How Do Regulators Influence Mortgage Risk? Evidence from an Emerging Market*

John Y. Campbell, Tarun Ramadorai, and Benjamin Ranish†

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Abstract

We employ loan-level data on over a million loans disbursed in India between 1995 and 2010 to understand how fast-changing regulation impacted mortgage lending and risk. Our methodology offers an alternative to regression discontinuity analysis that applies even when regulations create no discontinuities in the cross-section. We use cross-sectional differences in the time-series variation of delinquency rates, conditional on initial interest rates, to detect the effects of regulations favoring smaller loans. We also find that a change in the classification of non-performing assets reduced both delinquency probabilities and losses given delinquency.

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†Campbell: Department of Economics, Littauer Center, Harvard University, Cambridge MA 02138, USA, and NBER. Email john_campbell@harvard.edu. Ramadorai: Saïd Business School, Oxford-Man Institute of Quantitative Finance, University of Oxford, Park End Street, Oxford OX1 1HP, UK, and CEPR. Email tarun.ramadorai@sbs.ox.ac.uk. Ranish: Department of Economics, Littauer Center, Harvard University, Cambridge MA 02138, USA. Email: branish@fas.harvard.edu.

1 Introduction

How does mortgage regulation influence the structure and performance of housing finance? This paper answers the question by analyzing administrative data on over 1.2 million loans originated by an Indian mortgage provider, relating loan pricing and delinquency rates to the changing details of Indian mortgage regulation.

A more common approach to this question is to compare mortgage systems across countries. Casual observation reveals striking cross-country differences. A recent survey by the International Monetary Fund (IMF 2011) shows that among developed countries, homeownership rates range from 43% in Germany to about 80% in southern European countries. The level of mortgage debt in relation to GDP varies from 22% in Italy to above 100% in Denmark and the Netherlands. The terms of mortgage instruments are overwhelmingly adjustable-rate in southern Europe, and fixed-rate in the United States. Mortgages are funded using a wide variety of mechanisms, including deposit-financed lending, mortgage-backed securities, and covered bonds.

Government involvement in mortgage markets also varies across countries, and it is likely that this explains at least some of the cross-country variation in housing finance. However, it is hard to disentangle regulatory effects from other factors that may affect household mortgage choice across countries, including historical experiences with interest rate and inflation volatility, which can have long-lasting effects because consumers can be slow to adopt new financial instruments (Campbell 2012).

An appealing alternative approach is to trace the effects of mortgage regulation over time within a single country rather than rely entirely on cross-country evidence that can be contaminated by unobserved differences across countries. The difficulty in doing this is that developed countries tend to have fairly stable systems of financial regulation, so one rarely has the opportunity to track the effects of sharp regulatory changes. Slow changes, such as those that occurred in the US during the early and mid-2000s, may well be important but it is hard to show this convincingly. For this reason academic writers and public policy commentators have reached no consensus on the degree to which regulation, rather than other factors, caused the US mortgage credit boom.[1]

Mortgages are rapidly becoming important financial instruments in emerging markets. Here, financial regulation is at least as intrusive and much less stable. In addition, long-lasting historical influences are likely to be less important in emerging markets because their rapid growth and financial evolution reduce consumer inertia. For this reason, emerging markets are ideal laboratories in which to examine the effects of mortgage regulation.

This paper studies the mortgage market in India, a large and complex emerging economy. India has been studied extensively by the economics profession, which has mainly analyzed issues of poverty and development (see, for example, Besley and Burgess, 2000, and Banerjee et al., 2007), or the impact of the Byzantine system of laws and regulations on industrial organization and firm output (see Aghion et al., 2008, and von Lilienfeld-Toal, Mookherjee, and Visaria, 2012 for example). India underwent an economic liberalization in the early 1990s and subsequently experienced rapid economic growth that accelerated further in the 2000s. During this time the financial sector has become much larger and more sophisticated, but remains highly regulated, with a significantly nationalized banking sector.

It is only very recently that authors such as Anagol and Kim (2012) have begun to study India in the context of financial regulation and its impacts on fast-changing Indian capital markets. The provision of housing finance is evolving particularly rapidly (Tiwari and Debata 2008, Verma 2012). Regulatory norms have changed frequently, albeit with a continuing emphasis on funding housing for low-income households. There is increased competition between mortgage lenders, and this may have contributed to rapidly increasing house prices since 2002. Indian mortgages include both fixed and variable rate loans, but there has been a significant shift over time towards the latter.

The challenge in emerging markets, India included, is to find adequate data. Many questions about mortgage finance can only be answered using microeconomic data, either at

[1] A range of views can be found in Acharya, Richardson, van Nieuwerburgh, and White (2011), Baily (2011), Ellis (2008), International Monetary Fund (2011), and US Treasury and Department of Housing and Urban Development (2011), among other sources. Dahl, Evanoff, and Spivey (2000), Kroszner (2008), and Agarwal, Benmelech, Bergman, and Seru (2012) debate the importance of the Community Reinvestment Act (CRA) in encouraging risky lending to lower-income borrowers.

the household level or the loan level. There is now a vast literature looking at such data in the US, but it is harder to find in less wealthy countries with rapidly changing financial systems.[2] We are fortunate to have access to loan-level administrative data from an Indian mortgage provider. We analyze over 1.2 million mortgages disbursed by the mortgage provider between 1995 and 2010, and attempt to understand the determinants of mortgage rate setting and delinquencies.

Our ability to use microeconomic data is important because pure time-series variation in mortgage risk, even if correlated with changing regulation, may also be explained by the changing state of the macroeconomy. Instead, we measure cross-sectional variation in the time-series movements of mortgage delinquency, and link this cross-sectional variation to the incentives created by regulations. One widely used implementation of this approach uses a regression discontinuity design, seeking to identify a discontinuous change in behavior around a threshold created by regulation. However this approach confronts numerous challenges, the most obvious being when regulations do not have clearly identifiable points of discontinuity. Even when regulatory discontinuities do exist, they may alter the incentives and behaviors of market participants in a manner that blurs identification near regulatory boundaries. Both of these issues arise in the Indian context, leading us to pursue an alternate approach. Specifically, we link time-variation in regulatory incentives to cross-sectional variation in their expected impacts on different types of mortgages, as well as to geographical variation across local offices operated by the mortgage provider.

Our approach yields two main findings on the relation between regulation and mortgage risk. First, throughout the period of study, small and micro loans are particularly favoured by the Indian regulatory environment. We uncover evidence that the implicit subsidies to such loans show up in a higher propensity for them to default than can be accounted for by their mortgage rates at issuance and all other determinants in the model. This tendency is highly statistically significant, is greater for micro loans than for small loans marginally

[2] Some recent mortgage studies using US microeconomic data include Adelino, Gerardi, and Willen (2009), Agarwal et al (2011), Amromin et al (2011), Bhutta, Dokko, and Shan (2010), Demyanyk and van Hemert (2011), Foote et al (2010), Johnson and Li (2011), Keys et al (2010), Melzer (2011), Mian and Sufi (2009), and Piskorski, Seru, and Vig (2011).

under the subsidy-qualifying threshold, and is observed in all cohorts of loan issuance over the sample period.

The obvious approach of looking for a discontinuity in the delinquency rate at the subsidy-qualifying threshold is complicated by the responses of higher-income home-buyers, who have incentives to benefit from subsidies by taking out small loans just underneath the qualifying threshold. To the extent that such loans are safer than other loans of similar size, these actions would result in a blurring of the otherwise expected discontinuity in delinquency rates observed on either side of the threshold.

We therefore adopt our alternative approach, and relate the magnitude of the excess delinquency propensity of small and micro loans to time-series variation in the tightness of the constraint favoring these loans. The regulator only periodically adjusts the nominal subsidy-qualifying threshold, while nominal house prices (which determine the nominal sizes of loans demanded) have increased over time. This means that the share of unqualified loans, a proxy for the tightness of the constraint on the mortgage provider to make qualifying loans, varies over time. We find that the excess delinquency propensity of small and micro loans covaries significantly with this measure of constraint tightness, providing evidence that regulation affects mortgage risk. We also document that there is important geographical variation in delinquency rates, which operates in a fashion consistent with a strategic response of the mortgage provider to the regulatory incentives which it faces.

The second important change that we track in the Indian regulatory environment occurs in March 2004. At this point, the regulatory definition of "non-performing assets," changes from previously referring to loans that are six-months delinquent to those that are three-months delinquent. Since provisioning requirements against delinquencies are tied to this definition, we expect that this change creates incentives for the mortgage provider to monitor loans earlier, and potentially to improve loan screening. Although the regulatory change is itself discrete, it is not clear at what point in the life of a delinquent loan it will trigger action by our mortgage provider, so once again a straightforward regression discontinuity design is not feasible.

To investigate, we track loans as soon as they are flagged as delinquent, which is when they are one month behind on payments. Following the regulatory change, we find that these one-month delinquent loans are far less likely to subsequently become three-months delinquent. Furthermore, using a subsample of 10,000 loans for which we have a complete time series of payment histories, we uncover evidence that is consistent with greater effort on the part of the mortgage provider to monitor delinquencies in response to this regulatory change. In particular, we find that debt collection rates on one-month delinquent loans are accelerated in the interval before they hit the new three-month mark for classification as a non-performing asset. Importantly, perhaps as a result of incentivizing mortgage lenders to act early on delinquent loans, we find that this change substantially lowers the likelihood of experiencing longer-term defaults. This impact on long-term defaults is even larger than that arising from a 2002 legal change in the ability of mortgage providers to more easily repossess or restructure non-performing assets. Moreover, we identify that the primary impact of the regulation is on improved ex-post monitoring rather than on better ex-ante screening.

Taken together, these two findings provide compelling evidence that regulatory norms impact the risk of delinquencies experienced by our Indian mortgage provider on loans issued. Our evidence complements recent findings using U.S. data on the impacts of regulatory norms on mortgage screening (Keys et al. 2011), and is also related to work on how mortgage credit expansion in the U.S., particularly in sub-prime zipcodes, contributed to the recent crisis (Mian and Sufi 2009). Our evidence on the role played by subsidies in the increased delinquency rates on small loans contributes to the debate on whether such subsidies in other countries, such as the U.S. Community Reinvestment Act (CRA), had similar effects (see, for example, Dahl, Evanoff, and Spivey 2000, Kroszner 2008, and Agarwal, Benmelech, Bergman, and Seru 2012). Finally, our model shows that controlling for a range of determinants of mortgage risk, the time when a loan is issued has significant explanatory power, a finding related to the analysis of Demyanyk and van Hemert (2011) who perform a similar analysis to explain U.S. sub-prime mortgage risk.

The organization of the paper is as follows. Section 2 sets the stage by describing the Indian macroeconomic environment and the Indian system of mortgage regulation during the quarter century since 1985, together with the mortgage data we employ. Further details of Indian mortgage regulation are provided in an online regulatory appendix (Campbell, Ramadorai, and Balasubramaniam 2012). Section 3 introduces our model of mortgage delinquencies, which we use to explore the effects of regulation—specifically, implicit subsidies to small and micro loans and risk weights on high loan-value mortgages—on the relative delinquency rates of different types of loans. Section 4 discusses the change in the regulatory definition of non-performing assets in 2004 and its consequences for observed delinquency and repayment patterns. Section 5 concludes. Additional empirical evidence on the Indian mortgage market is reported in an online empirical appendix (Campbell, Ramadorai, and Ranish 2013).

2 The Macroeconomic and Regulatory Environment

2.1 Macroeconomic Trends

To set the stage, Table 1 summarizes the history of several important Indian macroeconomic variables over the quarter-century from 1985–2010, including annual real GDP growth, CPI inflation, and government bond yields. Regulatory and macroeconomic reform in the early 1990s was followed by growth in the 4-8% range until the early 2000s, when growth accelerated above 8%, briefly slowed again only by the global financial crisis in 2008. Meanwhile inflation was high and volatile during the 1990s, with volatility particularly elevated around the reform period and in 1998–99. A period of more stable inflation followed in the 2000s, but inflation accelerated at the very end of our sample period.

Indian government bond yields over the same period are also quite volatile. The 1-year yield declines from double-digit levels in the mid-1990s, with a brief reversal in the late 1990s related to the volatile inflation experienced at the same time. After a low of about 5% in the early 2000s, the 1-year yield spikes up to almost 8% in 2008, again related to concerns about inflation. The 10-year yield is smoother but also undergoes a large decline from the mid-1990s until the early 2000s.

Figure 1 plots real house price indexes, both for India as a whole and for five broad regions. The real rate of house price appreciation for the country as a whole is also reported in Table 1. We compute these indexes using the mortgage provider's own property cost data, but data from the National Housing Bank (NHB) show similar patterns. Indian house prices were relatively stable until the early 2000s and then began to increase rapidly, particularly in the south of the country. The southern index peaks in 2008 while some other regions peak in 2009. Thus India took part in the worldwide housing boom despite many differences in other aspects of its macroeconomic performance.

These house price movements are important for our study because they interact with government policies favoring smaller loans. As house prices increase, fewer loans naturally qualify for favorable regulatory treatment, creating time-series variation in the tightness of regulatory constraints on mortgage lending. Understanding this effect requires a detailed explanation of the Indian regulatory system, which we now provide.

2.2 The Regulatory Environment

Mortgages in India are originated by two types of financial institutions, banks and housing finance companies (HFCs). Banks are regulated by the Reserve Bank of India (RBI), while housing finance companies are regulated by the National Housing Bank (NHB), but most regulations apply in fairly similar form to the two types of institution. This fact is important for our study, as we are unable to publicly identify whether our mortgage provider is a bank or an HFC.

Figure 2 summarizes the details of mortgage regulation in India in a relatively parsimonious fashion. The top half of the figure shows regulations that applied to banks, and the bottom half to HFCs. The regulations that remained constant throughout the period are listed in Roman font, whereas the ones that changed over the period are in italic font. In light of the significant changes that took place from 2001 to 2002, we separate the timeline into the "first period," i.e. prior to March 2001, and the "second period" which extends from April 2001 until the end of the sample period. In the middle of the figure, we summarize subsidy schemes for micro-lending with the length of the bars accompanying these schemes identifying their start and end dates relative to the timeline.

Regulations can be divided into two types: those that restrict the funding of mortgage lending, and those that incentivize lending to favored borrowers. Until 2001, mortgage funding was regulated in a fairly traditional manner, using leverage restrictions on banks and HFCs, and interest-rate ceilings on deposit-taking HFCs. From 2002 onwards, these measures were augmented by capital requirements against risk-weighted assets following the internationally standard Basel II framework. The RBI and NHB distinguished small and large loans, and loan-value (LTV) ratios above and below 75%, and set different risk weights for these different categories with frequent changes for loans below 75% LTV. In this way the regulators shifted the risk capital available to banks and HFCs, and the incentives for aggressive mortgage origination.

Another noteworthy change in the regulatory environment is highlighted on the timeline, and occurred on March 31, 2004 for banks, and one year later, i.e., March 31, 2005 for HFCs. At this time the RBI redefined an asset as a "non-performing asset" (or NPA) if payments (on interest or principal) remained overdue for a period of ninety days or more, from the previous 180 day period allowed before assets were so classified. One important implication of the classification of an asset as an NPA is that it incurs provisioning requirements, meaning that the capital available to a mortgage lender holding such an asset reduces as the lender is required to hold precautionary capital to cover expected losses.

Related to this NPA redefinition, an important law which came into force somewhat earlier (in July 2002), was the Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest (SARFAESI) Act. This law enabled the easier recovery of NPAs via securitization, reconstruction, or direct repossession, bypassing the need for secured creditors to seek permission from debt recovery tribunals (see von Lilienfeld-Toal, Mookherjee, and Visaria, 2012, for evidence of the impacts of the establishment of these tribunals in 1993). In our analysis, we separately evaluate the impact of these two changes, namely the redefinition of NPAs in 2004, and the introduction of SARFAESI in 2002, on delinquencies experienced by the mortgage provider.

Lending to small borrowers is an important political goal in India. Banks are subject to a quantity target for Priority-Sector Lending (PSL), which includes loans to agriculture, small businesses, export credit, affirmative action lending, educational loans, and – of particular interest to us – mortgages for low-cost housing. The PSL target is 40% of net bank credit for domestic banks (32% for foreign banks), and there is a severe financial penalty for failure to meet the target, namely, compulsory lending to rural agriculture at a haircut to the repo rate. This regulation does not directly apply to HFCs, but bank lending to an HFC qualifies for the PSL target to the extent that the HFC makes mortgage loans that qualify, i.e., are below the specified nominal PSL threshold. The overall effect of the PSL system is to provide an incentive, directly for banks, and indirectly for HFCs, to originate small mortgages that finance low-cost housing purchases.

In addition to the PSL system, other schemes have been introduced at various points in time over the sample period to subsidize new or refinanced micro-lending – i.e., loans of sizes well below the PSL-qualifying threshold. The mid-section of Figure 2 shows the various schemes that were in place to incentivize mortgage lending in very small loan sizes. These schemes apply to both banks and HFCs. Most recently, interest rate subventions have been put in place for the first year of repayments on small loans, payments that are passed through to the borrower in the form of a reduced interest rate, for housing loans up to a maximum size. Special subsidy and refinancing schemes in place for very small rural loans (the Golden Jubilee Rural Housing Finance Scheme or GJRHFS, and the Indira Awas Yojana) and for borrowers qualifying for affirmative action (the Differential Rate of Interest scheme) are also shown in the figure, over the period for which they applied. Taken together, these schemes increase the subsidy for tiny loans over and above the standard subsidy to PSL-qualifying loans.

As is evident from the brief description above, it is not a trivial task to document the changes in the system of Indian mortgage regulation as these have been frequent, and are not summarized in any one place. The online regulatory appendix, Campbell, Ramadorai, and Balasubramaniam (2012), provides further details about the regulatory system, and serves as a comprehensive guide to Indian mortgage regulation over the period of our study.

2.3 Evolution of the Mortgage Market

Both macroeconomic and regulatory forces have contributed to rapid change in the Indian mortgage market. Table 2 illustrates the changes in three relevant characteristics of mortgages issued by our lender: the shares of variable-rate mortgages, small PSL-qualifying loans, and mortgages with high loan-cost ratios above 75%.

The first two columns of Table 2, Panel A show the variable-rate share in the number and value of mortgages disbursed. There has been a dramatic shift in the Indian mortgage system away from fixed-rate and towards variable-rate mortgages, with one brief interruption in 2004. Our lender made very few fixed-rate mortgages after 2007. During the period of transition through 2002, variable-rate mortgages were somewhat larger on average than fixed-rate mortgages, as shown by their higher share of value in the second column of the table.

The next two columns of Panel A show the share of mortgages that are below the PSL threshold, separately for variable-rate and fixed-rate mortgages. The share below the PSL threshold peaks in 2001 (for variable-rate mortgages) and 2000 (for fixed-rate mortgages), and then declines precipitously during the 2000s. The PSL-qualifying share is somewhat higher for fixed-rate mortgages, reflecting their smaller average size.

The final two columns of Panel A show the share of mortgages with loan-cost ratio above 75%, again separately for variable-rate and fixed-rate mortgages. We use the loan-cost ratio, available in the data from our mortgage provider, as a proxy for the loan-value ratio, the subject of Indian mortgage regulation. Cost is equal to value plus any administrative or legal fees incurred to purchase the property. The share of mortgages with loan-cost ratio above 75% trends upwards, increasing particularly rapidly in the early 2000s (for variable-rate mortgages) and late 1990s (for fixed-rate mortgages).

Both these trends are driven in part by the increase in house prices during the mid-1990s and mid-2000s, shown earlier in Table 1 and Figure 1. Figure 3 illustrates this point in a different way. The solid line in the figure is the unqualified lending share, the fraction of mortgages disbursed that are above the PSL threshold and thus do not qualify for the

PSL target. This fraction rises as house prices increase, particularly in the mid-1990s and mid-2000s, but falls discontinuously when the PSL threshold is adjusted. Later in the paper, we use the unqualified lending share as a proxy for the tightness of the regulatory constraint favoring small loans.

Figure 3 also reports the intensity of regulatory preference for loans with loan-value ratio below 75%. This is measured as the difference in risk weights for loans above and below the 75% loan-value threshold. It is zero until January 2002, when it rises rapidly to a maximum of 0.5 by the middle of 2003.

Our data display not only time-series variation in the fractions of loans below the PSL threshold and above 75% loan-cost ratio, but also geographical variation, which arises naturally from variation in local housing market conditions. Panel B of Table 2 reports the cross-sectional mean, standard deviation, minimum, and maximum fractions of PSL-qualified and high loan-cost mortgages, calculated across local offices of our mortgage lender. The cross-sectional (across local offices) standard deviations are 19% for PSL-qualified loans and 11% for high loan-cost mortgages. In the empirical work of the next section we exploit this variation to try to detect geographical variation in the mortgage lender's responses to regulatory pressures.

Table 3 presents more details on cohorts of loans issued in each year. Panel A reports cross-sectional cohort means of mortgage terms and delinquency rates. Initial interest rates on variable-rate and fixed-rate mortgages track one another very closely until 2002, and are both close to the Indian prime rate shown in Table 1, despite some variation in the spread between long-term and short-term government yields. In the period 2003–06, the variable mortgage rate is well above the fixed rate and has an unusually high spread over the 1-year bond yield, a feature shared with the Indian prime rate. This period has a generally high market share for variable mortgages, but does include an episode in 2004 when our mortgage lender shifted back towards fixed mortgage issuance. Variable mortgage rates decline after 2008, a period where our lender made few fixed-rate mortgages.

Panel A also summarizes cohort means of loan maturity, loan-cost ratios, and loan-income ratios. The previously discussed increase in loan-cost ratios is visible here too, but loan maturity and loan-income ratios are much more stable. This pattern contrasts with mortgage trends during the 2000s in the US, where loan-income ratios increased while loan-value ratios were relatively stable (Campbell and Cocco 2012).

The right-hand column reports the cohort 90-day delinquency rate, the annual probability that an outstanding and not-yet-delinquent loan experiences a 90-day delinquency, calculated separately for each disbursal-year cohort and calendar year, and then averaged over calendar years for each cohort. The early 2000s appear unusual in the sense that the cohort default rate for mortgages disbursed in these years is high relative to the other cohorts in the sample period, despite loan characteristics such as loan-cost and loan-income ratios not changing much on average. The 2004 fixed-rate cohort, however, appears to have a significantly reduced default rate.

Figure 4 summarizes the history of Indian mortgage delinquency in a simpler way. It plots the overall delinquency rate (the fraction of all outstanding mortgages, regardless of the date of issue, that are 90 days past due), seasonally adjusted using a regression on monthly dummies, for both fixed-rate mortgages (solid line) and variable-rate mortgages (dashed line). The main feature of this figure is the large spike in delinquencies in 2002–03, particularly for fixed-rate mortgages. Delinquencies decline to quite low levels by 2005, and remain low to the end of our sample period despite the weak housing market in 2009–10.

Panel B of Table 3 shows the cross-sectional standard deviation of loan characteristics and initial interest rates. In the early 2000s there is a large spike in the cross-sectional dispersion of variable mortgage rates. This spike coincides with the period of increased delinquencies documented earlier, and may reflect increased efforts by our mortgage lender to distinguish among borrowers by estimating their default risk and setting mortgage rates accordingly. For fixed mortgage rates, while the same pattern is not evident in the cross-sectional dispersion of initial interest rates, there does seem to be an increase in the early 2000s in the cross-sectional dispersion of loan-cost ratios, which reduces again in 2004.

In the remainder of this paper, we explore in more detail the relation between mortgage regulation and these movements in mortgage delinquencies.

3 A Model of Mortgage Delinquencies

In this section we attempt to shed light on the factors which contributed to changes in the mortgage delinquency rate over time and across cohorts, paying special attention to the changing regulations described in the previous section. In order to do so, we propose and estimate a model of mortgage delinquencies, recognizing that their determinants include demographic characteristics of borrowers, measurable characteristics of loans, cohort-specific variation, and (imperfectly observable) variation in macroeconomic conditions.

In our baseline specification, we model the probability of observing a delinquency as a function of all of these determinants:

$$\Pr[\delta_{i,c,b,r,t}] = (\alpha + \alpha_r + \alpha_c + \alpha_b + \Sigma_k \beta_{rk} L_{ikt} + \Sigma_j \gamma_j D_{ijt} + \rho_r r_i) Z_{r,t-1} + e^{\delta}_{i,t}, \qquad (1)$$

where $\delta_{i,c,b,r,t}$ is an indicator for an observed 90-day delinquency in loan i with interest-rate type r (fixed or variable) in cohort c originated in branch b, at time t. That is, c denotes the loan origination date and t denotes the observation date. The model includes fixed effects for each interest rate type, α_r, branch α_b, and cohorts, α_c. In each case, we drop one dummy as we have an intercept in the model. The model also includes loan characteristics L_{ikt} indexed by k, and demographic characteristics D_{ijt} indexed by j, for each borrower i. These characteristics can potentially vary over time, although in practice most of the ones we measure are constant over time. The initial interest rate on the mortgage, r_i is also included as an explanatory variable in the model.[3] The coefficient on initial interest rate and on loan term (in the set of loan characteristics L) have a subscript r to indicate that separate coefficients are allowed here for fixed and variable rate mortgages; loan term and initial interest rate do not necessarily relate to risk in the same way for fixed and variable rate mortgages. In the subsequent sections, we augment this basic specification to include time-series variation in regulatory thresholds, interacted with dummies to capture cross-sectional

[3]The model is estimated at the annual frequency t; to eliminate monthly seasonal variation, we de-mean all left- and right-hand side variables at the monthly frequency and add back the annual mean. This change is innocuous, having little impact on our results.

variation in the expected impacts of these changes.

The model allows for an unobserved macroeconomic shock $Z_{r,t-1}$ to impact these determinants multiplicatively, and we allow a separate set of shocks to affect fixed and variable rate mortgages. While in practice the time-series of estimated fixed and variable rate shocks appear quite similar, this flexibility is important, since the macroeconomic shocks that drive delinquency may be different if mortgage rates adjust to interest rate movements (Campbell and Cocco 2012).

Given the presence of macroeconomic shocks, the estimated coefficients on the branch and cohort fixed effects, and loan and demographic characteristics show the extent to which these factors alter the propensity for a loan to default as macro conditions vary. To fix ideas, consider a high estimated value of a particular cohort effect – this would indicate a high propensity of loans in that cohort to default when times are bad, i.e., when $Z_{r,t-1}$ is high. The choice of $Z_{r,t-1}$ rather than Z_{rt} as the macroeconomic shock influencing delinquency at time t captures the fact that 90-day delinquencies are not realized contemporaneously with deteriorations in macroeconomic circumstances. Rather, we expect to see delinquencies materialize some period of time after negative macroeconomic shocks, as delinquencies result from borrower-level cash-flow problems, which likely occur with a lag.

We employ a two-stage estimation procedure, in which the first stage comprises T cross-sectional regressions estimated across all loans outstanding, and not yet delinquent, in each year $t \in T$. In the second stage, we employ the classical minimum distance estimator (see, for example, Wooldridge 2002) to extract estimates of Z_t and the static parameters of the model. As a check on our procedure, we confirm that two-stage estimation produces estimates that are very close to those obtained via single-step estimation using non-linear least squares. To obtain standard errors for the second stage estimates we use a cross-sectional correlation consistent bootstrap procedure, in which we draw a set of time periods equal to the total number of years (15) in our data $t_b^1, ..., t_b^{15} \in T$ with replacement, and assemble a simulated dataset for each bootstrap draw b. We then re-run the second stage regressions for $b = 500$ draws.

Figure 5 plots a weighted average of the estimated macroeconomic shocks for fixed and variable rate mortgages, Z_{rt}. The figure also shows two different measures of macroeconomic conditions: real GDP growth, and the average real rate of growth in corporate sales, firm fixed assets, and firm net worth estimated from the population of Indian firms available in the Prowess database.[4] The figure, in which all series are standardized for ease of comparison, shows that estimated Z_{rt} seem closely, although not perfectly related to these other measures. All three measures indicate that 2002 and 2003 were periods of particularly poor macroeconomic conditions, with a complete recovery in the Indian macro environment only by 2005. Thus our model explains the spike in delinquencies in 2002–03, illustrated in Figure 4, by macroeconomic shocks occurring at that time.

3.1 Household- and Loan-Level Determinants of Delinquency

The demographic variables that we employ include the borrower's gender, marital status, number of dependents, and dummies for age (up to age 35, 36-45, and 46 and above), for education (high-school measured by higher-secondary certificate or HSC, college, postgraduate, and missing), for a finance-related educational qualification, and for a repeat borrower. The loan characteristics include the loan-cost ratio, log loan amount, log loan-income ratio, and dummies for whether the loan was paid by salary deduction or via a special scheme with the employer, as well as dummies for special loan characteristics (tranched issuances and refinancings), specific loan purposes (home extension or improvement), and mortgage contract terms (loan maturities 6-10 years, 11-15 years, or 16 years and above, estimated separately for fixed and variable-rate mortgages). We also include a dummy for mortgages observed in the first year of issuance.

To control for house-price movements, we also include in the set of loan characteristics regional house-price appreciation up to time t from the time of the disbursal of the loan. For variable-rate loans only, we control for the change in the 1-year Indian government bond yield since issuance. Finally, we include a dummy variable which takes the value of 1 if

[4] This database comprises the population of listed and large unlisted Indian firms, and is considered to be the main source of information on Indian corporates (see, for example, von Lilienfeld-Toal, Mookherjee, and Visaria, 2012).

a loan is disbursed from a branch in the 12 months prior to a state election, to capture the possibility (documented by Cole 2009 for Indian agricultural lending) that in election seasons there may be pressure to disburse politically expedient loans, which have a higher propensity to be delinquent.

Table 4 reports the estimated coefficients on these demographic and loan characteristics. These are typically statistically significant, with the theoretically expected sign. Older male and repeat borrowers have a higher delinquency rate, while more educated borrowers have a lower rate. Interestingly, however, a finance-related educational qualification slightly increases the delinquency rate, possibly because financial-sector income is more volatile. Mortgages with higher loan-income and loan-cost ratios are more likely to become delinquent, but the absolute size of a loan lowers the delinquency rate. Loans paid through salary deduction or administered through employers have lower delinquency rates. Loans with long maturity have higher delinquency rates, as do fixed-rate mortgages. The latter result may be related to the generally downward trend of interest rates during this period in India, although our variable that measures the change in the Indian one-year government bond rate since issuance (for variable-rate mortgages only) does not enter the regression significantly. Regional house prices have a powerful effect on delinquency, as one would expect, but we do not find any evidence that loans disbursed in election seasons are unusually likely to become delinquent.

All of these variables are significant in the presence of the initial mortgage interest rate, which however enters the regression significantly as well. This implies that the mortgage lender does have information relevant for predicting delinquency, and uses it to set rates, but does not fully adjust the initial mortgage rate to the probability of delinquency conditional on observable borrower and loan characteristics.

3.2 Regulation and Delinquencies: PSL Norms

In order to assess the impact of regulation on delinquencies, we next include regulatory variables in our regression along with all the demographic and loan characteristics except the log loan amount (which would be collinear with our regulatory variables). Table 5 shows the results, excluding the coefficients on demographic and loan characteristics which are very similar to those reported in Table 4. The top part of Table 5 reports variables related to PSL norms, while the bottom part looks at the effect of risk weights on mortgages with high loan-cost ratios.

Table 5 includes three specifications, labeled A, B, and C. Specification A includes a piecewise linear function of log loan size, with a kink at the PSL threshold. In addition, the slope below the PSL threshold is interacted with the unqualified lending share, which as previously discussed we use as a proxy for the intensity of regulatory pressure to originate small loans. When the unqualified lending share is high, house prices are high relative to the PSL threshold and the mortgage lender is particularly keen to originate PSL-qualifying loans since these are in short supply. Consistent with this view, we find that delinquency rates increase as loan sizes get smaller, but the effect is statistically significant only below the PSL threshold, and the slope of this relationship gets steeper when the unqualified lending share is high.

Figure 6 summarizes this result graphically. The top panel of the figure shows the variation in the delinquency rate associated with log loan size relative to the PSL threshold. Above the threshold, there is almost no effect, but the smallest loans have a delinquency rate that is 1.5% higher when the unqualified lending share is one standard deviation below its mean, and over 2% higher when the unqualified lending share is one standard deviation above its mean.

This finding raises interesting questions about the behavior of our mortgage lender. If the lender reacts to PSL policy by lowering interest rates equally on all qualifying mortgages, then as we have discussed earlier, higher-income borrowers have an incentive to increase their downpayments so that their loan size shrinks to a qualifying level. To the extent that these borrowers are safer, their reaction blurs the discontinuity in delinquency rates (conditional on interest rates) that we would otherwise observe at the PSL threshold. But then it should be profitable for the lender to lower interest rates further on mortgages just below the PSL threshold, and raise them for micro loans far below the threshold, eliminating the slope that we illustrate in Figure 6. The fact that we do not see this may reflect limited capacity of the lender to fine-tune mortgage rates in response to variables that predict delinquency (such as the educational variables reported in Table 4), or political pressures or institutional preferences favoring micro loans.

Specification B considers geographic variation in delinquency rates and PSL-qualified lending. This specification retains the variables from specification A, which continue to have very similar estimated coefficients, but adds three new variables. The first is the unqualified lending share in the sub-branch originating each loan. This has a negative coefficient, consistent with the view that loans originated in wealthy areas (where PSL-qualifying loans are relatively scarce) are safer than loans originated in poor areas. Then, the sub-branch-specific unqualified lending share is demeaned in each cohort (to avoid contaminating the interpretation of the coefficients we have discussed so far), and interacted with both loan size below the PSL threshold, and the interaction of this variable with the overall unqualified lending share (creating a triple interaction). Both these interactions are statistically significant and negative. This tells us, first, that the spread in delinquency rates between poor and wealthy areas is narrower for smaller loans, and second, that the narrowing of the delinquency spread for small loans is stronger when there is more intense regulatory pressure to originate small loans. Putting these effects together, the mortgage lender appears to respond to regulatory incentives to originate small loans by increasing risky small lending particularly in sub-branches that do relatively little PSL-qualifying lending. Such a reaction may be rational given the overall lower risk of loans originated in these sub-branches.

The bottom panel of Figure 6 illustrates this result by plotting the spread in delinquency rates between a sub-branch with an unqualified lending share one standard deviation below the mean, and a sub-branch with an unqualified lending share one standard deviation above the mean. The spread narrows as loan size declines, but this narrowing is negligible when the overall unqualified lending share is one standard deviation below the mean, and substantial (about 50 basis points for loans two standard deviations smaller than the PSL threshold) when the overall unqualified lending share is one standard deviation above the mean.

The final specification in Table 5, specification C, shows that the time-series and cross-sectional effects on mortgage risk, discussed above, can be summarized using a single variable interacted with loan size, the sub-branch-specific unqualified lending share. In other words, the pattern of mortgage risk in our data is similar to what we would expect if each sub-branch of the mortgage lender were an independent entity responding to regulatory pressure summarized by the sub-branch's own unqualified lending share.

The patterns in mortgage risk shown in Table 5 suggest that the mortgage lender responds to regulatory pressure by increasing the volume of PSL-qualifying loans. Table 6 reports some more direct evidence that this is the case. Panel A of the table looks at four changes in the PSL threshold, and records growth rates of mortgage lending within narrow bands of loan size (either 1% or 2.5%) around the old and new thresholds. Since the old threshold becomes irrelevant for PSL-qualifying lending, while the new threshold becomes relevant, one would expect regulatory pressure to increase lending immediately above the old threshold relative to lending immediately below, and to increase lending immediately below the new threshold relative to lending immediately above. Panel A of Table 6 reports the average of lending growth above minus below the old threshold, and below minus above the new threshold, within one year of the threshold change. The estimated effect is large, at 41% for a 1% band and 30% for a 2.5% band, although it also has a large standard error.

Panel B of Table 6 looks at geographical variation in the volume of PSL-qualifying lending. We estimate a regression predicting the change in log share of sub-branch lending below last month's PSL threshold, using the lagged sub-branch PSL share, a dummy for a PSL threshold change, and the dummy interacted with the lagged sub-branch PSL share. An increase in the threshold lowers the propensity to make loans below the old threshold, and this effect is stronger in sub-branches with low PSL shares, that is in sub-branches in wealthy areas. The interaction effect has the sign we would expect given the results of Table 5, although it is not statistically significant.

3.3 Regulation and Delinquencies: Risk Weights

We also use our regression (1) to examine the effect of changing risk weights for mortgage loans with high loan-value ratios. The bottom part of Table 5 predicts delinquencies using a piecewise linear function of the loan-cost ratio, with kinks at 65% and 85%. The slope in the intermediate range between 65% and 85%, which is most affected by risk weights, is interacted with the difference in risk weights between loans above and below a 75% loan-value ratio. As the mortgage provider reports only the loan-cost ratio, which is conceptually similar but not identical to the loan-value ratio (because legal and administrative fees are included in cost but not in value), the inflection points at loan-cost ratios of 65% and 85% are equivalent to an assumption that loan-cost ratios above 85% are always above 75 % loan-value, and conversely for loans below loan-cost ratios of 65%. The distinction between loan-cost and loan-value ratios eliminates any sharp discontinuity at 75% loan-cost ratio and once again prevents us from using regression discontinuity analysis.

The results of this exercise are not much affected by the choice of specification A, B, or C. In all cases the effect of the loan-cost ratio on delinquency is strongest in the intermediate range. This is consistent with the view that extremely low loan-cost ratios have little impact on loan risk (since the loan is extremely well collateralized already), while extremely high loan-cost ratios are unusual loans that are only made in special circumstances to particularly high-quality borrowers. The interaction effect is negative, implying that high risk weights for mortgages with high loan-value ratios tend to reduce relative delinquency rates for mortgages with high loan-cost ratios. However, the interaction effect is not statistically significant. Figure 7 illustrates the result graphically for the case of specification A.

Although these findings are not strong statistically, they are relevant for the suggestion of Kashyap, Rajan, and Stein (2008) that capital requirements against risk-weighted assets should be countercyclically adjusted. In our Indian data, reductions in the risk weight on high loan-value mortgages are associated with higher levels of mortgage delinquencies for mortgages with high loan-cost ratios. This suggests that Kashyap, Rajan, and Stein's policy can influence the riskiness of mortgage lending.

4 The Classification of Non-Performing Assets

In this section we examine another regulatory change that took place during our sample period. On March 31, 2004 for banks, and March 31, 2005 for HFCs, the classification of "non-performing assets" (or NPAs) was changed to 90 days past due from the previous time period of 180 days past due. This regulatory reclassification of 90-day delinquencies, and its implications for provisioning requirements, may have contributed to the unusually low 90-day delinquency rates reported in Table 3 for more recent loan cohorts. One mechanism by which this might occur is that the reclassification may have given our mortgage lender the incentive to more intensively monitor shorter-term delinquencies (say 30 days past due), and to take earlier action to forestall 90-day delinquency. As described earlier, we do not take a firm stand on the exact month of delinquency in which there might be a discontinuity, but rather, track loans before and after the regulatory change, across their time-path of delinquency.

We therefore evaluate the expected loss given a delinquency before and after the regulatory reclassification. This expected loss is the product of the probability of experiencing a delinquency and the loss given delinquency. Table 7 looks at the first of these two elements, computing transition probabilities of loans that hit the 30-day delinquency threshold to the 90-day delinquency mark, as well as the transition probability of 90-day delinquencies to the 180-day delinquent mark. The table shows that across the entire sample period, 22.7% (22.8%) of 30-day (90-day) delinquent loans eventually become 90 days (180 days) delinquent.

As we are unable to publicly identify whether the mortgage provider is a bank or an HFC, we use the earlier RBI implementation date of 31 March 2004 as the date of the regulatory change, to cover all possibilities. When we look separately at the pre-April 2004 period for the 30-day delinquencies, the transition probability is 29%, which is almost twice as high as the post-March 2004 transition probability of 14.9%. The reduction, of 14.1%, is highly statistically significant. Clearly, following the change in the definition of NPAs to the shorter 90-day limit, the mortgage provider substantially reduced this transition probability, potentially by exerting effort to pursue borrowers more aggressively. The 90-day to 180-day transition probability also reduces following the 2004 reclassification, but by a much smaller 2.3%, suggesting that once the loan becomes classified as an NPA, there are relatively fewer incentives to take action. Another possibility, of course, is that the loans reaching the 90-day delinquency mark are simply very difficult to collect on despite the lender's exertions.[5]

To better understand the magnitude of loss given delinquency, we acquire a sample of 10,000 loans from the total population of loans. As our focus is to understand the determinants of mortgage risk, we randomly sample 2,500 fixed-rate and 2,500 variable-rate loans from the set of 90-day delinquent loans, and a further 2,500 fixed-rate and 2,500 variable-rate loans from the set of loans that do not experience a 90-day delinquency. In each sub-sample of 2,500 loans, we further ensure that we sample an equal number (1,250) from the early period in the data (disbursed prior to January 2000) and the later period (disbursed between January 2000 and December 2004). We have verified that this 10,000 loan sample has statistically indistinguishable characteristics from the population of loans from which we draw. For each one of these 10,000 loans, we are able to track the full payment history over time, as well as deviations from contracted repayments. We can compute the latter as we are also given the equated monthly installment (EMI) for each of these loans in each month, which is the expected monthly principal repayment plus interest amount. We ensure that we weight any measures constructed using this sample, so that they are reflective of the larger population of loans from which the sampling occurred.

For each loan in the sample, we construct a measure of losses accrued over time. To do so, we accumulate payments and EMI over time, and compute the "cumulative installment deficit" (or CID) as Min(0, cumulative payment-cumulative EMI)/EMI. This measure takes the value of zero if monthly payments exceed or equal the EMI, and is negative otherwise, indicating when borrowers are in arrears. The cumulation ensures that if overpayments are

[5] It is also worth noting here that the 2002 implementation of SARFAESI, described above, allowed for easier restructuring and repossession of delinquent loans. However the small change in the 90-180 day transition probability despite this regulatory change mirrors the insignificant post-SARFAESI change in the ΔCID debt collection rate that we define and analyze below. These results suggest that at least for housing loans, this particular regulatory change may not have had very large effects.

made to redress arrears, these are allowed to push the measure towards zero. The division by EMI puts the cumulative installment deficit into units of required monthly payments.

Figure 8 plots the CID measure around 30-day delinquencies, before and after the regulatory change to the definition of NPAs. The measure is cross-sectionally demeaned by both cohort-year and calendar-year, to ensure that we are not picking up cohort or macroeconomic effects. In both panels of Figure 8, date 0 is the first date that the loan is declared 30-days delinquent (values below 1 are possible because of the cross-sectional demeaning). The top panel shows that prior to the change in the regulatory definition of NPAs, loans declared 30-days delinquent on average inflicted a cost on the mortgage provider of roughly 1.1 EMIs after a year. Post-March 2004, there is a substantial recovery in this number, with such 30-delinquent loans roughly 0.3 EMIs delinquent 12 months later. The bottom panel of the figure shows that this change in the behavior of the CID after the regulatory redefinition of NPAs is highly statistically significant.

We undertake this analysis more formally by estimating how changes in the CID vary following a 30-day delinquency, but prior to hitting the 90-day threshold, both before and after the regulatory redefinition of the NPA period. To do so, we estimate expected debt collection rates – changes in the CID – as a polynomial function of the level of the CID prior to the 90-day delinquency mark (i.e., a CID level of -3), allowing for a jump in the rate at the 90-day delinquency mark, and modelled as a linear function of the CID beyond the 90-day delinquency mark. As before, we include time- and cohort-specific fixed effects during estimation to ensure that we are not merely picking up some of the broader changes detected earlier in the regulatory and macroeconomic environment.

Figure 9 shows how the estimated debt collection rate varies before and after the 90-day delinquency threshold, before and after the regulatory redefinition of NPAs in March 2004. The figure clearly reveals that following the regulatory redefinition of NPAs, the debt collection rate prior to hitting the 90-day mark increased substantially relative to the pre-regulatory change period, with a significant discontinuity at the 90-day threshold, where the debt collection rate falls sharply.[6] We also consider whether the introduction of SARFAESI

[6] The increase in the debt collection rate prior to the 90-day delinquency mark, and the discontinuity

had any significant impacts on the ability to collect on debts, and find that while there is a mild increase in the pre-90 day debt collection rate, it is dwarfed by the change following the NPA redefinition (moreover, the small discontinuity evident in this line at the 90-day mark is statistically insignificant).

While these changes to debt collection rates are clearly evident in the data, one potential worry is that the redefinition of NPAs from 180 to 90 days simply shifted the inevitable recovery of cash from delinquent borrowers by the 90-day difference between these two dates. In other words, perhaps the change merely provided a time-value improvement in the net cash flows of the mortgage provider, but no more substantial impacts.

To address this question, Figure 10 shows the cumulative distribution function (CDF) of the change in the CID (time- and cohort-demeaned) in the year following the first 30 day delinquency. This CDF is plotted for three time periods, namely, January 1995 to June 2002, when SARFAESI was first implemented; July 2002 to March 2004, the date of the redefinition of NPAs; and post-April 2004 until the end of the sample period in 2010. We plot the figure on a log scale to focus attention on the very worst cases (i.e., those loans with the greatest degradation in CID over the year following the date of first 30-day delinquency), as these loans are the most likely candidates for a complete write-off.

The figure shows that the post-NPA redefinition CDF first-order stochastically dominates both the pre- and post-SARFAESI CDFs, showing a substantial reduction in the incidence of high degradation in the CID. While SARFAESI appears to have had some beneficial impacts for the very worst cases, this is dwarfed by the large impact of the NPA redefinition. These substantial impacts on eventual bad debts of this regulatory redefinition are striking, as it appears that there are important real benefits to incentivizing mortgage providers to detect and take early action on delinquencies.

Finally, in Figure 11 we document some evidence that the change in the regulatory classification of NPAs affected mortgage origination as well as mortgage monitoring practices.

at that mark are both economically and statistically significant. The online empirical appendix plots the difference between the pre- and post- NPA redefinition debt collection rates with associated bootstrap confidence intervals.

This figure reports the same curve as in Figure 10, separately for loans originated in a six-month window before the NPA reclassification and in a six-month window after the reclassification. The left tail of the distribution is noticeably thicker for loans originated before the reclassification, even though both cohorts of loans are experiencing delinquency after the reclassification and hence are subject to post-reclassification monitoring by the mortgage lender. This implies that the reclassification induced the mortgage lender to tighten mortgage origination standards slightly as well as to monitor mortgages more closely.

In summary, a simple change in the regulatory definition of NPAs appears to have significantly moderated mortgage delinquencies. The impacts are visible in both the probability of delinquency and the eventual loss given delinquency, and they are somewhat stronger for mortgages originated after the NPA reclassification.

5 Conclusion

The Indian regulatory and macroeconomic environment has changed dramatically during the last two decades. A fast-developing housing finance system has coped with significant variation in default rates and interest rates, and regulatory changes in the incentives to originate mortgages in general, and small loans in particular. In this paper we have explored the effects of such regulatory changes on mortgage risk.

Our empirical strategy links time variation in regulation with expected cross-sectional impacts on different types of mortgages. We view this approach as an appealing alternative to regression discontinuity analysis for studies analyzing the impacts of regulation on market outcomes, especially in situations where discontinuities are hard to identify, or in environments where the discontinuities at thresholds are blurred by the responses of market participants.

We have presented evidence that regulatory subsidies for low-cost housing distorted the efficient markets relationship between interest rates and subsequent delinquencies, and that changes to the definition of non-performing assets impacted behavior in response to early evidence of payment delinquencies. While it is difficult to generalize findings from one country, the effect of the regulatory redefinition of NPAs does suggest that even seemingly minor regulatory changes can have important impacts on mortgage monitoring and origination practices, and hence on mortgage risk.

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Table 1: Indian Macroeconomic Statistics - 1985 through 2010

Real GDP and CPI Inflation are computed as the difference in year-end GDP or price levels. Interest rates (government yields and prime rate) are computed as the average across all days (ten year government yield series) or month-ends (one year government yield and prime rate series) in each calendar year. Aggregate real home price appreciation is computed as follows. First, nominal home price appreciation is computed by sub-branch as the change in annual median home value for loans originated by that sub-branch. Aggregate nominal home price appreciation is then computed as a weighted average of the sub-branch home price appreciation measures using the number of loans disbursed by location as weights. The series is inflation adjusted using the All India CPI inflation reported by the World Bank. This method of computation is robust to shifts in loan origination between sub-branches with different housing costs.

Variable:	Real GDP Growth	Aggregate Real Home Price Appreciation	CPI Inflation	Yield on One Year Indian Government Bonds	Yield on Ten Year Indian Government Bonds	Indian Prime Lending Rate
Source:	World Bank	Lender Data, World Bank	World Bank	CMIE Business Beacon	Global Financial Database	Global Financial Database
1985	5.23%		5.56%		8.98%	16.50%
1986	4.77%		8.73%		9.80%	16.50%
1987	3.96%		8.80%		10.15%	16.50%
1988	9.64%		9.89%		10.66%	16.50%
1989	5.95%		6.16%		11.59%	16.50%
1990	5.53%		8.97%		12.46%	16.50%
1991	1.06%		13.87%		12.88%	17.88%
1992	5.48%		11.79%		13.61%	18.92%
1993	4.77%	-6.90%	6.36%		13.21%	16.25%
1994	6.65%	1.07%	10.21%	10.00%	13.44%	15.00%
1995	7.57%	1.39%	10.22%	12.48%	13.85%	15.50%
1996	7.56%	2.57%	8.98%	12.49%	14.03%	15.96%
1997	4.05%	5.62%	7.16%	9.01%	12.74%	13.83%
1998	6.19%	-5.27%	13.23%	8.95%	12.59%	13.54%
1999	7.39%	5.65%	4.67%	10.26%	12.28%	12.54%
2000	4.03%	6.96%	4.01%	10.00%	11.51%	12.25%
2001	5.22%	3.17%	3.68%	8.06%	10.01%	12.50%
2002	3.77%	1.68%	4.39%	6.19%	7.67%	12.00%
2003	8.37%	14.99%	3.81%	5.05%	6.16%	11.46%
2004	8.28%	21.61%	3.77%	4.93%	6.46%	10.92%
2005	9.32%	20.26%	4.25%	5.75%	7.50%	10.75%
2006	9.27%	19.01%	5.80%	6.78%	8.19%	11.19%
2007	9.82%	21.53%	6.37%	7.59%	8.50%	13.02%
2008	4.93%	9.96%	8.35%	7.98%	8.66%	13.31%
2009	9.10%	0.09%	10.88%	4.45%	7.66%	12.19%
2010	8.81%	-1.38%	10.00%	5.98%	8.45%	11.00%

Table 2: Level and Variation in Loan Disbursal Share Meeting Regulation Relevant Thresholds

Loan disbursals below the PSL threshold and above loan-cost ratios of 75% are given as the share of the total value of loans disbursed in the given year. Sub-branch variation is the standard deviation of sub-branch specific values, which are computed first by averaging across all loan disbursals in each sub-branch-year in which more than 100 loans were disbursed, and then averaging over years for each sub-branch which made more than 100 disbursals in at least five years. The regulatory source documents are detailed in the online regulatory appendix. Statistics for fixed rate mortgage disbursals after 2007 are not shown due to limited fixed rate lending in these years.

A: Share of Loan Disbursals Meeting Regulation Relevant Thresholds

	Variable Rate Share of Disbursals		**Variable Rate Mortgages**		**Fixed Rate Mortgages**	
	By Count	By Value	Below PSL Threshold	Loan-Cost Ratios Above 75%	Below PSL Threshold	Loan-Cost Ratios Above 75%
1995	37.86%	42.98%	74.06%	21.84%	76.07%	19.10%
1996	47.45%	51.78%	68.77%	22.40%	69.38%	19.26%
1997	55.29%	60.84%	66.83%	24.21%	68.30%	19.64%
1998	59.04%	66.78%	79.15%	30.17%	84.59%	24.92%
1999	65.55%	71.32%	80.62%	36.45%	85.71%	31.57%
2000	75.70%	81.65%	87.12%	44.42%	91.64%	41.44%
2001	75.32%	82.31%	83.07%	49.39%	89.57%	43.29%
2002	84.40%	89.83%	78.88%	55.58%	90.67%	42.84%
2003	94.14%	94.16%	71.21%	60.70%	69.34%	52.13%
2004	84.51%	79.97%	67.95%	63.63%	51.67%	64.59%
2005	90.40%	92.09%	64.69%	66.97%	76.81%	61.04%
2006	90.44%	92.87%	46.06%	65.94%	67.56%	58.27%
2007	95.76%	97.72%	43.03%	65.34%	67.03%	53.61%
2008	99.44%	99.80%	42.73%	62.71%		
2009	99.87%	99.97%	38.30%	60.34%		
2010	99.97%	99.99%	36.45%	64.26%		

B: Variation in Share Across Sub-Branches

	Mean	Standard Deviation	Minimum	Maximum
Below PSL Threshold	73.64%	19.05%	21.90%	99.47%
Loan-Cost Ratios Above 75%	58.73%	10.88%	28.81%	88.21%

Table 3: Summary Statistics on Loan Characteristics by Disbursal Year

This table provides yearly means (Panel A) and standard deviations (Panel B) of important characteristics for the more than 1.2 million mortgage loans disbursed by the lender. Cohort delinquency rates are computed as the annual probability that an outstanding and not-yet-90-day-delinquent loan experiences a 90 day delinquency. This probability is computed separately for each disbursal-year cohort and calendar year. The delinquency rate below represents the time-series average across calendar year estimates for each disbursal-year cohort. Statistics for fixed rate disbursals are removed for the years 2008 through 2010, as fixed rate disbursals account for well under one percent of disbursals (by count or value) in each of these years. Similarly, cohort 90-day delinquency rate is omitted for loans disbursed after 2007 as these loans have not been around long enough to reliably estimate a delinquency rate.

A: Cross-Sectional Means

	Initial Interest Rate		Loan Term (Years)		Loan-Cost Ratio		Loan-Income Ratio		Cohort 90-Day Delinquency Rate	
	Variable	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**
1995	15.22%	15.00%	13.96	11.66	0.58	0.54	3.73	3.52	1.70%	2.27%
1996	16.39%	16.14%	13.21	10.89	0.57	0.54	3.69	3.45	1.98%	2.56%
1997	15.54%	15.25%	13.18	10.38	0.58	0.55	3.69	3.38	1.76%	2.79%
1998	14.45%	14.09%	13.08	10.06	0.61	0.57	3.67	3.28	1.84%	3.12%
1999	13.58%	13.39%	12.88	10.63	0.64	0.61	3.62	3.31	1.78%	4.38%
2000	12.58%	12.83%	12.95	10.55	0.67	0.67	3.58	3.20	2.13%	4.58%
2001	11.78%	11.76%	12.72	10.23	0.68	0.64	3.56	3.23	2.16%	5.27%
2002	10.92%	10.82%	13.15	10.03	0.70	0.64	3.49	3.21	2.53%	4.63%
2003	10.68%	9.41%	12.88	12.76	0.72	0.65	3.45	3.54	2.36%	2.20%
2004	10.82%	8.13%	14.07	15.13	0.73	0.71	3.65	3.75	2.18%	0.91%
2005	10.42%	8.83%	15.16	15.17	0.74	0.69	3.75	3.72	1.75%	1.26%
2006	10.85%	10.45%	15.23	15.59	0.73	0.70	3.74	3.69	1.53%	1.12%
2007	11.03%	12.26%	15.03	14.68	0.73	0.68	3.75	3.58	1.18%	1.43%
2008	10.79%		15.38		0.72		3.78			
2009	9.51%		14.31		0.71		3.72			
2010	8.39%		15.59		0.73		3.84			

B: Cross-Sectional Standard Deviations

	Initial Interest Rate		Loan Term (Years)		Loan-Cost Ratio		Loan-Income Ratio	
	Variable	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**	**Variable**	**Fixed**
1995	0.94%	1.13%	2.51	4.24	0.18	0.20	0.47	0.71
1996	1.28%	1.53%	2.73	4.26	0.18	0.20	0.49	0.74
1997	0.84%	1.22%	2.72	4.49	0.18	0.20	0.51	0.83
1998	0.71%	1.09%	2.81	4.69	0.18	0.20	0.51	0.86
1999	0.51%	0.77%	3.00	4.52	0.18	0.19	0.52	0.80
2000	1.21%	0.85%	3.61	4.57	0.18	0.19	0.57	0.85
2001	1.06%	0.97%	3.97	4.56	0.18	0.24	0.61	0.83
2002	1.46%	0.92%	4.43	4.63	0.19	0.24	0.70	0.81
2003	2.08%	0.89%	4.85	4.77	0.19	0.26	0.78	0.67
2004	2.04%	0.60%	4.97	4.55	0.18	0.21	0.72	0.59
2005	1.73%	0.48%	4.92	4.52	0.18	0.22	0.68	0.60
2006	1.24%	0.76%	4.95	4.48	0.18	0.22	0.70	0.63
2007	0.67%	1.00%	4.41	4.78	0.18	0.23	0.69	0.71
2008	0.59%		4.57		0.18		0.70	
2009	0.77%		5.00		0.18		0.72	
2010	0.37%		4.55		0.17		0.64	

Table 4: 90 Day Delinquency Model

This table presents coefficient estimates and standard errors from estimates of equation (1) in the paper. The estimation takes place in two stages. First, cross-sectional estimates are produced for each year. Coefficients below are produced from the cross-sectional estimates by classical minimum distance (See Wooldridge 2002, p442-446). Excluded from coefficients below are cohort, branch, and monthly fixed effects, and separate macroeconomic scaling effects Z_t for fixed and variable rate mortgages. Standard errors are given in italics to the right of coefficients, and are computed by bootstrapping calendar years. Coefficients that are statistically significant at 5% and 10% two-sided level are in bold and italicized type respectively. All coefficients and standard errors are multiplied by 100 for readability.

	Coefficient	S.E.
Borrower Characteristics:		
Log Number of Dependents	-0.047	*0.052*
Male Borrower	**0.236**	*0.024*
Married Borrower	*0.059*	*0.033*
Borrower age 36-45	**0.095**	*0.012*
Age 46 and up	**0.240**	*0.043*
Dummy: Repeat Borrower	**0.397**	*0.110*
Dummy: Qualification Missing or Unidentified	**-0.142**	*0.055*
Dummy: HSC Equivalent	**-0.480**	*0.067*
Dummy: BA Equivalent	**-0.741**	*0.093*
Dummy: Post-Grad Equivalent	**-1.123**	*0.091*
Dummy: Finance-Related Qualification	**0.189**	*0.029*
Loan Characteristics:		
Initial Interest Rate (Variable Rate Mortgages)	**0.449**	*0.041*
Initial Interest Rate (Fixed Rate Mortgages)	**0.321**	*0.038*
Change in One-Year Government Bond Yield Since Disbursal (Variable Rate Mortgages Only)	*0.078*	*0.041*
Regional Log Home Price Appreciation Since Disbursal	**-0.952**	*0.248*
Log Loan to Income Ratio (winsorized at 1st, 99th)	**0.792**	*0.065*
Log Loan Amount	**-0.835**	*0.109*
Loan to Cost Ratio	**2.958**	*0.127*
Dummy: Usually Paid by Salary Deduction	**-1.889**	*0.102*
Dummy: Loan administered through employers	**-0.268**	*0.054*
Dummy: Loan is a Refinancing	**0.448**	*0.098*
Dummy: Loan is for a Home Extension	**-0.160**	*0.043*
Dummy: Loan is for a Home Improvement	**0.239**	*0.076*
Dummy: Tranched Issuance	**-0.524**	*0.124*
Dummy: 6 to 10 Year Loan (Variable Rate Mortgages)	**0.191**	*0.081*
Dummy: 11 to 15 Year Loan (Variable Rate Mortgages)	**0.653**	*0.115*
Dummy: 16 Year+ Loan (Variable Rate Mortgages)	**1.496**	*0.178*
Dummy: 6 to 10 Year Loan (Fixed Rate Mortgages)	**0.754**	*0.117*
Dummy: 11 to 15 Year Loan (Fixed Rate Mortgages)	**1.228**	*0.142*
Dummy: 16 Year+ Loan (Fixed Rate Mortgages)	**0.646**	*0.116*
Dummy: Fixed Rate Mortgage	**1.790**	*0.649*
Dummy: Year of Loan Issuance	**-2.531**	*0.133*
Dummy: Disbursed Within 12 Months of State Election	-0.010	*0.047*

Table 5: Regulatory Impact on 90 Day Delinquency

This table presents coefficient estimates and standard errors from estimates of equation (1) in the paper, estimated as in Table 4. Unqualified lending share is the share of loan disbursals (by value) made over the past year which are associated with loans larger than the latest PSL threshold. Sub-branch unqualified lending share is the same statistic, computed at the sub-branch level, and cohort de-meaned sub-branch unqualified lending share is the cross-sectionally de-meaned version of the sub-branch level statistic. All "unqualified lending share" variables are scaled to a mean of zero and variance of one for ease of interpretation. Coefficients that are statistically significant at a 5% or 10% two-sided level are in bold and italicized type respectively. All coefficients and standard errors are multiplied by 100 for readability. R-squared is calculated as the average of the variance of fitted values to variance of dependent variable in each cross-section.

	[A]		**[B]**		**[C]**	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Loan Size Based (PSL) Regulation:						
Slope Above PSL Threshold	-0.105	*0.106*	0.074	*0.086*	0.059	*0.087*
Slope Below PSL Threshold	**-0.889**	*0.084*	**-0.853**	*0.080*	**-0.794**	*0.098*
Unqualified Lending Share X Slope Below PSL Threshold	**-0.145**	*0.044*	**-0.136**	*0.047*		
Sub-Branch Unqualified Lending Share			**-0.322**	*0.027*	**-0.431**	*0.037*
Cohort De-meaned Sub-Branch Unqualified Lending Share X Slope Below PSL Threshold			**-0.063**	*0.022*		
Cohort De-meaned Sub-Branch Unqualified Lending Share X Unqualified Lending Share X Slope Below PSL Threshold			**-0.060**	*0.018*		
Sub-Branch Unqualified Lending Share X Slope Below PSL Threshold					**-0.076**	*0.025*
Loan Leverage Based Regulation:						
Loan-Cost Ratio, Slope Below 65%	**3.080**	*0.271*	**2.929**	*0.247*	**2.935**	*0.244*
Loan-Cost Ratio, Slope Between 65 and 85%	**3.556**	*0.384*	**3.545**	*0.361*	**3.581**	*0.368*
Difference in Cohort Risk Weights on Loans Above vs Below 75% LTV X Slope Between Loan-Cost Ratio of 65 and 85%	-1.244	*1.533*	-1.415	*1.607*	-1.720	*1.682*
Loan-Cost Ratio, Slope Above 85%	**-2.195**	*0.717*	**-1.986**	*0.680*	**-1.968**	*0.674*
Borrower Characteristics	Yes		Yes		Yes	
Loan Characteristics	Yes		Yes		Yes	
Cohort Fixed Effects	Yes		Yes		Yes	
Annual Macroeconomic Effects (Separate for Fixed, Variable Rate Mortgages)	Yes		Yes		Yes	
21 Branch Dummies	Yes		Yes		Yes	
R-squared	0.0156		0.0157		0.0157	

Table 6: Lending Volume Responses to PSL Regulation

In panel A, the estimated value, α, is: [(growth above minus growth below old threshold)+(growth below minus growth above new threshold)]/2. Growth is measured by first drawing cutoffs above and below the thresholds representing either 1% or 2.5% of aggregate lending activity in the year prior to PSL threshold changes. We then look at growth in the share of loans disbursed within those ranges in the year following the PSL threshold change. In panel B, the sub-branch lending share below the past month's PSL threshold is predicted with lagged PSL lending share and a dummy to indicate increases in the PSL threshold, which is also interacted with lagged PSL lending share. Increases in the PSL threshold are hypothesized to result in reductions in lending below the old (lower) PSL thresholds, and these reductions are expected to be even larger for sub-branches with lower PSL lending shares. Sub-branch observations are weighted proportionally to their share of the number of loans disbursed in the surrounding 12 month period. Standard errors in italics are based on bootstraps of the four events where PSL thresholds change in panel A, and of years in panel B.

A: Difference in Lending Growth Below and Above PSL Thresholds at Threshold Changes

	using 1% cutoffs		using 2.5% cutoffs	
	Coef.	S.E.	Coef.	S.E.
α	41%	*25%*	30%	*20%*

B: Cross-sectional Responsiveness of PSL Lending Growth to PSL Threshold Changes

Dependent Variable: Change in Log Share of Sub-Branch Lending Below Last Month's PSL Threshold

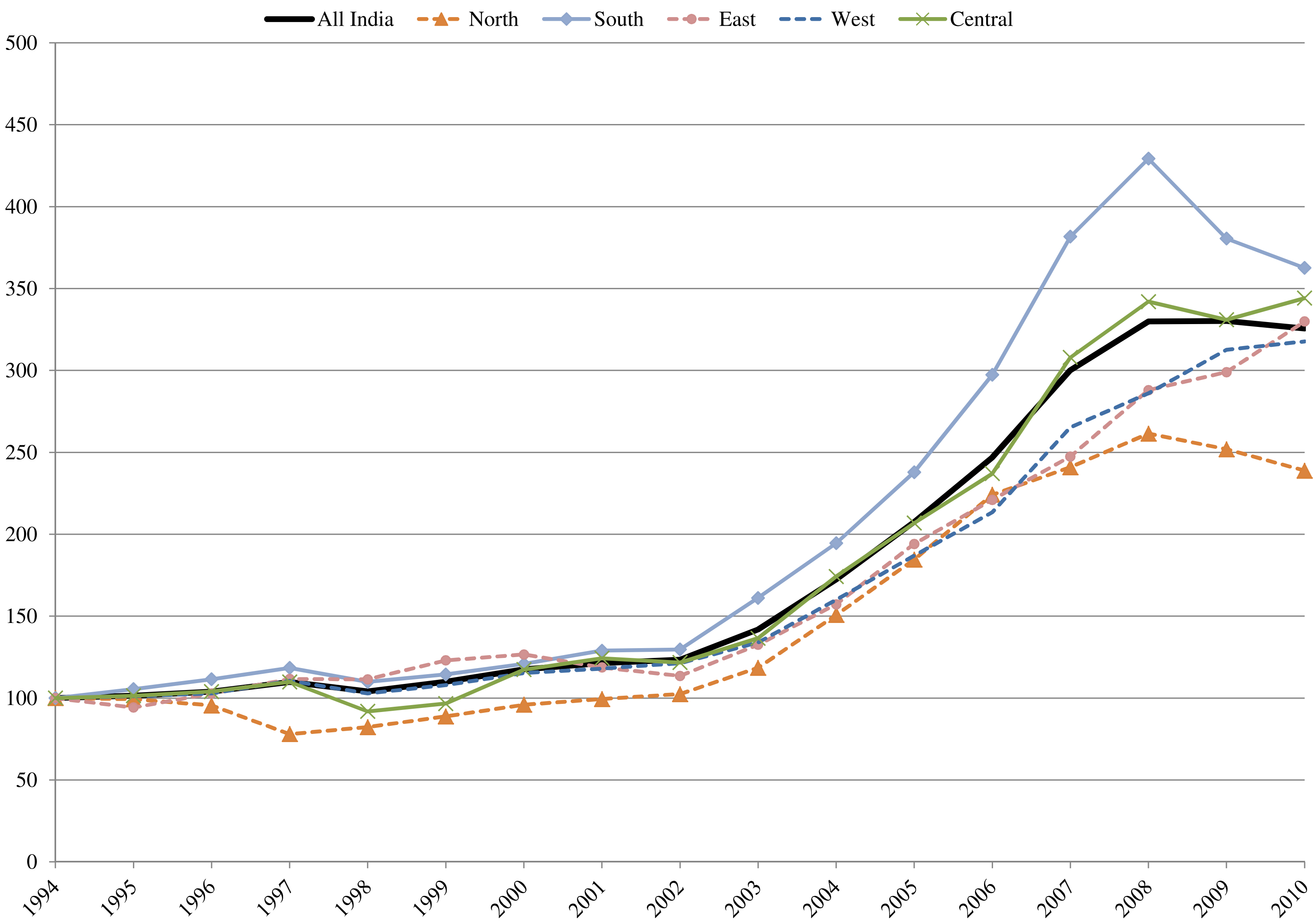
	[w/o Sub-Branch FE]		[with Sub-Branch FE]	
Constant	**-0.052**	*0.010*		
De-meaned Lagged Sub-Branch PSL Share	0.017	*0.034*	-0.068	*0.044*
Dummy: PSL Threshold Changes	**-0.044**	*0.017*	**-0.051**	*0.020*
De-meaned Lagged Sub-Branch PSL Share X PSL Threshold Changes	0.052	*0.046*	0.054	*0.048*

Table 7: Probability of Transition to Later Stage of Delinquency

This table presents the probability that initial 30 and 90 day mortgage delinquencies become 90 and 180 day mortgage delinquencies respectively within six months following the initial delinquency. This transition probability is first computed for all loans with initial delinquencies in a given month, and the probabilities shown below are the time-series average of these monthly cross-sectional estimates, where the average is taken over the indicated time periods. Standard errors are given in italics and constructed by bootstrapping from the population of monthly cross-sectional estimates from each time period indicated. All coefficients are highly statistically significant.

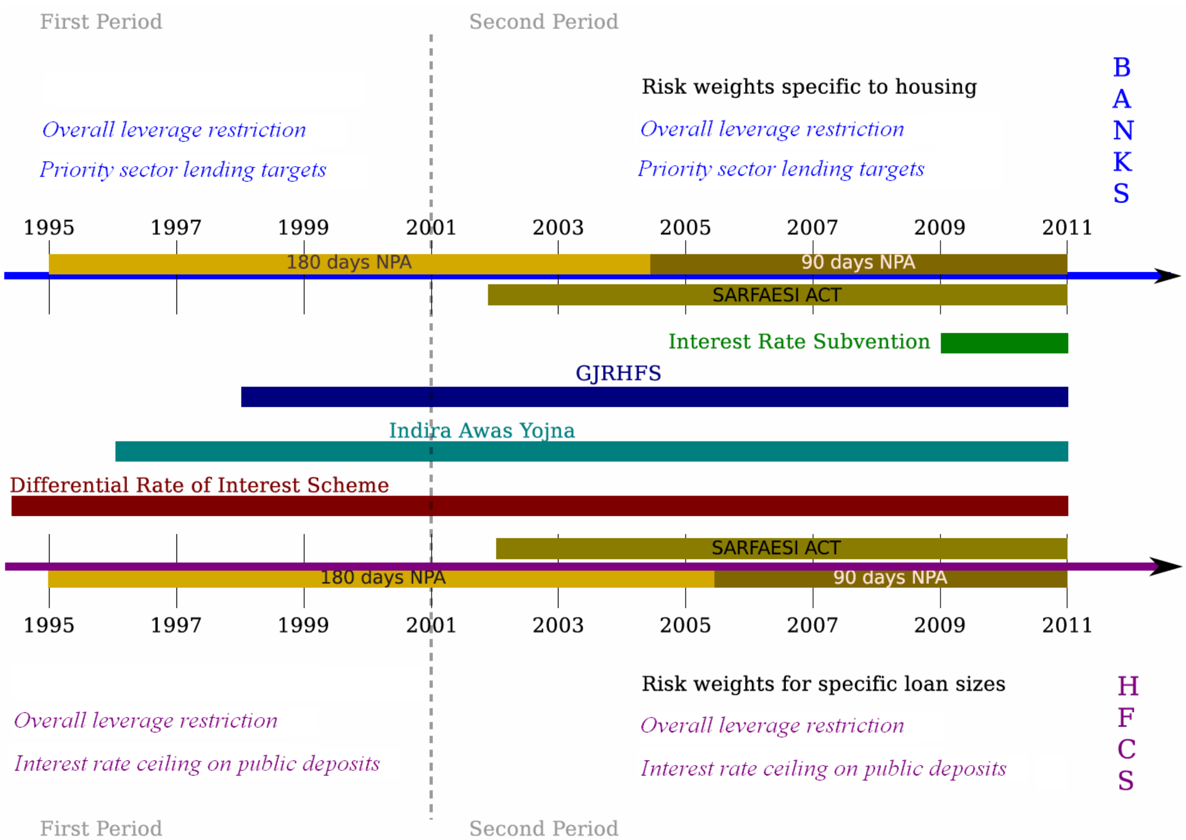
	Probability of 30 day Delinquency Transitioning to 90 day Delinquency		Probability of 90 day Delinquency Transitioning to 180 day Delinquency	
Month Relative	Value	SE	Value	SE
For Initial Delinquencies Occurring:				
All Months (Jan 1996-Dec 2010)	22.7%	*0.3%*	22.8%	*0.4%*
Jan 1996-Mar 2004 (180day NPA Regime)	29.0%	*0.5%*	23.9%	*0.6%*
April 2004-Dec 2010 (90d NPA Regime)	14.9%	*0.4%*	21.6%	*0.6%*
Difference Around April 2004	-14.1%	*0.7%*	-2.3%	*0.9%*

Figure 1: CPI Adjusted House Price Appreciation Indices



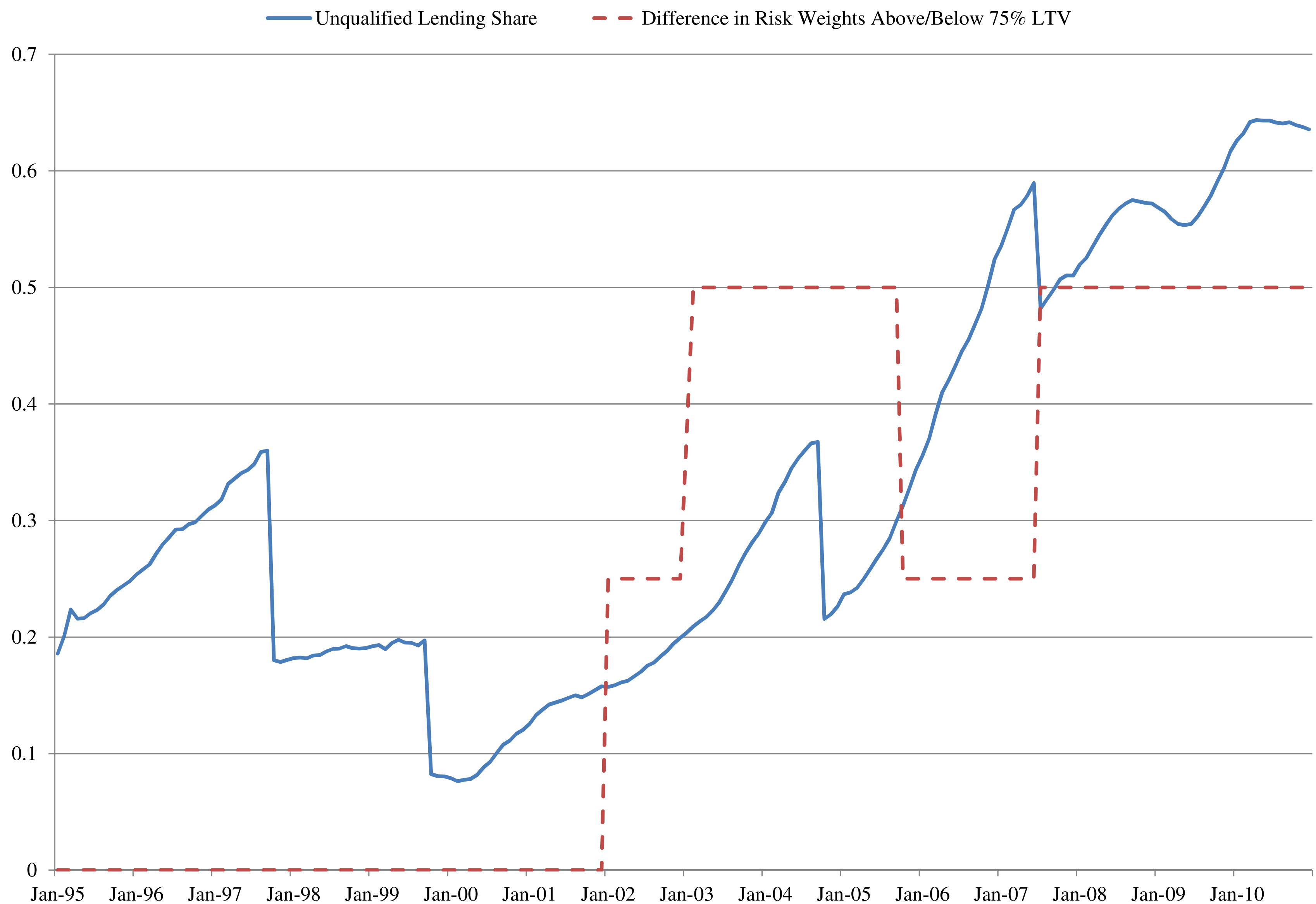
Regional (north, south, east, west, central) and all India home price appreciation are constructed as disbursal count weighted averages of home price appreciation by sub-branch. Appreciation by sub-branch is computed as the change in annual median home value corresponding to loans disbursed to that sub-branch. This method of computation is robust to shifts in loan origination between locations with differing housing costs. CPI figures used for adjustment are from the World Bank.

Figure 2: Timeline of Indian Mortgage Regulation



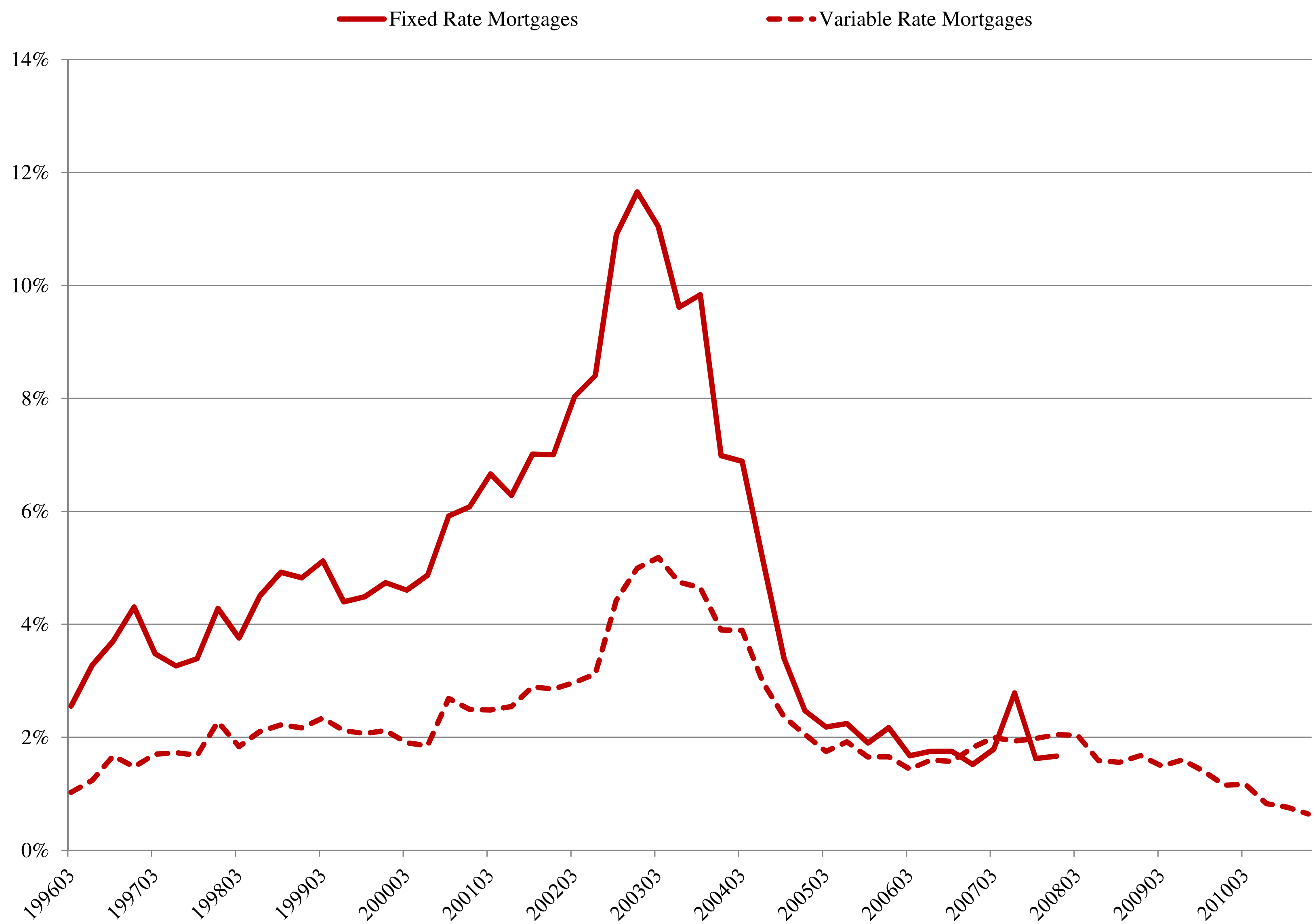
This figure summarizes regulation affecting mortgage lending in India, with the top half representing the form of regulations affecting banks and the bottom half representing the form of regulations affecting housing finance companies (HFCs). The solid bars in the middle section represent the timeline of programs affecting mortgage lending by both banks and HFCs. A division of regulations is drawn in 2001 (separating "first" and "second" periods) as that is when changing risk weights became a primary means of banking regulation in India. For further details on Indian mortgage regulation, see the online regulatory appendix.

Figure 3: Time-Series Intensity of Loan Size and Leverage Based Regulation



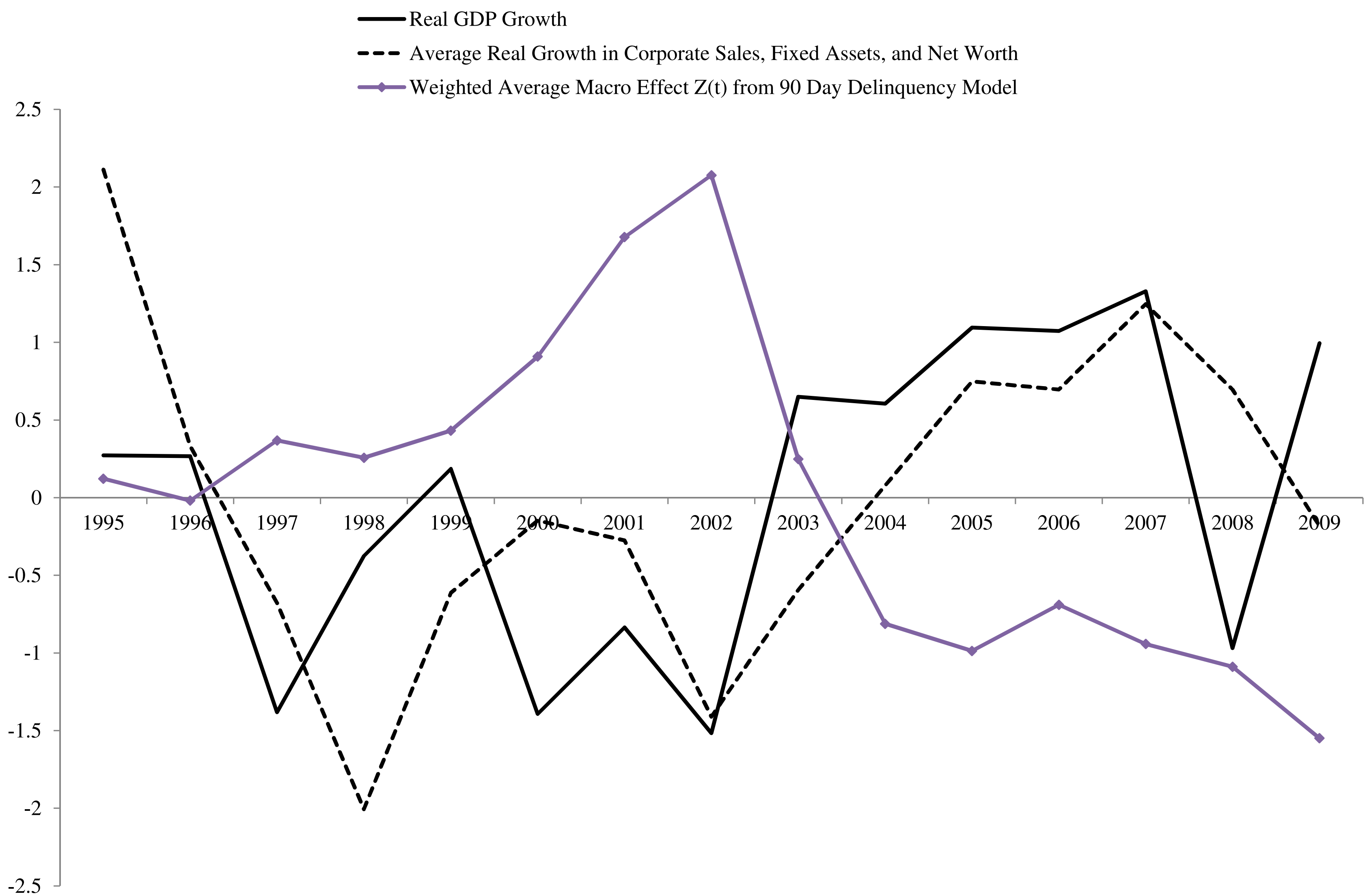
Unqualified lending share is equal to the fraction of value of loans disbursed in the past 12 months representing loans larger than the current PSL qualifying threshold. Sources for the regulatory limits are given in the online regulatory appendix.

Figure 4: Annualized Seasonally-Adjusted 90-Day Delinquency Rate



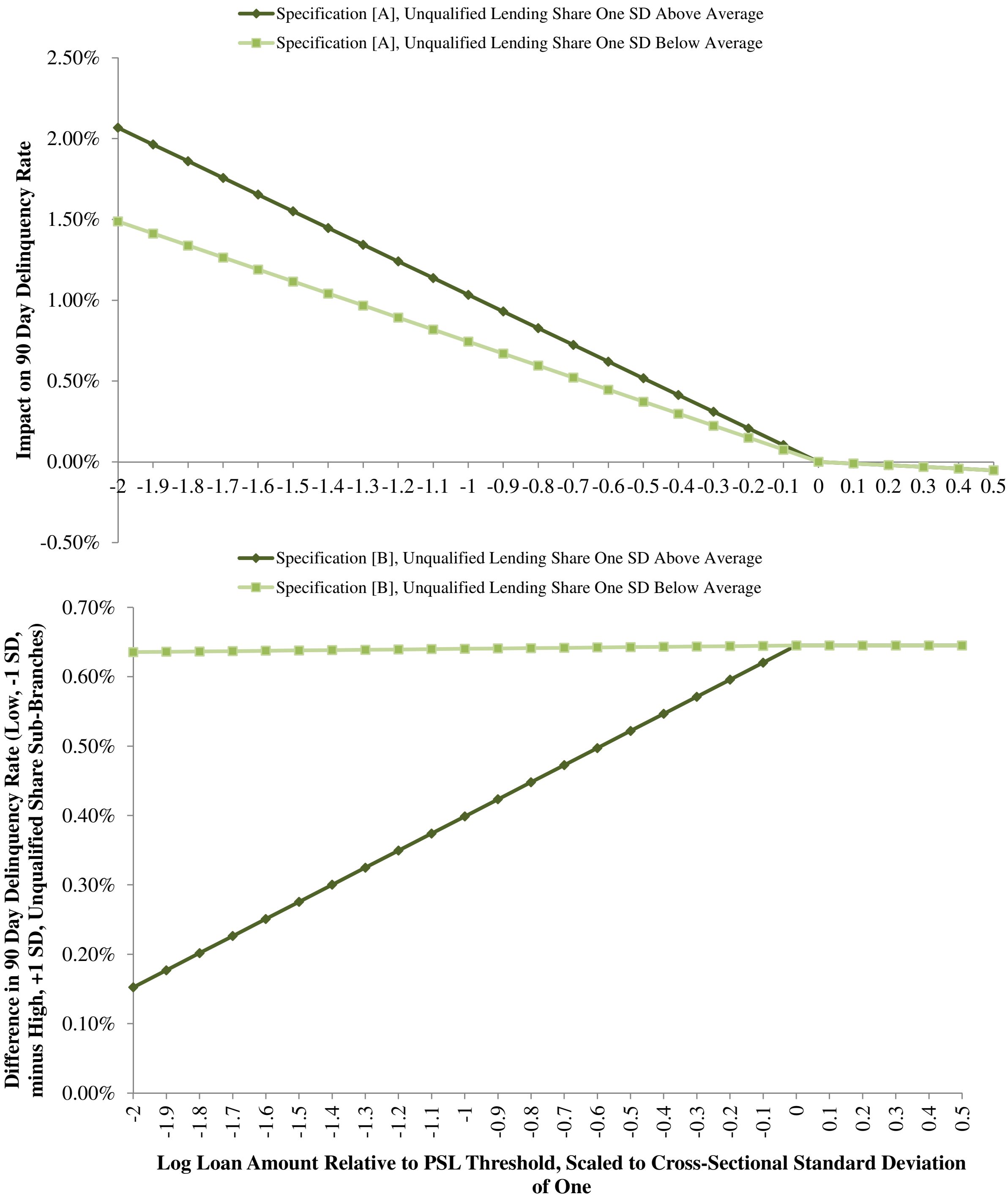
Seasonal adjustments are computed by regressing log quarterly 90 day delinquency rates (for all outstanding fixed or variable rate mortgages) on a set of year and calendar quarter dummies. The calendar quarter dummies from the log default rate regressions are exponentiated, normalized to one, and are used as scaling factors to seasonally-adjust the quarterly delinquency rates. The resulting de-seasoned quarterly delinquency rates (DEFQ) are annualized by the transformation $1-(1-DEFQ)^4$.

Figure 5: Macro Delinquency Effects and Other Indian Macroeconomic Time Series



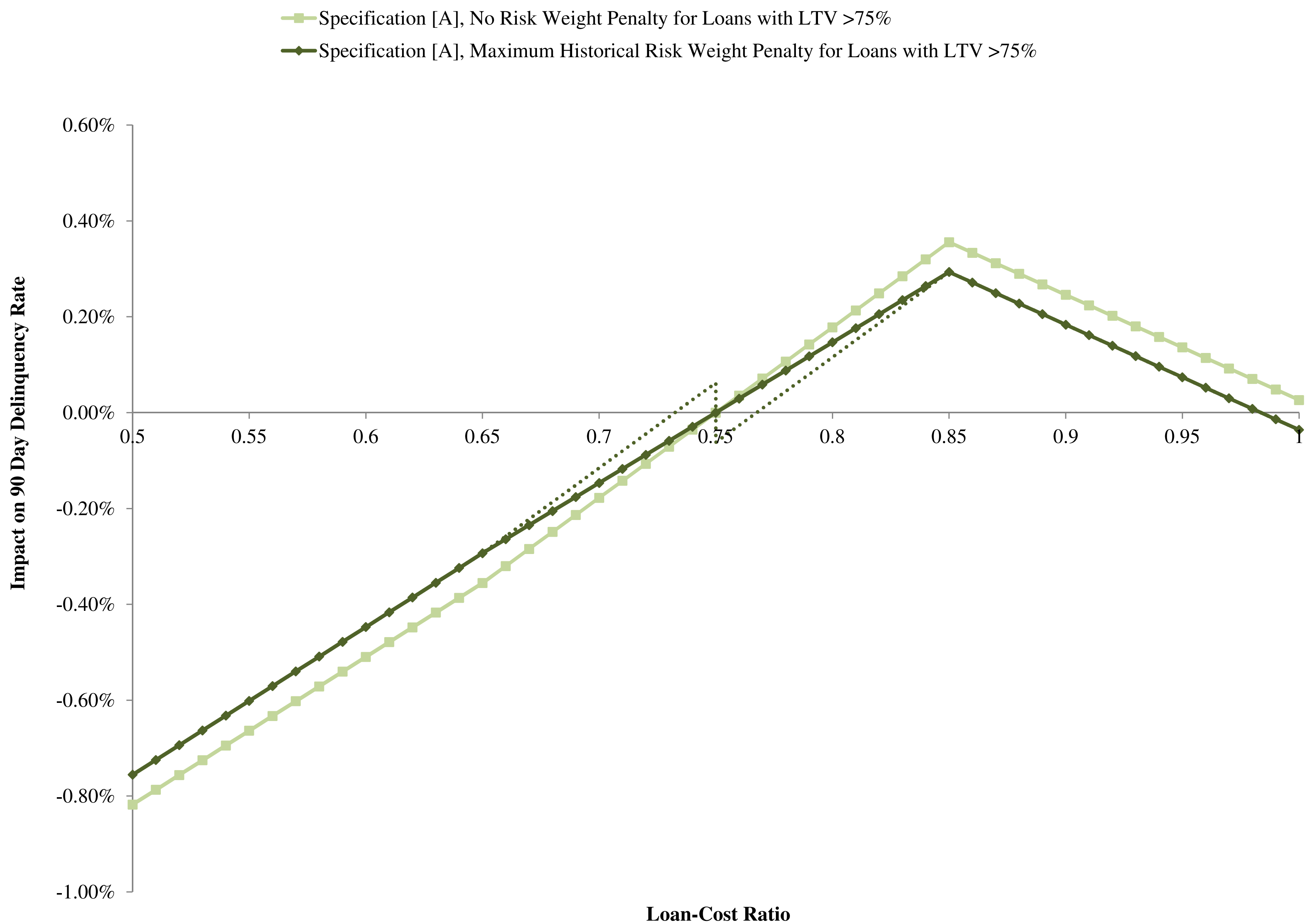
Real GDP growth is from the World Bank. Average real growth in corporate sales, fixed assets, and net worth is the average of the three constituent time series, which are taken from the Prowess database. CPI inflation (from the World Bank) is subtracted from this series. The weighted average macro effect is the disbursal value weighted average of the fixed rate and variable rate macroeconomic effects Zt estimated in the delinquency model with each scaled to a time-series mean of one. All plotted variables plotted are standardized (mean zero and variance one).

Figure 6: Impact of PSL Regulations on 90 Day Delinquencies by Loan Amount



The plotted series are constructed from coefficients in Table 5. The cross-sectional standard deviation of log loan amount is about 0.86.

Figure 7: 90 Day Delinquencies by Loan-Cost Ratio (Specification [A])

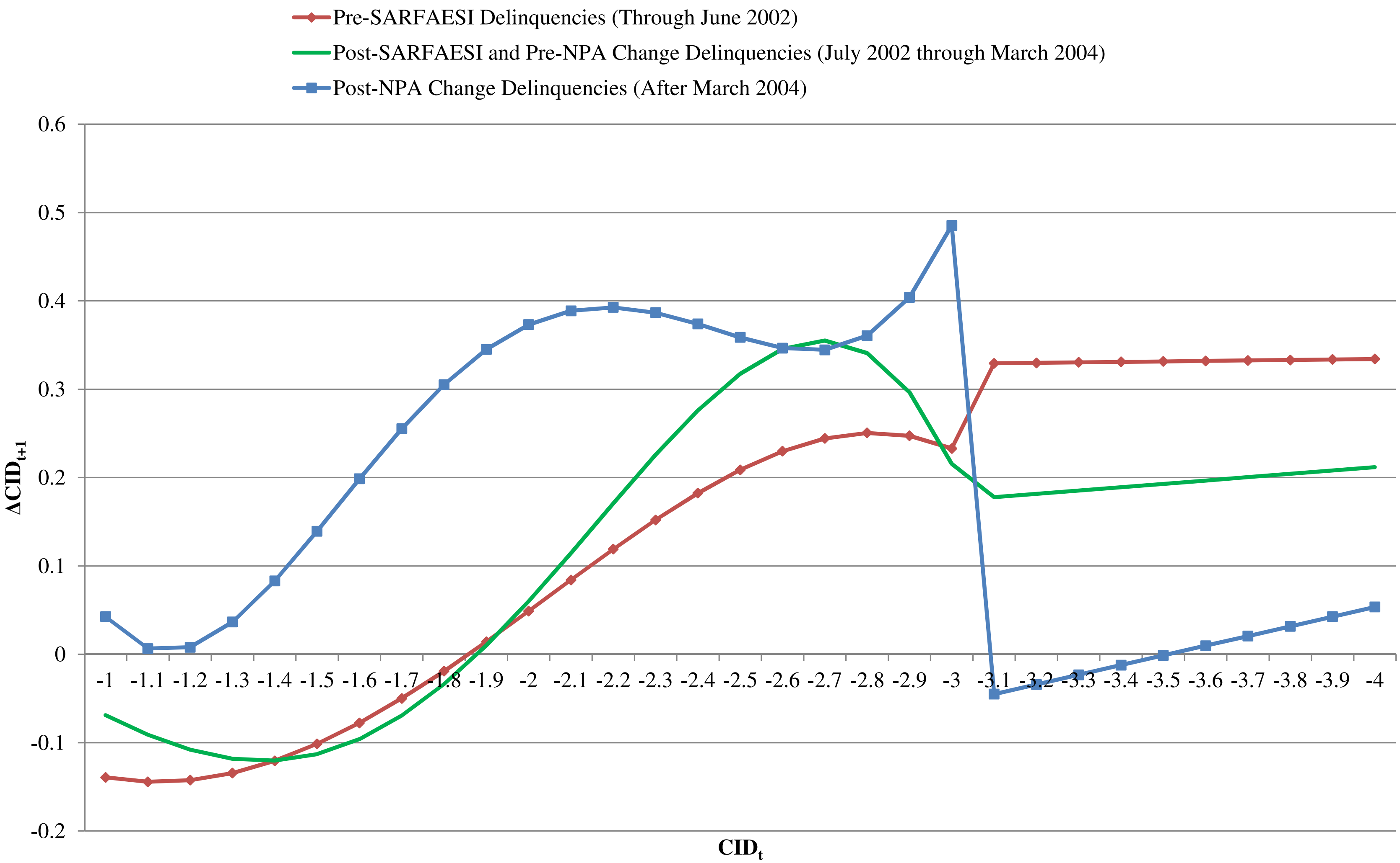


The plotted series are constructed from coefficients in Table 5.

Figure 8: Cumulative Installment Deficit around Delinquencies

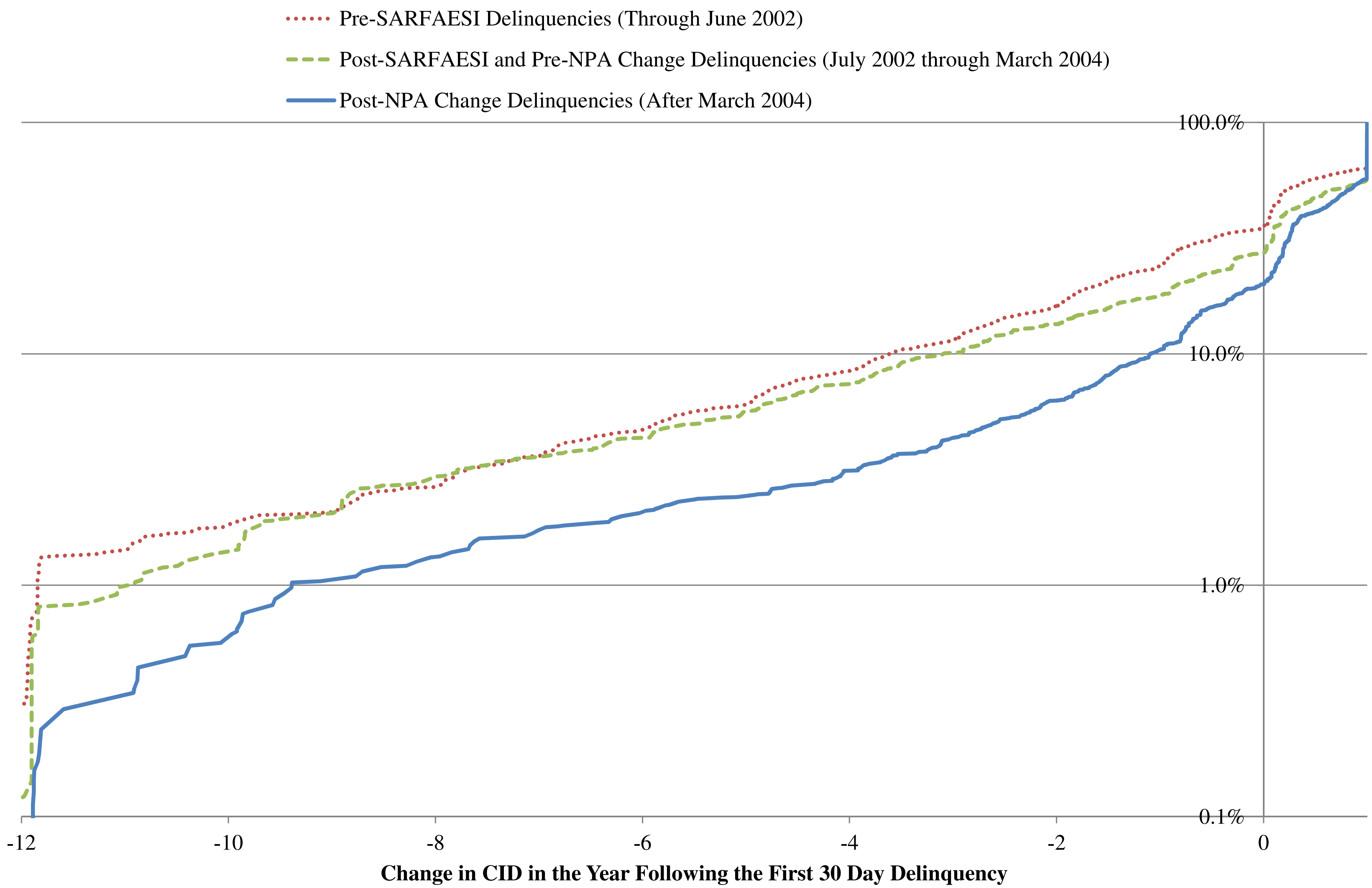
Predicted cumulative installment deficit (CID) is given by the estimated coefficients on time to delinquency (interacted with a post-March 2004 dummy) from a regression predicting changes in the cumulative installment deficit (value of delinquent installments in terms of expected monthly installments). The post-March 2004 dummy allows for a different pattern of installment deficits to emerge around delinquencies following the change in regulatory definition of non-performing assets. This model includes time and cohort fixed effects. Top Panel: The plotted series are cumulative sums of the changes in installment deficits estimated from the model with cohort and time fixed effects removed. Bottom Panel: The series shown is the difference in the series plotted in the top panel accumulated backwards and forwards in time from the month of delinquency. The 90% confidence intervals shown are computed by bootstrapping years of observations separately from the groups 1996-2003 and 2004-2010.

Figure 9: Predicted ΔCID_{t+1} Post-30 Day Delinquency (ΔCID is a Debt Collection Rate)



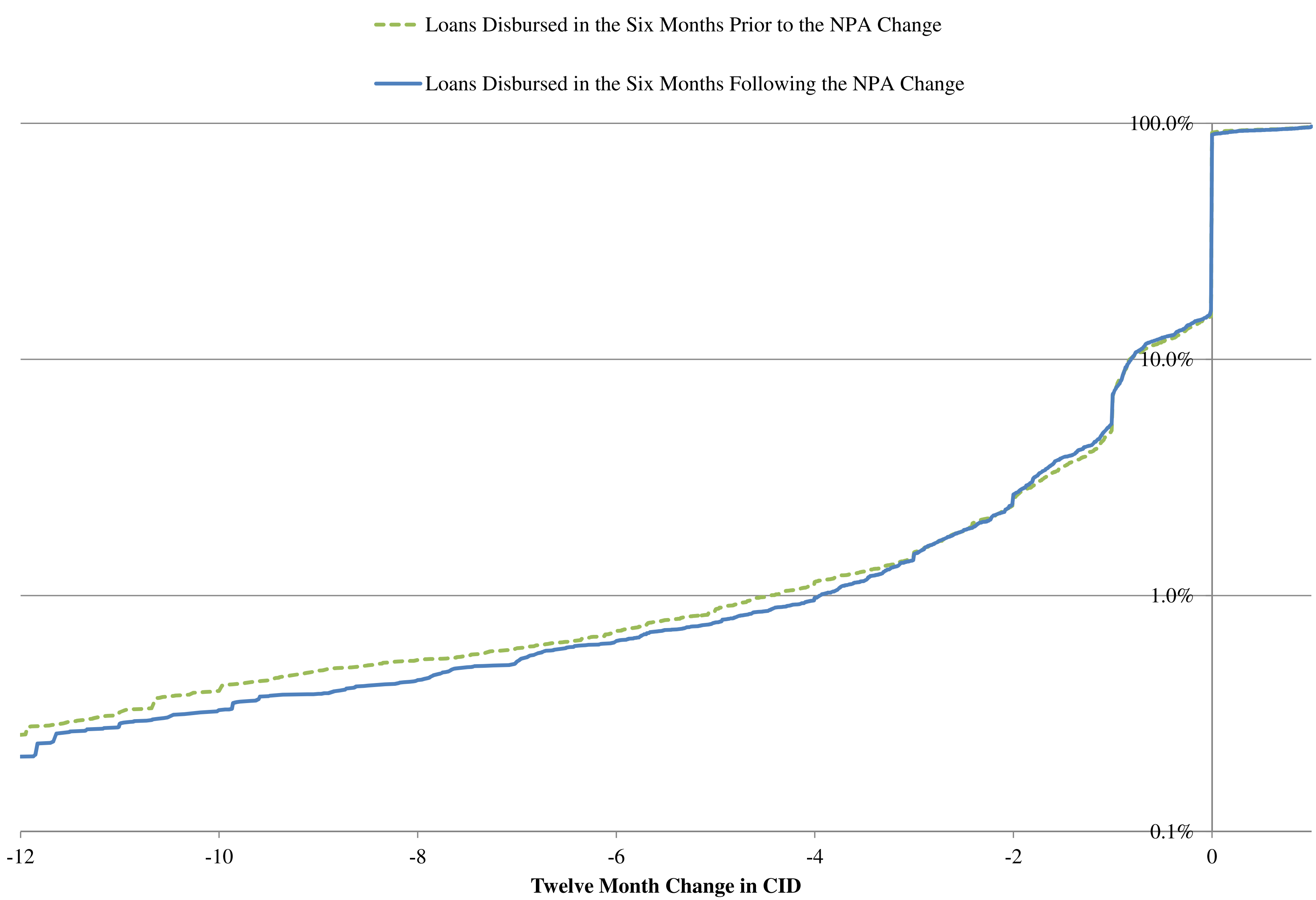
The expected debt collection rates (ΔCID) plotted below are produced from least squares regressions which fit ΔCID as a set of (1) year fixed effects, (2) cohort fixed effects, and (3) if the observation is a loan within six months following a 30 day delinquency, a nonlinear function of the current cumulative installment deficit (CID). The nonlinear function of CID is a fourth degree polynomial for CID levels below three months (90 days), and linear beyond three months of delinquencies with a jump allowed to occur at the three month horizon. Observations used for the regression are account-days (from a sample of 10,000 mortgage loans) that occur within the time window corresponding to each regression. Weights are used in the regression so that results are reflective of the larger population of loans from which the sampling occurred.

Figure 10: Cumulative Empirical Distribution of Change in CID 12 Months Post-30 Day Delinquency



Changes in cumulative installment deficit (CID) over a one year period are regressed on (1) a set of dummies indicating if a 30 day delinquency first occurred 1, 2, 3...12 months ago, (2) cohort fixed effects, and (3) time fixed effects. These regressions are run separately for each of the three time periods indicated. The cumulative distribution functions plot the residual plus fitted value on the "12 months after 30 day delinquency" dummy. Weights are used in the regressions and construction of the CDFs so that results are reflective of the larger population of loans from which the sample was drawn. For the roughly 10% of loans which leave the books within a year of the 30 day delinquency, the CID at the time of the loan's termination is used in the distribution.

Figure 11: Cumulative Empirical Distribution of Change in CID for Loans Disbursed Around the NPA Definition Change



The cumulative installment deficits used are based on observations of payment histories for 357 mortgages disbursed in the six months prior to and 422 mortgages disbursed in the six months following the NPA definition change. The Kolgorov-Smirnov test statistic for the difference in the two CDFs has a p-value of about 0.10.