Liquidity Risk, Maturity Management And The Business Cycle

Atif Mian
University of California, Berkeley and NBER

João A.C. Santos
Federal Reserve Bank of New York and NOVA School of Business and Economics

May 2011
[PRELIMINARY AND INCOMPLETE]

ABSTRACT

Using the Shared National Credit data on syndicate loans from 1988 to 2010, we find that *liquidity risk*, i.e. the propensity to rollover and refinance outstanding debt and the availability of undrawn loan commitments is strongly pro-cyclical. We argue that firms try to minimize exposure to liquidity risk through active *maturity management*: they refinance early in normal times to keep their effective maturity structure long and thus minimize the need to refinance in tight credit conditions. We construct an unbiased estimate of the hazard ratio of refinancing early versus at-maturity, and show that it is highly pro-cyclical. Moreover, firms with strong fundamentals are best able to successfully pick the timing of their refinancing decisions. Maturity management by credit worthy firms makes their refinancing propensity *more* cyclical than other firms.

* The results or views expressed in this study are those of the authors and do not necessarily reflect those of the Board of Governors of the Federal Reserve System or the Federal Reserve Bank of New York. Mian: (510) 643 1425, atif@haas.berkeley.edu; Santos: (212) 720-5583, joao.santos@ny.frb.org.

A fundamental feature of corporations is that they have long-lived assets while external funding is of limited maturity. Thus firms continually have to go back to banks and renegotiate, or refinance, the maturity of their outstanding loan commitments. The inability of the financial system to guarantee funds for the entire duration of a corporation's life keeps firms susceptible to a sense of fragility: What if banks refuse to rollover their loans the next time they go for extension?

Such concerns expose firms to *liquidity risk*, i.e. costs associated with the necessity to refinance and rollover existing debt. As the recent financial crisis reminded us, liquidity risk is strongly correlated with the business cycle. For example, loan officer surveys consistently show that credit conditions tighten significantly during recessions. Similarly, the price of risk in terms of credit spreads increases during weak economic times.

How can firms deal with liquidity risk – especially given its negative correlation with the business cycle? A natural strategy would be for forward-looking firms to minimize the possibility that they may be forced to rollover bank debt in weak economic times when liquidity is either costly or simply unavailable. One way to implement this strategy is through dynamic *maturity management*: Firms can refinance and extend the maturity of loans during normal times well before these loans become due. Then, to the extent liquidity freezes are limited in duration firms can "ride out" liquidity shocks.

In this paper we argue that this is indeed how some firms behave - in particular those with strong fundamentals and credit worthiness. We utilize a previously unexplored data set on syndicate loans, the Shared National Credit (SNC) program run by the Federal Deposit Insurance

Corporation, the Federal Reserve Board, the Office of the Comptroller of the Currency, and the Office of Thrift Supervision.[1]

A unique feature of this data set is that it follows a syndicate loan over time and tracks if (and when) the loan is refinanced to extend its date of maturity. We can thus track the evolution of refinancing behavior over time and in the cross-section of U.S. corporations. Our data, which covers the period from 1988 to 2010, enable us to analyze the relationship between liquidity risk and maturity management over the course of three business cycles.

We find that liquidity is strongly pro-cyclical. The propensity to refinance a loan is more than fifty percent higher in normal times compared to recessions. Conditional on getting refinanced, a loan's maturity gets extended for longer duration during business cycle peaks compared to recessions. Furthermore, firms' access to unused lines of credit is pro-cyclical as well. The percentage of loan commitment that is unused goes down by seventeen percent in recessions.

There is considerable evidence that firms actively manage their maturity structure through early refinancing of outstanding loans. In particular, sixty five percent of loans that get refinanced do so with over a year still left in existing maturity - forty percent do so with over two years left in existing maturity. Furthermore, the pattern of early refinancing is not constant through time, but displays a distinct cyclical pattern. The relative propensity (hazard ratio) to refinance early versus at-maturity increases by over fifty percent during business cycle peaks relative to recessions.

One concern with interpreting the hazard ratio result is that loans that are not refinanced until the last year of their maturity are different in important ways than loans that get refinanced earlier. In

[1] Bord and Santos (2011) uses this data to investigate whether the rise of the CLO business contributed to riskier lending in the corporate market.

fact our own results show that refinancing propensity is strongly related to firm fundamentals including sales growth, credit rating, access to public equity, and excess debt capacity[2]. Hence firms that do not refinance their loans until the last moment and hence are most exposed to rollover risk are systematically weaker firms.

Could the *cyclical* pattern in hazard ratio of early versus at-maturity refinancing be driven by unobserved differences in loans refinanced early versus at-maturity? To test for this, we adopt the approach introduced by Khwaja and Mian (2008) and focus on borrowers that have multiple loans of differing maturities. The methodology thus utilizes only within firm-year variation to construct an unbiased hazard ratio estimate over time. We find that the unbiased hazard ratio constructed in this manner is as pro-cyclical as the earlier estimate.

The tendency to manage maturity structure by refinancing early is strongest for firms with high credit worthiness. In fact the overall propensity to refinance is significantly *more* cyclical for firms with high un-used debt capacity, firms with investment grade rating, and firms with access to equity markets. The sensitivity of refinancing likelihood in the cross-section with the above measures of credit worthiness also displays a strong pro-cyclical pattern. In fact this sensitivity becomes almost negligible in the midst of recessions.

The cyclical nature of the cross-sectional sensitivity of refinancing likelihood with respect to credit worthiness highlights the counter-cyclical demand for refinancing due to maturity management by credit worthy firms. In particular, *ceteris paribus,* one would have expected banks to cut back on the marginal, i.e. less credit worthy firm first, when credit conditions tighten during recessions. Similarly, one would expect less credit worthy firms to be “high beta”

[2] Excess debt capacity is measured as percentage of total loan commitments that remain unused by a firm.

in general and display a more pro-cyclical refinancing pattern. The fact that we find evidence completely to the contrary is suggestive of the power of maturity management: liquidity demand becomes counter-cyclical for credit worthy firms as they choose not to refinance at the same rate when liquidity costs rise.

There is a fascinating theoretical debate on liquidity risk and its impact on firm performance and the economy. The literature is too vast to adequately synthesize here but the book by Holmstrom and Tirole (2011) provides an excellent summary. The key focus of this literature is the refinancing problem that firms continually face. However, despite the intense theoretical focus on this question, not much is unknown empirically due to a paucity of relevant data. Our paper brings a novel data set to shed light on this important question.

Our finding that maturity extension through early refinancing is closely linked to credit worthiness is consistent with theoretical work such as Flannery (1986), Diamond (1991), Hart and Moore (1994), and Berglof and von Thadden (1994) that argues that banks would deliberately want to keep maturity structure short in order to gain more leverage and control vis-à-vis less credit worthy firms. Our finding that credit worthy firms minimize the need to be forced to refinance in tough times is consistent with theoretical work such as Froot, Sharfstein and Stein (1993). Such maturity risk management is also useful from a macro perspective since it lowers potential mismatches between liquidity supply and demand in times of trouble.

There have been a number of empirical studies on the determinant of overall corporate debt maturity (Barclays and Smith (1995), Stohs and Maer (1996), Guedes and Opler (1996), Johnson (2003), and Berger et al (2005)). These studies primarily focus on the cross-sectional relationships between a firm's characteristics and its choice of corporate debt maturity. Our paper in contrast focuses on the dynamic refinancing choice and its relationship with business cycle and firm credit worthiness.

A recent related paper is Almeida, Acharya and Campello (2011) who show that low beta firms manage their liquidity through bank credit lines while high beta firms prefer cash. If we consider low beta firms as more credit worthy, then our results imply that low beta firms can afford to rely more on credit lines because they are better able to manage the maturity risk via early refinancing of loans in good times.

The rest of the paper is organized as follows. Section I describes the data and presents summary statistics. Section II presents aggregate trends in credit conditions, refinancing propensity, and maturity structure. Section III presents the main empirical results while section IV discusses the possible interpretations of our results and section V concludes.

I. Data and Summary Statistics

A. Data

Our main data source for this project is the Shared National Credit (SNC) program run by the Federal Deposit Insurance Corporation, the Federal Reserve Board, the Office of the Comptroller of the Currency, and the Office of Thrift Supervision.[3]

The SNC program gathers, at the end of each year, confidential information on all credits --- new as well as credits originated in previous years --- that exceed $20 million and are held by three or more federally supervised institutions. For each credit, the program reports the identity of the borrower, the type of the credit (e.g. term loan, credit line), its purpose (e.g. working capital, mergers and acquisitions), origination amount, origination date, maturity date, rating, and

[3] The confidential data were processed solely within the Federal Reserve for the analysis presented in this paper.

information about the syndicate. The program reports both the outstanding amount on a loan, as well as the total loan commitment that the borrower may withdraw.

The SNC data not only reports the total commitment of a syndicate loan, but also breaks down this loan commitment by lead bank and *all* of the participant banks in the syndicate. We thus know the identity of all participating banks in a syndicate, as well as their relative share in the total loan.

Since the SNC program gathers information on each syndicate loan at the end of every year (December 31st), we can link loans over time and construct variables that capture changes in loan terms (such as maturity date or loan commitment) as well as changes in the amounts drawn-down by borrowers each year. Similarly, we can follow the performance of loans over time in terms of credit ratings.

We also follow the performance of borrowers that are publicly listed by matching our SNC data with financials data from Compustat and stock price data from CRSP. On the lender side we merge data on bank financials for the lead bank. This data come from the Reports of Condition and Income compiled by the FDIC, the Comptroller of the Currency, and the Federal Reserve System. The data include the bank's capital-to-asset ratio, its size, profitability and losses / charge-offs. Wherever possible we obtain bank data at the holding company level using the Y9C reports. If these reports are not available then we rely on Call Reports which have data at the bank level.

Table 1 tabulates the basic description of the SNC data. The data covers 50,469 unique syndicate loans over 1988 to 2010 for a total of 156,041 loan-year observations (column 1). Our unit of analysis in this paper is going to be loan-year. While the coverage of SNC loans increases over time, on average we have four to eight thousand syndicate loans in a given year. A syndicate loan may disappear from the SNC data set over time if the lead bank no longer falls under the Fed's jurisdiction, or if the size of the loan is no longer large enough to warrant reporting by the lead bank. While we are cognizant of this potential incompleteness in our panel, we do not believe it biases the core results of our paper in any obvious direction.

There are a total of 22,156 distinct corporate firms (borrowers) represented in our data with 3,312 to 5,360 firms in any given year (column 2). Some of our tests focus on firms with multiple loans in the same year, such that the loans have different number of years left till maturity. Column (4) reports the number of such firms every year. In total there are 5,749 firm-years that satisfy this constraint. The number of lead banks varies from 305 to 163 over the sample period with a total of 661 unique banks. Finally, column 6 reports the distribution of industries in our sample, with manufacturing being the most represented industry.

B. Summary Statistics

The top panel in Table 2 characterizes our sample of syndicate loans. The average loan commitment is 188 million dollars, with the 10^{th} and 90^{th} percentile being 15 million and 409 million respectively. Thus our data covers large corporate loans. The average outstanding loan is about half the amount of average commitment as the average draw down percentage is 57 percent. 84 percent of loans have an investment grade rating. On average, lead banks lend 23 percent of the syndicate loan, 20 percent of lead banks are foreign, and 32 percent of a syndicate loan is funded by "shadow banks" - defined as non-commercial financial institutions.

A key variable of interest in our paper is whether a loan gets refinanced at a point in time. We construct the average propensity to refinance in the following manner. A syndicate loan *i* is defined to be refinanced in year *t* if its date of maturity at the end of year *t* is greater than the date of maturity for the same loan at the end of year *t-1*. In the event a loan is observed at the end of year *t-1* but not observed later on, we assume that the loan was not refinanced. Since it is possible for loans to sometimes drop out of our sample for reasons mentioned before, our definition of refinancing *underestimates* the level of true refinancing. However, we are mostly interested in the time-series variation in refinancing likelihood, and there is no particular reason to think that the cyclical pattern would be biased in any direction due to our variable construction. The unconditional refinancing probability is 21.7%.

The upper-left, upper-right and lower-left panels of Figure 1 plot the distribution of maturity structure and changes in maturity structure for syndicate loans. The upper-left panel shows that close to eighty percent of the time, there is no change in the maturity date of a loan. However, conditional on a change in maturity date, it is mostly extended by one year followed by two and three years respectively. The modal maturity of loans at origination is five years, but maturities of up to seven years at origination are fairly common (lower-left panel). Since remaining maturity declines over time after origination, the distribution of maturity left is shifted to the left in the upper-right panel. It is also smoothed out since maturity left is measured as of December 31st of each year, and loans are originated throughout the year.

The lower-right panel shows the draw-down percentage distribution is bi-model. One-third of loans are fully drawn down, while one-quarter of loans have not been utilized at all. The distribution is fairly uniform within these two extremes. In the analysis that follows, we will make important use of the information that some firms are borrowing up to their maximum capacity and thus may be credit constrained. This is a novel feature of our data set that we can observe total commitments as well as how much firms draw down against these commitments.

The bottom panel of Table 2 presents firm financials for the subset of borrowers that are publicly traded. The average firm has assets worth 3.5 billion dollars, with total sales worth 2.4 billion dollars. The average growth in sales is 15 percent and the average return on assets is 2 percent.

II. Liquidity And The Business Cycle: Aggregate Patterns

A. Credit Conditions

We begin by highlighting the aggregate trends in banking sector credit conditions. The top-left panel in figure 2 plots bank charge-offs normalized by total assets (un-weighted and weighted by bank assets) over time at a quarterly frequency. The dashed vertical lines represent recessions as dated by NBER. Bank charge-offs are heightened during times of economic weakness leading to losses on bank capital. Such losses to capital can potentially make banks more conservative in their lending practices and tighten credit standards.

The top-right panel plots the average response to loan officers survey on credit tightening for large and medium C&I loans. Loan officers consistently report that they have "tightened" lending standards around recessions. The tightening could either be driven by supply-side conditions – for example due to losses to bank capital seen earlier – or by demand-side conditions such as greater uncertainty about firms' future cash flows.

The bottom two panels plot credit spreads that capture the price of risk in the economy. The bottom-left panel plots the TED spread, i.e. the difference between 3 month LIBOR and 3 month U.S. T-bill rate. The bottom-right panel plots corporate credit spread as measured by BAA spread minus AAA over time. Both spreads highlight an increase in the price of risk during weak economic growth, although the 2007-09 recession stands out in terms of magnitude. The bottom line from figure 2 is that credit conditions tighten and banks become more conservative on average during recessions. The fundamental reasons for these changes may be driven by supply or demand side factors. However, what is relevant for us is that all else equal, a forward-looking firm would want to avoid having to refinance or seek new credit during times of tightening credit conditions.

B. Corporate Liquidity

A unique feature of our data is that we directly observe the refinancing likelihood of a loan at a point in time, which is often the key variable of interest in the theoretical literature on corporate liquidity. The construction of this variable is already discussed in section II. The top panel in figure 3 plots the evolution of refinancing probability over time.

The propensity to refinance a loan shows strong cyclical properties. Refinancing probability is 17.1% on average during recession years, while it reaches 30.7% and 28% respectively at the peak of business cycles. These refinancing probabilities are not conditioned on the time left in current maturity, and combine both term loans and credit lines. While we will separately condition on years left till maturity later on, the time-series refinancing pattern looks similar for both credit lines and term loans[4].

The middle panel plots the average years that maturity is extended by, conditional on a loan being refinanced. The size of maturity extension conditional on refinancing also displays some cyclicality. The lower panel displays the share of outstanding loans at the end of a given year that is new loans. The percentage of loans that are new in a given year is also pro-cyclical. During recessions, only 18.6% of loans are new loans issued in those years for the first time. This proportion reaches 25.1% and 25.7% at business cycle peaks.

[4] The key distinction between credit lines and term loans is their maturity at origination, a variable that we will explicitly account for in our analysis later on.

C. Undrawn Loan Commitments

While the ability to refinance an outstanding loan is an important measure of liquidity for firms, another relevant metric is the availability of unused lines of credit. These are loan commitments that firms can tap into in case of a sudden liquidity need. An important advantage of our data set is that we observe not just the outstanding loan amount, but also the total loan commitment that banks have issued.

The top panel in figure 4 plots the average percentage of total loan commitment that is drawn down by a firm. The draw down percentage is pro-cyclical. While the average draw down percentage is 60.8% during recessions, it reaches as low as 53.3% and 50.3% in normal years. The cyclical pattern in draw down percentage is present through all of the three recessions during our sample period. While some have pointed out to the sharp increase in corporate drawn down rates in the most recent recession (Ivashina and Sharfstein (2010)), our results show that this pattern is representative of previous recessions as well. Finally, the draw down percentage consistently begins to rise well before the onset of a recession.

The percentage of drawn down is not uniform across all loans. As figure 1 demonstrated, some loans are not drawn upon at all, while other are maxed out. Loans that are fully drawn may be of particular interest as they potentially reflect firms facing financial constraints. The lower panel plots the percentage of loans that are fully drawn out over time[5]. As with the average draw down ratio, the percentage of loans that are fully drawn down is pro-cyclical as well. Interestingly the percentage of loans that are fully drawn out is *higher* in the 2001 recession than in the 2007-09 recession.

[5] Loans with draw down percentage greater than 95% are defined as "fully drawn out".

D. Effective Maturity

As new loans get issued and old loans get refinanced, the overall maturity structure of outstanding syndicate loans constantly changes. The average effective maturity of all outstanding syndicate loans is of interest from a liquidity risk perspective since shorter maturities indicate greater susceptibility to financial fragility. Figure 5 uses information on the date of maturity for each outstanding loan as of December 31st of each year to plot the average effective maturity over time.

The plot shows that there is a trend as well as a cycle in the evolution of average maturity over time. There is an unmistakable downward trend in average maturity of outstanding syndicate loans over time. While average maturity is close to four years in 1988, it declines to just over two and a half years in 2010. This drop of almost a year and a half in effective maturity should be of independent interest. For example, one possibility worth exploring is that increased reliance on short term borrowing (such as Repo transactions) forced banks to favor shorter term lending over time.

Of more immediate interest for us is the embedded cyclicality in average maturity over time. If we take out the downward trend, there remains a strong cyclical component such that average maturity declines by about six months during recessions. The decline in average maturity during recessions may be driven by two separate factors. First, banks may issue new loans of shorter maturity. We find that the maturity of new loans issued does decline during recessions. Second, borrowers may be more likely to refinance early in non-recession years and thus extend the maturity of their outstanding loans. As we show in more detail in subsequent analysis, this second channel is very much operative as well.

The evidence in section II shows that all measures of credit conditions and corporate liquidity display significant business cycle cyclicality. In particular, while credit conditions and risk spreads tighten during recessions, corporate liquidity as measured by the propensity to refinance an existing loan and availability of unused lines of credit goes down during recessions. In the section that follows, we investigate how firms' decision to refinance early versus at-maturity is influenced by business cycle conditions.

III. Maturity Management And The Business Cycle

We now investigate how firm refinancing of loans varies across borrowers and over time. Of particular interest is the analysis of how firms try to protect themselves against the cyclical fluctuations in credit conditions and liquidity.

A. Refinancing And Borrower Characteristics

We test how the probability of refinancing depends on borrower characteristics by estimating the following regression specification.

Where Y is an indicator variable for whether the syndicate loan i of borrower j from lead bank b is refinanced during year t. According to equation (1), the probability of refinancing may depend on loan characteristics and borrower characteristics . Since we want to focus our attention to the dependence of refinancing on loan and borrower characteristics, we non-parametrically absorb any time-series fixed effects and any bank-specific shocks by including bank-year fixed effects . While the left hand side variable captures whether a loan is refinanced during year t, all of the right hand side variables are measured as of the end of year t-1.

Equation (1) may be estimated using a non-linear procedure such as logit. However, for simplicity and ease of interpreting coefficients, we present all our results using the linear probability model. Nonetheless all of our results are robust to using a logit estimation procedure.

Column (1) of Table 3 estimates equation (1) without bank-year fixed effects. The results indicate that loan with high credit rating, loan commitments that are not drawn to the maximum, credit lines, loans of publicly listed companies, loans with fewer years left till maturity, and loans with shorter maturity at origination are all more likely to get refinanced. Even without any time fixed effects, these loan and borrower level attributes collectively explain ten percent of the variation in the left hand side indicator variable. These results suggest that loan level attributes are quite important for determining the likelihood of refinancing.

The magnitude of these coefficients is quite large as well. While the average propensity to refinance a loan is around twenty one percent (Table 2), loans with an investment grade rating are 6.7 percentage points more likely to get refinanced. Loan commitments that are drawn down more are less likely to be refinanced, and this effect is non-linear with the refinancing probability dropping suddenly for loans that are fully drawn down. Credit lines are 2.6 percentage points more likely to get refinanced. Firms with access to public equity are 4.1 percentage points more likely to get refinanced. Finally, as loans get closer to maturity date, they are more likely to get refinanced.

Column (2) includes year fixed effects to control for average time variation in refinancing probability and thus only exploits cross-sectional variation in borrower attributes to identify coefficients of interest. It also includes separate fixed effects for number of years left in maturity, and number of years for maturity at origination. The fixed effects thus non-parametrically control for any effect of maturity structure on refinancing likelihood. We also add industry fixed effects to control for variation driven by industry differences.

While the R-square increases to 0.17 with the addition of various fixed effects, our coefficients of interest remain largely unaffected. The effect of draw down percentage is now even more non-linear, with refinancing probability dropping discontinuously by 3.5 percentage points for loans that are fully drawn out. This result suggests that loans that are completely drawn out are fundamentally different from other loans and likely reflect that such borrowers are financially constrained. We shall explore this classification further in later results.

Column (3) repeats the analysis for column (2), but restricts the analysis to borrowers that are publicly listed. Doing so brings the added advantage that we can now include variables such as change in log sales, return on assets and sales over assets that capture borrower performance. The coefficients on loan level attributes are similar, with the effect of credit rating and financial constraints being even more important than before. Of the new firm performance variables added, only growth in sales comes in significant. A one standard deviation increase in sales growth increases the refinancing probability by 0.64 percentage points.

Columns (4) and (5) add bank-year fixed effects to columns (2) and (3) respectively. Bank-year fixed effects absorb any time-varying shocks at the lead bank level that might effect the refinancing probability. For example, if there are certain bank-specific credit supply shocks such as hits to bank capital, these are completely absorbed through the bank-year fixed effects. While the R-square increases by about five to eight percent, the coefficients on borrower and loan characteristics are materially unaffected.

Columns (6) and (7) replicate columns (4) and (5), but restrict analysis to loans that have less than one year left till maturity. These are loans that are under greater pressure to get refinanced. We find that borrower attributes matter more strongly for this set of loans. In particular, the effect of credit rating and of commitment being fully drawn out almost doubles.

Overall the results in Table 3 show the important of loan and borrower characteristics in determining refinancing likelihood. Since we include bank-year fixed effects, none of the estimated coefficients are driven by supply-side shocks to individual banks. We have also seen – not surprisingly – that propensity to refinance increases as loans get closer to maturity date. However, how likely is it for loans well before their maturity date to get refinanced? We next investigate this question more carefully since refinancing early may be one strategy through which borrowers minimize their exposure to liquidity risk.

B. Refinancing Early Versus At-Maturity

The top-panel in figure 6 separates the probability to get refinanced by the number of years left till maturity (blue-solid line). The average probability to get refinanced is over fifty percent for loans with less than a year left till maturity, and declines as number of years till maturity increases. However, refinancing probability remains significant even for loans with multiple years left till maturity.

We classify refinancing of loans that have more than a year left in maturity as "early refinancing", and of loans with less than a year left in maturity as "at-maturity" refinancing. The red-dash line plots the share of refinancings that are done for loans with a given number of years left till maturity. While about forty five percent of refinancings are done "at-maturity", the remaining fifty five percent are "early refinancings".

While the average rate of refinancing is higher for loans at-maturity, the results from Table 3 suggest that loans that remain non-refinanced until the last year of their maturity are systematically different from loans that get refinanced early. In particular, loans that reach maturity before being considered for refinancing are likely to be loans with lower credit worthiness.

Since the worse credit worthiness lowers the propensity to refinance on average, an implication of the selection effect for loans refinanced early versus at-maturity is that the "gradient" of the solid blue line in the top-panel of figure 6 is biased downwards. We test for this by first estimating a version of the solid blue line of top-panel in a regression framework by estimating the following OLS regression equation and plotting the coefficients on indicator variables for years left till maturity:

Where Y is refinancing indicator variable, is a vector of indicator variables (fixed effects) that turn 1 if the number of years left till maturity is between *n* and *n+1*. *n* varies from 0 to 10, with all loans above 10 years left in maturity top-coded at 10. represent fixed effects for the number of years of maturity at origination of a loan (also going from 0 to 10), and are year fixed effects[6].

The dotted blue line in lower-panel of Figure 6 plots the coefficients . We next re-estimate these coefficients after adding borrower-year ( ) fixed effects in equation (2). Borrower-year fixed effects force comparison to be within-firm in a given year. It thus compares within firm-year differences in refinancing rates for borrowers that have multiple loans such that one loan is maturing in the coming year, and another loan has more than one year left till maturity. Coefficients with borrower-year fixed effects added to equation (2) are thus immune from the borrower selection effects mentioned earlier. Our strategy is similar to the firm-year fixed effects strategy introduced by Khwaja and Mian (2008) to isolate the impact of credit supply shocks.

[6] For exposition clarity, we suppress coefficient estimates of fixed effects from the specification whenever these coefficients are not reported in tables.

The dashed red line in lower panel plots the coefficients with borrower-year fixed effects. As expected the gradient of the red line is higher than the gradient of OLS coefficients, consistent with the notion that OLS gradient is biased downwards due to unobserved borrower heterogeneity. Overall the results in Figure 6 suggest that early refinancings are an important aspect of borrower maturity management – something that we explore in more detail in the next section.

C. Hazard Ratio for Early Versus At-Maturity Refinancing Over the Business Cycle

The top panel in figure 7 breaks down the time variation in probability of refinancing by loans that are maturing within the next year, i.e. at-maturity refinancing (left axis) and loans that are maturing after more than one year, i.e. early refinancing (right axis). While both early and at-maturity refinancing likelihoods are pro-cyclical, early refinancing is more cyclical than at-maturity refinancing. In particular while the average probability is much lower for early refinancing versus at-maturity refinancing (16.6% versus 52.2%), the swings in refinancing likelihood for early refinancing are larger in absolute terms. Thus in proportionate terms (or in terms of the odds ratio), early refinancing is a lot more sensitive to business cycle fluctuations than at-maturity refinancing.

This can be seen more clearly from the lower panel that explicitly estimates the hazard ratio (odds ratio) of refinancing early versus at-maturity separately for each year. The hazard ratio is constructed by maximizing for each year *t* the following likelihood function:

The estimated odds ratio statistic captures the hazard ratio or relative propensity of refinancing early versus at maturity. The blue dashed-dotted line plots the hazard ratio estimates over time, and shows that these estimates are pro-cyclical. The magnitude of cyclicality is quite large as well, as the relative propensity to refinance early almost doubles at its peak relative to the low level during recessions.

Table 4 presents formal estimate of the hazard ratio with appropriately clustered standard errors. We first compute the average hazard ratio over the sample period by maximizing the following likelihood function over the entire sample.

Equation (4) is similar to equation (3), but incorporates year fixed effects since the maximization is done over the entire sample rather than each year separately as in (3). It also includes industry fixed effects, and fixed effects for number of years of maturity at origination as controls. The statistic reflects the average hazard ratio (odds ratio) over the entire sample period. Standard errors are clustered at the lead bank level. There are a total of 649 distinct lead banks over the entire regression sample.

Column (1) presents the average hazard ratio estimate over the entire sample. In order to convert the estimated coefficient into hazard ratio, we need to take its exponent, i.e. in Table 4. The estimated hazard ratio is 0.45 and very tightly estimated. Thus on average the likelihood of early refinancing is 45% that of at-maturity refinancing. This result is materially unaffected if we add our previous controls to column (1), i.e. credit rating, drawn down percentage, fully draw down indicator variable, indicator variable for credit line, and an indicator variable for whether the borrower is publicly listed.

Column (2) tests for the cyclical properties of the hazard ratio by interacting the hazard ratio coefficient with indicator variables for each recession separately. The results indicate that the hazard ratio is significantly lower in both the 2001 and 2007-09 recessions, with the drop in

2007-09 recession being the largest. Hazard ratio is lower in 1991 recession as well, but the magnitude of drop is small and statistically not significant.

Column (3) tests directly for the correlation of hazard ratio with business cycle variation as reflected by GDP growth. It removes year fixed effects from the estimation and instead includes the annual growth rate in real GDP along with its interaction with the hazard ratio coefficient. The positive and statistically significant coefficient on GDP growth shows that refinancing probability increases as growth picks up.

More importantly for our analysis, the interaction term between hazard ratio estimate and GDP growth shows the cyclical nature of hazard ratio. The hazard ratio of refinancing early versus at-maturity is significantly higher when economic growth is stronger. A one standard deviation increase (1.87) in GDP growth increases the relative likelihood of refinancing early by fourteen percent. Column (4) replaces GDP growth with year dummies to control for any possible time varying shock. The interaction term between hazard ratio and GDP growth becomes stronger.

As we mentioned earlier as well, one concern with the hazard ratio estimate is that loans refinanced at-maturity are likely to be different in unobservable ways to loans that are refinanced early. While this may bias the *level* of hazard rate estimate, it is not clear how such a bias would impact the sensitivity of hazard rate with respect to the business cycle. Nonetheless as outlined earlier, we can adopt the approach that only considers borrowers with loans of multiple maturities in a given year such that one of the loans is maturing in the coming year (i.e. is at-maturity) and another loan is maturing with more than one year left in maturity. Restricting our analysis to this subsample guarantees that early versus at-maturity loans are coming from the same borrower on average.

The red dashed line in the lower panel of Figure 7 plots the year-by-year estimate of the hazard ratio after restricting the sample to borrowers that satisfy the above multiple maturity criteria. The resulting graph shows that once any inherent bias in hazard ratio is removed, the hazard ratio remains pro-cyclical. This is further confirmed by column (5) of Table 4 that restricts sample to borrowers with multiple loans in a given year, such that one loan is maturing in the coming year and another sometime afterwards. The interaction between hazard ratio and GDP growth remains strongly positive and statistically significant.

D. Refinancing Over The Business Cycle And Borrower Type

We have seen that refinancing depends strongly on years left till maturity and more importantly the relative propensity of early versus at-maturity refinancing displays strong pro-cyclical properties. We next test how the refinancing pattern of syndicate loans over time varies by borrower type, holding constant the maturity of a loan. To do so, we first regress refinancing indicator variable (0/1) on fixed effects for the number of years left till maturity, and fixed effects for the number of years of maturity at origination of a loan[7]. The residual from this regression has thus been stripped of any fixed differences in refinancing propensity driven by the maturity structure of a loan either at origination or at the time of observation.

Figure 8 plots this residual over time separately for various borrower categories[8]. The top panel plots the refinancing likelihood – stripped of the effect of maturity structure – separately for loans that are drawn down to the maximum (red dotted line), and loans that have only used less than five percent of their total loan commitment (blue solid line). The comparison thus focuses

[7] i.e. Pit = …

[8] The shape of graphs in Figure 8 is similar if we did not strip away the maturity structure effect first. However, conceptually we want to focus on the variation that is not driven by differences in the maturity structure. We therefore show results after stripping away the fixed effect of maturity structure.

on borrowers that are likely to be financially constrained (the red dotted line) and borrowers with excess debt capacity (blue solid line).

Borrowers with excess debt capacity are more pro-cyclical than financially constrained borrowers. For example, while financially unconstrained borrowers have refinancing likelihood that is five to ten percentage points higher, refinancing likelihoods become identical for both type of firms in the 2008-09 recession. Similarly, there is a sharp drop in refinancing likelihood for borrowers with financial slack in the wake of the 1998 liquidity crisis, suggesting that more credit worthy firms deliberately cut back on refinancing loans when liquidity costs rise.

The middle panel in figure 8 compares loans with an investment grade rating with non-investment grade loans. As before, investment grade loans are more pro-cyclical. In fact most of the overall time-variation in refinancing likelihood is driven by investment grade loans. The bottom panel of figure 8 compares loans from borrowers with access to public equity (blue solid line) with loans from borrowers that are private (red dashed line). Once again borrowers with greater access to external financing display greater cyclical tendency in terms of refinancing probability.

The results in Figure 8 suggest that the time variation in refinancing likelihood is driven by demand-side considerations, i.e. credit worthy firms deliberately choose to not refinance in weak economic times. It is hard to imagine scenarios under which the supply-side (i.e. banks) would impose a harsher treatment on more credit-worthy borrowers in weak economic times[9]. We test more explicitly for how the sensitivity of refinancing likelihood *in the cross-section* varies with borrower fundamentals over time by estimating the following regression specification:

[9] For example, Erel etal (2011) find that capital raising tends to be pro-cyclical for noninvestment-grade borrowers and counter-cyclical for investment-grade borrowers, and attribute this to “the effect of macroeconomic conditions on the supply of capital”.

Where is some measure of borrower credit worthiness (fundamentals) such as credit rating, percentage of loan commitment that is drawn out, and whether borrower has access to equity markets. The coefficient captures the sensitivity of refinancing likelihood to these borrower fundamentals. denote fixed effects for number of years left in maturity, number of years of maturity at the time of origination, and year.

Figure 9 plots the estimates of separately for regressions where is either credit rating, unused loan commitment percentage, and indicator for equity market access. There is clear evidence of a strong pro-cyclical pattern. The sensitivity of refinancing likelihood to borrower fundamentals *declines* considerably during recessions. For example, refinancing likelihood becomes also insensitive to borrower fundamentals during the 2007-09 recession!

Table 5 explicitly tests for the correlation between refinancing and borrower-quality sensitivity, and business cycle strength by updating equation (5) to:

where *BIZS* reflect business cycle strength, and is either measured by indicator variable for NBER non-recession year, or growth in real GDP during the year. captures the correlation of interest. A high means that refinancing sensitivity to borrower quality *increases* during good times and decreases during bad times – as seen already in Figure 9.

Panel A reports the coefficient of interest ( ) separately for each business cycle strength variable (NBER non-recession year dummy and annual real GDP growth), and variable capturing borrower quality (credit rating, financial slack, and access to public equity). We consistently find a strong correlation between business cycle strength and sensitivity of refinancing to borrower fundamentals.

As we argued above, the result in Panel A is hard to explain by supply-side shocks affecting high and low credit quality firms differentially. As a further robustness check, Panel B replicates the analysis in Panel A, but this time further incorporate bank-year fixed effects in the regression specification. These fixed effects control for any bank-level shock in a given year influencing the refinancing likelihood for firms borrowing from that lead bank. The coefficient of interest is materially unaffected by the addition of bank-year fixed effects, even though the R-square (not reported) increases from around 15 percent to 18-20 percent.

So far we included the three borrower quality attributes separately in each recession. Of course the three measures are positively correlated with each other. In order to test if each of these variables has an independent effect, we include all three collectively in Panel C and report the coefficient on these variables interaction with business cycle variable. While the magnitude for some of the variables goes down, all three remain strong and statistically significant. As always, all standard errors are clustered at the lead-bank level.

IV. Discussion of Alternative Interpretations

Firms with better credit worthiness are more cyclical in their refinancing probability, and the sensitivity of refinancing to borrower credit worthiness is strongly pro-cyclical. These results are driven by the proclivity of credit worthy borrowers to refinance early at a significantly higher rate in period when credit conditions are loose. We have interpreted these core results as evidence in favor of active maturity management to minimize costs associated with liquidity risk. Could there be alternative explanations consistent with the collective evidence put together in this paper? The first explanation to consider is that perhaps supply-side fluctuations on the banking side are driving the observed patterns. There is little doubt that supply-side – e.g. credit lending standards – play an important role in generating the variation in liquidity risk over time. For example, evidence from loan officer surveys reported in Figure 2 reflects supply-side changes in lending standards as well. However, aggregate changes in supply-side conditions reflected in loan officer surveys for example are likely to generate very different patterns across borrowers than those observed in the data.

For example, as credit conditions become tight in 1998, the recession of 2001, or the recession of 2007-09, banks will impose a harsher discipline on the "marginal" borrower first. These are likely to be less credit worthy borrowers who may end up being the first to be denied credit, or given credit at harsher terms. Thus we would expect supply side changes to make the refinancing propensity of less credit worthy firms to be more cyclical. All of our results are strongly pointing in the other direction, suggesting that there is a strong demand-side channel that works in the opposite direction. We have interpreted this demand-side channel as maturity management by credit worthy firms.

An alternative demand-based explanation for our results could be that perhaps the natural demand for more credit worthy firms is *more* cyclical. Under this hypothesis, our results are not driven by some active maturity management by good quality firms. Instead they simply reflect the fact that refinancing needs are naturally more cyclical for credit worthy firms.

While this view is hypothetically possible, we think it runs counter to the traditional view as well as historical empirical evidence. For example, it is traditionally viewed that "high beta" firms tend to be small, young, startup firms or firms with uncertain cash flows going forward. These are the firms that often has low credit rating, and are most susceptible to fluctuations in the business cycle. Thus under the standard demand-side view, we should expect credit worthy firms to show more asynchronicity with respect to liquidity risk and the business cycle.

V. Concluding Remarks

The question of liquidity and maturity management in general, and in relation to the business cycle in particular holds a central place in financial economics. Yet most of the work in this area remains theoretical, primarily due to a paucity of data necessary to adequately answer the questions of interest. In this paper, we hope to have made an important contribution to this debate.

The novel feature of our data is that we can directly observe the refinancing propensity of outstanding syndicate loans and the utilization rate of total loan commitments. An added advantage is the loan-level coverage of a wide cross-section of firms over twenty two years that include three important recessions.

Our analysis reveals a strong pro-cyclical pattern in refinancing likelihood as well as the utilization rate of loan commitments. A striking feature of the refinancing behavior is the tendency to favor early refinancing especially in normal times versus recessions. This tendency is the strongest for credit worthy firms with strong fundamentals.

A surprising result is that the refinancing likelihood is more cyclical for borrowers with strongest credit record, suggesting that firms deliberately withhold their demand for refinancing in weak economic times and times when the cost of liquidity is high. Such firms have more ability to wait for better times both because they have longer effective maturities to be higher rate of early refinancings before, and because they may have alternative sources of financing if bank financing becomes excessively restrictive. The net impact of more cyclical refinancing by better quality firms is that cross-sectional sensitivity of refinancing with respect to borrower quality decreases sharply in recessions.

There are a number of interesting and promising questions raised by the overall findings of this paper that we hope future scholars will take up. For example, this paper focused on how demand-side factors influence the refinancing choice and maturity structure. In terms of supply-side factors, our focus was to either control for possible bank-specific shocks through bank-year fixed effects, or to argue that the observed patterns are unlikely to be generated by supply-side forces. Of course bank specific supply-side shocks may have an independent effect on liquidity and maturity structure that is worth investigating in the future.

The secular decline in maturity of syndicate loans also warrants further investigation. One possibility is that increased reliance on short-term borrowing through the Repo market forced banks to issue less long-term loans. This is a question worth investigating in light of the debate on the consequences of shadow banking system on credit. Another question related to the shadow banking system is the role played by shadow financial institutions in the syndicate structure. Our data includes information on participant banks and can be used to investigate the type of investments favored by the shadow banking institutions.

On the supply side, the role of foreign financial institutions in possibly mitigating the adverse effects of domestic liquidity shocks can also be analyzed more carefully using the data analyzed in this paper. For example, did foreign lead banks step in to buffer liquidity in the syndicate market in the aftermath of the 2007-08 financial crisis? More generally, the micro-level detail of the data utilized in this paper offers exciting opportunities to more carefully understand the link between financial shocks, corporate financial policy and the real economy.

References

Acharya, V. D. Gale and T. Yorulmazer, 2009. ``Rollover risk and market freezes,'' Working paper, Federal Reserve Bank of New York.

Allen, F. and G. Gale, 2007. Understanding Financial Crises. Oxford University Press.

Almeida, Heitor; V. Acharya and M. Campello, 2011. "Aggregate Risk and the Choice between Cash and Lines of Credit," Working Paper, NYU.

Almeida, Heitor; Murillo Campello, Bruno Laranjeira, Scott Weisbenner, 2010. "Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis," NBER Working Paper No. 14990

Altonji, Joseph; Todd E. Elder and Christopher R. Taber. 2005. "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools," Journal of Political Economy.

Barclay, M and Clifford Smith, 1995. "The Maturity Structure of Corporate Debt," Journal of Finance 50(2), 609-631.

Bergl¨of, E. and E. Von Thadden. 1994. "Short-Term Versus Long-Term Interests: Capital Structure with Multiple Investors." Quarterly Journal of Economics 109, 1055–1084.

Bernanke, Ben and Mark Gertler. 1989. "Agency Costs, Net Worth, and Business Fluctuations," American Economic Review, American Economic Association 79(1), 14-31.

Biais, B., Mariotti, T., Plantin, G., and J.C. Rochet. 2007. "Dynamic security design: Convergence to continuous time and asset pricing implications." Review of Economic Studies 74 (2), 345-390.

Berger, A.N., M.A. Espinosa-Vega, W.S. Frame, and N.H. Miller. 2005. "Debt Maturity, Risk, and Asymmetric Information." Journal of Finance 60, 2895–2923.

Biais, B., Mariotti, T., Plantin, G., and J.C. Rochet, and S. Villeneuve. 2010. "Large Risks, Limited Liability, and Dynamic Moral Hazard," Econometrica 78(1), 73-118.

Bolton, P., T. Santos, and J. Scheinkman, 2009. "Outside and Inside liquidity," NBER Working Paper No. 14867.

Bord, Vitaly, and João A.C. Santos, 2011. "Did the rise of CLOs lead to riskier lending?" Working paper, Federal Reserve Bank of New York.

Brunnermeier, Markus K. and Martin Oehmke, 2010. "The Maturity Rat Race," NBER Working Paper No. 16607.

Brunnermeier, Markus K, and Lasse H. Pedersen, 2009. “Funding and market liquidity,” Review of Financial Studies 22 (6), 2201-2238.

Bryant, John. 1980. “A model of reserves, bank runs and deposit insurance,” Journal of. Banking and Finance 43, 749-761.

Caballero, R., and A. Krishnamurthy. 2002. “A dual liquidity model for emerging markets,” American Economic Review Papers and Proceedings, 92(2), 33-37.

Caballero, R., and A. Simesk,. 2010. “Fire sales in a model of complexity,” Working paper. Department of Economics, MIT.

Castiglionesi, F., F. Feriozzi, and G. Lorenzoni. 2010. “Financial integration and liquidity crises,” Working paper, Tilburg University and MIT.

Dang, T.V., G, Gorton, and B. Holmstrom. 2010. “Financial crises and the optimality of debt for liquidity provision,” Working paper, Yale University.

DeMarzo, P., and M. Fishman. 2007a. “Agency and optimal investment dynamics,” Review of Financial Studies 20 (1),151-188.

DeMarzo, P., and M. Fishman. 2007b. “Optimal long-term financial contracting,” Review of Financial Studies 20 (6), 2079-2128.

Diamond, D., 1991. “Debt Maturity Structure and Liquidity Risk,” Quarterly Journal of Economics 106(3), 709-737.

Diamond, D., 1997. “Liquidity, banks, and markets,” Journal of Political Economy 105(5), 928-956.

Diamond, D., and P. Dybvig. 1983. “Bank runs, deposit insurance, and liquidity,” Journal of Political Economy 91, 401-419.

Diamond, D., and R. Rajan. 2009. “Fear of fire sales and credit freeze,” Mimeo. University of Chicago.

Erel, Isil; Brandon Julio, Woojin Kim, Michael S. Weisbach, 2011. “Macroeconomic Conditions and Capital Raising,” Working Paper.

Farhi, E., and J. Tirole. 2009. “Collective moral hazard, maturity mismatch and systemic bailouts,” Mimeo, Harvard University and Toulouse School of Economics.

Farhi, E., Golosov, M., and A. Tsyvinski. 2009. “A theory of liquidity and regulation of financial intermediation,” *Review of Economic Studies* 76(3), 973-992.

Flannery, Mark J., 1986. “Asymmetric Information and Risky Debt Maturity Choice,” Journal of Finance 41(1), 19-37.

Froot. K.A., D.A. Scharfstein and J.C. Stein. 1993. "Risk management: Coordinating corporate investment and financial policies," Journal of Finance 48(5), 1629-1658.

Guedes, Jose and Tim Opler. 1996. "The Determinants of the Maturity of Corporate Debt Issues," Journal of Finance 51(5), 1809-1833.

Gorton, G., and G, Pennacchi. 1990. "Financial intermediaries and liquidity creation," Journal of Finance 65(1), 49-71.

Hart, O., and J.Moore. 1994. "A Theory of Debt Based on the Inalienability of Human Capital," Quarterly Journal of Economics 109, 841–879.

He, Zhiguo and Wei Xiong. 2011. "Rollover risk and credit risk," Forthcoming Journal of Finance.

Hellwig, M. 1994. "Liquidity provision, banking, and allocation of interest rate risk," European Economic Review 38(7), 1363-1390.

Holmstrom, B., and J. Tirole, 1998. "Private and public supply of liquidity," Journal of Political Economy 106: 1-40.

Holmstrom, Bengt and Jean Tirole, 2011. "Inside and Outside Liquidity," The MIT Pres.

Ivanisha, V., and D. Scharfstein. 2010. "Bank lending during the financial crises of 2008," Journal of Financial Economics 97, 319-38.

Johnson, Shane, 2003. "Debt Maturity and the Effects of Growth Opportunities and Liquidity Risk on Leverage," Review of Financial Studies 16(1), 209-236.

Khwaja, Asim and Atif Mian, 2008. "Tracing the Impact of Bank Liquidity Shocks," American Economic Review 98, 1413-1442.

King, Mervyn, 1994. "Debt Deflation: Theory and Evidence," European Economic Review 38, 419-445.

Krishnamurthy, A., and A. Vissing-Jorgensen. 2010. "The aggregate demand for Treasury debt," Working paper. Northwestern University.

Lorenzoni, G. 2008. "Inefficient credit booms," Review of Economic Studies 75 (3), 809-833.

Mian, Atif and Amir Sufi. 2009. "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis," Quarterly Journal of Economics 124, 1449-1496.

Mian, Atif and Amir Sufi. 2010. "Household Leverage and the Recession of 2007 to 2009," IMF Economic Review. May.

Mian, Atif R. and Sufi, Amir, 2011. "House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crisis," Forthcoming American Economic Review.

Stohs, Mark and David C. Mauer , 1996. “The Determinants of Corporate Debt Maturity Structure,” Journal of Business 69(3), 279-312.

Strahan, P.J., E, Gater, and T. Schuermann. 2006. “How do banks manage liquidity risk? Evidence from deposit and equity markets in the fall of 1998,” in M. Carey and R. Stulz, eds., *Risks of Financial Institutions.* Chicago: NBER/University of Chicago Press, 105-27.

Sufi, A. 2007. “Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans,” Journal of Finance 62, 629–668.

Table 1
Data Tabulation

This table presents the tabulation of data over time and across some categories of interest. The original SNC data is at the level of a syndicate loan, and tracks each loan over time. Information on each loan is provided as of December 31st of each year. Column (1) reports number of loans each year in our data, column (2) reports the number of borrowers (firms) each year, column (3) reports the sub-sample of firms in (2) that borrow from more than one lead-bank in a given year, column (4) reports the sub-sample of firms in (2) that have multiple loans such that one loan is maturing in the current year, and another is maturing later in time. Column (5) reports the number of lead banks by year, and column (6) breaks down syndicate loan panel by industry.

	(1)	(2)	(3)	(4)	(5)		(6)
Year	**# of loans**	**# of firms**	**# of firms with multiple banks**	**# of firms with multiple maturities**	**# of lead banks**	**Industry**	**# of loans**
1988	4,309	3,312	227	146	236	Agriculture-Mining	7,395
1989	4,853	3,701	265	146	279	Utilities	11,626
1990	5,332	4,011	266	169	305	Construction	11,108
1991	5,221	3,895	258	178	283	Manufacturing	46,934
1992	5,522	3,947	264	207	279	Trade	19,639
1993	5,643	3,980	237	237	265	Transport	5,969
1994	6,397	4,338	230	285	272	Information	12,557
1995	7,026	4,687	217	272	260	Real Estate	11,214
1996	7,576	4,986	239	320	211	Services	21,462
1997	8,745	5,539	253	359	209	Unknown	8,137
1998	7,539	4,550	195	331	183		
1999	8,376	4,805	175	383	178		
2000	8,463	4,747	165	395	162		
2001	7,880	4,559	153	439	137		
2002	7,194	4,325	130	436	133		
2003	6,428	3,988	114	360	135		
2004	5,952	3,947	89	229	135		
2005	6,141	4,206	83	148	140		
2006	6,711	4,567	94	126	155		
2007	7,603	4,962	114	153	160		
2008	7,809	5,107	164	182	170		
2009	7,280	4,803	134	183	156		
2010	8,041	5,360	151	65	163		
Total	156,041 (50,469 unique loans)	102,322 (22,165 unique firms)	4,217	5,749	4,606 (661 unique banks)	Total	156,041

Table 2
Summary Statistics

This table presents summary statistics for the Shared National Credit (SNC) program data on syndicate loans where the lead bank is a commercial bank. The data track each loan over time. Information on loans is provided as of December 31st of each year.

	N	Mean	SD	10th	50th	90th
Loan level data						
Total Commitment	156,041	188651	433005	15,000	73000	409106
Total Outstanding	156,039	81995	236233	0	26137	189741
Draw Down Percentage	156,039	0.57	0.42	0	0.66	1.00
Investment Grade?	156,041	0.84	0.35	0	1.00	1.00
Non Accrual?	71,026	0.049	0.22	0	0.00	0.00
Lead Bank Share	156,041	0.23	0.21	0	0.19	0.50
Foreign Lead Bank?	156,041	0.20	0.40	0	0.00	1.00
%age Shadow Bank Participation	155,731	0.32	0.29	0	0.29	0.75
Refinanced?	144,416	21.67	41.20	0	0.00	100.00
Change in Draw Down Percentage	102,889	0.023	0.28	0	0.00	0.32
Firm level data						
Total Assets	24,615	3544	18259	35.83	583.77	13724
ΔLog Sales	24,615	0.15	0.48	-0.42	0.09	1.01
Return on Assets	24,615	0.02	0.74	-0.16	0.03	0.15
Total Sales	24,615	2409	9529	22.14	488.27	9287
Sales on Assets	23,270	1.13	4.13	0.13	0.92	2.65

Table 3
Liquidity And Borrower Fundamentals

This table presents results of regressing whether a syndicate loan gets refinanced in year *t* (0/1) on variables capturing borrower quality and fundamentals as of *(t-1)*. A unit of observation is a syndicate loan, and data cover a period from 1988 to 2010. The estimation procedure is OLS (linear probability), and standard errors are clustered at the lead bank-year level (average of 221 lead banks over 22 years).

	Dependent Variable: Loan Refinanced At Time *t* ?						
						Less than one year left in maturity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RHS variables as of *(t-1)*							
Investment Grade?	6.68	6.58	9.12	6.61	9.84	13.53	18.25
	(0.446)	(0.434)	(1.096)	(0.456)	(1.238)	(1.385)	(4.278)
Draw Down (%)	-1.36	0.07	-0.56	-0.37	0.66	-0.17	-2.87
	(0.628)	(0.502)	(0.960)	(0.500)	(0.996)	(1.732)	(4.171)
Draw Down > 95% ?	-2.57	-3.52	-5.66	-2.87	-5.74	-8.62	-8.73
	(0.503)	(0.403)	(0.965)	(0.419)	(1.031)	(1.542)	(4.629)
Log change in sales			1.32		1.28		1.84
			(0.575)		(0.609)		(2.575)
Return On Assets			0.01		0.00		0.53
			(0.017)		(0.017)		(0.365)
Sales over Assets			-0.02		-0.02		-0.16
			(0.039)		(0.045)		(0.159)
Credit Line?	2.60	2.82	0.30	2.44	-0.25	7.65	8.27
	(0.497)	(0.350)	(0.770)	(0.374)	(0.829)	(1.212)	(2.891)
Publicly Listed?	4.11	5.42		5.08		4.83	
	(0.420)	(0.353)		(0.358)		(1.181)	
Maturity Left (in yrs)	-4.58						
	(0.107)						
Maturity at Origination (yrs)	-0.88						
	(0.084)						
Bank-Year Fixed Effects				yes	yes	yes	yes
Industry Fixed Effects		yes	yes	yes	yes	yes	yes
Maturity Left Fixed Effects		yes	yes	yes	yes	yes	yes
Year Fixed Effects		yes	yes	yes	yes	yes	yes
Maturity At Origination Fixed Effects		yes	yes	yes	yes	yes	yes
N	147,552	147,456	36,232	147,456	36,232	21,032	4,480
R^2	0.1	0.165	0.165	0.213	0.252	0.263	0.376

**,*,+ Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively

Table 4
Hazard Ratio Estimate Of Early Versus At-Maturity Refinancing

This table presents results of maximum likelihood estimation of …. , where *y* is an indicator for whether a syndicate loan gets refinanced in year *t* (0/1). A unit of observation is a syndicate loan, and data cover a period from 1988 to 2010. Standard errors are clustered at the lead bank-year level (average of 221 lead banks over 22 years).

	Loan Refinanced At Time *t* ?				
	(1)	(2)	(3)	(4)	(5)
RHS variables as of *(t-1)*					
Hazard rate for early vs. at maturity	-0.80	-0.77	-1.01	-1.02	-0.96
	(0.019)	(0.019)	(0.029)	(0.032)	(0.046)
HR * 1990 Recession		-0.06			
		(0.059)			
HR * 2001 Recession		-0.33			
		(0.050)			
HR * 2007-09 Recession		-0.58			
		(0.068)			
HR * ΔGDP			0.069	0.078	0.047
			(0.009)	(0.010)	(0.015)
ΔGDP			0.013		
			(0.0055)		
Industry Fixed Effects	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes		yes	yes
# of Years Of Maturity At Origination Fixed Effects	yes	yes	yes	yes	yes
N	147,858	147,762	147,858	147,858	15,576

**,*,+ Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively

Table 5
Liquidity And Borrower Fundamentals Over The Business Cycle

This table presents coefficient (ß) on the interaction of borrower quality/fundamentals attribute *X* with time dummies for recessions and average GDP growth respectively. The full regression is specified as: , where *Y* is an indicator variable on whether a syndicate loan gets refinanced in year *t*. Borrower fundamentals attributes are measured as of (t-1), and include indicator variable for investment grade rating, percentage loan commitment drawn down, indicator variable for borrower being listed on the stock exchange, and log change in sales between *(t-2)* and *(t-1)*. A unit of observation is a syndicate loan, and data cover a period from 1988 to 2010. The estimation procedure is OLS (linear probability), and standard errors are clustered at the lead bank-year level (average of 221 lead banks over 22 years).

Panel A (Overall Estimate)

Regressions include maturity left, maturity at origination and year fixed effects.

Investment Grade	Draw Down (%)	Publicly Listed?	Investment Grade	Draw Down (%)	Publicly Listed?
Recession Years Interaction			Average GDP Growth Interaction		
(1)	(2)	(3)	(4)	(5)	(6)
-6.33**	4.17**	-3.99**	1.34**	-0.42*	0.46*
(0.89)	(0.81)	(0.80)	(0.21)	(0.20)	(0.21)

Panel B (Absorbing bank-year shocks)

Regressions include maturity left, maturity at origination and bank-year fixed effects.

Recession Years Interaction			Average GDP Growth Interaction		
Investment Grade	Draw Down (%)	Publicly Listed?	Investment Grade	Draw Down (%)	Publicly Listed?
-7.23**	4.33**	-3.98**	1.39**	-0.45*	0.49*
(0.90)	(0.81)	(0.80)	(0.22)	(0.20)	(0.21)

Panel C (All credit quality variables concurrently)

Regressions include maturity left, maturity at origination and bank-year fixed effects, and all credit quality variables concurrently.

Recession Years Interaction			Average GDP Growth Interaction		
Investment Grade	Draw Down (%)	Publicly Listed?	Investment Grade	Draw Down (%)	Publicly Listed?
-5.92**	2.70**	-3.23**	1.25**	-0.26	0.46*
(0.85)	(0.75)	(0.77)	(0.20)	(0.17)	(0.19)

**,*,+ Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively

Table 6
Early Refinancing, Business Cycle And Borrower Type

This table presents results of maximum likelihood estimation of …. , where *y* is an indicator for whether a syndicate loan gets refinanced in year *t* (0/1) …. on variables capturing borrower quality and fundamentals as of *(t-1)*. A unit of observation is a syndicate loan, and data cover a period from 1988 to 2010. The estimation procedure is OLS (linear probability), and standard errors are clustered at the lead bank-year level (average of 221 lead banks over 22 years).

	Loan Maturity Extended At Time *t* ?							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RHS variables as of *(t-1)*								
Investment Grade? * ΔGDP		3.42					2.59	4.76
		(0.65)					(0.49)	(1.97)
Investment Grade?		10.18					3.13	4.31
		(4.42)					(1.38)	(3.41)
ΔGDP	3.53							
	(0.36)							
Publicly Listed? * ΔGDP			1.90				1.67	
			(0.29)				(0.26)	
Publicly Listed?			137.00				83.10	
			(50.77)				(30.27)	
Draw Down > 95% ? * ΔGDP				0.49			0.61	0.90
				(0.05)			(0.07)	(0.22)
Draw Down > 95% ?				0.01			0.03	0.00
				(0.00)			(0.01)	(0.00)
ΔSales * ΔGDP					1.27			1.26
					(0.14)			(0.14)
ΔSales					0.73			0.66
					(0.23)			(0.21)
ROA * ΔGDP						1.02		1.00
						(0.06)		(0.05)
ROA						0.98		1.01
						(0.15)		(0.13)
Year Fixed Effects		yes	yes	yes	yes	yes	yes	yes
Maturity At Origination Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
N	126,805	126,805	126,805	126,805	31,801	33,643	126,805	31,798
	0.030	0.045	0.049	0.049	0.054	0.053	0.055	0.062

**,*,+ Coefficient statistically different than zero at the 1%, 5%, and 10% confidence level, respectively

Figure 1
Frequency Distribution Of Credit Variables

This figure plots the frequency distribution for some key variables in our data. A unit of observation is a syndicate loan, and the data cover period from 1988 to 2010. "Change in maturity" refers to the change in maturity date of a loan (if any), "Maturity left" measures the days left till maturity of a given loan in our sample, "Maturity at origination" refers to the maturity of a loan at the time it was originated, "Draw down percentage" refers to the percentage of total loan commitment currently drawn down by the borrowing firm.

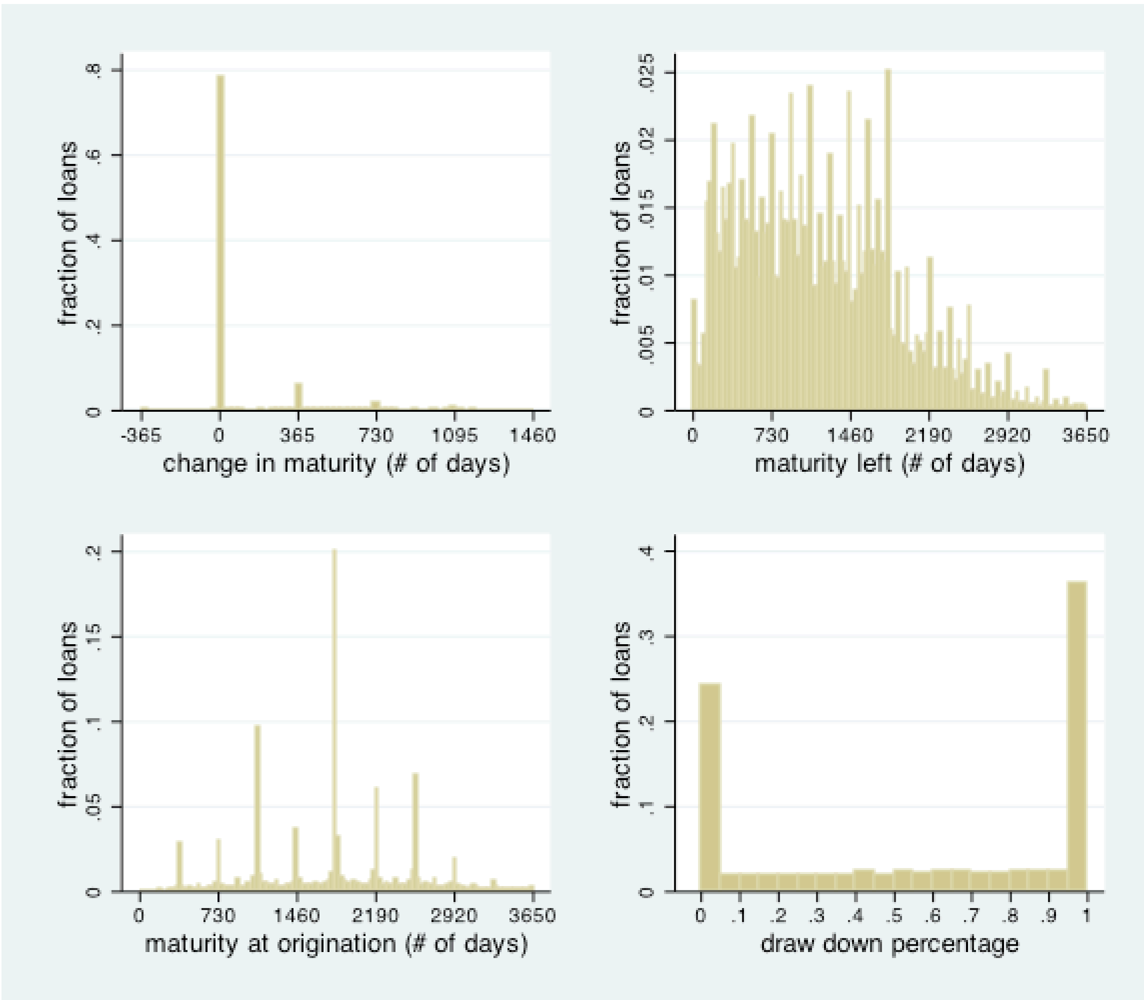

Figure 2
Credit Condition And Spreads Over Time

This figure plots quarterly bank charge-offs over assets, loan officer loan tightening survey for large and medium C&I loans, TED spread (difference between 3 month LIBOR and 3 month U.S. T-bill rate), corporate credit spread (BAA minus AAA) over time. The red and blue lines for the charge-off to assets chart represent weighted and un-weighted ratios respectively. Vertical dashed lines represent NBER-dated recessions.

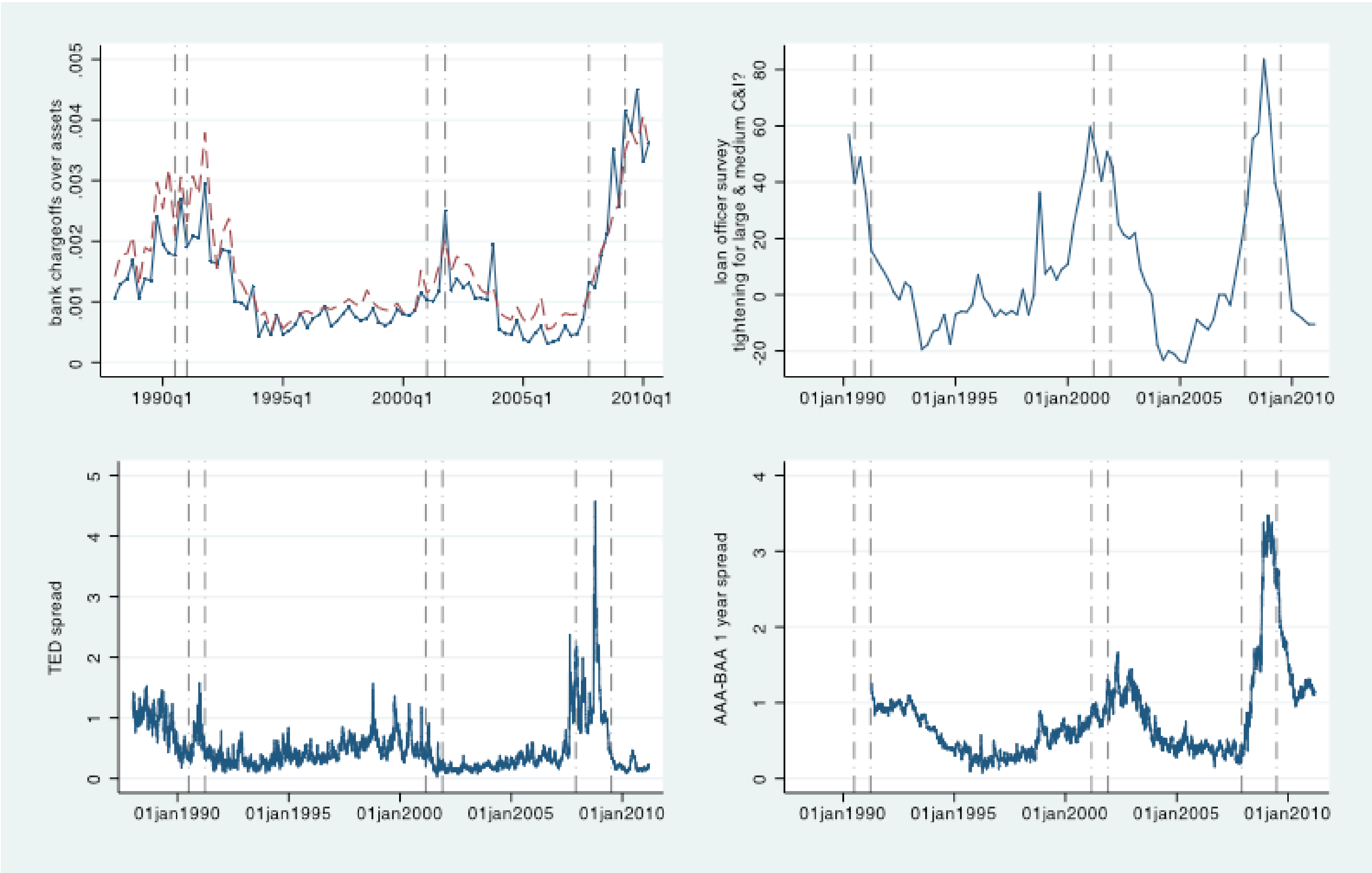

Figure 3
Time Series Of Corporate Liquidity

The top panel plots the average propensity for syndicate loans to be refinanced in a given year. The middle panel plot the average maturity extension conditional on refinancing, and the bottom panel plots the share of total loans in a given year that are new originations. Vertical dashed lines represent NBER-dated recessions.

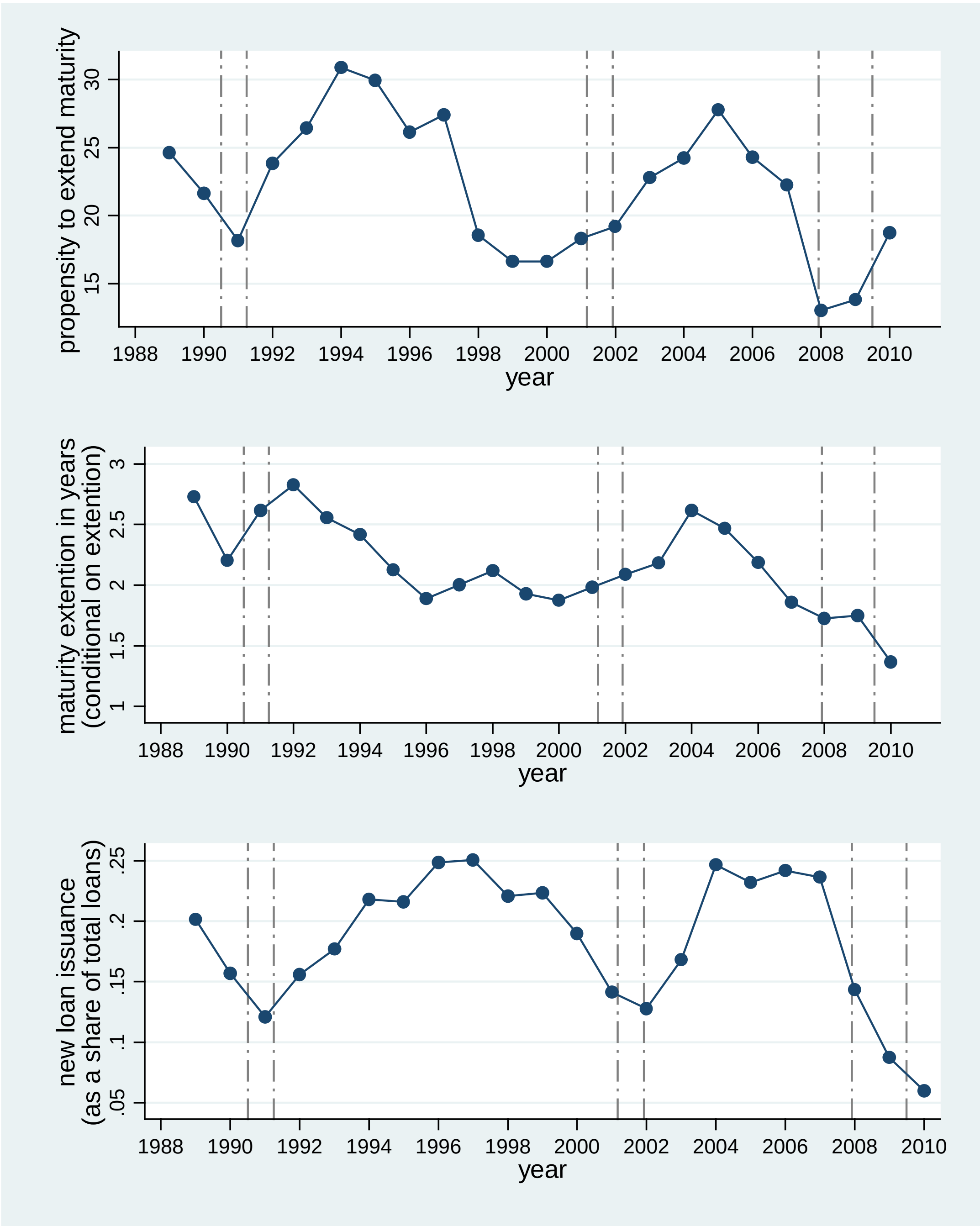

Figure 4
Intensive Liquidity: Draw Down Percentage

The top panel plots the average drawn down percentage (loan outstanding divided by loan commitment) over time. The lower plans plot the percentage of loans that are fully drawn down. Vertical dashed lines represent NBER-dated recessions.

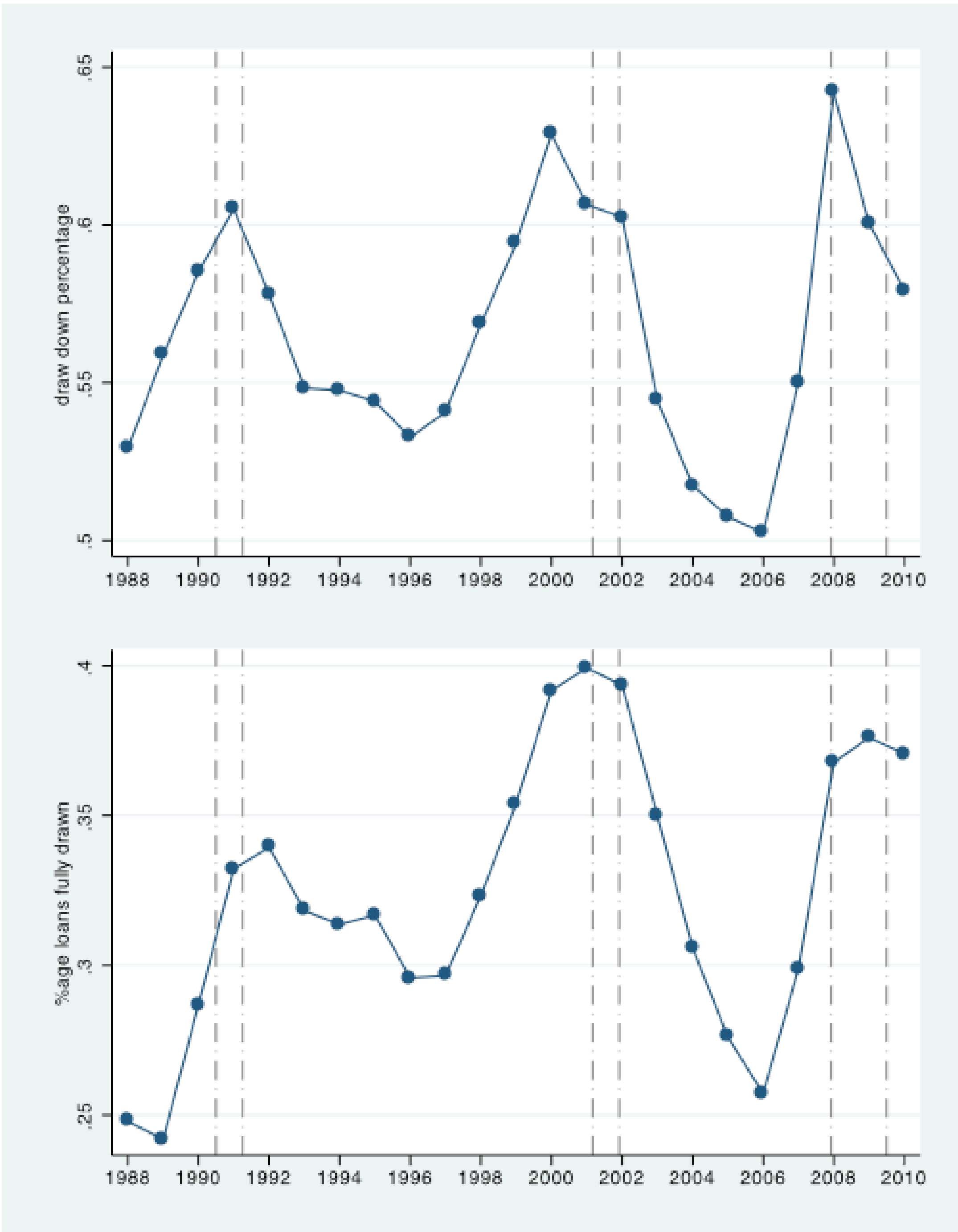

Figure 5
Effective Maturity Over The Business Cycle

The figure plots the average maturity left of all outstanding syndicate loans at the end of a year. Vertical dashed lines represent NBER-dated recessions.

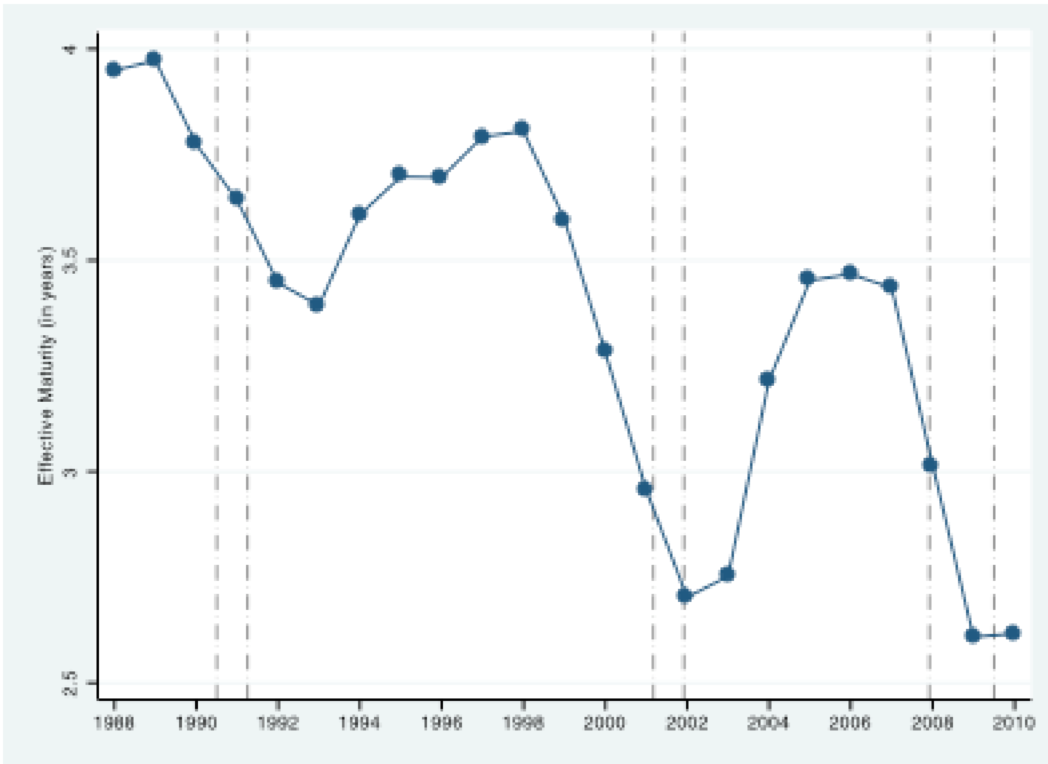

Figure 6
Propensity to Extend Maturity And Maturity Left

The top panel plots the propensity to refinance a loan over the 1988 to 2010 period against the number of years left until the expiration of the existing loan. "0" means the loan has less than one year left till maturity, "1" means the loan has between 1 and 2 years left till maturity, and so on. "10+" means the loan has ten or more years left till maturity. The blue (dotted) line in bottom panel plots coefficients on "Years left till maturity" indicator variables with an indicator variable that equals 1 if a loan is refinanced as the dependent variable. The omitted category is loans with over 10 years left till maturity. The red (dashed) line plots the same coefficients, but includes borrower-year fixed effects, thus comparing loans of differing maturities within the *same* firm-year.

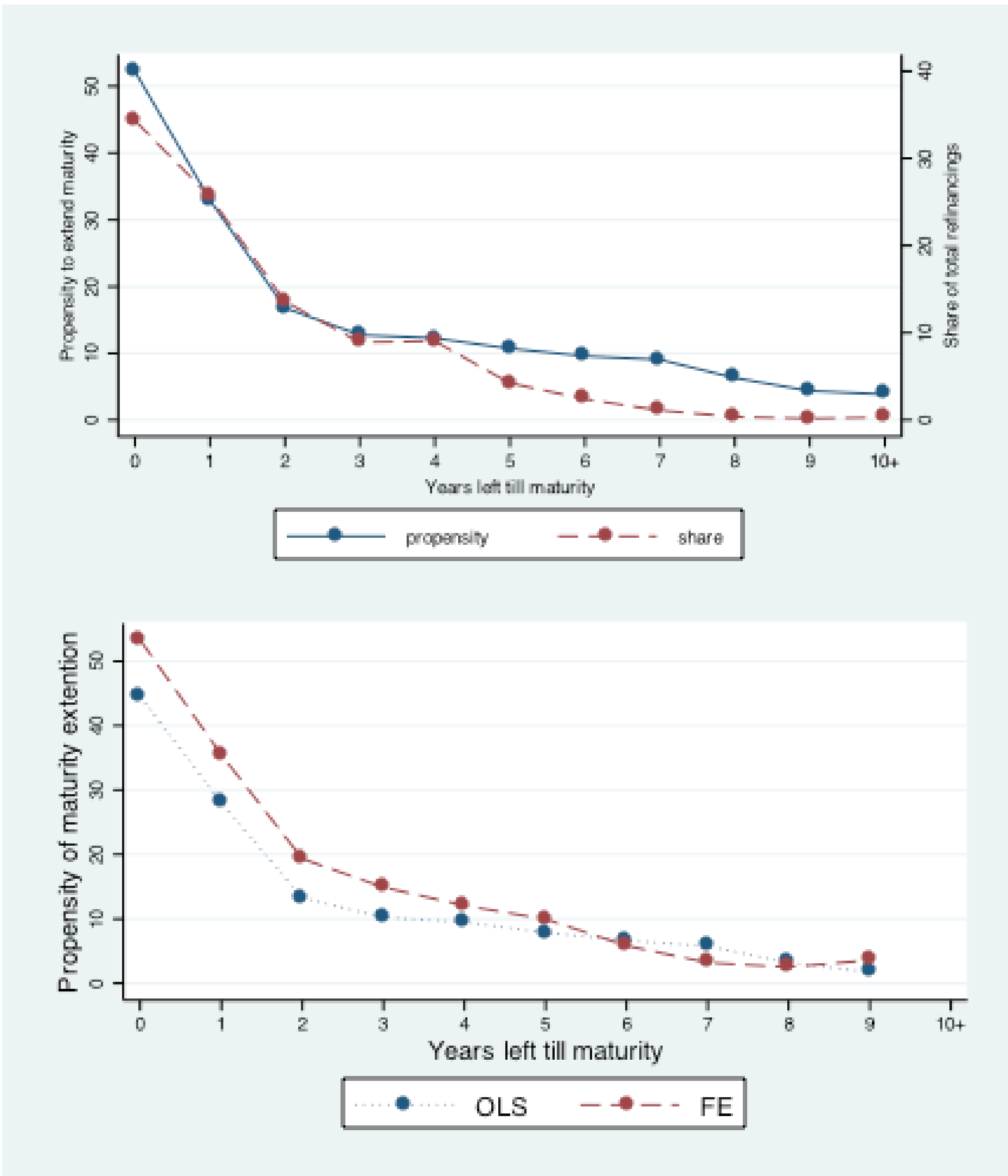

Figure 7

Hazard Ratio For Early Vs. At-Maturity Refinancing

The upper panel plots refinancing likelihood for loans maturing within the next year (blue-dashed line and left axis), and for loans maturing in more than one year (red solid line and right axis). The lower panel plots the hazard ratio estimate for early versus at-maturity refinancing based on the MLE procedure described in text. The red line includes borrower-year fixed effects, thus limiting the comparison to loans of differing maturities issued to the *same* firm in a given year.

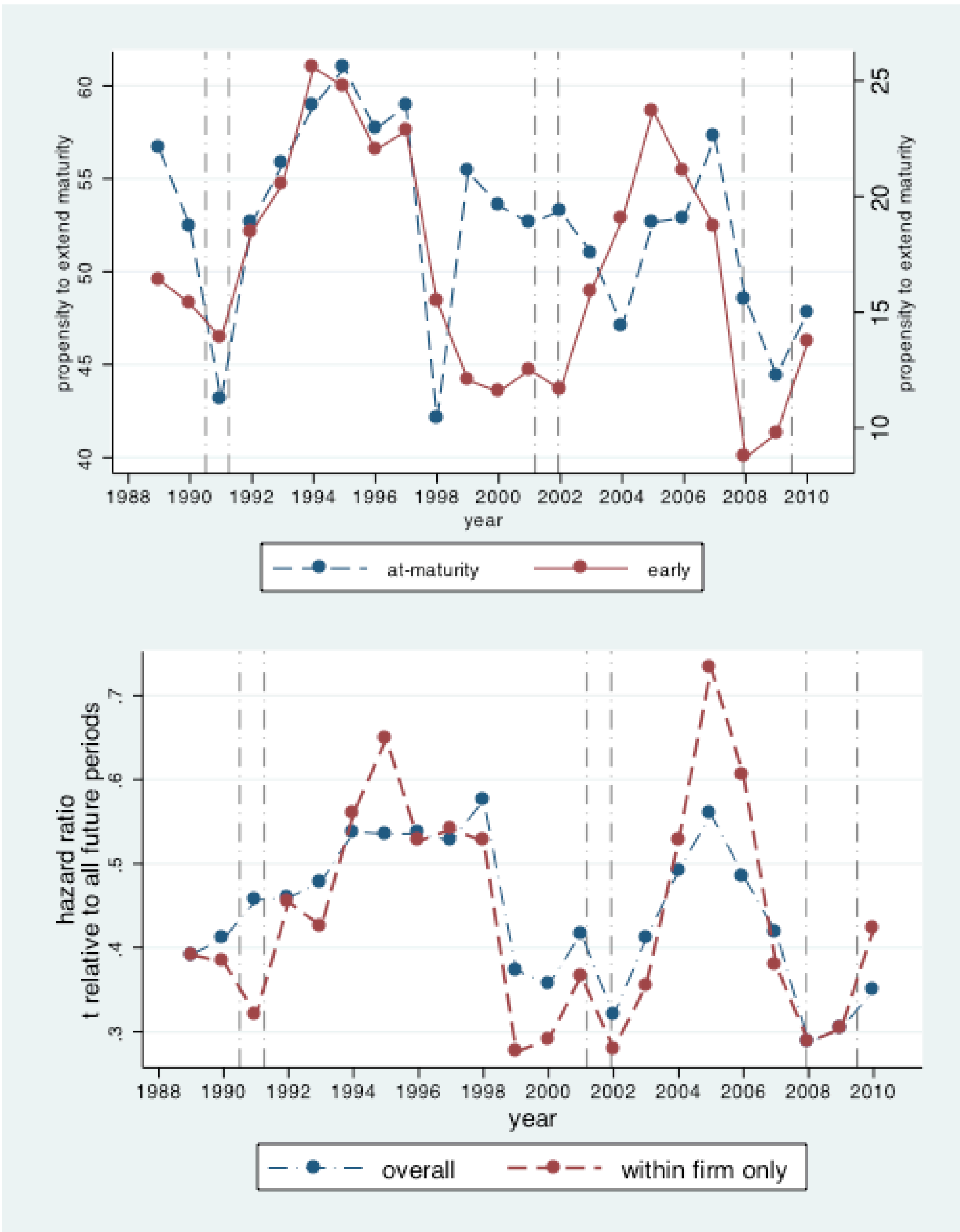

Figure 8
Maturity Refinancing By Loan Type

The blue (dashed) line in the top panel plots the propensity to refinance to extend maturity for investment grade loans that have more than one year left in the expiration of their existing loan maturity. The red (dotted) line plots the same for non-investment grade firms. The blue (dashed) line in the bottom panel plots the propensity to refinance to extend maturity for loans from firms that are publicly listed on the stock exchange. The red (dotted) line does the same for non-investment grade firms.

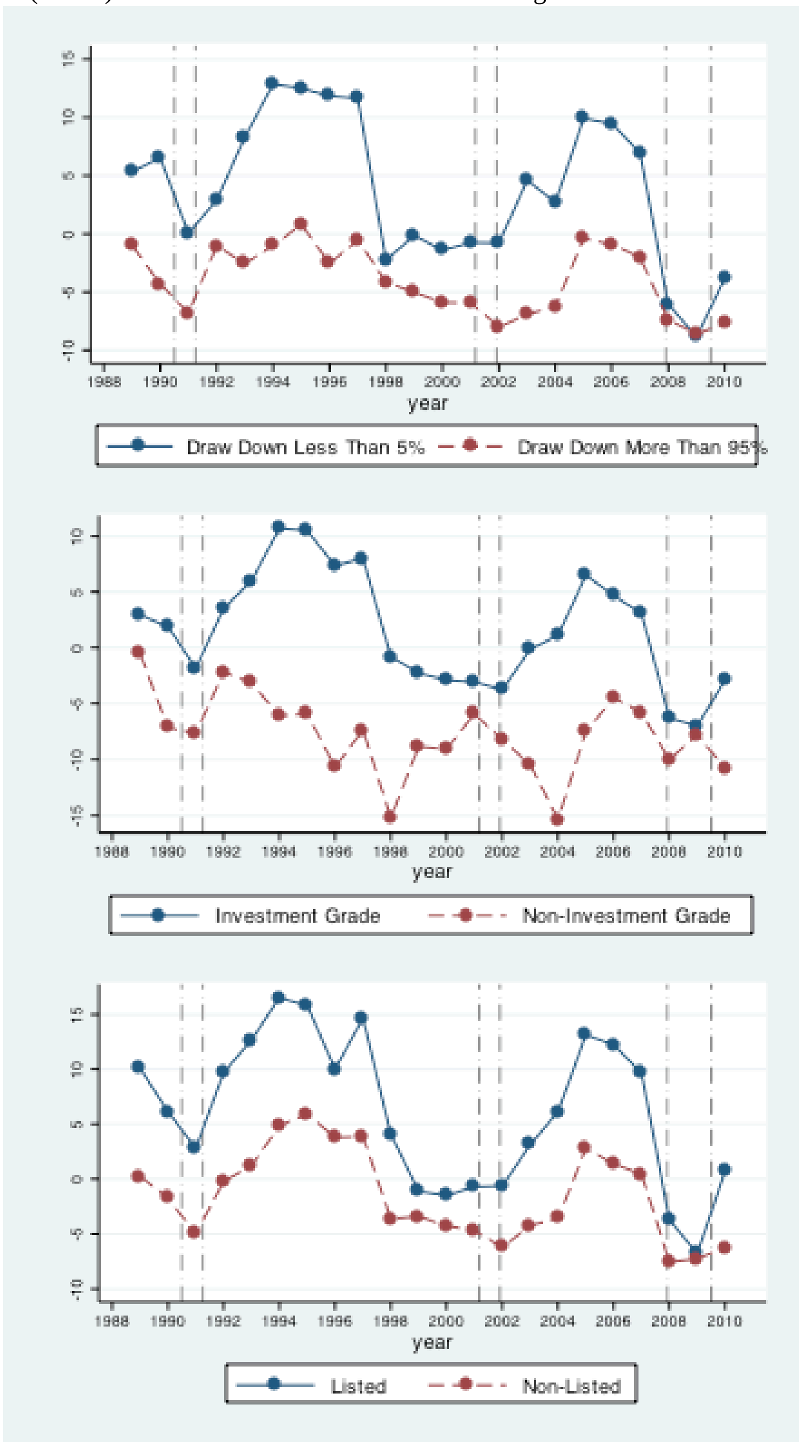

Figure 9
Dependence Of Refinancing On Borrower Attributes Over Time

This figure presents results of regressing whether a syndicate loan gets refinanced in year *t* (0/1) on variables capturing borrower quality and fundamentals as of *(t-1)*. A separate regression is run every year, and each regression includes lead bank fixed effects, number of years left till maturity fixed effects, and number of years for maturity as of origination fixed effects. Vertical dashed lines represent NBER-dated recessions.

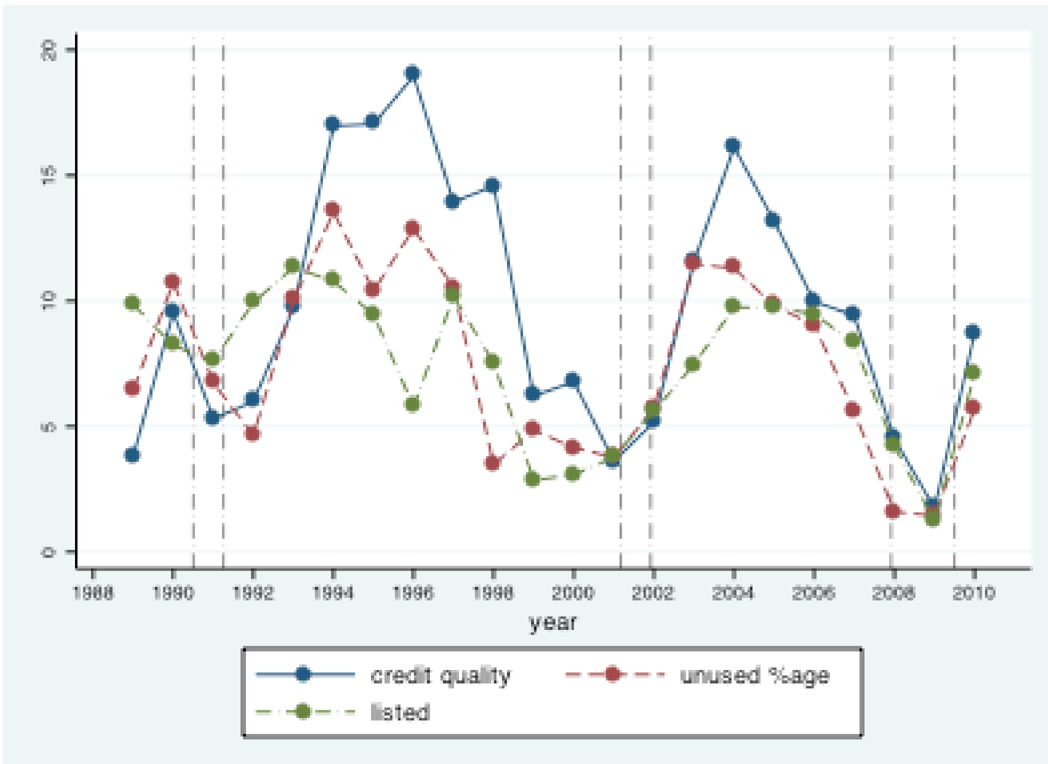

Figure 10
Early Refinancing By Borrower Type

This figure presents results of regressing whether a syndicate loan gets refinanced in year *t* (0/1) on variables capturing borrower quality and fundamentals as of *(t-1)*. A separate regression is run every year, and each regression includes lead bank fixed effects, number of years left till maturity fixed effects, and number of years for maturity as of origination fixed effects. Vertical dashed lines represent NBER-dated recessions.