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

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

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Abstract

To understand the effects of regulation on mortgage risk, it is instructive to track the history of regulatory changes in a country rather than to rely entirely on cross-country evidence that can be contaminated by unobserved heterogeneity. However, in developed countries with fairly stable systems of financial regulation, it is difficult to track these effects. We employ loan-level data on over a million loans disbursed in India over the 1995 to 2010 period to understand how fast-changing regulation impacted mortgage lending and risk. We find evidence that regulation has important effects on mortgage rates and delinquencies in both the time-series and the cross-section.

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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. However emerging markets pose a different challenge, that of finding adequate data. Many questions about mortgage finance can only be answered using microeconomic data, either at 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]

This paper uses high-quality microeconomic data to study 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 (for a recent example see 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

[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.

[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).

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.

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 both the macroeconomic and microeconomic determinants of mortgage rate setting and delinquencies. These data reveal three interesting findings which relate regulation to mortgage risk. First, simple plots reveal a significant spike in delinquencies in the early 2000s. When we estimate a model which relates delinquencies to demographic information, loan characteristics, and macroeconomic shocks, we find that even after controlling for these determinants, the spike in delinquencies shows up in the cohort effects for loans issued in those years. We connect these estimated cohort effects to a number of regulatory changes which encouraged mortgage lending at that time, and we regard this as strong, albeit circumstantial evidence for regulatory effects on mortgage defaults.

Second, in addition to this time-series evidence on aggregate mortgage default rates, we provide evidence on the impacts of regulation from the cross-section of defaults conditioned on various loan attributes. In particular, 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 just under the subsidy-qualifying threshold, and is observed in all cohorts of loan issuance over the sample period. We also find that the magnitude of the excess delinquency propensity of small and micro loans appears to vary over time in a way that can be connected to the tightness of the constraint favoring these loans.

Third, we find a significant and somewhat abrupt decline in three-month payment delinquencies beginning in early 2004. We connect this finding to the fact that the regulatory definition of "non-performing assets," a definition which is associated with provisioning requirements against such delinquent loans, changes in March 2004, from previously referring to loans that are six-months delinquent to those that are three-months delinquent. Following this change, we find that 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 more 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.

Taken together, these three 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 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. Finally, our findings are relevant to the suggestion of Kashyap, Rajan, and Stein (2008) that capital requirements against risk-weighted assets should be countercyclically adjusted. We find that a reduction in the risk-weight on housing finance following a period of low GDP growth is associated with high levels of mortgage delinquencies for loans issued in those cohorts, implying that Kashyap, Rajan, and Stein's policy can influence the riskiness of mortgage lending.

The organization of the paper is as follows. Section 2 sets the stage by describing the Indian macroeconomic environment over our period of study, the mortgage data that we employ, and the Indian system of mortgage regulation. Further details on that system are provided in an online regulatory appendix (Campbell, Ramadorai, and Balasubramaniam 2012). Section 3 introduces our model of mortgage delinquencies, which we use to show that changing demographic characteristics of borrowers, loan characteristics, or estimated macro shocks cannot fully explain the high delinquency rate in the early 2000s. Instead, changing regulation to encourage mortgage lending appears to be responsible. Section 4 presents evidence that regulation has also affected the relative pricing of small and large mortgages, and discusses the change in the regulatory definition of non-performing assets in 2004 and its consequences on 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 2012).

2 The Macroeconomic and Regulatory Environment

2.1 Macroeconomic and Mortgage Finance Trends

To set the stage, Table 1 illustrates the history of several important macroeconomic variables over the past quarter-century in India, 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 considerable volatility 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 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 house price indexes, both for India as a whole and for five broad regions. We compute the 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.

Over this same period, the Indian mortgage market was experiencing rapid change. Figure 2 illustrates one aspect of this change, namely a shift from a predominantly fixed-rate mortgage system to one that is dominated by variable-rate lending. The figure plots the share of variable-rate loans in total issuance by our mortgage provider. Starting at about 40% of dollar value in the mid-1990s, the variable-rate share increases above 90% by the early 2000s, then briefly dips to 60% in 2004 before again rising and reaching 100% by the end of our sample period. The cause of the brief shift back towards fixed-rate mortgages in 2004 is an interesting question that we discuss later in the paper.

Figure 3 plots the delinquency rate (the fraction of mortgages 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 a large spike in delinquencies in 2002–03, particularly for fixed-rate mortgages. This spike is one of the features of the data that we attempt to explain using our model, which we introduce in the next section. 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.

Table 2 shows how our mortgage lender responded to the market conditions described above. Panel A reports cross-sectional 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 the episode in 2004 when our mortgage lender shifted back towards fixed mortgage issuance. Variable mortgage rates decline after 2008, a period where fixed mortgages have essentially disappeared from our dataset.

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-to-cost and loan-to-income ratios not changing much on average. The 2004 cohort, especially for fixed rate loans, however, appears to have a significantly reduced default rate, which we connect to the spike in fixed rate issuance later in the paper.

Panel B of Table 2 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-to-cost ratios, which reduces again in 2004.

In the remainder of this paper, we relate several of the summary statistics described above to changes in the Indian regulatory environment for housing finance. Our empirical work requires a basic understanding of the regulatory structure in India, to which we now turn.

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 4 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 black, whereas the ones that changed over the period are in colored 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-to-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 in July 2002, also highlighted on the timeline, 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 a strong 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 4 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 to this paper, Campbell, Ramadorai, and Balasubramaniam (2012), provides further details about the regulatory system.

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.

We model the probability of observing a delinquency as a function of all of these determinants:

$$\Pr[\delta_{i,c,b,t}] = (\alpha + \alpha_c + \alpha_b + \Sigma_k \beta_k L_{ikt} + \Sigma_j \gamma_j D_{ijt} + \rho r_{i,c,b}) Z_{t-1} + e^{\delta}_{i,c,b,t}, \tag{1}$$

where $\delta_{i,c,b,t}$ is an indicator for an observed 90-day delinquency in loan i in cohort c originated in branch b, at time t. That is, c denotes the loan origination date and t denotes the delinquency date. The model includes fixed effects for branches, α_b, and cohorts, α_c (in each case, we drop one dummy as we have an intercept in the model). It 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, $r_{i,c,b}$ is also included as an explanatory variable in the model.[3]

Finally, the model allows for an unobserved macroeconomic shock Z_{t-1} to impact these determinants multiplicatively. Thus the estimated coefficients on the branch and cohort fixed effects, 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_{t-1} is high. The choice of Z_{t-1} rather than Z_t 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 estimate the model separately for fixed-rate and variable-rate loans, employing 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

[3] The model is estimated at the annual frequency t; to eliminate monthly 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.

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.

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 log loan-to-cost ratio, log loan-to-income ratio, a piecewise linear function of log loan size in relation to the PSL threshold (discussed in more detail later in the paper), dummies for origination branch, 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). 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 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.

3.1 Regulation and Delinquencies: Time-Series Evidence

Table 3 shows the estimated coefficients on the demographic and loan characteristics from equation (1), which predominantly appear to have signs consistent with intuition about their likely impacts on delinquencies. For the sake of brevity, Table 3 does not present the estimated macroeconomic shocks and cohort effects with associated standard errors, but we present these in the online empirical appendix (Campbell, Ramadorai, and Ranish 2012). We do plot these series, however, in Figures 5 and 6.

Figure 5 plots the estimated macroeconomic shocks Z_t. Our estimates are weighted by the relative fractions of fixed and variable rate loan issuance from the separate specifications that we estimate for these two types of loans, a strategy that we continue to adopt in the remaining figures in the paper in order to conserve space. 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_t seems 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.

Figure 6 shows how delinquencies vary by their cohort of issuance. The series that we plot in this figure is the sum of cohort average fitted values on borrower and loan characteristics ("hard information"), and the estimated cohort effects from the model $(\alpha + \alpha_c)$ ("soft information" which is unobservable to the econometrician), again weighted by loan issuance across fixed and variable rate loans. The bars plotted in the figure capture the effect of being issued in a particular year on the delinquency propensity of loans in the sample, after controlling for macroeconomic shocks.[5] The figure shows that the spike in the delinquency rate seen in 2002, 2003, and 2004 is connected to loan issuance cohort, not only to prevailing macroeconomic circumstances in these years.

[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).

[5] Note that the estimation of the cohort effects already controls for variation in interest rates at the loan level. We also estimate a version of equation (1) in which we replace the interest rate at issuance with the spread over the one-year Indian government bond yield (in the case of variable-rate loans) or ten-year government bond yield (in the case of fixed-rate loans). The resulting figure is presented in the online empirical appendix, and is similar to Figure 6, although somewhat noisier because Indian mortgage rates do not move closely with government bond yields, which are therefore an imperfect benchmark.

Figure 7 takes this analysis a step further. We separately plot the (demeaned) hard and soft information components of the total cohort effect shown in Figure 6. We superimpose two lines that summarize relevant changes in the regulatory environment for both banks and HFCs. The solid line shows the interest-rate ceiling applied to deposits issued by HFCs minus the yield on one-year Indian Government bonds. This spread is multiplied by five for scaling purposes and its scale is shown on the right vertical axis. From 1997 until 2001 there was no interest-rate ceiling, but a ceiling was reintroduced in 2002 and slightly tightened in 2003 and again in 2004. Both hard and soft information components of cohort-level variation in delinquencies steadily increase during the period with no interest-rate ceiling, i.e., the absence of an interest-rate ceiling is associated with steadily increasing delinquency rates, presumably from the looser funding constraint. While this is consistent with the view that a relatively unrestricted supply of credit to HFCs in this period stimulated lending, with delayed consequences for default, this must be viewed with the caveat that we are unable to publicly identify whether our mortgage provider is a bank or an HFC. Mian and Sufi (2009) present a similar view of developments in the US during the 2000s.

The other, dashed line in Figure 7 summarizes changing risk weights for housing loans, following their introduction in April 2001, constructed by averaging the risk weights that apply to banks and to HFCs for loans with less than 0.75 LTV, and scaled as shown on the right vertical axis. The figure plots (100% - Risk Weight), as a measure of the looseness of the restriction on lending. The loosening of the risk weight restriction in 2002, 2003, and 2004 coincides precisely with the increased delinquency rates attributable to soft information in those years, and a subsequent tightening of the risk weight restriction in 2005 and 2006 coincides with unusually low values of the soft information component of delinquencies. In 2005 and 2006, however, there is an increase in the level of delinquencies attributable to hard information, which partially offsets the decline in the soft information component, leading to a relatively mild decline in cohort-level delinquencies especially in 2005. The online empirical appendix shows that the growth of aggregate HFC and bank housing credit spikes up in 2005 and 2006, suggesting that competition between Indian financial institutions may be another factor to consider for a complete understanding of these patterns. Finally, in 2004, despite continued loose risk weight restrictions, the soft information component is slightly lower than its level in 2003, and we connect this to the shift away from variable-rate to fixed-rate loans by the mortgage provider – the online empirical appendix plots the cohort effects separately for fixed and variable loans, and shows that the soft information component of the 2004 cohort effect is relatively lower for fixed-rate loans than for variable-rate loans.

In sum, while one must always be cautious about the interpretation of any pure time-series correlation, Figure 7 suggests that changes in regulation are an important factor driving the aggregate delinquency patterns in our data.

4 Regulation and Delinquencies: Cross-Sectional Evidence

4.1 The Effect of Priority Sector Lending Norms

Risk weights and interest rate ceilings are not the only regulatory instruments through which the Reserve Bank of India affects mortgage lending and risk. Priority-sector lending (PSL) norms also exist and have cross-sectional effects, diverting lending towards favored small loans. They do this both through the RBI's quantity targets for banks, and currently, through interest-rate subventions for loans up to a certain size. If PSL norms are important, they might induce mortgage lenders to make riskier loans to small borrowers.

Table 4 presents statistics on the importance of priority-sector lending by our mortgage provider, showing the fraction of loan value issued below the prevailing nominal PSL-qualifying threshold in each year from 1995 to 2010. For variable rate loans, this fraction declines from roughly 70% in the early years of our sample to 33% in 2010. Micro-loans (which we classify very simply as those smaller than one-half of the PSL-qualifying threshold) account for between a third and a little more than a half of the total set of PSL-qualifying variable rate loan issuance. For fixed rate loans, the fraction of PSL-qualifying loans in total issuance by value fluctuates between 65% and 85%, with a sharp reduction in 2004 to 48% of total loan issuance. This reduction in 2004, when combined with the lower fixed rate cohort effect in that year which we refer to in the previous section, suggest that the mortgage provider reduced its reliance on these (potentially more risky) loans in 2004.

Of course, mortgage lenders might make risky small loans in the absence of any regulatory incentives, if they are able to charge higher mortgage rates to compensate for the higher risk (Duca and Rosenthal 1994). As a first simple way to evaluate whether loans below the PSL qualifying threshold are riskier even after controlling for mortgage rates, Table 3 allows for separate slopes for loan sizes above and below the PSL threshold at loan disbursal when estimating equation (1). If subsidies are responsible for the relationship between loan size and the propensity to be delinquent, then the slope below the PSL threshold should be estimated to be negative and statistically significant, because as we know from Figure 4, there are additional subsidies for micro-lending at loan sizes well below the PSL threshold. However, there should be no consistent relationship between loan size and the propensity to be delinquent for loan sizes above the PSL-qualifying threshold.

Table 3 shows that indeed, for loans below the PSL threshold, loan size has a substantial and statistically significant negative effect on the propensity for a loan to be delinquent. However, above the PSL-qualifying threshold, while there is a small and marginally statistically significant negative slope estimated for variable rate loans (roughly one-fifth the size of the slope below the threshold), the slope is small, *positive* and marginally statistically significant for fixed rate loans. We view this as evidence that the PSL subsidy distorts the efficient-market relationship between interest rates and delinquencies, and that loans below the PSL-qualifying threshold are riskier than those above it.

The negative slope below the PSL-qualifying threshold suggests that micro-loans (i.e., those well below the PSL-qualifying threshold) are even riskier than those just below the threshold. To evaluate the relative riskiness of different loan sizes, we estimate a version of equation (1) in which we interact the cohort effects with two dummy variables, the first of which identifies whether a loan is below the PSL-qualifying threshold at the time it is made, and the second which identifies whether a loan is below one-half the PSL-qualifying threshold at the time it is made (this is to identify the impact of being a micro loan).

Table 5 shows the estimated unconditional mean and cohort effects (cohort-specific deviations from the unconditional mean) interacted with the size dummies from this model. Panel A reports results for variable-rate mortgages, and panel B for fixed-rate mortgages. The table reveals several interesting patterns. First, the probability of being delinquent is far higher on average for PSL-qualifying and micro loans than for those above the PSL-qualifying threshold. Second, there is an interesting time pattern to these cohort effects. Figure 8 plots the excess delinquency propensity over non-subsidized loans in each cohort (combining the unconditional mean and the cohort effect) for both PSL-qualifying and micro loans. Variable-rate and fixed-rate cohort effects are weighted by the issuance of each type of mortgage. In every one of the cohort-years in the data, micro loans have a far higher propensity to be delinquent, and PSL-qualifying loans also have a higher propensity in every cohort-year except 1998. There is an interesting U-shaped pattern in these excess propensities, that is, they are higher at the very beginning of the sample period, decreasing in the late 1990s, and then increasing from roughly the middle of the sample period until the end of the sample period.

We overlay two measures of the tightness of the PSL constraint in each cohort-year on this plot. The first is the negative of the (log) ratio of the nominal PSL-qualifying threshold deflated by house price appreciation. The PSL-qualifying threshold is increased periodically, and when it is raised by more than the increase in house prices, the constraint is effectively looser. Conversely, if the PSL-qualifying threshold remains at the same nominal level when house prices rise substantially, the constraint is more binding. The second measure tracks the tightness of the PSL constraint by subtracting aggregate credit extended to the priority sector by public sector banks, Indian private sector banks, and foreign banks operating in India from the mandatory PSL lending requirement of these institutions. If more than the mandatory amount of PSL credit is extended by banks, this revealed preference for PSL lending suggests that the constraint is less binding, and vice versa.

Figure 8 shows that the pattern of excess PSL delinquency propensities trends upwards but also roughly tracks the tightness of the PSL constraint. During the late 1990s, excess delinquency propensities were declining as the PSL constraint became less binding, while during the 2000s excess delinquency propensities trended up as rising house prices tightened the PSL constraint. To interpret these results, one should keep in mind two points. First, results for the last few years of the sample period may be distorted by the fact that recent loans may not yet have experienced delinquencies by the end of the sample period. Second, as Table 4 shows, while still substantial, PSL-qualifying loans are a smaller fraction of the mortgage book in the late 2000s.

Nevertheless, we do conclude that there is substantial evidence that small subsidized loans have delinquency risk over and above larger unsubsidized loans which cannot be accounted for by their interest rates. This effect appears to vary with the tightness of the PSL constraint, although overall, the excess default propensities appear to have been increasing over time.

4.2 Change in the Classification of Non-Performing Assets

The discussion on regulation earlier noted another relevant change that took place over the sample period that we consider: on March 31, 2004 for banks, and March 31, 2005 for HFCs, the classification of "non-performing asset" (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 the associated implications of this change for provisioning requirements may also have contributed to the unusually low delinquency rates seen in Figure 7 for more recent loan cohorts. Of course, this also raises the important question of whether our previous results using 90-day delinquencies are confirmed using data on 180-day delinquencies – a plausible model of behavior is that a mortgage provider might care more about "official" NPAs (rather than delinquencies of a shorter term than the regulatory minimum) as these have tangible balance sheet implications. Another important question that arises here is whether the regulatory re-classification of NPAs had other impacts on behavior such as an increased emphasis on monitoring shorter-term delinquencies (say 30 days past due), as any reduction in the minimum delinquency period might be expected to feed through to the earlier monitoring of mortgage default risk.

To answer the first of these questions, we re-estimate the model with 180-day delinquencies on the left-hand side replacing 90-day delinquencies. The online empirical appendix to the paper shows that while, as we might have expected, the average delinquency rate is lower when we consider 180-day delinquencies, the pattern of the cohort-time fixed effects is consistent with that found using 90-day loans. This provides reassurance that our earlier results are not simply driven by the use of a variable that is perhaps less immediately important (prior to 2004-5) to the mortgage provider.

To answer the second question, we 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 6 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%, and 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 exertions of effort.[6]

[6]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.

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). The online empirical appendix (Campbell, Ramadorai, and Ranish 2012) verifies 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 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 9 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 9, 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 1.2 EMIs after a year. Post-March 2004, there is a substantial recovery in this number, with such 30-delinquent loans roughly 0.2 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 10 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.[7] We also consider whether the introduction of SARFAESI 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

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

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 11 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.

Taken together, a simple change in the regulatory definition of NPAs to a shorter length of delinquency appears to have generated significant impacts on the expected loss given delinquency of the mortgage provider. The impacts appear to be felt in reductions in the probability of delinquency, as well as in the eventual loss given delinquency, and strongly suggest a significant change in mortgage provider behavior in relation to borrowers in arrears. While it is difficult to generalize findings from one country, these results do suggest that even seemingly innocuous changes in regulatory definitions can have important impacts on mortgage risk.

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. We have presented evidence that regulation may have contributed to a surge in delinquencies during the early 2000s, that 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. Our paper contributes to the growing body of literature on the impacts of regulators and regulatory norms on risks in financial markets.

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Table 1: Indian Macroeconomic Statistics - 1985 through 2010

Real GDP and CPI Inflation are computed as the difference in levels as of the end of the given calendar year. 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 loan origination location as the change in annual median home value for loans originated in that location. Aggregate nominal home price appreciation is then computed from the loan origination location home price appreciation using the number of loans disbursed by location as weights. The series is converted from nominal to real using All India CPI inflation reported by the World Bank. This method of computation is robust to shifts in loan origination between locations with differing 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: Summary Statistics on Loan Characteristics by Disbursal Year

This table provides year wise 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 3: 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. Standard errors are given in italics below the corresponding coefficients, and are computed by bootstrapping calendar years. Coefficients that are statistically significant at a 5% two-sided level are in bold type. The null hypothesis is that the macroeconomic effects equal one and all other coefficients equal zero. All coefficients (except macroeconomic effects Z_t) and associated standard errors are multiplied by 100 for readability.

	Variable Rate	**Fixed Rate**
A: Loan and Borrower Characteristics		
Loan Characteristics:		
Initial Interest Rate	**0.418**	**0.378**
	0.041	*0.054*
Change in One-Year Government Bond Yield Since Disbursal	**0.132**	
	0.065	
Regional Log Home Price Appreciation Since Disbursal	**-0.809**	**-2.484**
	0.411	*0.738*
Log Loan to Income Ratio (winsorized at 1st, 99th)	**0.605**	**1.227**
	0.081	*0.064*
Log Loan to Cost Ratio	**1.281**	**2.720**
	0.092	*0.135*
Dummy: Usually Paid by Salary Deduction	**-1.731**	**-3.021**
	0.117	*0.161*
Dummy: Loan administered through employers	**-0.279**	**-0.385**
	0.069	*0.190*
Dummy: Loan is a Refinancing	**0.475**	0.161
	0.099	*0.151*
Dummy: Loan is for a Home Extension	**-0.178**	**-0.392**
	0.044	*0.098*
Dummy: Loan is for a Home Improvement	**0.335**	**0.384**
	0.090	*0.155*
Dummy: Tranched Issuance	**-0.558**	-0.279
	0.151	*0.470*
Dummy: 6 to 10 Year Loan	**0.167**	**1.129**
	0.064	*0.198*
Dummy: 11 to 15 Year Loan	**0.661**	**1.727**
	0.084	*0.240*
Dummy: 16 Year+ Loan	**1.460**	**1.604**
	0.164	*0.212*
Dummy: Year of Loan Issuance	**-2.478**	**-3.903**
	0.148	*0.351*
Dummy: Disbursed Within 12 Months of State Election	-0.015	0.038
	0.054	*0.098*
Piecewise-Linear Loan Size Controls		
Log(Loan Amount / PSL Threshold at Loan Disbursal), Below PSL Threshold	**-0.887**	**-1.678**
	0.148	*0.101*
Log(Loan Amount / PSL Threshold at Loan Disbursal), Above PSL Threshold	-0.192	0.399
	0.103	*0.215*

Continued on Next Page

	Variable Rate	Fixed Rate
Borrower Characteristics:		
Log Number of Dependents	**-0.114**	**0.225**
	0.046	*0.066*
Male Borrower	**0.182**	**0.492**
	0.027	*0.059*
Married Borrower	0.042	0.149
	0.042	*0.091*
Borrower age 36-45	**0.080**	**0.116**
	0.013	*0.059*
Age 46 and up	**0.227**	**0.221**
	0.044	*0.075*
Dummy: Repeat Borrower	**0.425**	**0.850**
	0.117	*0.135*
Dummy: Qualification Missing or Unidentified	-0.125	-0.142
	0.068	*0.084*
Dummy: HSC Equivalent	**-0.396**	**-0.857**
	0.074	*0.082*
Dummy: BA Equivalent	**-0.633**	**-1.241**
	0.104	*0.089*
Dummy: Post-Grad Equivalent	**-1.016**	**-1.796**
	0.098	*0.109*
Dummy: Finance-Related Qualification	**0.177**	**0.209**
	0.028	*0.064*
Cohort Fixed Effects?	Yes, Appendix Table A1	
Annual Macroeconomic Effects?	Yes, Appendix Table A1	
21 Branch Dummies?	Yes	
Monthly Fixed Effects?	Yes	

Table 4: Share of Loan Disbursals Above and Below Priority Sector Lending (PSL) Threshold Values

The share of loan disbursals above and below the PSL threshold and 0.5 times the PSL threshold are given as the share of the total value of loans disbursed in the given year. The PSL threshold levels are sporadically reset (October 22, 1997, October 29, 1999, April 29, 2003, October 26, 2004, and July 2, 2007 are reset dates between 1995 and 2010). The regulatory source documents are detailed in the online regulatory appendix. The distribution of fixed rate mortgage issuances after 2007 is not shown due to the limited extent of fixed rate lending in these years.

	Variable Rate Share of Disbursals		**Variable Rate Mortgages**			**Fixed Rate Mortgages**		
	By Count	By Value	Above PSL Threshold	Below PSL Threshold	Below 0.5X PSL Threshold	Above PSL Threshold	Below PSL Threshold	Below 0.5X PSL Threshold
1995	37.86%	42.98%	31.60%	68.40%	30.29%	29.01%	70.99%	37.78%
1996	47.45%	51.78%	36.95%	63.05%	27.07%	35.89%	64.11%	32.08%
1997	55.29%	60.84%	40.09%	59.91%	24.43%	38.27%	61.73%	30.39%
1998	59.04%	66.78%	26.67%	73.33%	40.06%	20.91%	79.09%	49.65%
1999	65.55%	71.32%	27.79%	72.21%	37.43%	21.80%	78.20%	45.77%
2000	75.70%	81.65%	23.36%	76.64%	47.66%	16.58%	83.42%	59.91%
2001	75.32%	82.31%	28.05%	71.95%	42.50%	17.49%	82.51%	61.95%
2002	84.40%	89.83%	32.52%	67.48%	39.23%	15.49%	84.51%	64.97%
2003	94.14%	94.16%	34.44%	65.56%	38.51%	34.88%	65.12%	40.57%
2004	84.51%	79.97%	35.35%	64.65%	34.28%	51.60%	48.40%	21.43%
2005	90.40%	92.09%	37.43%	62.57%	33.57%	24.81%	75.19%	45.40%
2006	90.44%	92.87%	56.03%	43.97%	21.21%	35.09%	64.91%	34.43%
2007	95.76%	97.72%	59.76%	40.24%	17.10%	35.61%	64.39%	39.08%
2008	99.44%	99.80%	60.32%	39.68%	15.53%			
2009	99.87%	99.97%	64.58%	35.42%	13.19%			
2010	99.97%	99.99%	66.72%	33.28%	9.69%			

Table 5: Delinquency Model With Cohort X Size Effects

This table presents coefficient estimates and standard errors from estimates of equation (1) in the paper, modified to include interactions between size dummies and cohort effects. See notes to Table 3 for a brief description of the estimation procedure and control variables. Standard errors are given in italics below the corresponding coefficients, and are computed by bootstrapping calendar years. The null hypothesis is that all unconditional averages, cohort-specific, and size effects are zero. Coefficients are in bold type where this null is rejected at a 95% two-sided confidence level. Coefficients and associated standard errors are multiplied by 100 for readability. Panel A presents variable rate mortgage results, and Panel B, fixed.

	Delinquency Rate for Loans Above PSL Threshold	Additional Delinquency Fixed Effect for Loans Below PSL Threshold	Further Delinquency Fixed Effect for Loans Below 0.5 X PSL Threshold
A: Variable Rate Mortgages			
Unconditional Averages			
	1.348	**0.323**	**0.617**
	0.064	*0.037*	*0.056*
Cohort-Specific			
1995	-0.288	-0.350	**-0.383**
	0.367	*0.281*	*0.110*
1996	-0.439	**-0.269**	**-0.480**
	0.332	*0.111*	*0.104*
1997	**-0.940**	**-0.253**	**-0.325**
	0.302	*0.083*	*0.069*
1998	**-0.602**	**-0.368**	-0.097
	0.276	*0.119*	*0.081*
1999	**-0.352**	-0.112	-0.154
	0.139	*0.063*	*0.084*
2000	**0.555**	**-0.386**	-0.205
	0.102	*0.085*	*0.105*
2001	**0.442**	**-0.214**	-0.070
	0.172	*0.096*	*0.097*
2002	**0.859**	**0.213**	-0.212
	0.167	*0.096*	*0.127*
2003	**0.817**	0.294	-0.135
	0.238	*0.174*	*0.236*
2004	0.213	**0.398**	0.292
	0.201	*0.133*	*0.298*
2005	-0.499	0.323	**0.920**
	0.286	*0.169*	*0.285*
2006	-0.539	**0.360**	**0.675**
	0.301	*0.122*	*0.262*
2007	-0.553	0.337	**0.470**
	0.332	*0.189*	*0.236*
2008	-0.205	0.143	0.162
	0.382	*0.101*	*0.226*
2009	0.217	0.039	**-0.233**
	0.651	*0.134*	*0.116*
2010	1.314	**-0.154**	**-0.224**
	0.703	*0.028*	*0.056*
Loan and Borrower Characteristics?			Yes, Same as Table 4
Annual Macroeconomic Effects?			Yes
21 Branch Dummies?			Yes
Monthly Fixed Effects?			Yes

Table 5: Delinquency Model With Cohort X Size Effects (Contd.)

Panel B: Fixed rate mortgages. Cohort effects from 2008 through 2010 are ignored as the limited number of fixed rate issuances in these years makes estimation of associated cohort effects imprecise.

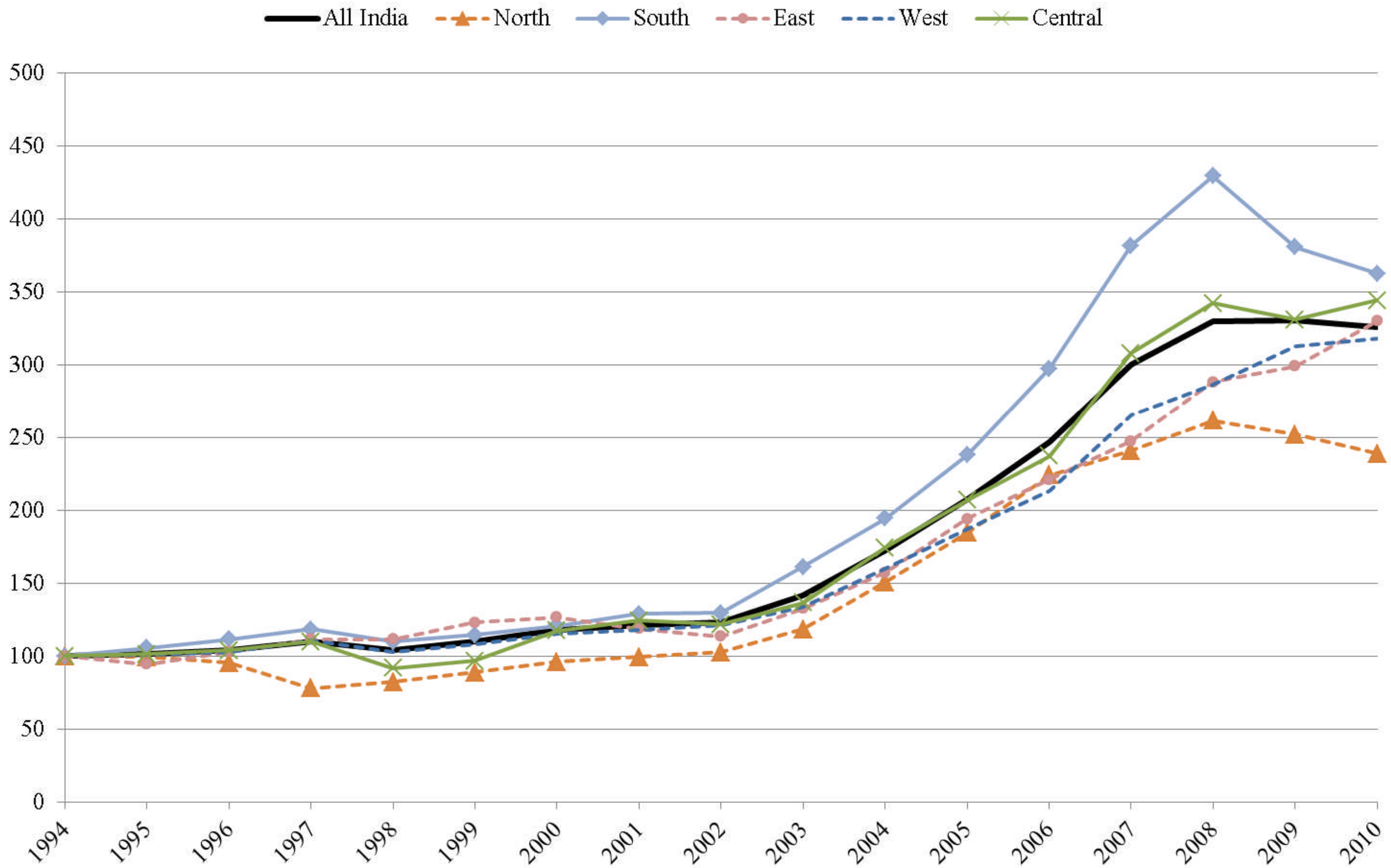
	Delinquency Rate for Loans Above PSL Threshold	**Additional Delinquency Fixed Effect for Loans Below PSL Threshold**	**Further Delinquency Fixed Effect for Loans Below 0.5 X PSL Threshold**
B: Fixed Rate Mortgages			
Unconditional Averages, 1995-2007			
	2.075	**0.397**	**1.310**
	0.169	*0.086*	*0.112*
Cohort-Specific			
1995	-1.103	-0.056	-0.200
	0.805	*0.299*	*0.224*
1996	-0.816	-0.186	-0.020
	0.737	*0.297*	*0.283*
1997	-0.591	-0.272	-0.150
	0.706	*0.195*	*0.209*
1998	-0.088	-0.582	-0.202
	0.734	*0.393*	*0.184*
1999	0.214	**-0.548**	-0.053
	0.667	*0.168*	*0.294*
2000	0.179	0.216	0.025
	0.587	*0.401*	*0.198*
2001	**1.758**	-0.242	-0.055
	0.601	*0.498*	*0.451*
2002	2.077	0.513	0.089
	1.129	*0.787*	*0.577*
2003	0.773	0.318	0.048
	0.772	*0.261*	*0.548*
2004	-0.167	0.522	-0.534
	0.820	*0.291*	*0.288*
2005	-0.709	0.217	0.664
	0.760	*0.184*	*0.507*
2006	-0.928	0.165	0.145
	0.732	*0.244*	*0.518*
2007	-0.599	-0.066	0.244
	0.676	*0.496*	*0.788*
Loan and Borrower Characteristics?			Yes, Same as Table 4
Annual Macroeconomic Effects?			Yes
21 Branch Dummies?			Yes
Monthly Fixed Effects?			Yes

Table 6: 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 (180 day NPA Regime)	29.0%	*0.5%*	23.9%	*0.6%*
April 2004-Dec 2010 (90 day 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



Notes: Regional (north, south, east, west, central) and all India home price appreciation are constructed as disbursal count weighted averages of home price appreciation by loan origination location. Appreciation by loan origination location is computed as the change in annual median home value corresponding to loans disbursed in that location. 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: Variable Rate Share of Mortgage Disbursals

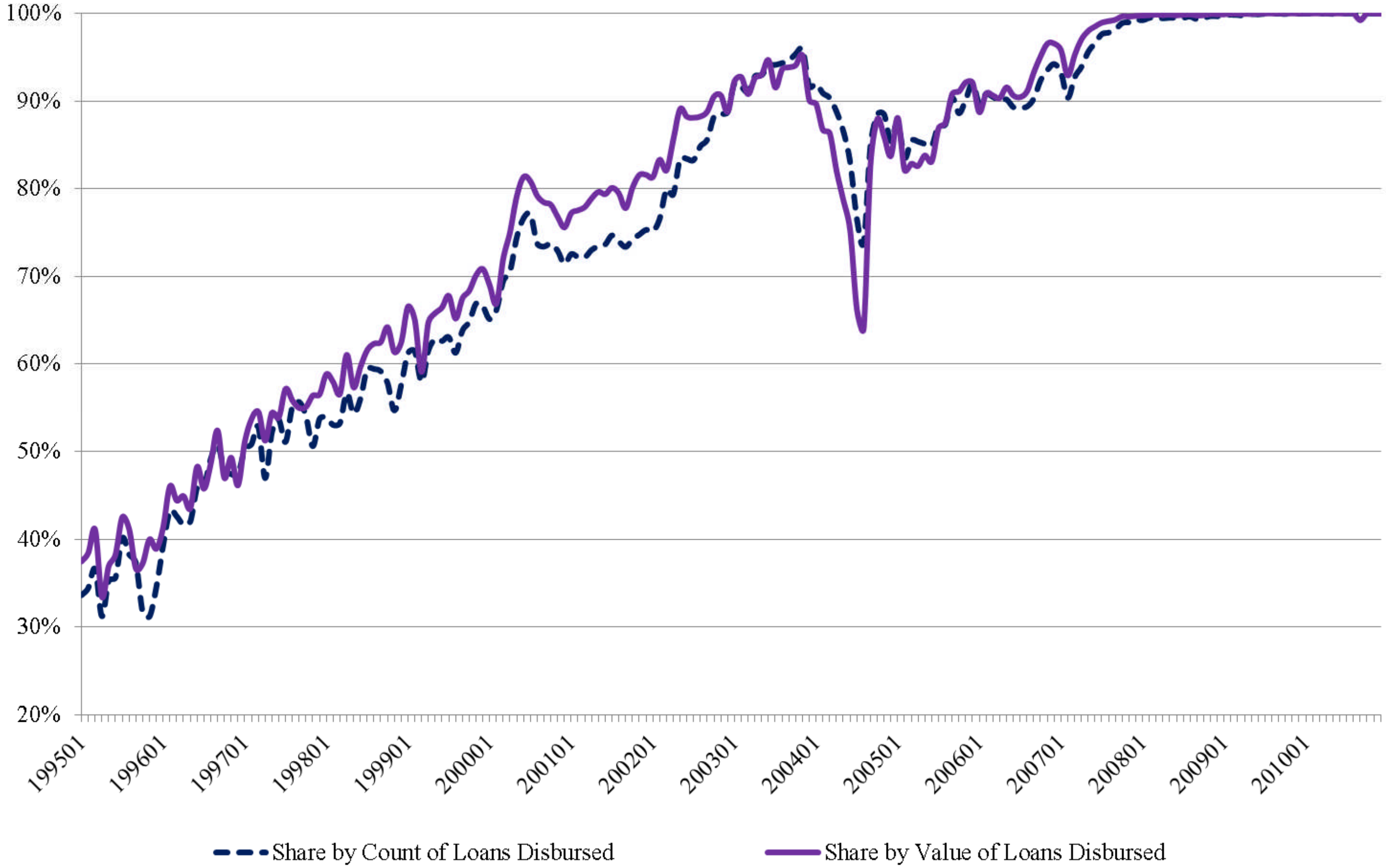
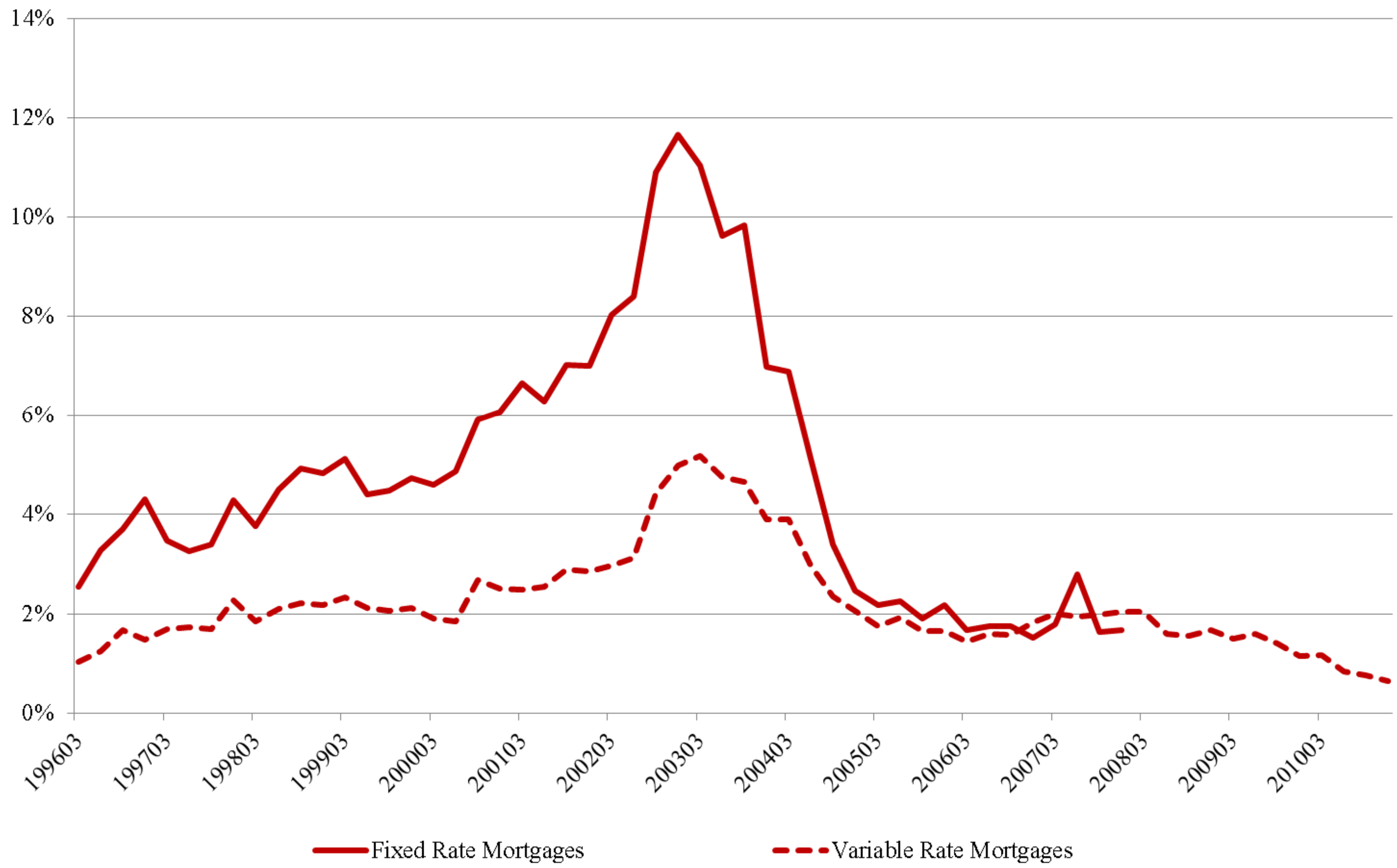
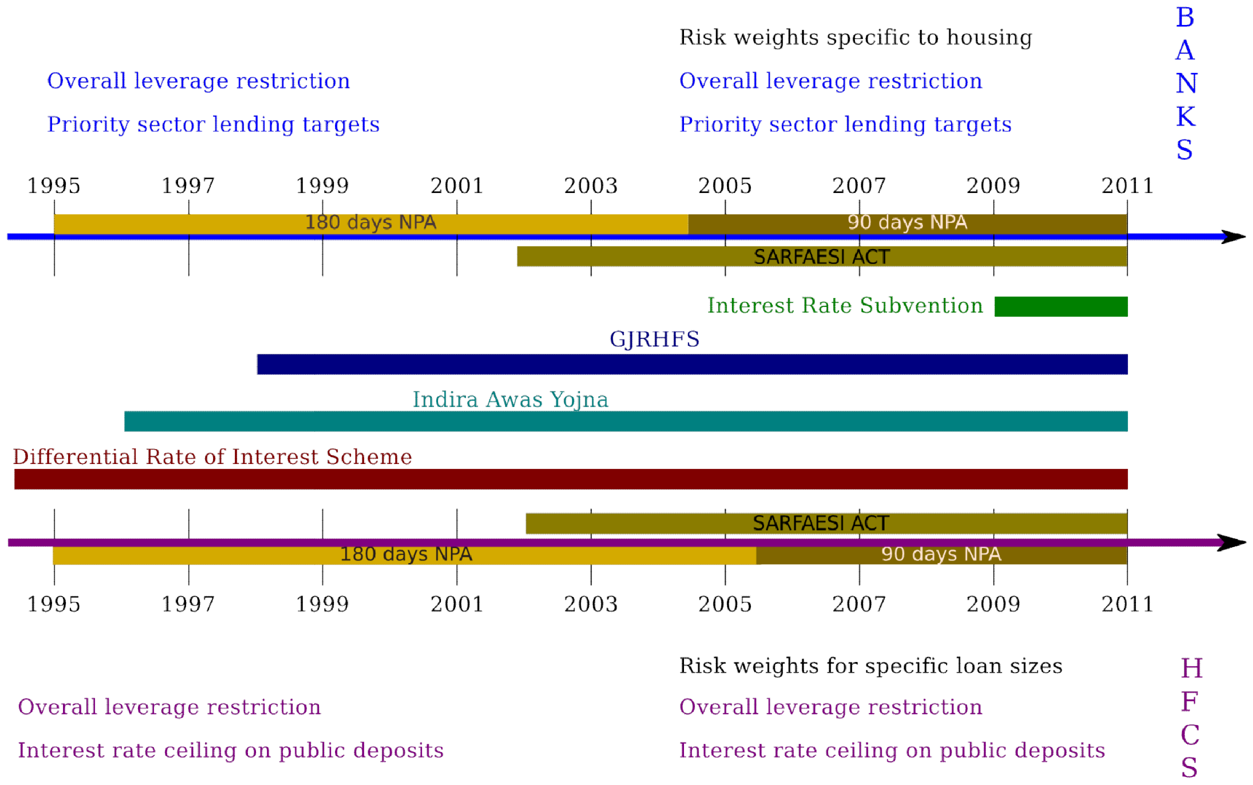


Figure 3: Annualized Seasonally-Adjusted 90-Day Delinquency Rate



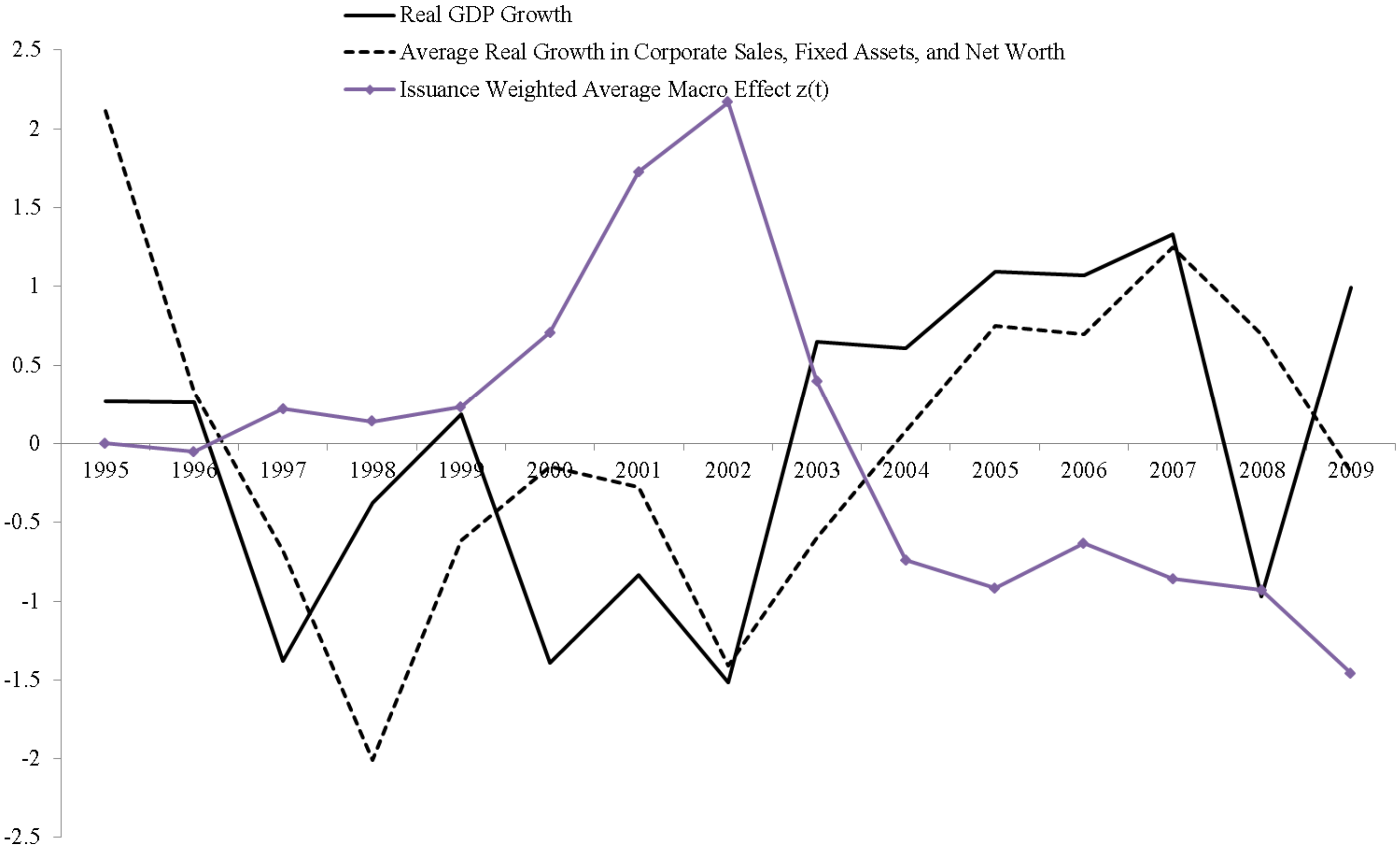
Notes: Seasonal adjustments are computed by regressing log quarterly 90 day delinquency rates (for all outstanding fixed or variable rate mortgages) on a set of year and calendar quarter dummies. The calendar quarter dummies from the log default rate regressions are exponentiated, normalized to one,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

Figure 4: Timeline of Indian Mortgage Regulation



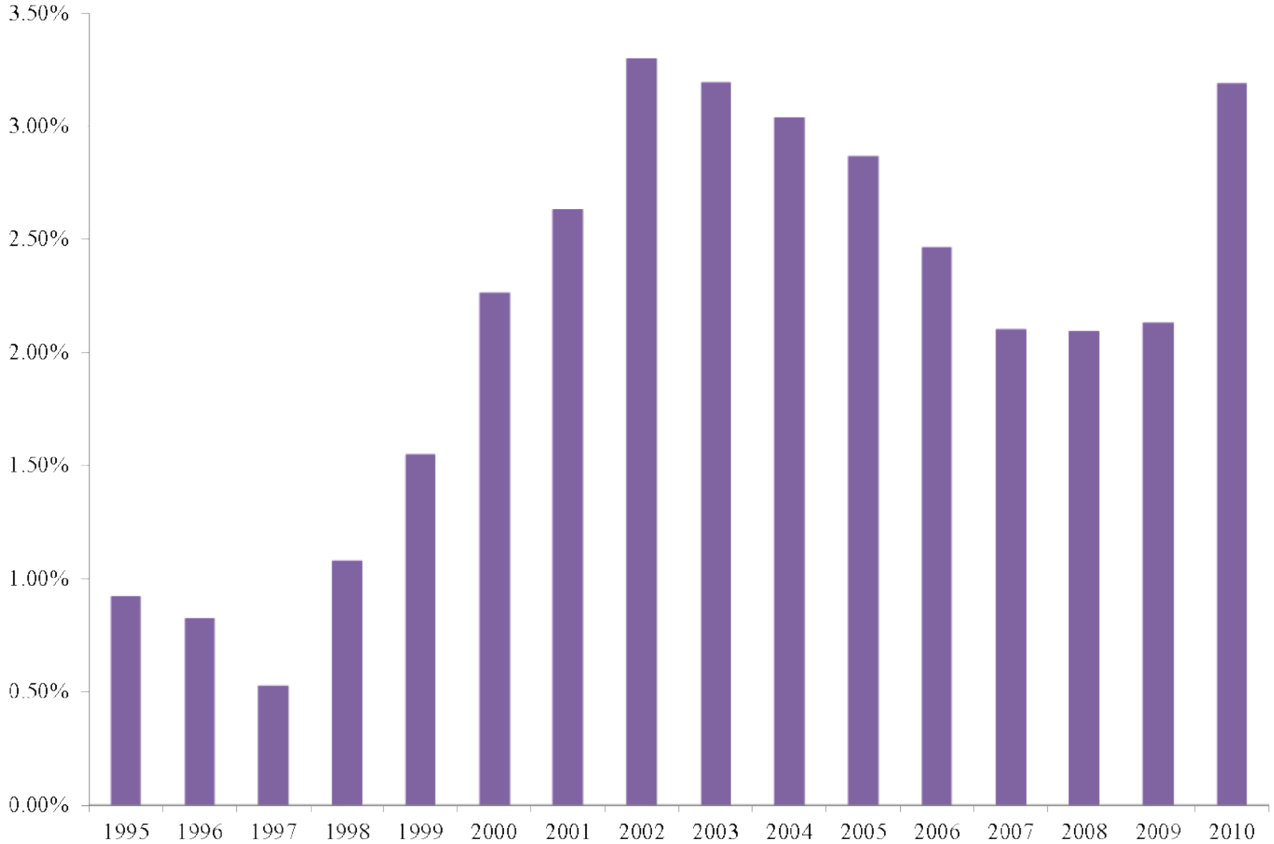
Notes: This figure summarizes regulation affecting mortgage lending in India, with the top half representing the form of regulations affecting banks and the bottom half representing the form of regulations affecting housing finance companies (HFCs). The solid bars in the middle section represent the 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 5: Macro Delinquency Effects and Other Indian Macroeconomic Time Series



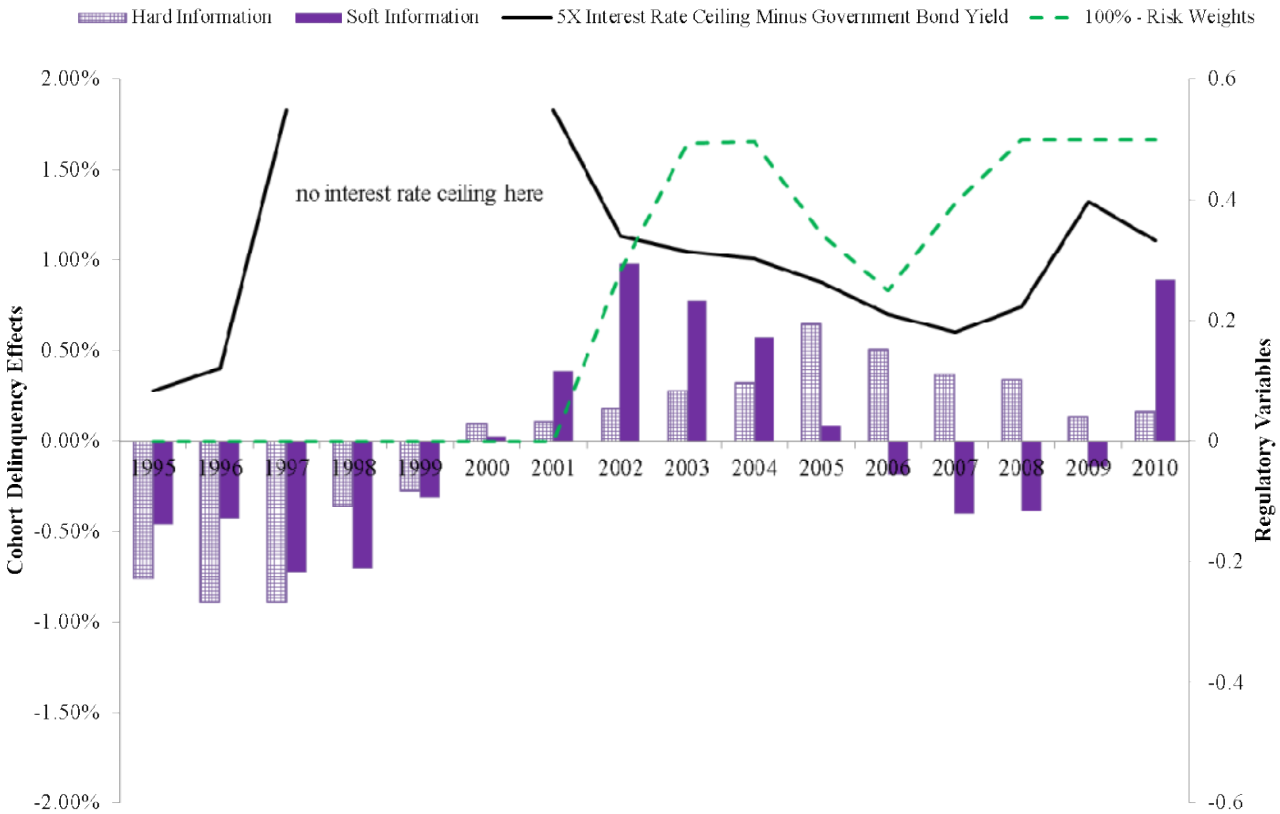
Notes: Real GDP growth is from the World Bank. Average real growth in corporate sales, fixed assets, and net worth is the average of the three constituent time series, which are taken from the Prowess database. CPI inflation (from the World Bank) is subtracted from this series. The issuance weighted average macro effect is the weighted average of the fixed rate and variable rate macroeconomic effects Z_t estimated in the delinquency model (Equation 1), where the weights are equal to the fraction of the total value of mortgage loans disbursed that are fixed or variable rate. All variables plotted are standardized.

Figure 6: Issuance Weighted Cohort Delinquencies



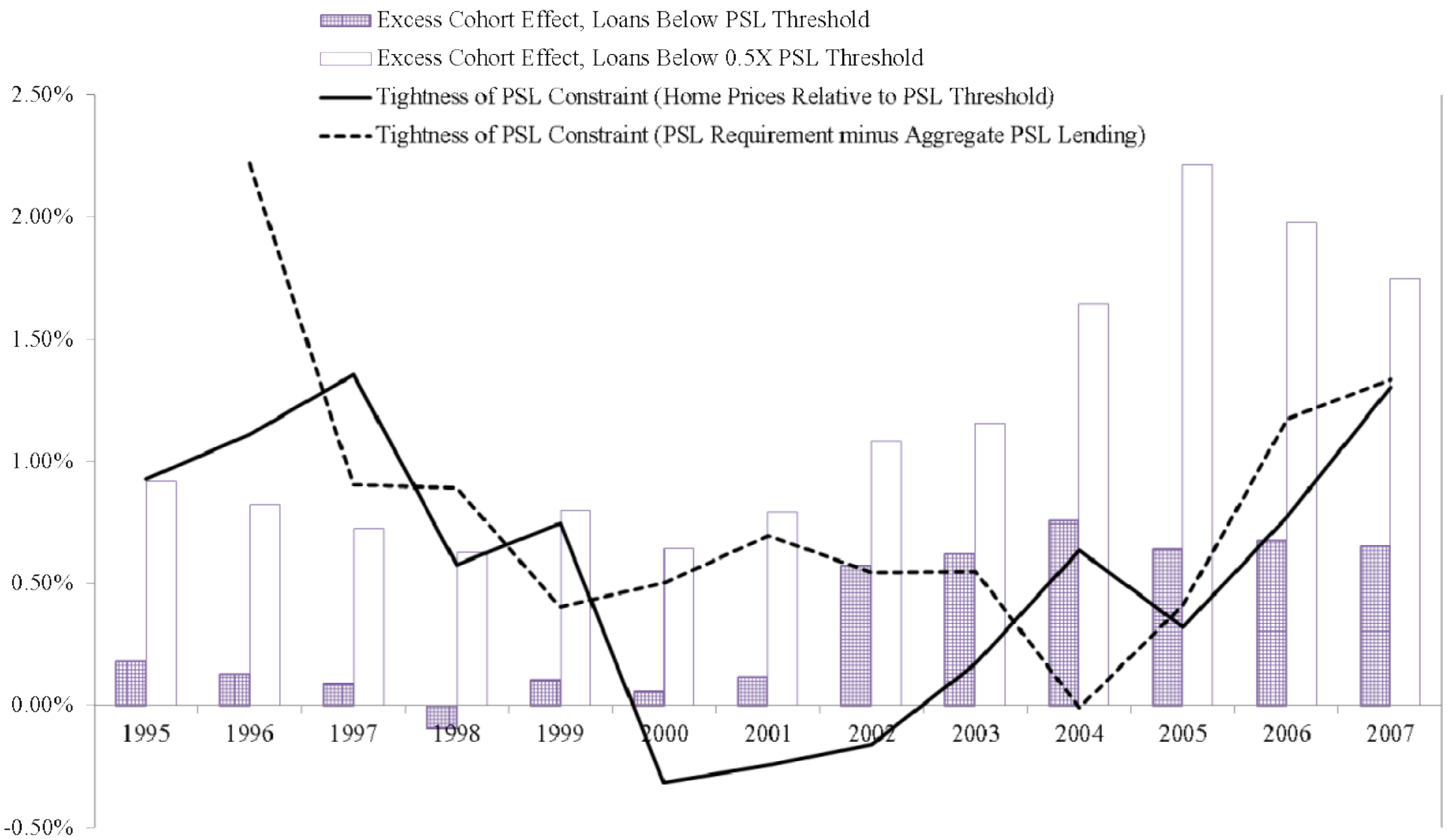
Notes: The plotted cohort effects are the sum of the cohort fixed effects (estimated from the delinquency model, Equation 1) and cohort average fitted values on loan and borrower characteristics (detailed in Table 3). These effects describe each cohort's propensity towards delinquency which is not explained by initial interest rates or macroeconomic conditions affecting delinquencies in all cohorts. The series is a weighted average of the effects derived separately for variable and fixed rate mortgages, where the weights for a given year are equal to the share of variable and fixed rate issuance for that cohort.

Figure 7: Abnormal Cohort Delinquencies Attributed to Hard and Soft Information



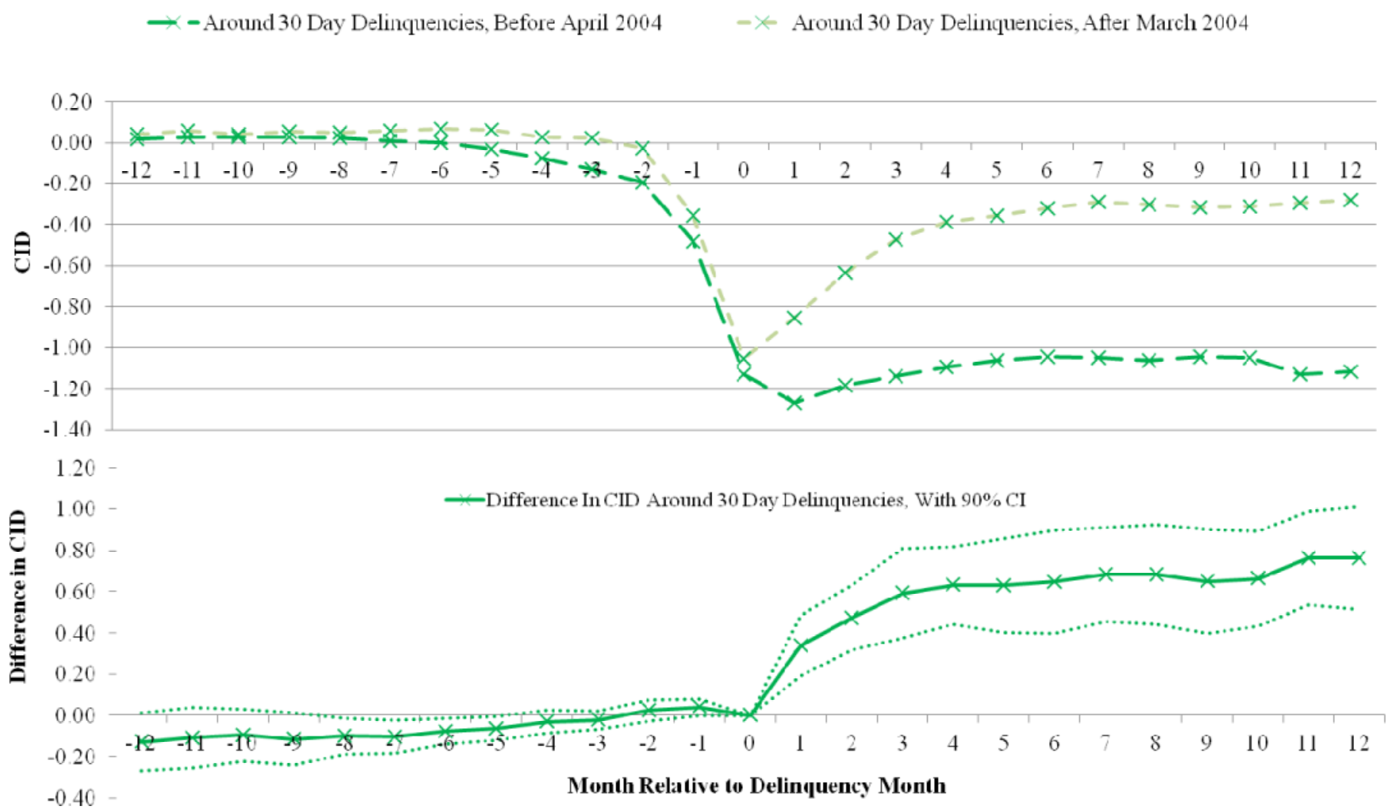
Notes: The plotted cohort effects are a decomposition of the de-meaned abnormal cohort delinquencies in Figure 6 into (1) hard information - delinquencies attributed to loan and borrower attributes (cohort average fitted values from the delinquency model) and (2) soft information - delinquencies attributed to other cohort effects (cohort fixed effects in the delinquency model). The interest rate ceiling is a maximum interest rate that housing finance companies are allowed to pay to depositors. Risk weights are used to determine capital requirements for banks and HFCs, with higher risk weight assets requiring greater capital provisioning. The risk weight series is the average of the risk weights applicable to banks and HFCs lending where loan-to-value is below 0.75. Where such risk weights change in the middle of a year, each risk weight is weighted by the fraction of the year for which it was applicable.

Figure 8: Issuance Weighted Excess Cohort Delinquencies for Loans Below PSL Thresholds



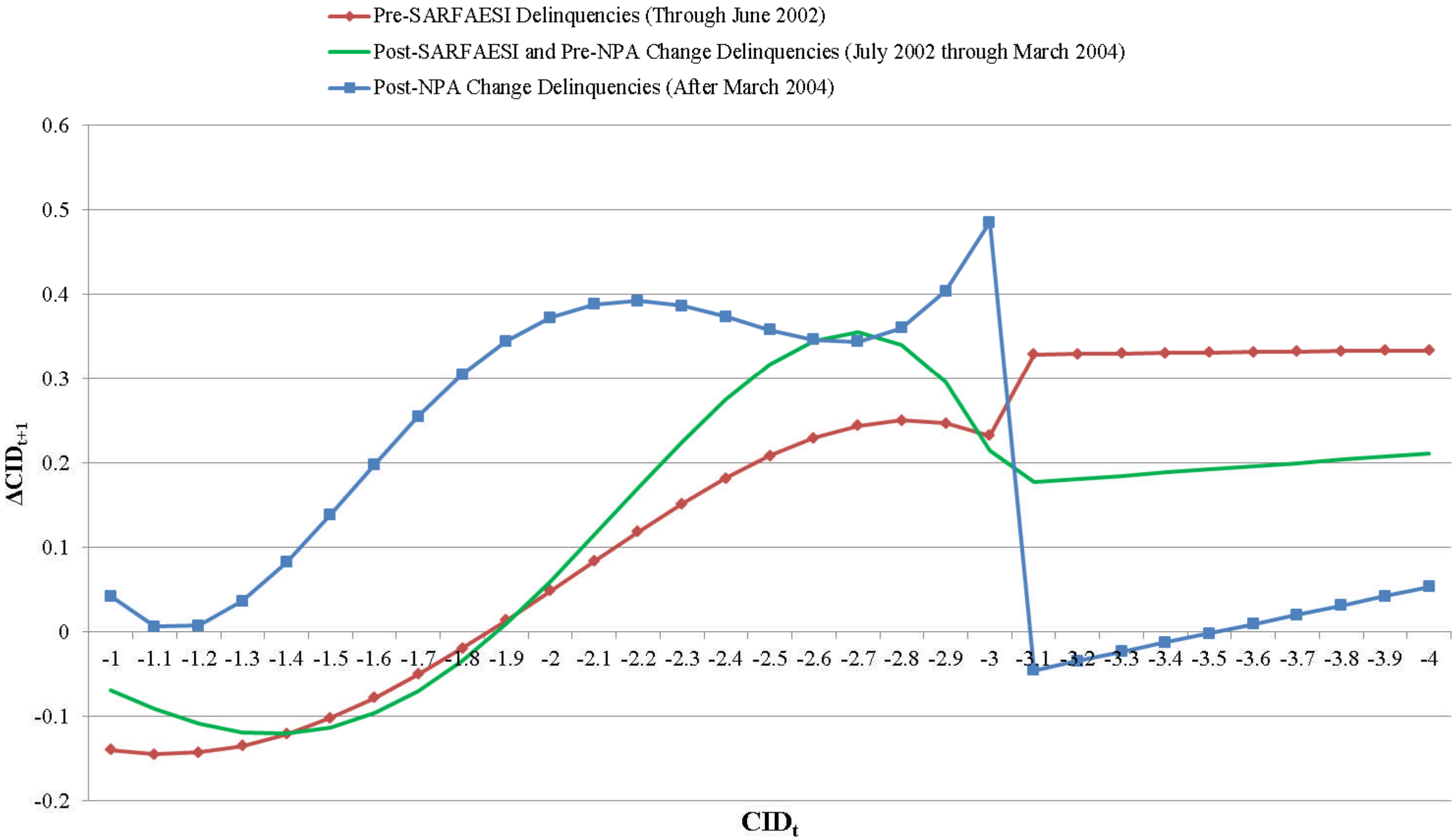
Notes: The issuance weighted average cohort delinquency effects are the weighted average of the fixed rate and variable rate excess cohort effects from the delinquency model using cohort X size fixed effects, where the weights are equal to the fraction of the total value of mortgage loans disbursed that are fixed or variable rate. These effects represent the incremental propensity towards delinquency of smaller loans beyond the propensity of loans larger than the priority sector lending threshold in effect at the time of the loan disbursal. The first proxy for the tightness of PSL constraints equals minus the log home-price adjusted priority sector lending threshold, which is a measure of the fraction of properties for which mortgages are unlikely to qualify as priority sector (as properties are too expensive). The second proxy is the priority sector lending requirement (as a percentage of total credit) minus aggregate domestic bank priority sector lending. Both proxies are plotted in standardized units. Priority sector lending thresholds are detailed in the online regulatory appendix.

Figure 9: Cumulative Installment Deficit around Delinquencies



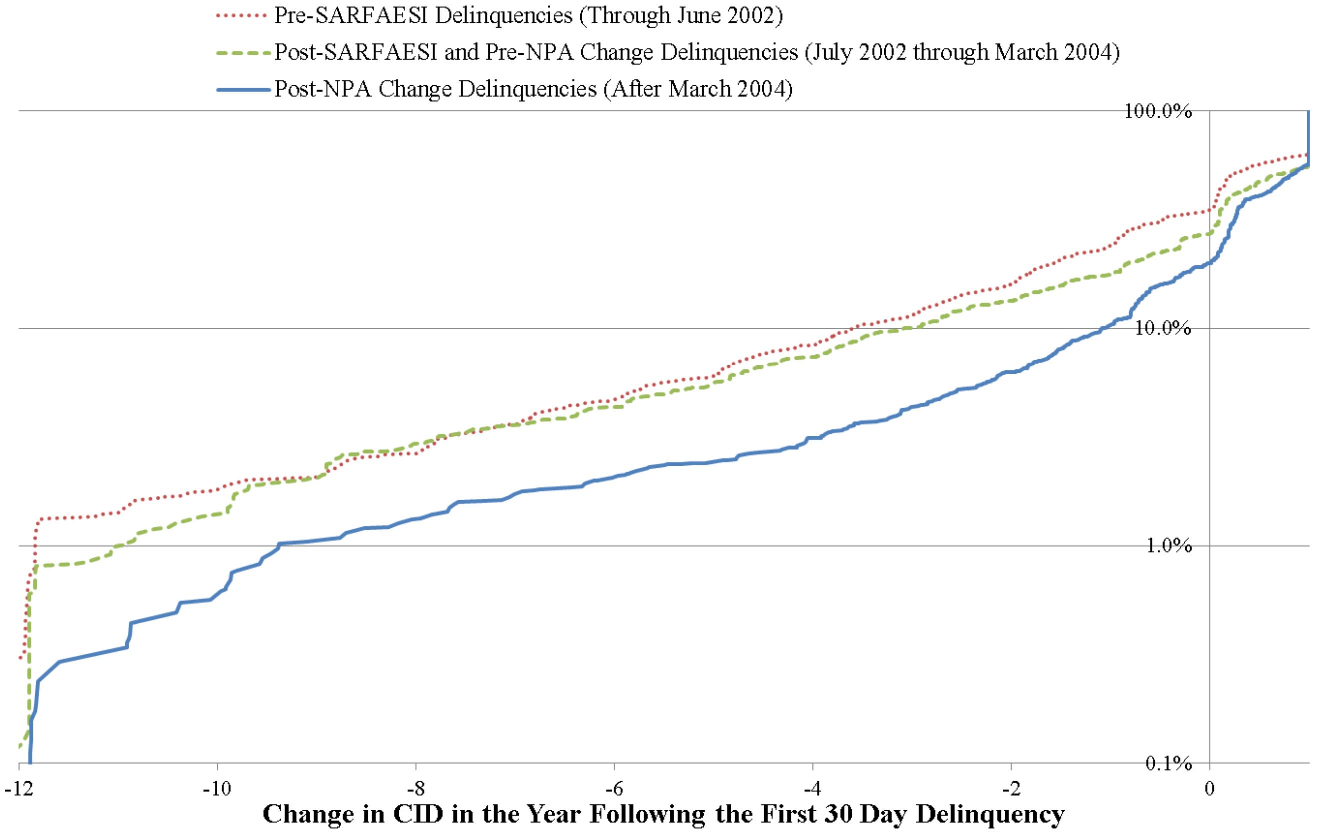
Notes: Abnormal installment deficit is given by the estimated coefficients on time to delinquency (interacted with a post-March 2004 dummy) from a regression predicting changes in the cumulative installment deficit (value of delinquent installments in terms of expected monthly installments). The post-March 2004 dummy allows for a different pattern of abnormal installment deficits to emerge around delinquencies following the change in regulatory definition of non-performing assets. This model includes time and cohort fixed effects and is run separately for 30 and 90 day delinquencies. Top Panel: The cumulative installment deficit is the cumulative sum of the abnormal installment deficits estimated from the model. 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 10: Predicted ΔCID_{t+1} Post-30 Day Delinquency
(ΔCID is a Debt Collection Rate)



Notes: 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 11: Cumulative Empirical Distribution of Change in CID 12 Months Post-30 Day Delinquency



Notes: 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.