 0.66 | 1.06 | 0.62 | 0.99 | 0.57 | 0.99 |
| Single | 0.25 | | 0.43 | 0.50 | 0.14 | 0.34 | 0.39 | 0.49 |
| Married | 0.65 | | 0.57 | 0.50 | 0.77 | 0.42 | 0.61 | 0.49 |
| Homeowner | 0.45 | | 0.65 | 0.48 | 0.77 | 0.42 | 0.78 | 0.42 |
| Age | 42.72 | 11.94 | 38.20 | 11.03 | 48.16 | 11.37 | 43.89 | 13.27 |
| Years in Job | 8.82 | 8.28 | 9.42 | 8.39 | 11.54 | 9.96 | 9.38 | 7.83 |
| Internal Grade | 62.01 | 3.71 | -- | | 63.66 | 5.48 | -- | |
| Risk | 62.90 | 5.56 | 59.09 | 3.82 | 62.27 | 3.86 | 60.02 | 2.34 |
| Corr (Internal Grade, Risk) | 0.583 | | -- | | 0.512 | | -- | |

**Appendix Table 2: Engel-Adjusted Method for Demand, Extended**

The sample is representative agents for 510 zip codes, each with two observations, one before and one after the law. The dependent variable in columns 1-4 is the mean approved amount in the zip code. The dependent variable in columns 5-8 is the mean approval rate in the zip code. Requested amount is the actual zip code mean requested amount in the odd-number columns. In the even columns, the pre-period requested amount is actual and the post period is the actual pre-period requested amount times the engel decline in home consumption over the period. (See the text for description. Post-law is a dummy for being after June 2010. The entire sample period is January 2009 to June 2011. Robust standard errors are reported in parentheses. . ***,**, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent Variable | Approved Amount for Zip Code Agent | | | | Approval Rate within Zip Code | | | |
| Requested Definition: | rted to Float | Engel | Actual | Engel | Fixed | Float | Ln(Actual) | Ln(Engel) |
| Requested Amount | 0.566*** | 0.567*** | 0.566*** | 0.567*** | 0.0577* | 0.0586* | 0.0489 | 0.0497* |
| | [0.0495] | [0.0496] | [0.0511] | [0.0511] | [0.0300] | [0.0300] | [0.0300] | [0.0300] |
| Requested Post-Law | -0.241*** | -0.224*** | -0.242*** | -0.225*** | -0.0215 | -0.0217 | -0.019 | -0.0187 |
| | [0.0563] | [0.0574] | [0.0574] | [0.0584] | [0.0347] | [0.0335] | [0.0341] | [0.0331] |
| Credit Risk Very Low | | | -- | -- | | | -- | -- |
| Credit Risk Low | | | 2,166 | 2,204 | | | 0.0389*** | 0.0389*** |
| | | | [1,387] | [1,391] | | | [0.0145] | [0.0145] |
| Credit Risk Middle | | | 4,186*** | 4,393*** | | | 0.0462*** | 0.0463*** |
| | | | [1,446] | [1,446] | | | [0.0155] | [0.0155] |
| Credit Risk High | | | 5,263*** | 5,370*** | | | 0.0455*** | 0.0454*** |
| | | | [1,528] | [1,534] | | | [0.0154] | [0.0154] |
| Credit Risk Very High | | | 7,490*** | 7,690*** | | | 0.0869*** | 0.0871*** |
| | | | [1,707] | [1,722] | | | [0.0177] | [0.0177] |
| HHIncome Very Low | | | -- | -- | | | -- | -- |
| HHIncome Low | | | 4,049*** | 4,141*** | | | 0.0326** | 0.0324** |
| | | | [1,396] | [1,395] | | | [0.0149] | [0.0150] |
| HHIncome Middle | | | 3,435** | 3,321** | | | 0.0254 | 0.0249 |
| | | | [1,475] | [1,482] | | | [0.0162] | [0.0162] |
| HHIncome High | | | 4,928*** | 4,928*** | | | 0.0405** | 0.0399** |
| | | | [1,659] | [1,662] | | | [0.0171] | [0.0171] |
| HHIncome Very High | | | 3,763* | 3,618* | | | 0.019 | 0.018 |
| | | | [2,028] | [2,044] | | | [0.0194] | [0.0195] |
| Post-Law | -9,631** | -7315 | -9,077* | -6803 | -0.0838 | -0.0755 | -0.109 | -0.107 |
| | [4,821] | [4,735] | [4,939] | [4,859] | [0.394] | [0.381] | [0.389] | [0.376] |
| Credit Risk | 382.3*** | 388.4*** | | | 0.00425*** | 0.00427*** | | |
| | [68.82] | [68.87] | | | [0.000687] | [0.000688] | | |
| HH Income | 0.172 | 0.166 | | | 2.46E-07 | 1.83E-07 | | |
| | [0.113] | [0.115] | | | [1.01e-06] | [1.02e-06] | | |
| Constant | -75,801*** | -77,007*** | 2,420 | 2,272 | -0.937** | -0.949** | 0.00512 | -0.00381 |
| | [14,476] | [14,468] | [4,412] | [4,413] | [0.369] | [0.370] | [0.340] | [0.340] |
| Observations | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 | 1,020 |
| R-squared | 0.732 | 0.731 | 0.731 | 0.73 | 0.593 | 0.594 | 0.592 | 0.592 |

**Appendix Table 3: Primay Home Rate Spreads by Risk, Pre- & Post-Law**

Reported are the interest rate spread over euirbor expressed in rateX100, across 5 income and 5 risk buckets. Panels A, B, and C present the pre-period bucket means, the post-period bucket means, and the difference. In the difference calculations of significance along the margins, the observations in the post period are weighted to reflect the bucket distribution in the pre period.

| Panel A: Pre-Law Period | Variable Rate | | | | | | Fixed Rate | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Highest Risk | High Risk | Medium Risk | Low Risk | Lowest Risk | All | Highest Risk | High Risk | Medium Risk | Low Risk | Lowest Risk | All |
| Very Low Income | 2.24 | 2.07 | 2.01 | 1.82 | 2.01 | 2.09 | 3.58 | 3.43 | 3.88 | 3.79 | 3.61 | 3.63 |
| Low Income | 2.17 | 2.03 | 1.93 | 1.72 | 1.73 | 1.98 | 3.34 | 3.53 | 3.74 | 3.69 | 3.63 | 3.53 |
| Middle Income | 2.27 | 2.16 | 2.04 | 1.75 | 1.75 | 2.01 | 3.28 | 3.57 | 3.54 | 3.42 | 3.72 | 3.47 |
| High Income | 2.35 | 2.23 | 2.16 | 1.96 | 1.70 | 2.04 | 3.19 | 3.29 | 3.50 | 3.58 | 3.46 | 3.40 |
| Very High Income | 2.44 | 2.41 | 2.37 | 2.34 | 2.06 | 2.24 | 3.01 | 2.75 | 2.86 | 3.13 | 3.21 | 3.05 |
| All | 2.26 | 2.14 | 2.09 | 1.93 | 1.88 | 2.07 | 3.34 | 3.35 | 3.44 | 3.45 | 3.39 | 3.39 |

| Panel B: Post-Law Period | Variable Rate | | | | | | Fixed Rate | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Highest Risk | High Risk | Medium Risk | Low Risk | Lowest Risk | All | Highest Risk | High Risk | Medium Risk | Low Risk | Lowest Risk | All |
| Very Low Income | 3.48 | 3.40 | 3.01 | 2.76 | 3.16 | 3.19 | 3.65 | 3.70 | 3.74 | 3.74 | 3.62 | 3.68 |
| Low Income | 3.67 | 3.13 | 2.98 | 2.32 | 3.00 | 2.95 | 3.89 | 3.56 | 3.66 | 3.84 | 3.68 | 3.72 |
| Middle Income | 3.47 | 3.07 | 3.21 | 2.68 | 2.66 | 2.89 | 3.36 | 3.47 | 3.42 | 3.60 | 3.47 | 3.49 |
| High Income | 3.40 | 3.54 | 3.11 | 2.82 | 2.89 | 3.10 | 3.15 | 3.36 | 3.43 | 3.45 | 3.51 | 3.42 |
| Very High Income | 3.38 | 3.43 | 3.33 | 3.22 | 2.96 | 3.10 | 3.31 | 2.93 | 2.90 | 3.16 | 3.40 | 3.25 |
| All | 3.48 | 3.34 | 3.15 | 2.90 | 2.92 | 3.06 | 3.45 | 3.38 | 3.32 | 3.45 | 3.46 | 3.42 |

| Panel C: Difference | Variable Rate | | | | | | | Fixed Rate | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Highest Risk | High Risk | Medium Risk | Low Risk | Lowest Risk | All | st. error | Highest Risk | High Risk | Medium Risk | Low Risk | Lowest Risk | All | st. error |
| Very Low Income | 1.240 | 1.330 | 1.002 | 0.937 | 1.154 | 1.101*** | (0.077) | 0.066 | 0.264 | -0.145 | -0.044 | 0.009 | 0.056 | (0.075) |
| Low Income | 1.502 | 1.097 | 1.049 | 0.596 | 1.275 | 0.976*** | (0.093) | 0.547 | 0.031 | -0.080 | 0.155 | 0.053 | 0.198 | (0.075) |
| Middle Income | 1.199 | 0.905 | 1.167 | 0.930 | 0.911 | 0.883*** | (0.082) | 0.076 | -0.109 | -0.122 | 0.176 | -0.248 | 0.018 | (0.079) |
| High Income | 1.045 | 1.306 | 0.946 | 0.854 | 1.187 | 1.062*** | (0.073) | -0.040 | 0.062 | -0.071 | -0.133 | 0.055 | 0.023 | (0.075) |
| Very High Income | 0.944 | 1.019 | 0.958 | 0.885 | 0.900 | 0.863*** | (0.064) | 0.294 | 0.186 | 0.039 | 0.032 | 0.186 | 0.207** | (0.071) |
| All | 1.224*** | 1.204*** | 1.065*** | 0.963 | 1.047*** | 0.994*** | (0.036) | 0.113 | 0.035 | -0.126 | -0.001 | 0.073 | 0.035 | (0.037) |
| st. error | (0.073) | (0.074) | (0.071) | (0.081) | (0.067) | (0.036) | | (0.093) | (0.082) | (0.087) | (0.081) | (0.075) | (0.037) | |