

Liquidity Risk And Maturity Management Over The Credit Cycle

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ABSTRACT

We use the Shared National Credit data on syndicate loans to investigate U.S. firms' refinancing behavior over the last two decades. As credit conditions tighten, refinancing likelihood goes down and draw down on loan commitments increases sharply. Surprisingly, refinancing propensity is most sensitive to credit market conditions for credit worthy firms. We show that this is a result of active maturity management by credit worthy firms to avoid being exposed to liquidity risk. Credit worthy firms refinance early at a significantly higher rate when credit conditions are good in order to keep the effective maturity of their loans long. They can then afford to refinance at a lower rate when credit conditions tighten. We show that these results are driven by variation in credit market conditions and not business cycle fluctuation.

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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 loans and credit 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 or demand a high price 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 at a time when credit is tight. A large body of work investigates the possible origins of liquidity risk and its impact on the real economy¹. Yet our empirical understanding of how firms respond to the risk of inability to rollover existing debt is quite limited. A key reason for this deficiency is that we lack data on the financing and re-financing behavior of firms over a long period of time that encompasses various credit cycles.

Aggregate fluctuations in liquidity risk can be gauged from figure 2 that plots responses of senior loan officers on lending standards and spreads they charge for large and medium sized firms. Credit conditions fluctuate widely over time leading to large “credit cycles”. Given these credit cycles, one would expect a forward-looking firm to minimize the possibility that it is forced to refinance debt when lending standards are tough or spreads too high. The extent to which some firms are able to manage this risk in turn tells us about the sector of the economy most exposed to liquidity risk.

¹ Holmstrom and Tirole (2011) provide an excellent summary. Some of the relevant literature includes Allen and Gale 2007, DeMarzo and Fishman 2007, Farhi and Tirole. 2011, Gorton and Pennacchi 1990, He and Xiong. 2011, and Krishnamurthy and Vissing-Jorgensen 2010.

How can firms minimize liquidity risk generated by credit cycles? One natural strategy is for firms to engage in dynamic *maturity management*. They 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. Of course the ability to successfully reduce liquidity risk through maturity management may depend on firm fundamentals and credit worthiness.

Understanding the extent to which maturity management influences liquidity risk requires that we observe the refinancing behavior of firms through the peaks and troughs of various credit cycles. While accessing such information has proven very difficult in the past, we take advantage of 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.

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. Moreover our data covers the period from 1988 to 2010, enabling us to analyze the relationship between liquidity risk and maturity management over the course of three business and credit cycles.

We find that refinancing is strongly related to the credit cycle. The propensity to refinance a loan is more than fifty percent higher in normal times compared to when credit conditions are tight. Conditional on getting refinanced, a loan’s maturity gets extended for longer duration when credit conditions are good. Firms’ access to unused lines of credit is strongly related to the credit

cycle as well. The percentage of drawn-down loan commitment increases by seventeen percent when credit conditions are tight.

There is considerable evidence that the cyclical in refinancing behavior is closely related to maturity management by firms. Effective maturity of loans increases by about sixteen percent when refinancing is high in times of easy credit. Moreover, 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.

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 when credit conditions are good. 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 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 capacity². 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

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

construct an unbiased hazard ratio estimate over time. We find that the unbiased hazard ratio constructed in this manner is as cyclical as the earlier estimate.

Thus a higher propensity to refinance early when credit conditions are relaxed makes the effective maturity of loans longer. However, the tendency to manage maturity structure by refinancing early is not uniform across firms. It is strongest for firms with high credit worthiness. In fact the overall propensity to refinance is significantly *more* sensitive to credit conditions for credit worthy firms such as firms with high un-used debt capacity, firms with investment grade rating, and firms with access to equity markets.

A corollary of the above result is that the sensitivity of refinancing likelihood to measures of credit worthiness in the cross-section is highest when credit conditions are good and becomes almost negligible when credit conditions are tight. This result shows that maturity management leads to a drop in the *demand* for refinancing by credit worthy firms when credit conditions are tight. We also consider alternative explanations for this finding and show that these explanations are inconsistent with our finding.

First if the differences in cyclical variation in refinancing between high and low credit worthy firms were driven by supply-side channel, we would have expected an opposite results. In particular, as credit conditions tighten banks are more likely to cut back on the marginal, i.e. less credit worthy, firms first. We would thus expect the sensitivity of refinancing to firm credit worthiness to increase when credit conditions are tight. Alternatively we would expect less credit-worthy firms to experience larger drops in refinancing likelihood when credit conditions tighten. We find completely the opposite result suggesting the power of maturity management effect.

A second alternative explanation for our finding is that there is no active maturity management done by credit worthy firms, but instead their natural demand for credit is more cyclical. We find this unlikely a priori as less credit worthy firms are more likely to be “high beta” in general and display a more pro-cyclical properties. The fact that we find evidence to the contrary is again suggestive of the power of maturity management. We further show that none of our results are driven by fluctuations in aggregate demand as measured by GDP growth. Instead the cyclical patterns are all driven by fluctuations in credit conditions as measured by senior loan officer surveys.

Our results highlight the role that maturity management plays in reducing exposure to liquidity risk. Since credit-worthy firms are the ones successful at doing so, our results also emphasize the endogenous nature of firms “caught” in a liquidity squeeze. Firms that are unable to maintain longer maturity debt during normal times and hence more likely to be forced to rollover debt in tight credit conditions are systematically worse quality firms.

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 risk management literature such as Froot, Scharfstein 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 Mauer (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.

Our paper is closest in spirit to Roberts and Sufi (2009) who use SEC filings to show that renegotiation of syndicate loans happens often and is mostly voluntary driven by improvements in credit quality and credit market conditions. Our focus is more on the inter-play between refinancing choice at the firm level and credit / business cycle dynamics as our data covers three recessions and follows loans until the end of their maturity period.

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 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.

Earlier studies of the syndicate loan market (see e.g. Sufi (2007) and Santos and Winton (2008)) use loan origination data from DealScan. The key advantage over DealScan that SNC offers is its

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

tracking of the same syndicate loan over time. We can thus track both the performance as well as refinancing behavior of loans over time.

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 10th and 90th 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-modal. 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 middle 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. The lower panel of Table 2 presents summary statistic for our key macro variables (at annual frequency) measuring credit cycle and business cycle conditions. Business cycle strength is measured by GDP growth while credit cycle strength is measured by senior loan officer survey responses to questions regarding loan spread increase and lending criteria tightening. The survey questionnaire has a scale of -100 to 100 that we re-normalize after dividing by 100. The number

of observations is less for the senior loan officer survey as the survey starts in 1990⁴. The correlation between loan spreads and loan tightening response is very high at 91.8%. GDP growth and credit conditions tightening are negatively correlated. The correlation is -22.1% at an annual frequency, and increases to -57.5% at quarterly frequency.

II. Liquidity And The Business Cycle: Aggregate Patterns

A. Credit Conditions

We begin by highlighting aggregate trends in banking sector credit conditions. The top panel in Figure 2 plots the average response to loan officers survey on credit tightening for large and medium C&I loans. The dashed vertical lines represent recessions as dated by NBER. Loan officers consistently report that they have “tightened” lending standards around recessions. However, sometimes (e.g. 1998) credit conditions tighten significantly without corresponding drop in GDP growth. The bottom panel reports the senior loan officer responses to questions regarding increases in spreads. The plot is very similar to the upper panel with a quarterly correlation of 89.5%.

Overall credit 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.

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

⁴ GDP growth is from 1989 to 2010 and senior loan officer data from 1990 to 2010. 1988 is not included in GDP growth summary statistics because we need one year of “pre” data in running our regressions.

liquidity. The construction of this variable is already discussed in section II. 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 and when credit conditions are tight, while it reaches 30.7% and 28% respectively at the peak. 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 loans⁵.

In the appendix (appendix figure 2) we also plot the average number of years that maturity is extended by conditional on a loan being refinanced. The size of maturity extension conditional on refinancing also displays some cyclicalities. Appendix figure 2 also plots the share of outstanding loans at the end of a given year that is new loans. While our focus in this paper is on refinancing and not first time loans issues, 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 peaks.

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.

⁵ 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.

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 and varies strongly with credit conditions. 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 business and credit 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 Scharfstein (2010)), our results show that this pattern is representative of previous recessions as well. In particular, the draw down percentage begins to rise before the onset of a recession in all three recessions. The rise is also strongly related to credit market conditions. For example, drawn down percentage rises sharply in 1998 and beyond when credit conditions tighten significantly (see figure 2).

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 time⁶. As with the average draw down ratio, the percentage of loans that are fully drawn down is closely related to business and credit cycles as well. Interestingly the percentage of loans that are fully drawn out is *higher* in the 2001 recession than in the 2007-09 recession.

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

⁶ Loans with draw down percentage greater than 95% are defined as “fully drawn out”.

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 time⁷.

Of more immediate interest for us is the embedded cyclical component 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 measures of credit conditions and corporate liquidity display significant cyclical component. In particular, as credit conditions tighten and risk spreads widen,

⁷ Brunnermeier and Oehmke (2011) discuss how a maturity rat race between banks could lead to declining maturity for bank funding.

corporate liquidity as measured by the propensity to refinance an existing loan and the availability of unused lines of credit goes down. In the section that follows, we investigate how firms' decision to refinance early versus at-maturity is influenced by credit cycle conditions.

III. Maturity Management And The Credit 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.

$$Y_{ijbt} = \alpha + \beta_1 * X_{ijb,t-1} + \beta_2 * Z_{jb,t-1} + \gamma_{bt} + \varepsilon_{ijbt} \quad (1)$$

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 X and borrower characteristics Z . 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 γ_{bt} . 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 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 result indicates that loans 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 importance 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. Forty five percent of refinancings are done “at-maturity” and 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:

$$Y_{ijbt} = \alpha + \beta_n * \gamma_n + \gamma_{norig} + \gamma_t + \varepsilon_{ijbt} \quad (2)$$

Where Y is refinancing indicator variable, γ_n 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. γ_{norig} represent fixed effects for the number of years of maturity at origination of a loan (also going from 0 to 10), and γ_t are year fixed effects⁸.

The dotted blue line in lower-panel of Figure 6 plots the coefficients $\hat{\beta}_n$. We next re-estimate these coefficients after adding borrower-year (γ_{jt}) 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 β_n 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.

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

⁸ For exposition clarity, we suppress coefficient estimates of fixed effects from the specification whenever these coefficients are not reported in tables.

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. Probability of Early 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 vary with the credit cycle, early refinancing is more cyclical than at-maturity refinancing. For example, when credit conditions tighten in 1998 and remain tight for a few years (see figure 2), early refinancing likelihood drops more aggressively over the time period.

Importantly, 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 odds ratio of refinancing early versus at-maturity. This odds ratio is estimated using the following logit model separately for each year:

$$\Pr[Y_{ijbt} = 1] = \frac{1}{1 + e^{-(\beta_t * LM_{ijbt} + \gamma_{norig})}} \quad (3)$$

Where LM is an indicator variable for “long maturity” syndicate loans, defined as loans with more than one year left till maturity. γ_{norig} are fixed effects for the number of years of maturity of a loan at origination. $\hat{\beta}_t$ thus compares the early versus at-maturity refinancing likelihood for

loans that had the same maturity at origination but differ in effective maturity because of the time when they were originated.

Equation (3) is estimated separately for each year. The blue dashed-dotted line in the lower panel of figure 7 plots the estimated $\hat{\beta}_t$. Given the logit specification, $\hat{\beta}_t$ represents the log of the odds ratio for early versus at-maturity refinancing over time⁹. The odds ratio is correlated with credit conditions and the magnitude of cyclicality is large as well.

As we mentioned earlier, one concern with the odds 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 the odds ratio estimate, it is not clear how such a bias would impact the cyclicality of the odds ratio with respect to the credit cycle. Nonetheless as outlined before, 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 $\hat{\beta}_t$ after restricting the sample to borrowers that satisfy the above multiple maturity criteria. The resulting graph shows that once any inherent bias in early refinancing is removed, odds ratio becomes even more cyclical with respect to credit conditions.

Table 4 formally tests for the correlation of early versus at-maturity odds ratio by interaction the *LM* indicator variable with measures of credit cycle and business cycle strength (*MACRO*).

Equation (3) is thus updated to:

⁹ Since we are interested in estimating the odds ratio, we switched to a logit model in this section instead of our usual choice of linear probability models.

$$\Pr[Y_{ijbt} = 1] = \frac{1}{1 + e^{-(\beta_1 * LM_{ijbt} + \beta_2 * (LM_{ijbt} * MACRO_t) + \gamma_{norig} + \gamma_t + \gamma_{ind})}} \quad (4)$$

Equation (4) adds year fixed effects (γ_t) since the estimate is done over the entire sample rather than each year separately as in (3) and industry fixed effects (γ_{ind}). The coefficient of interest is β_2 that captures how the odds ratio is correlated with macro conditions. Standard errors are clustered at the lead bank level as always. There are a total of 649 distinct lead banks over the entire regression sample.

Column (1) presents the average odds ratio over the entire sample without including macroeconomic variables. In order to convert the estimated coefficient into an odds ratio, we need to take its exponent, i.e. e^{β_1} , in Table 4. The estimated odds ratio is 0.26 and very tightly estimated. Thus on average, the probability of early refinancing is 26% 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 directly for the cyclical properties of the odds ratio by interacting the long maturity indicator variable with indicator variables for each recession separately. The results indicate that odds ratio is significantly lower in both the 2001 and 2007-09 recessions, with the drop in the 2007-09 recession being the largest. The odds ratio is actually higher in the 1991 recession, but the magnitude of increase is small and statistically not significant.

Columns (3) and (4) tests directly for the correlation of the odds ratio with credit conditions as reflected by results from loan officers surveys on credit tightening and credit spreads. The negative and statistically significant coefficient on the surveys shows that the relative odds of refinancing early decrease as credit is tightened or as credit spread increases. Using column (3)

estimate, a one standard deviation increase in credit tightening (0.23) leads to a 20.7 percent decline in odds ratio of refinancing early.

Column (5) replaces credit condition variables with GDP growth that captures overall business cycle conditions. The interaction is positive and statistically significant. A one standard deviation decline in GDP growth (1.83) leads to a 16.5% decline in the odds ratio of refinancing early. The result in column (5) raises the question of whether the cyclical variation in early refinancing odds ratio is simply a business cycle phenomena as opposed to being related to credit conditions. We test for this explicitly in column (6) by including both credit condition and GDP growth interactions in the same regression.

While GDP growth and credit conditions are naturally correlated, once we include both only the coefficient on credit conditions interaction remains significant and strong in terms of magnitude. This result can also be visually glanced from the lower panel of figure 7: The odds ratio for early refinancing declines sharply when credit conditions tighten (as in 1998) even if GDP growth does not suffer an equivalent decline.

Finally, column (7) restricts our sample to borrowers with multiple loans in a given year, such that one loan is maturing in the coming year and another sometime afterwards. Doing so corrects for the concern that loans maturing within the next year are systematically coming from worst quality firms. With the sample restriction, the interaction term with respect to credit conditions becomes even stronger. Thus for the *same* set of firms, their decision to refinance early versus at maturity is strongly related to credit conditions. As before, this result is not driven by a spurious correlation with business cycle strength as measured by GDP growth. Adding GDP growth interaction to column (7) increases the coefficient from -1.17 to -1.63.

D. Refinancing Over The Credit Cycle And Borrower Credit Worthiness

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. 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 categories¹⁰. 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 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.

¹⁰ The shape of graphs in Figure 8 is similar if we do 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.

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 sensitive to credit cycle costs. 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 maturity management demand-side effect. In particular, credit worthy firms deliberately choose not to refinance when credit standards tighten and loan officers demand higher spreads. 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 times¹¹. 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:

$$Y_{ijbt} = \alpha + \beta_t * X_{ijt} + \gamma_n + \gamma_{norig} + \gamma_t + \varepsilon_{ijbt} \quad (5)$$

Where X_{ijt} 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 β_t captures the sensitivity of refinancing likelihood to these borrower

¹¹ For example, Erel et al (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”.

fundamentals. γ_n , γ_{norig} , γ_t 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 β_t separately for regressions where X_{ijt} 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 measures of credit cycle and business cycle strength (*MACRO*) by updating equation (5) to:

$$Y_{ijbt} = \alpha + \beta_1 * X_{ijt} + \beta_2 * (X_{ijt} * MACRO_t) + \gamma_n + \gamma_{norig} + \gamma_t + \varepsilon_{ijbt} \quad (6)$$

where *MACRO* is either measured by GDP growth or senior loan officer responses during year t . β_2 captures the correlation of interest, i.e. how the sensitivity of refinancing with respect to credit worthiness varies over the credit / business cycle.

Columns (1) through (3) interact measures of credit worthiness with senior loan officer credit tightness index¹². The interaction coefficient is negative and statistically significant, implying that as credit conditions tighten refinancing becomes *less* sensitive to variables capturing credit worthiness including investment grade, availability of unused lines of credit, and access to equity markets. The magnitude of the interaction effect is very large as well. When credit conditions are very tight – as in 2008-09 – refinancing becomes almost insensitive to variables capturing credit worthiness.

The three credit attributes used in columns (1) through (3) are positively correlated with each other. The pair-wise correlation between investment grade rating, and draw down percentage and

¹² The results are essentially identical if we use the senior loan officer survey response on credit spreads instead.

publicly listed indicator variable is -0.25 and 0.087 respectively. The correlation between draw down percentage and publicly listed indicator variable is -0.19. Thus while these variables are correlated as expected, the correlation is far from perfect. Column (4) includes all three of these variables simultaneously and shows that the interaction with each of the three remains significant and quantitatively strong.

Column (5) repeats the regression but included bank-year fixed effects thus absorbing any variation driven by lead-bank specific annual shocks. The interaction coefficients remain largely unaffected. Bank-year fixed effects non-parametrically test if the cyclicalities in refinancing sensitivity to borrower attributes was spuriously driven by the type of banks that firms borrow from.

Column (6) replaces the *MACRO* variable with GDP growth that captures business cycle strength. All three interactions with GDP growth are significant. Thus the question arises whether our previous results were driven by credit market conditions or were spuriously driven by business cycle fluctuations that are correlated with credit market conditions.

Column (7) tests for this by including interactions for both credit market tightness and GDP growth. Once credit market interactions are added back in, the coefficients on GDP growth interaction go down significantly in magnitude and mostly become insignificant statistically. More importantly, the interaction with credit market conditions remains strong and statistically significant for all three variables capturing credit worthiness. As always, all standard errors are clustered at the lead-bank level.

IV. Discussion of Alternative Interpretations

Firms with better credit worthiness are more sensitive to credit market conditions in their refinancing probability, and these results are not driven by business cycle sensitivity. The cyclical variation in refinancing by credit worthy firms is driven by the proclivity to refinance early at a significantly higher rate in periods 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. However, in the absence of active maturity management aggregate changes in supply-side conditions reflected in loan officer surveys are unlikely to generate the results we find.

For example, as credit conditions tighten – say in 1998 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 that end up being the first to be denied credit, or given credit at harsher terms.¹³ Thus we would expect supply side changes to make the refinancing propensity of less credit worthy firms to be more sensitive to credit market conditions. We find completely the opposite.

Our results there suggest that there is a strong demand-side channel driven by maturity management effects that works in the opposite direction. Credit worthy firms deliberately

¹³ Santos (2011) shows that banks that experienced larger losses during the subprime crisis demanded higher interest rates on the loans they extended to corporations.

refinance early at a higher rate when credit conditions loosen up, and choose to refinance less aggressively when credit conditions are tight. They can choose to do so due to longer effective maturity, and possibly cheaper alternative sources of financing when cost of external financing goes up.

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 have low credit rating, and are most susceptible to fluctuations in the business cycle. Thus under the standard demand-side view, we would expect credit worthy firms to be less sensitive to business cycle fluctuation. Nonetheless we show that when we explicitly control for business cycle variation the sensitivity of refinancing with respect to credit conditions remains as strong for credit worthy firms.

V. Concluding Remarks

The question of liquidity risk and maturity management in relation to the credit cycle 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 and credit cycles.

Our analysis reveals a strong relationship between refinancing likelihood, utilization rate of loan commitments and credit conditions. A striking feature of the refinancing behavior is the tendency to favor early refinancing in normal times versus when credit conditions are tight. Such behavior enables firms to keep maturity long when credit is easy and hence have more ability to avoid having to refinance when credit terms are difficult. We find that credit worthy firms are best able to do so effectively. The net impact of more cyclical (with respect to the credit cycle) refinancing by better quality firms is that the type of firms that are most exposed to liquidity risk when credit conditions tighten are systematically weaker firms.

There are a number of interesting and promising questions raised by our findings that we hope future scholars will take up. For example, this paper focused on how demand-side factors influence the refinancing choice and hence 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.¹⁴

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

¹⁴ Bord and Santos (2011) show that banks that were under more liquidity pressure following the collapse of the market for asset-backed commercial paper in the fall of 2007 increased the cost they charge corporations for granting them access to liquidity.

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.

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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 observed as of December 31st of each year. 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.

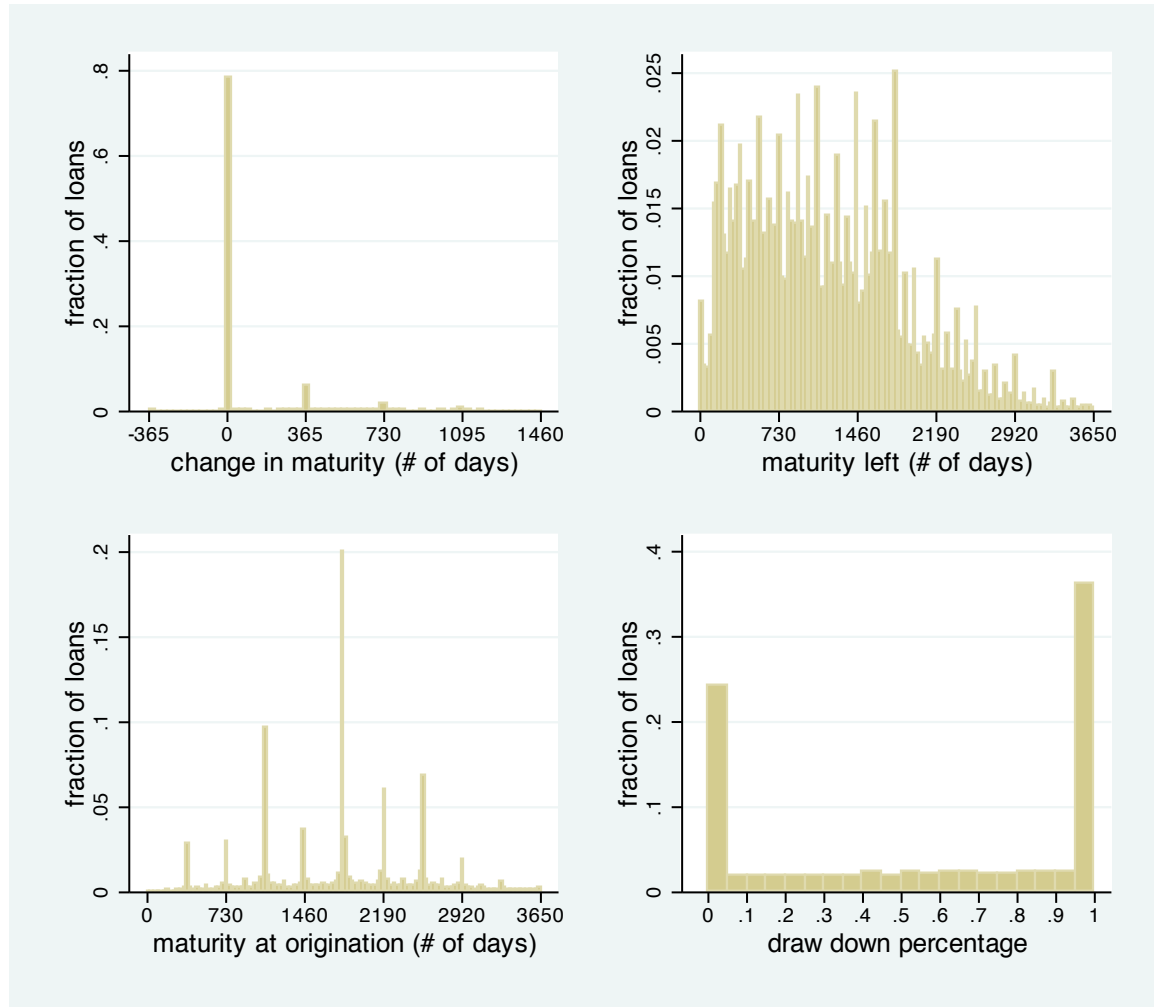


Figure 2
Loan Officers Survey Results

The top panel plots senior loan officer loan tightening survey for large and medium C&I loans. The bottom panel plots senior loan officer increasing spread survey for large and medium loans. Vertical dashed lines represent NBER-dated recessions.

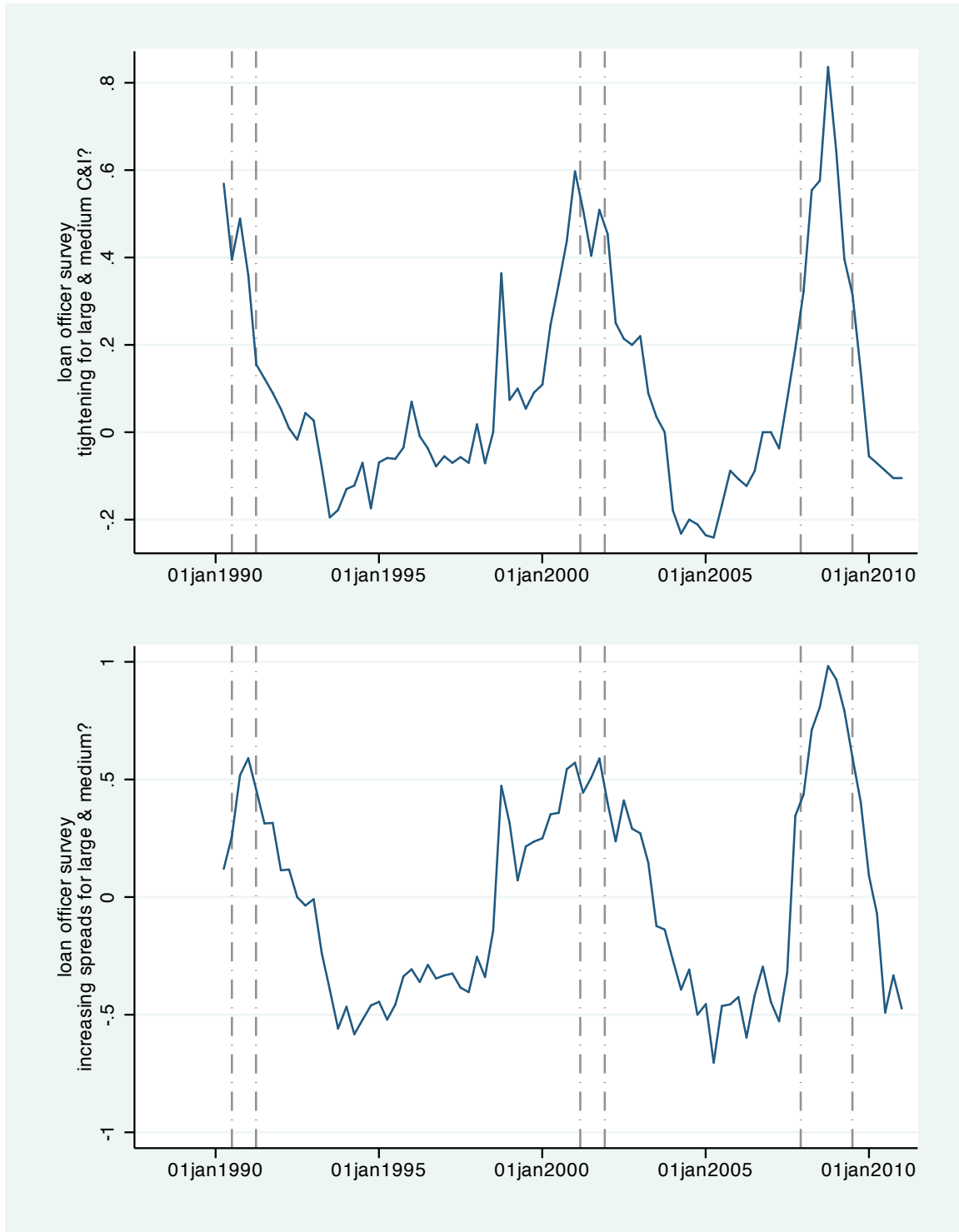


Figure 3
Propensity to Refinance

This figure plots the average propensity for syndicate loans to be refinanced in a given year. A loan is assumed to have not been refinanced if it does not appear in the sample in the subsequent year. Vertical dashed lines represent NBER-dated recessions.

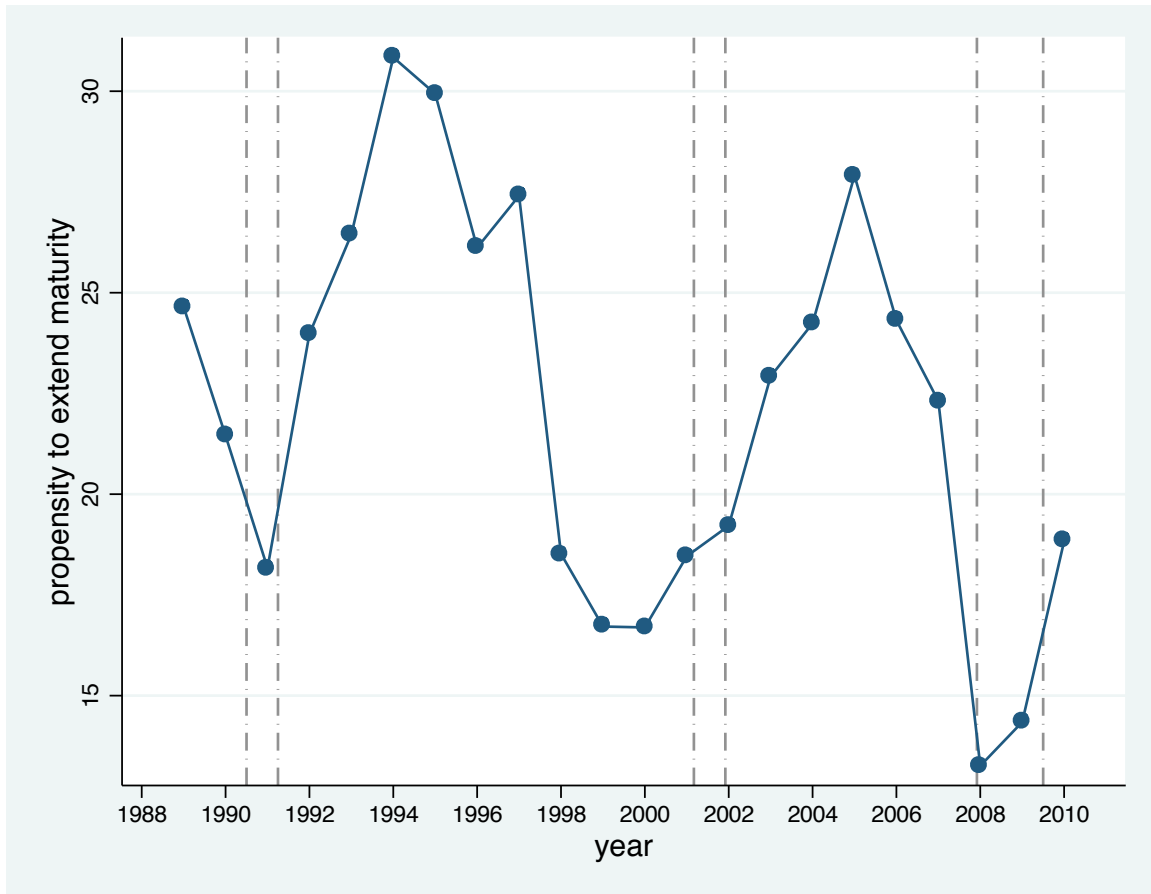


Figure 4
Intensive Liquidity: Draw Down Percentage

The top panel plots the average drawn down percentage (loan outstanding divided by loan commitment) for syndicate loans over time. The lower panels 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.

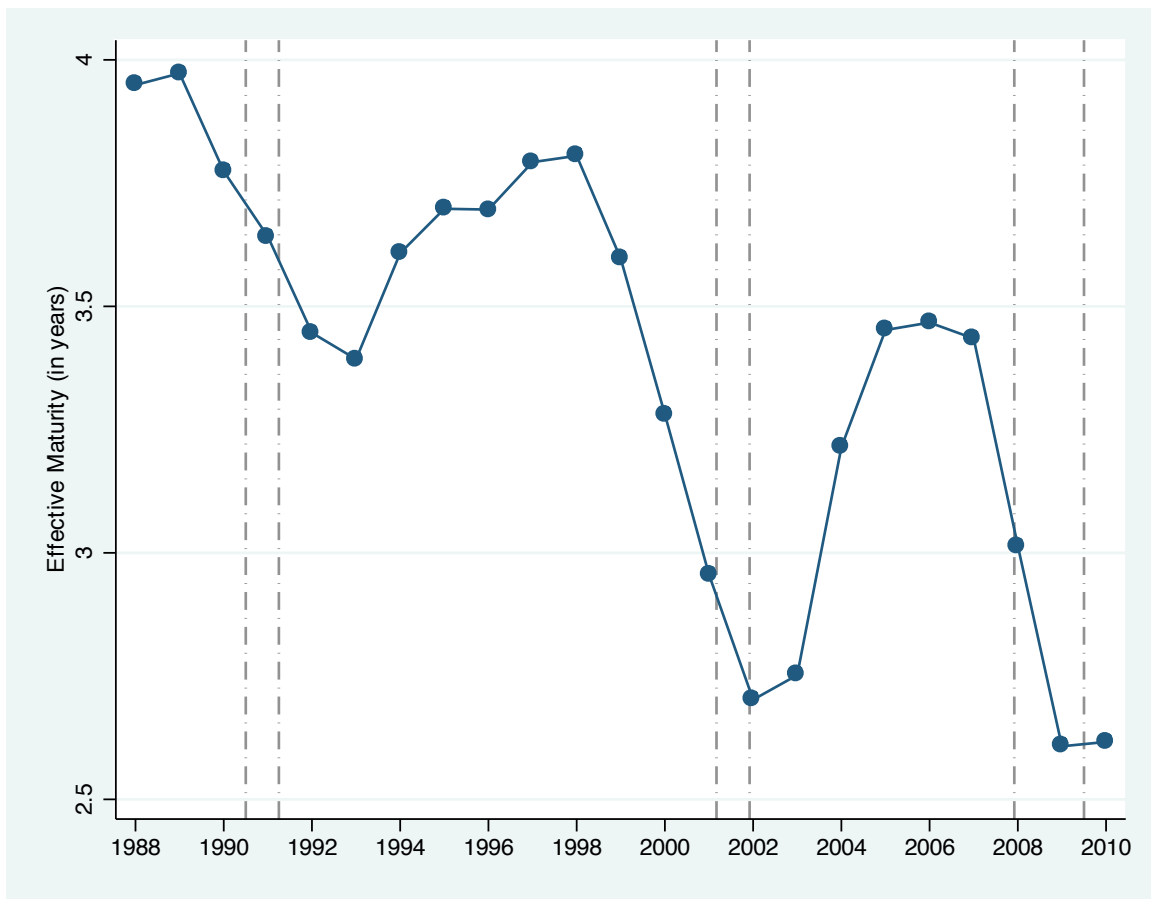


Figure 6
Propensity to Extend Maturity And Maturity Left

The top panel (left axis) 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 right axis plots the share of total refinancings that belong to refinancings with x years left till maturity. The blue (dotted) line in bottom panel plots the estimated coefficients $\hat{\beta}_n$ from the OLS regression: $Y_{ijbt} = \alpha + \beta_n * \gamma_n + \gamma_{norig} + \gamma_t + \varepsilon_{ijbt}$, where Y is an indicator variable for whether the syndicate loan i of borrower j from lead bank b is refinanced during year t (0/1). γ_n is the number of years till maturity fixed effect that turn 1 if the number of years left till maturity is between n and $n+1$, where n varies from 0 to 10. All loans above 10 years left in maturity are top-coded at 10. γ_{norig} is the number of years for maturity as of origination fixed effects (also going from 0 to 10). γ_t is the year fixed effects. The red (dashed) line plots the same coefficients, but includes borrower-year (γ_{jt}) fixed effects, thus comparing loans of differing maturities within the *same* firm-year.

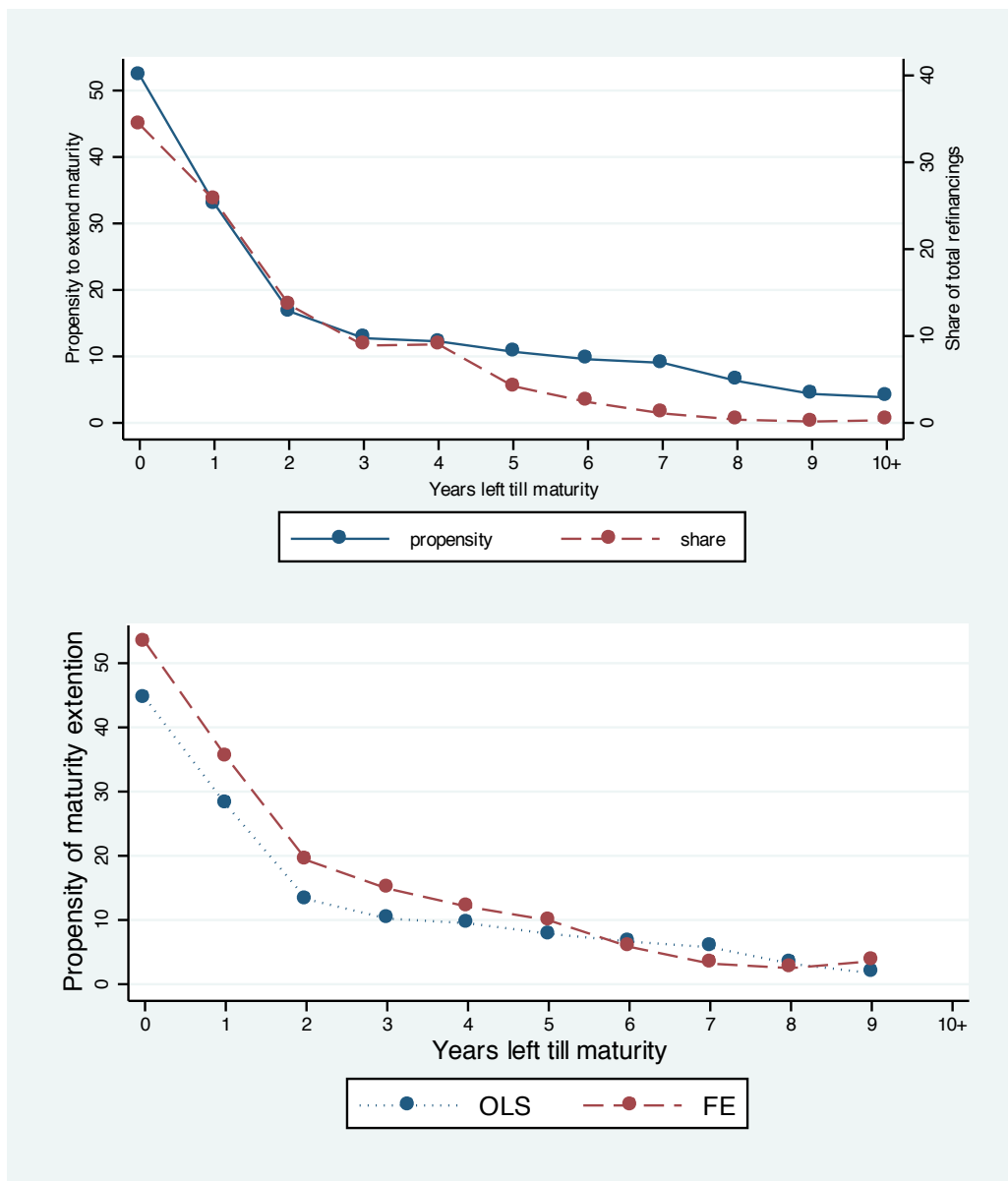


Figure 7
Probability of Early Vs. At-Maturity Refinancing

The top 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). In the bottom panel, the blue line plots the estimated coefficient ($\hat{\beta}_t$) of the following logit model separately for each year:

$\Pr[Y_{ijbt} = 1] = \frac{1}{1 + e^{-(\beta_t * LM_{ijbt} + \gamma_{norig})}}$, where Y is an indicator variable on whether the syndicate loan i of borrower j from lead bank b is refinanced during year t (0/1). The red line limits the sample to loans of differing maturities issued to the *same* firm in a given year. Vertical dashed lines represent NBER-dated recessions.

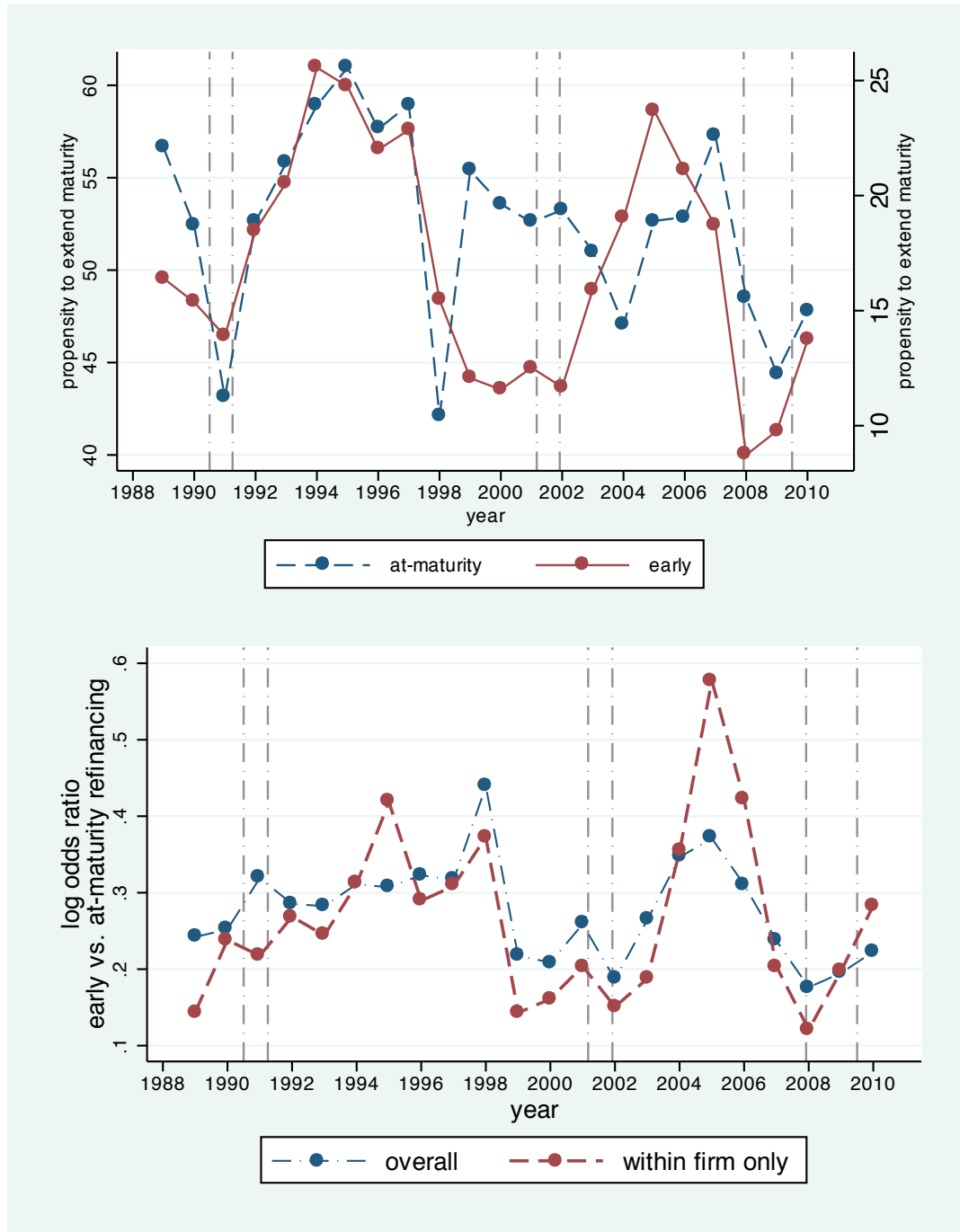


Figure 8
Maturity Refinancing By Loan Type

The figure plots the maturity-adjusted propensity to refinance over time for various category of firms. The maturity-adjustment is done by taking the residual after regressing the incidence of refinancing (0/1) on fixed effects for number of years of maturity at origination and fixed effects for number of years left till maturity at the time of observation. The top panel plots the maturity-adjusted refinance probability for loans that are less than 5% drawn down, and loans with more than 95% drawn down. The middle panel plots the same propensity for investment grade and non-investment grade loans respectively, and the lower panel for publicly-traded and non-publicly traded firms. Vertical dashed lines represent NBER-dated recessions.

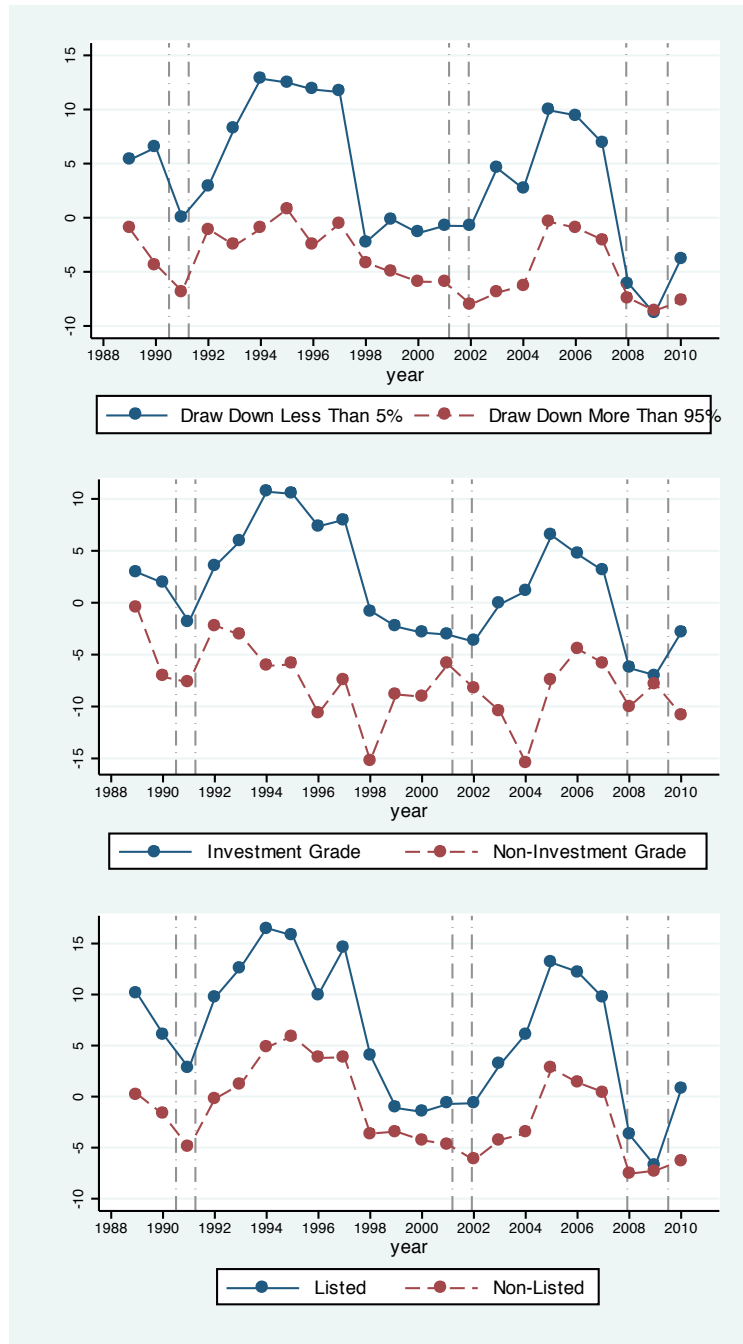
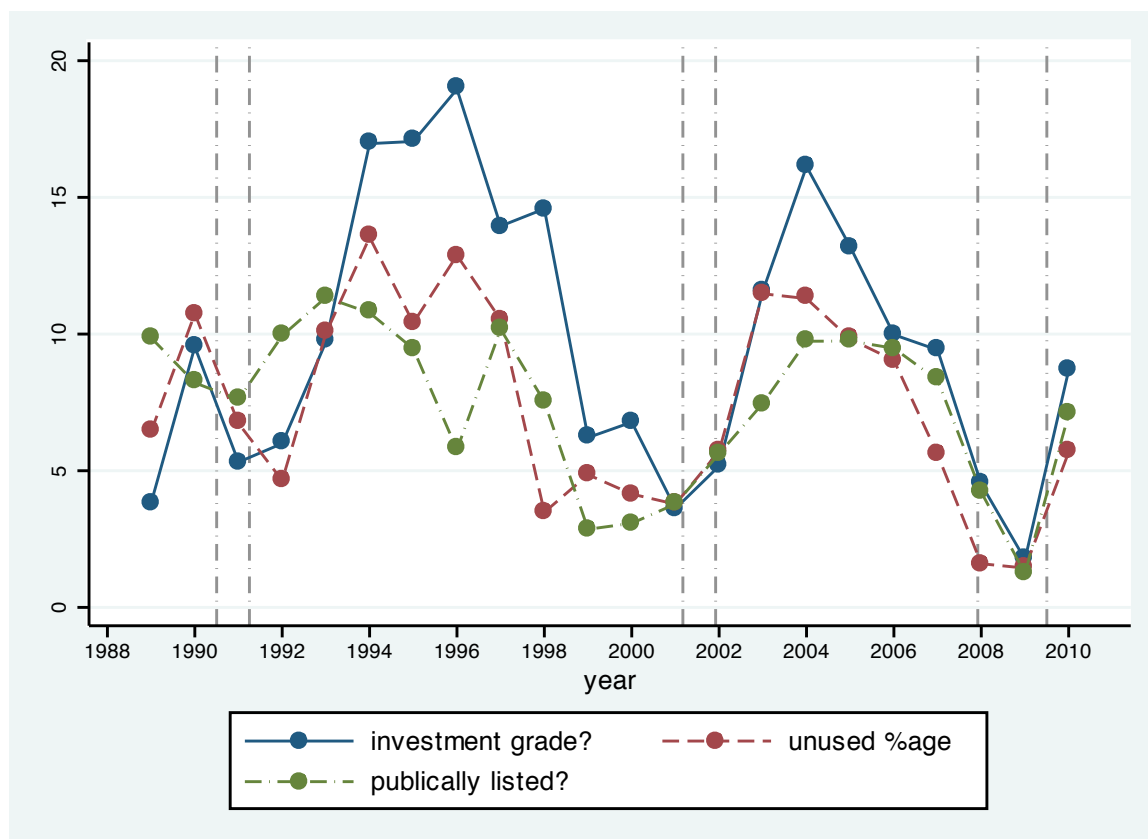


Figure 9

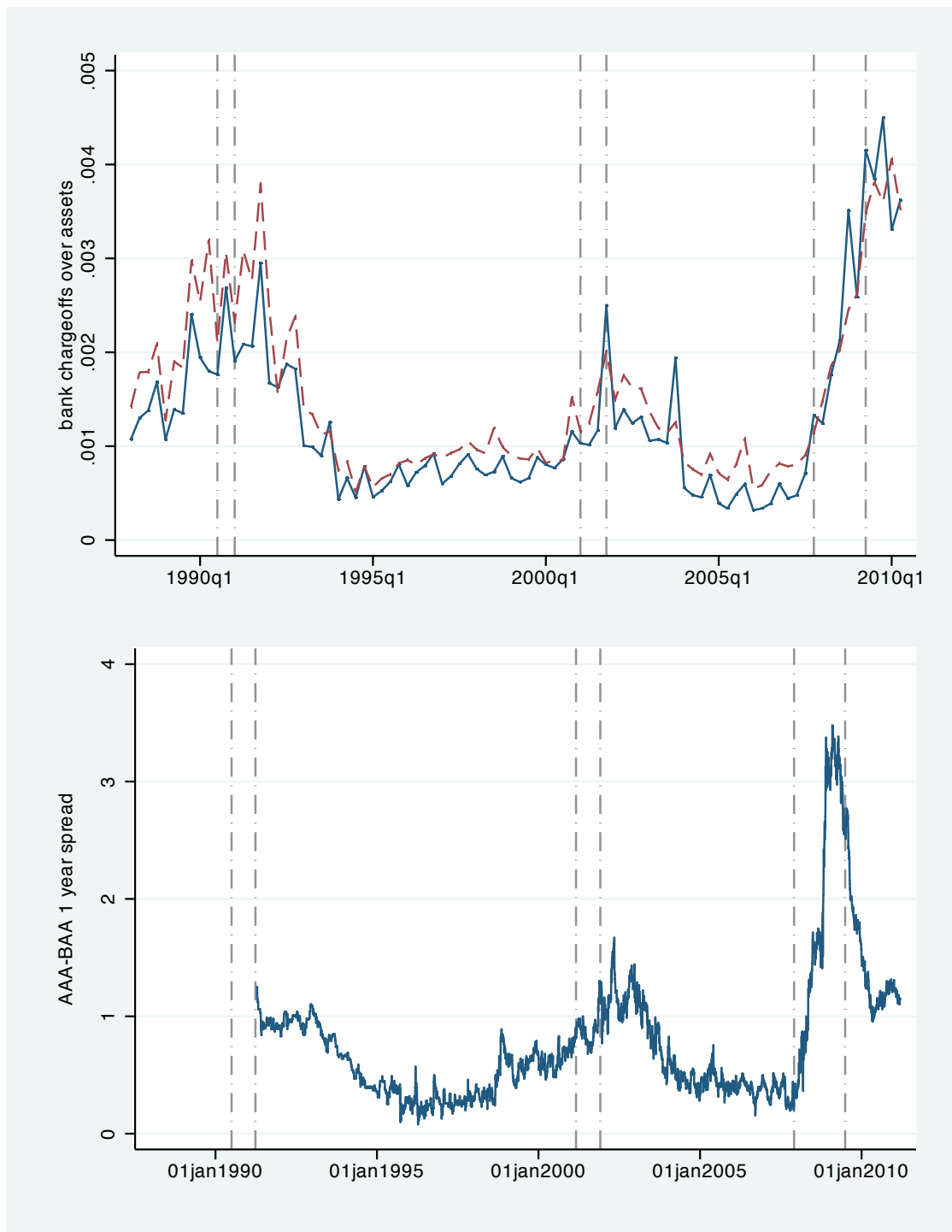
Dependence Of Refinancing On Borrower Attributes Over Time

This figure plots the $\hat{\beta}_t$ from the regression: $Y_{ijbt} = \alpha + \beta_t * X_{ij,t-1} + \gamma_n + \gamma_{norig} + \gamma_t + \varepsilon_{ijbt}$, where Y is an indicator variable for whether the syndicate loan i of borrower j from lead bank b is refinanced during year t (0/1) and X captures borrower attributes as of $(t-1)$. We plot $\hat{\beta}_t$ for three X 's: indicator variable for investment grade rating, unused loan commitment (i.e. one minus draw down percentage), and indicator variable for whether borrow is publically listed. A separate regression is run every year, and each regression includes number of years left till maturity fixed effects (γ_n), number of years for maturity as of origination fixed effects (γ_{norig}), and year fixed effects (γ_t). Vertical dashed lines represent NBER-dated recessions.



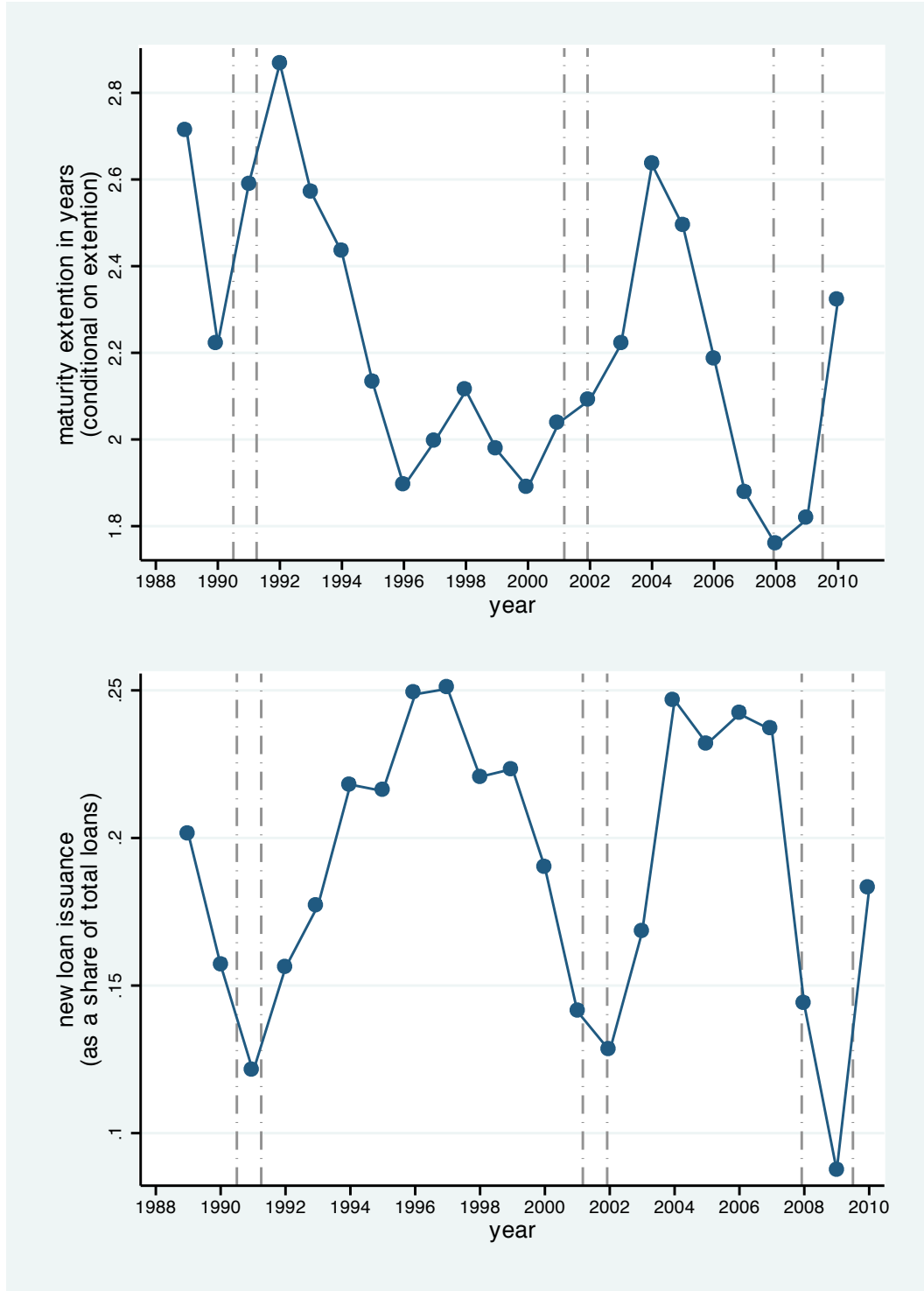
Appendix Figure 1 Credit Condition And Spreads Over Time

The top panel plots quarterly bank charge-offs over assets. The red and blue lines for the charge-off to assets chart represent weighted and un-weighted ratios respectively. The bottom panel plots the corporate credit spread (BAA minus AAA) over time. Vertical dashed lines represent NBER-dated recessions.



Appendix Figure 2 Time Series Of Corporate Liquidity

The top panel plots the average maturity extension conditional on refinancing. The bottom panel plots the share of total loans in a given year that are new originations. Vertical dashed lines represent NBER-dated recessions.



Appendix Figure 3 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.

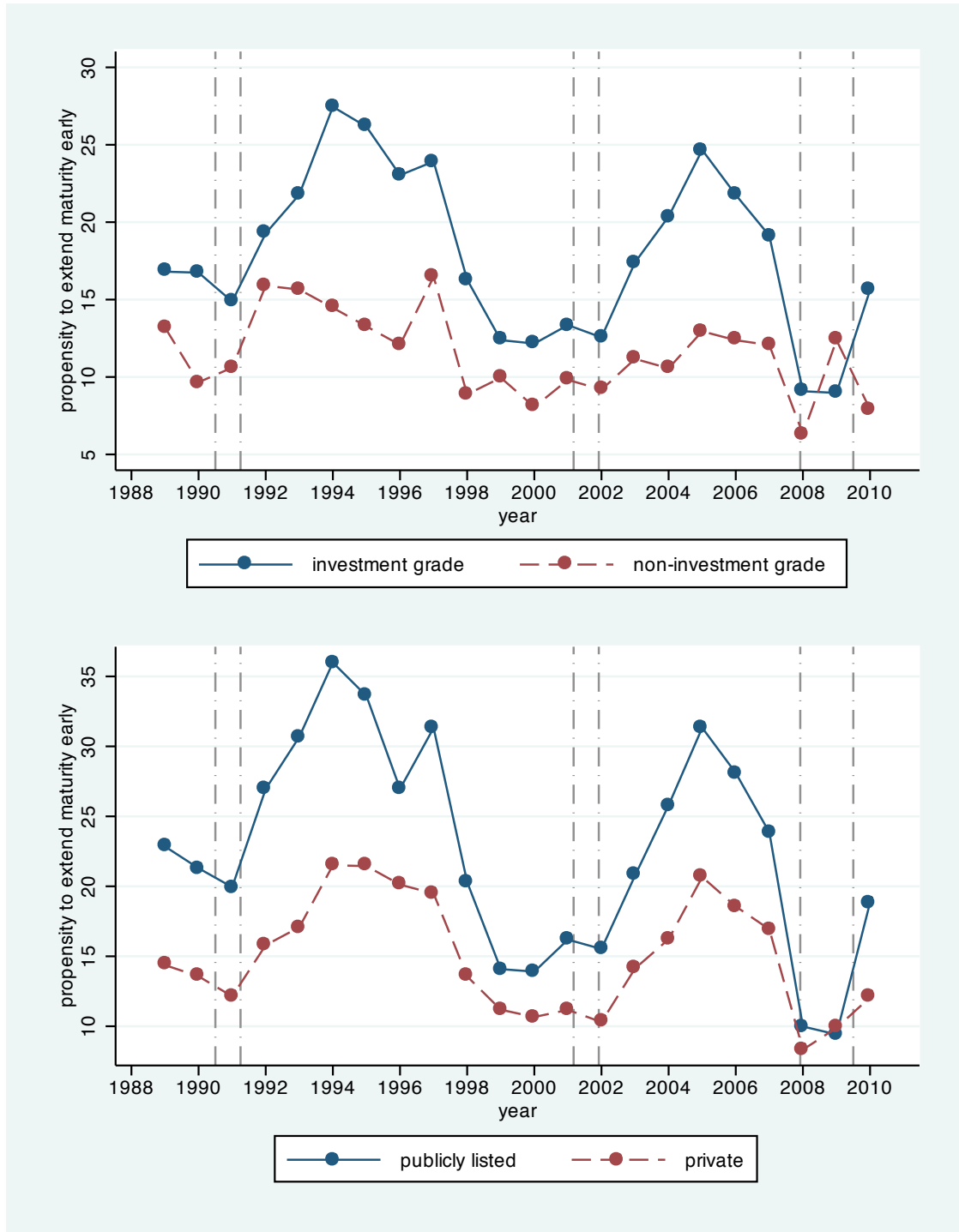


Table 1
Data Tabulation

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)
			# of firms with multiple banks	# of firms with multiple maturities	# of lead banks		# of loans
Year	# of loans	# of firms				Industry	
1988	4,309	3,312	227	146	236	Agriculture-	
1989	4,853	3,701	265	146	279	Mining	7,395
1990	5,332	4,011	266	169	305	Utilities	11,626
1991	5,221	3,895	258	178	283	Construction	11,108
1992	5,522	3,947	264	207	279	Manufacturing	46,934
1993	5,643	3,980	237	237	265	Trade	19,639
1994	6,397	4,338	230	285	272	Transport	5,969
1995	7,026	4,687	217	272	260	Information	12,557
1996	7,576	4,986	239	320	211	Real Estate	11,214
1997	8,745	5,539	253	359	209	Services	21,462
1998	7,539	4,550	195	331	183	Unknown	8,137
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. The data track each loan over time. Information on loans is provided as of December 31st of each year from 1988 to 2010. The top panel presents summary statistics for loan level data. “%age of shadow bank participation” is the percentage of loan that is funded by non-commercial banks, or financial firms outside of the Fed banking supervision. “Refinanced?” equals 1 if a loan is refinanced (or rolled over) in a given year. The middle panel reports summary statistics on borrowing firms, but the sample is limited to borrowers that are publically listed on a stock exchange. The bottom panel reports summary statistics on three macroeconomic variables.

	N	Mean	SD	10 th	50 th	90 th
<i>Loan level data</i>						
Total Commitment	156,041	188,651	433,005	15,000	73,000	409,106
Total Outstanding	156,039	81,995	236,233	0	26,137	189,741
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
<i>Firm level data</i>						
Total Assets	24,615	3,544	18,259	35.83	583.77	13,724
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	2,409	9,529	22.14	488.27	9,287
Sales on Assets	23,270	1.13	4.13	0.13	0.92	2.65
<i>Macro variables data</i>						
GDP Growth	22	2.55	1.83	0.40	2.71	4.45
SLOOS Tightening	21	0.10	0.23	-0.12	0.06	0.48
SLOOS Spread	21	-0.00	0.41	-0.44	-0.07	0.53

Table 3
Liquidity And Borrower Fundamentals

This table presents $\hat{\beta}_1$ and $\hat{\beta}_2$ from the regression: $Y_{ijbt} = \alpha + \beta_1 * X_{ijb,t-1} + \beta_2 * Z_{jb,t-1} + \varepsilon_{ijbt}$, where Y is an indicator variable for whether the syndicate loan i of borrower j from lead bank b is refinanced during year t (0/1). X and Z capture loan and borrower characteristics respectively as of $(t-1)$. Beginning in column (2), separate fixed effects for year, number of years left in maturity, number of years for maturity at origination, and industry are incorporated. Bank-year fixed effects are included from column (4) onwards. 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).

RHS variables as of $(t-1)$	Dependent Variable: Loan Refinanced At Time t ?						
							Less than one year left in maturity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Investment Grade?	6.68** (0.446)	6.58** (0.434)	9.15** (1.094)	6.61** (0.456)	9.87** (1.236)	13.53** (1.385)	18.30** (4.279)
Draw Down (%)	-1.35* (0.629)	0.07 (0.502)	-0.55 (0.960)	-0.37 (0.500)	0.67 (0.996)	-0.17 (1.732)	-2.86 (4.172)
Draw Down > 95% ?	-2.58** (0.503)	-3.52** (0.403)	-5.67** (0.965)	-2.87** (0.419)	-5.75** (1.031)	-8.62** (1.542)	-8.74+ (4.630)
Log change in sales			1.32* (0.576)		1.28* (0.610)		1.70 (2.574)
Return On Assets			-0.00 (0.013)		-0.01 (0.012)		0.52 (0.365)
Sales over Assets			0.02 (0.043)		0.03 (0.046)		-0.16 (0.159)
Credit Line?	2.60** (0.496)	2.82** (0.350)	0.30 (0.770)	2.44** (0.374)	-0.25 (0.829)	7.65** (1.212)	8.27** (2.892)
Publicly Listed?	4.11** (0.420)	5.42** (0.353)		5.08** (0.358)		4.83** (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
# of Years of Maturity Left Fixed Effects		yes	yes	yes	yes	yes	yes
Year Fixed Effects		yes	yes	yes	yes	yes	yes
# of Years of Maturity At Origination Fixed Effects		yes	yes	yes	yes	yes	yes
N	147,550	147,454	36,230	147,454	36,230	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
Estimate Of Early Refinancing

This table presents $\hat{\beta}_1$ and $\hat{\beta}_2$ from the logit model: $\Pr[Y_{ijbt} = 1] = \frac{1}{1 + e^{-(\beta_1 * LM_{ijbt} + \beta_2 * (LM_{ijbt} * MACRO_t) + \Gamma_{ijbt})}}$, where Y is an indicator variable for whether the syndicate loan i of borrower j from lead bank b is refinanced during year t (0/1). LM is an indicator variable for whether the loan has more than one year left till maturity. $MACRO_t$ is a measure of either credit conditions or business cycle strength during year t . Credit conditions are measured by senior loan offers surveys and business cycle strength is measured by average GDP growth. Fixed effects (Γ_{ijbt}) are specified in each column. The coefficient ($\hat{\beta}_1$) on LM thus captures the log of the odds ratio for early versus at-maturity refinancing (i.e. $\hat{\beta}_1 = \ln(\frac{\text{odds(early refinancing)}}{\text{odds(at-maturity refinancing)}})$). Column (7) limits the sample to loans of differing maturities issued to the *same* firm in a given year. 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).

RHS variables as of ($t-1$)	Loan Refinanced At Time t ?						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Long Maturity (LM)?	-1.36** (0.028)	-1.31** (0.033)	-1.27** (0.030)	-1.36** (0.029)	-1.59** (0.045)	-1.33** (0.087)	-1.26** (0.056)
LM * 1990 Recession		0.06 (0.097)					
LM * 2001 Recession		-0.28** (0.076)					
LM * 2007-09 Recession		-0.51** (0.115)					
LM * SLOOS Tightening			-0.90** (0.099)			-0.80** (0.194)	-1.17** (0.255)
LM * SLOOS Spread				-0.55** (0.062)			
LM * Δ GDP					0.09** (0.016)	0.02 (0.029)	
Industry Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes
# of Years Of Maturity At Origination	yes	yes	yes	yes	yes	yes	yes
Fixed Effects							
N	147,760	147,760	143,465	143,465	147,760	143,465	15,138

** , * , + 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 $\hat{\beta}_1$ and $\hat{\beta}_2$ from the regression: $Y_{ijbt} = \alpha + \beta_1 * X_{ij,t-1} + \beta_2 * (X_{ij,t-1} * MACRO_t) + \Gamma_{ijbt} + \varepsilon_{ijbt}$, where Y is an indicator for whether the syndicate loan i of borrower j from lead bank b is refinanced during year t (0/1). Borrower fundamentals attributes ($X_{ij,t-1}$) are measured as of $(t-1)$, and include indicator variable for investment grade rating, percentage loan commitment drawn down, and indicator variable for borrower being listed on the stock exchange. $MACRO_t$ is a measure of either credit conditions or business cycle strength during year t . Credit conditions are measured by senior loan offers surveys and business cycle strength is measured by average GDP growth. Fixed effects (Γ_{ijbt}) are specified in each column. 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).

RHS variables as of $(t-1)$	Loan Refinanced At Time t ?						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Investment Grade?	10.62** (0.48)			8.49** (0.47)	8.68** (0.49)	3.05** (0.62)	6.19** (1.13)
Investment Grade * SLOOS Tightness	-14.40** (1.71)			-11.18** (1.62)	-12.75** (1.65)		-8.11** (2.60)
Draw Down (%)		-8.08** (0.37)		-5.27** (0.37)	-4.93** (0.36)	-2.99** (0.48)	-5.30** (0.86)
Draw Down * SLOOS Tightness		10.14** (1.55)		6.40** (1.45)	6.46** (1.44)		7.20** (2.18)
Publicly Listed?			7.65** (0.40)	6.27** (0.39)	5.77** (0.40)	3.75** (0.50)	6.20** (0.91)
Publicly Listed * SLOOS Tightness			-10.67** (1.56)	-8.34** (1.48)	-6.95** (1.48)		-7.70** (2.26)
Investment Grade * GDP Growth						1.58** (0.23)	0.79* (0.35)
Draw Down * GDP Growth						-0.49** (0.16)	0.12 (0.23)
Publicly Listed * GDP Growth						0.52** (0.17)	-0.13 (0.26)
Bank-Year Fixed Effects					yes	yes	yes
Industry Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes	yes
# of Years Of Maturity At Origination Fixed Effects	yes	yes	yes	yes	yes	yes	yes
# of Years Of Maturity Left Fixed Effects	yes	yes	yes	yes	yes	yes	yes
N	143,168	143,166	143,168	143,168	143,166	143,168	143,166
R-sq	0.16	0.16	0.16	0.21	0.21	0.21	0.21

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