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Loans on sale:
Credit market seasonality, borrower need, and lender rent seeking

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Abstract

The market for corporate credit is characterized by significant seasonal variation, both in interest rates and the volume of new lending. Firms borrowing from banks during seasonal "sales" in late spring and fall issue at 19 basis points cheaper than winter and summer borrowers. Issuers during cheap seasons appear to have less immediate needs, but are enticed by low rates to engage in precautionary borrowing. High interest rate periods capture borrowers with unanticipated, non-deferrable investment needs. Consistent with models of intertemporal price discrimination, seasonality is strongly associated with market concentration among a few large banks with repeated interactions.

I. Introduction

Predictable and pronounced seasonal variation is not uncommon in commodity prices. Systematic seasonal patterns in the demand or supply of a product can lead to corresponding patterns in prices over the calendar year. Yet these seasonal patterns can only persist when it is difficult or costly to adjust demand or supply or to store the commodity, carrying it from one season to the next. For example, electricity prices are high in the summer months when demand outstrips supply which cannot adjust rapidly (see Figure 1-A). Meanwhile, inefficiencies in electricity storage prevent customers from buying during cheap seasons for later use. Wheat prices tend to fall during the harvest as "many farmers dispose of their crop as it is harvested to avoid…costs of handling and storage" (see Figure 1-B and Meinken (1955)).

The presence of pronounced seasonal variation in the cost of financial capital, however, is unexpected in a modern and diverse economy with well-developed capital markets. Storing capital is very low cost and, while individual industries may have specific seasonal funding demands, the aggregate seasonal component across a diverse set of industries is likely to be low. In this paper, we show that the market for syndicated loans is characterized by significant and predictable seasonal variation, both in interest rates and the volume of new loans. Firms borrowing during seasonal "sales" in late spring and fall (May/June and October) issue at 19 basis points cheaper and raise 50 percent more total funding than winter and summer borrowers (January/February and August). Although, seasonal volumes could easily be explained by coordinated variation in supply and demand, the predictability in market interest rates raises interesting questions. What kind of firms rationally borrow in high priced periods as opposed to moving their demand to less expensive months? What prevents lenders from competing away the seasonal markups that we observe?

From the borrower's perspective, we begin by noting that, if firms perceive predictable and meaningful variation in credit spreads, this should alter their issuance behavior. Thus one immediate challenge of the paper is to decompose seasonality into the underlying seasonal markups and compositional effects based on borrowers' best response to those seasonal markups. By way of analogy, if the cost of calling a plumber on Sunday night is expensive, Sunday night service calls will be different than those which occur Monday morning. The inability of customers to wait until Monday and difficulty of anticipating the problem may be related to the severity of the plumbing problem independent of the markup charged by the plumber.

Not unlike a plumber's Sunday service charge, we find evidence of an economically significant seasonal markup when comparing like firms, controlling for credit risk and project type. But we also find that the markup appears to drives strategic timing of issuance by firms within the year which has not been documented before. Higher credit quality firms time the market to take advantage of cheap issuance seasons, whereas weaker credits are relatively more prone to issuance during expensive seasons. This behavioral response by borrowers drives important selection effects in the data for which we need to control, but also seems to imply that firms perceive the documented seasonality as important to managing cost of capital.

Beyond credit quality, the characteristics and motivations of the firms that borrow in the expensive months are notable along a number of other dimensions. Their projects appear to be more unpredictable, their cost of storing capital more expensive, and their credit demand more urgent (i.e. their projects are less deferrable). Whereas higher credit quality firms can borrow on a precautionary basis and thus largely time the market based on pricing and not the arrival of investment opportunities, weaker credits appear to borrow on an as-needed basis and therefore may have urgent funding needs appear in expensive months.

Even if the movement of borrowers out of expensive months is not enough to eliminate the seasonal pricing we document, bank behavior could be. Thus for the seasonal pattern to persist we need to explain why the actions of lenders facing predictable variation in lending rates have not eliminated the seasonal pattern and what this implies about bank competition. In a competitive lending environment with constant costs, seasonality should disappear, as lenders shift supply to months with larger markups. To reconcile lenders' behavior with the data, we rely on the well-developed literature on strategic temporal pricing, beginning with models of retail sales by Varian (1980) and intertemporal price discrimination by Stokey (1979, 1981). In particular, however, our analysis is informed by a model of sales proposed by Conlisk, Gerstner, and Sobel (1984) who suggest that a monopolist seller facing the continuous arrival of buyers with varying reservation prices will optimally choose a predictable cyclical price path with high prices followed by recurrent discounting ("sales"). Intuitively, this pricing allows customers with less urgent needs and perhaps lower willingness to pay to time their purchases to coincide with cheap seasons, while higher willingness-to-pay customers will find it costly to delay their purchase, and thus can be captured at higher prices. Both the predicted seasonal pattern and the suggested sorting behavior based on urgency of need across seasons appear largely consistent with our findings.

While Conlisk, Gerstner, and Sobel's model is based on a monopolistic market, the syndicated loan market is better characterized as an oligopoly of large banks which set terms for the majority of transactions, and a competitive fringe of smaller bank and non-bank lenders. Given this structure, the repeated interaction and public nature of the syndicated loan market will be a necessary component of enforcing strategic interaction. Thus, in addition to matching the

broad predictions of their model to our data, we will document the role of competition in the syndicated lending market in generating the seasonal patterns we observe.

We are able to show that changes in concentration in the syndicated market across time (time series variation) and across industries (cross sectional variation) are strongly associated with changes in seasonality; the greater the concentration, the greater the seasonal variation from peak to trough. Finally, we document the importance of repeated interaction in enforcing a cooperative equilibrium. We show that during seasonal spikes in interest rates, small outsider lenders "elephant hunt", aggressively courting and successfully winning the business of large investment-grade borrowers usually served by the top banks. The increased competition from fringe lenders drives the counterintuitive pattern of decreased measures of lender concentration during high priced periods.

Our findings and interpretation draw from a wide range of distinct literatures. While ours is the first full accounting of seasonal patterns in modern credit markets, it follows a number of papers on turn of the century credit seasonality driven by agricultural demand, the role of the Federal Reserve Bank in stabilizing seasonal prices, and the link between seasonal cycles and business cycles (Miron (1996)). Our paper shows that seasonal effects remain important and moreover, are highly correlated with firm and loan characteristics. As a practical matter, this suggests that empirical work using loan level data should be careful to control for seasonal effects.

More generally, from the borrower's perspective, the paper provides new evidence on issuer market timing and suggests an important mechanism by which strategic precautionary issuance by large borrowers can help minimize costs of capital. Meanwhile, the evidence on lender behavior and, in particular, the suggestion of strategic and coordinated loan pricing over

time, provides a plausible alternative to marginal cost pricing under a perfectly competitive bank market. We suggest an equilibrium where banks with market power earn rents not based on the level of interest rates, but on strategic variation in interest rates. This has new implications for how we might test for the effects of lender competition going forward. Finally, outside of the literature on banking, our paper provides a novel application for classic models of intertemporal price discrimination.

Following a short description of the data and a presentation of the seasonal patterns in Section II, we examine the response by borrower demand (Section III) and lender supply (Section IV) to seasonal variation in interest rates. Section V contains a brief summary and a discussion of some implications of our results.

II. Data description and summary statistics

Since we need loan level detail, including borrower and lender information, to help shed light on the behavior that gives rise to seasonality, we focus our analysis on Thompson Reuter's DealScan database. Loans are recorded in the data as of the effective date of the facility, usually the first date that funds are available for drawdown (e.g. the closing date). Although longer times series of commercial loan interest rates and volumes on are available from the Federal Reserve Board, those series report new loans at the time of draw-down, irrespective of when lenders commit to terms and availability. In many cases, this is months or years in advance of the actual funds being disbursed.[1] The seasonality we find should therefore be interpreted as predictable variation in the outcome of negotiations between borrowers and lenders regarding the future availability and pricing of committed liquidity. One cost of relying on the DealScan data

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[1] For example, Ivashina and Scharfstein (2010) document a significant growth in loan volumes at the onset of the lending crisis due to borrowers drawing down on committed facilities, while new loan originations came to a standstill.

is its limitation to primarily the syndicated loan market. Although there is some information on large bilateral facilities—loans between a single bank and borrower— lenders have limited incentive to report details on privately negotiated loans and therefore, information on bilateral credit is limited to what can be found in borrowers' public disclosures.

Throughout our analysis, we use the facility start date—typically reported as the effective date of the loan facility— as the time stamp on the loan. Because of time spent in syndication and documentation, this is a lagged measure of the actual date on which the lead bank (and/or the syndicate) and the borrower agreed upon loan terms. For a small portion of the sample, the date which the lead arranger receives a formal mandate to syndicate the loan is reported. Using this date, we find that the peak interest rate season occurs for loans mandated in December and July, as opposed to February and August using the facility start date. Other than the lag, the pattern in interest rates is similar.

Our measurement of prices and quantities will primarily focus on two commonly used variables—*All-in-spread* and *Facility Amount*. *Facility Amount* refers to the amount of a term loan or the maximum amount a borrower can borrow under a revolving credit facility. The median facility amount for the full DealScan sample (from 1981 to 2012) is $67 million, consistent with the large size of the average borrower in the syndicated lending market, a point we'll return to in a moment. *All-in-spread* is the spread over a floating base rate (usually 3 or 6 month LIBOR) which borrowers will pay on any draw-downs on the facility, plus any transaction fees which are recurring in nature. This is an admittedly incomplete measure of the total payments which will go to the lender. It does not include commitment fees paid to lenders on the undrawn amounts available, nor does it include any upfront fees common to these transactions. It is also a static measure of interest rate which doesn't reflect contingencies for

step-ups or step-downs based on borrower condition, or the expectation of renegotiations following covenant violations.

With these caveats in mind, we interpret *All-in-spread* as a proxy for the yield required by lenders. The appendix provides evidence that the general seasonality in interest rates described using *All-in-spread* is consistent with similar patterns in both upfront fees (for transactions which report this variable) and commitment fees (for facilities with revolving loan components). The median *All-in-spread* reported in the data is 250 basis points (the mean is 254).

As we alluded to above, the borrowers captured in the DealScan database are large. For the portion of the sample which we can match to Compustat using the matching file provided by Roberts and Chava (2008), the median facility was to a borrower with assets of $984 million (reported in 2012 dollars). Lending in the sample is likewise dominated by a handful of large banks. Ranking lenders by the volume of loans arranged in the prior year, the top 10 banks from the prior year led 77% of total issuance volume, although as we will see later in the paper, this market structure has significant time series variation.

The summary statistics of primary interest to us, however, relate to the conditional distribution of interest rates and loan volumes by calendar month of the borrowing. Figure 2 plots the average monthly loan spread for new issue loans reported by DealScan from 1999 through 2007 (the solid line). A quick glance at the plot reveals seemingly predictable peaks in pricing every twelve months, often substantially removed from neighboring lower interest rates periods. To confirm that the pattern is not an artifact of the recent period, we calculated the average spread for each of the 12 calendar months for the non-overlapping sample covering 1987-1998. The monthly averages serve as a crude seasonal predictor and are plotted as the

dotted line in Figure 2. The monthly out-of-sample means line up closely with the peaks and troughs of observed spreads, with May and October issuance predictably 20 basis points cheaper than pricing peaks in January/February and August.[2] Figure 2b reports the same pattern over the entire sample period. Meanwhile, Figure 3 plots these predicted seasonal spreads, also estimated over the entire sample, against the average monthly issuance volume and the average number of transactions for each of the 12 months. Similar to their business cycle frequency counterparts, seasonal credit cycles have their highest interest rates during periods of reduced issuance volume, suggestive of a recurrent supply shock tracing out a demand curve.

Table 1 formalizes the test of seasonality by collapsing loan level spreads into monthly averages (and volumes into the log of monthly sums) to generate time series data on prices and quantities. Thus the unit of observation is a month-year. We will demonstrate the seasonal effect using loan level observations below. To test for seasonality, we fit the time series observations to models with dummy variables for each calendar month and either year dummies or autoregressive terms to capture business cycle variation in interest rates and issuance volumes. We then test for the equality of monthly dummy coefficients. The time series approach is attractive in that it allows for a natural treatment of the standard errors, which can be estimated following Newey and West (1987) with a rolling 12 month lag. It also allows us to characterize the nature of the observed seasonality following the classifications proposed by Miron (1996). Columns 1 and 2 use a simple model with month and year dummies to test the presence of calendar month seasonality on spreads and volumes, while columns 3 and 4 estimate an AR model with lags 1 through 4, in addition to a 12 month lag.[3]

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[2] The two series have a correlation coefficient of 0.52.
[3] The inclusion of a 12 month lag is motivated by Miron's differentiation between indeterministic and deterministic cycles. For indeterministic cycles, which present in the data as an autoregressive model with a positive loading on the 12th monthly lag, the seasonal peaks and troughs are not fixed in the calendar, but instead drift over time. In

In each of our time series tests, we strongly reject the null hypothesis that the coefficients on the 12 calendar month dummies are equal at the 1% level.[4] Meanwhile, we find no loading on the 12 month lag in the spread or volume time series, suggesting the seasonal effect is stationary and deterministic. In unreported results, we rerun both tests in first differences and find the monthly effects are both significant and significantly different from each other, even after removing possible unit roots in the two series. Meanwhile, the magnitude and timing of the cycle are generally consistent with the pattern seen in Figure 2, with local pricing peaks in late summer and winter, and troughs in early summer and fall.

The pattern observed in seasonal quantities is easy enough to reconcile with a story about labor market holidays, the timing of which is roughly coincident with low periods of issuance. Both CFOs and credit analysts alike who have preferences for leisure will have incentives to coordinate their leisure consumption at the same time, such that productivity is maximized during the rest of the year. Thus, we might expect low volumes for transactions starting in late December, and closing in January and February, with a similar pattern in the summer months. Harder to explain is the sustained seasonality in prices under the null hypothesis that 1) firms can costlessly move their demand for capital to low priced periods, either by timing investment projects or by storing capital when it is offered at a discount and 2) lenders should have the incentive to shift supply to periods where spreads are more attractive until the pricing patterns

small samples, we might expect to find a monthly pattern similar to the one in Figure 2. As the time series expands and the cycle migrates, however, the pattern would disappear. Under a deterministic cycle, the pattern is fixed over the calendar year, with peaks and troughs determined by constant monthly fixed effects.

Heston and Sadka (2008) and Keloharju, Linnainmaa, and Nyberg (2013) find such a seasonality in equity returns. Individual stocks or well diversified equity portfolios that do well in one month also do well in the future on an annual basis (e.g. 12 months, 24 months, 36 months etc.). Unlike our effect, it is not based on the calendar. The effect appears in all months, although it is stronger in January.

[4] Our analysis will focus on the seasonality in the interest rate spread over the benchmark (usually LIBOR). Although our focus is on the interest rate spread in the syndicated loan market, we checked for seasonality in three market interest rates: LIBOR (F-statistic=0.46, p-value=0.92), the Baa-Aaa bond spread (F-statistic=0.57, p-value=0.85), and the CDS spread (F-statistic=0.28, p-value=0.99). The F-statistics and associated p-values are reported in parenthesis (see Table I – columns 5-7 for details). None of the three series exhibit a calendar month seasonal pattern.

are eliminated. We tackle the timing of borrower demand given seasonality in Section III, and follow by investigating the incentives of lenders to compete away seasonal spreads in Section IV.

III. The demand side of seasonality

Taking the seasonal pattern in spreads as given, what prevents borrowers from shifting their demand from high into low priced periods until the pattern dissipates? For example, borrowers can raise precautionary funding during cheap periods, even when they have limited need, in order to avoid the high rate season. Alternatively, they may be able to delay projects which arise in expensive times. Note, however, the costs of taking either action in response to seasonal effects may vary by firm type. Returning to the example of weekend plumbing repairs discussed in the introduction, the inability of a customer to wait (or perhaps to anticipate and resolve plumbing issues with early maintenance and repair) may be correlated with the severity of and the repair cost associated with the problem, independent of the markup charged for a weekend consult. In the loan market setting, the firms who fail to anticipate or can't delay funding needs during expensive seasons are, by definition, different from those who hedge their financing needs in advance, or opt to forgo high priced borrowings. To the extent that those differences correlate with firm risk, even a small seasonal pattern may drive large selection effects. Thus, part of our challenge in this paper will be to break down the relative magnitudes, as well as the economic drivers behind the two related effects.

In order to isolate variation in borrowing costs over the seasons from the associated selection effects, we focus on samples of borrowers for which creditworthiness is relatively observable, or for which we have direct measures of risk premiums from outside the bank

market. Table 2 begins by using long-term credit ratings from Standard and Poor's and firm characteristics as a starting point for pinning down borrower risk. Specifically, we estimate the model

$$AllinSpread_{i,t} = \delta_t + \gamma_{industry} + \lambda Seasonal_t + \theta Rating_{i,t} + \beta X_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where *Seasonal* is the variable by which we parameterize the seasonal component of *AllinSpreads* (details below), θ is a dummy for each long-term debt rating category, δ_t and $\gamma_{industry}$ are year and industry dummies and X represents a vector of firm and deal level controls.[5] The goal of equation (1) is to identify the extent to which variation in borrowing costs is attributable to differences in borrower quality over the cycle as opposed to a true shift in borrowing cost, holding risk constant. For now, the analysis assumes that credit ratings provide a timely and complete picture of borrower risk.

Because business cycle variation is a first order determinant of loan spread, we include time fixed effects at the annual level (more granular time specifications would soak up the seasonal variation of interest). Time fixed effects also include an indicator for the second half of 2008 (in addition to a 2008 dummy) to account for high spreads on new loans issued in the midst of the crisis. Other model controls include size (log book value of assets), operating profit as a percentage of assets, book leverage, and tangibility of assets, defined as property, plant and equipment divided by total assets to capture firm characteristics which may hold sway over rates, even after controlling for firm rating. We also use 17 Fama-French industry dummies (Fama and French (1997)) to soak up industry factors which might be correlated with issuance timing. At

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[5] We restrict ourselves to package level observations within DealScan (a package reflects a group of facilities sold to an overlapping syndicate and governed by the same contract) under the assumption they are negotiated at the same time. Because spreads and maturity may vary within a package, we use the mean spread and the maximum maturity in regressions hereafter.

the deal level, we control for the maturity of the debt, whether or not DealScan reports any part of the loan as being secured by collateral, and the reported deal type.[6]

We present two distinct approaches to modeling the seasonal effect (*Seasonal*). First, we include dummy variables for expensive and cheap periods, where we define each season as the three month periods of locally high (low) interest rates, and correspondingly (low) high issuance volumes. Figure 2 and Table 1 both point to local interest rate spikes during the winter in January and February, and during the summer, in August. Meanwhile, seasonal low points in interest rates occur in late spring, specifically May and June and during the fall in October. Thus we define the expensive issuance season as the months January, February, and August and the cheap season as the months May, June and October.[7] The coefficients on dummy variables for these seasons capture the mean increase/decrease in spread relative to the rest of the year which is attributable to the seasonality, after conditioning out the effects of changing borrower quality and differences in loan terms.

Our second measure of seasonal effects uses a sample of firms from DealScan which cannot be matched to Compustat (and therefore are not included in the regressions) to estimate a predicted seasonal spread. This seasonal prediction is then included as a right hand side variable in our regressions. Assuming the samples are i.i.d., without any controls, we would expect a coefficient on the seasonal variable equal to unity. To the extent that seasonal variation in firm or deal characteristics contributes to seasonality, the coefficient will attenuate towards zero as controls are added. In a complete specification of all covariates with related seasonal

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[6] Deal type controls include dummies for the most common transaction types—corporate purposes, working capital, CP backup, debt repayment, takeover (including LBO's and acquisitions lines), and other. Loan spreads, along with all continuous control variables, are all winsorized at the 1% level.

[7] In choosing the expensive season months, note that we chose local peaks in interest rates that also coincided with reduced volumes (this is easiest to see in the interest rate/loan volume scatter plots in figure 3). These months are most consistent with a supply shock coming from banks which will be the subject of the analysis in the second half of the paper. Nonetheless, in the Appendix, we replicate key results using January/February/March as the expensive season with similar results.

components, the coefficient would be interpretable as the fraction of the total seasonal effect which is not due to selection.

Using the estimated seasonal effect from the holdout sample ensures that our tests are not biased by prior information about the seasonality. Moreover, it prevents individual transactions in our regressions from influencing the estimated seasonal effect to be used on the right hand side. Finally, including a single variable to capture seasonality puts structure on the seasonality. As an alternative, including 12 monthly dummies might allow us to test for some version of seasonality, but not tie our hands to specifically test whether or not the pattern we've observed and documented in unconditional tests holds up after conditioning on changing borrower risk profiles. Finally it gives us a direct measure of the extent to which seasonality is linked to selection versus pure shocks to prices.

Finally, our regressions cluster standard errors at both the firm and at the monthly level. It might seem preferable to cluster at the yearly, as opposed to monthly level, given the general rule of thumb that clustering along the larger dimension provides for a more robust correlation structure among the errors. However, we find that clustering at the yearly level produces standard errors which are considerably smaller than those obtained by monthly clustering.[8] We therefore err on the side of caution and report the generally more conservative standard error formulation and associated significance levels.

Columns 1-3 in Table 2 reports the mean variation in loan spreads across seasons under a variety of controls, with the benchmark case of only time dummies reported in column 1 and a seasonal spread of 19 basis points. Including only loan purpose, maturity, and security controls,

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[8] A possible reason is the small sample bias that arises from clustering on a dimension that has too few clusters (years). This becomes particularly problematic for the CDS sample used in the second part of Table 2 (and discussed in the following paragraphs) which includes less than 10 years of data (see Petersen 2009).

we see that loans closed in January, February, and August are assigned interest rates 11 basis point higher than loans closed during May, June and July. The difference, reported at the bottom of the table, is significant at the 1% level. This is consistent with seasonal variation in borrower need for different types of financing—a hypothesis we explore further in tables 4 and 5. Meanwhile, in columns 3 and 4, the seasonal effect attenuates to between 6 and 7 bps when we add the full set of controls to pin down borrower creditworthiness, including firm debt ratings (recall only rated firms are included in the regression), Compustat controls for size, profitability, leverage and asset tangibility, and even firm fixed effects. While the shrinking magnitude of seasonality after conditioning out firm and loan characteristics tells us that seasonal variation in borrower and loan type is an important part of rate seasonality, all else equal, observationally identical borrowers receive different credit terms depending on their season of need.[9]

Columns 5 and 6 repeat the specifications of 3 and 4, replacing season dummies with the seasonal prediction from the non-Compustat firm holdout sample, eliminating concerns about bias in our inference based on our prior knowledge of seasonality. Comparing firms with the same rating and even the same firm over time (in column 6), we find that 50-60% of the seasonal magnitudes observed in the holdout sample are still evident, even after controlling for firm and loan characteristics. It is worth noting how similar the coefficient estimates and R^2 are between columns (3) and (5) and columns (4) and (6). Although we control for seasonality in two very

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[9] The seasonal variation in loan spreads which we have documented is based on the calendar not the fiscal year. This raises the question of whether the pattern we document is truly a fiscal year phenomenon. Empirically distinguishing between a calendar and fiscal year pattern is difficult due to the multi-collinearity of the monthly dummies based on the calendar and fiscal year. In our sample, 76% of firms have a December fiscal year end. To test whether the seasonal pattern is different for firms with a non-December fiscal year-end we include an additional 11 dummy variables. The 11 dummy variables are equal to one for the second through twelfth month of the fiscal year if the firm has a non-December fiscal year end and zero otherwise. Thus for a firm with a March fiscal year end that closes their loan during March the fiscal month 12 dummy would be equal to one.

We re-estimated column (1) through (4) in Table 2 and found the inclusion of these fiscal month dummy variables had very little effect on the estimated difference between the loan spread in the expensive and cheap seasons. The expensive-cheap spread is 18.55 (p-value<0.01) in column (1) and 5.94 (p-value=0.019) in column (4). These numbers are almost identical to what we report in Table 2. The F-statistics that the fiscal year monthly dummies are jointly zero is not statistically significant. The p-value is 0.57 in column (1) and 0.82 in column (4).

distinct ways (e.g. dummy variables for the expensive and cheap periods in columns (3) and (4) and with the holdout sample in columns (5) and (6)), the data says they are measuring essentially the same pattern. The appendix replicates these main results over a variety of subsamples and alternative specifications and finds similar effects.

The rating sample results leave the analysis open to concerns that ratings are an incomplete or poor measure of borrower risk or, more to that point, the risk captured by ratings may not map one-to-one into loan spreads. Suppose for example, that market participants possess superior information than the rating agencies. Any seasonality in unobserved borrower creditworthiness may have a substantial effect on loan spreads but not be captured by controls. Moreover, limiting yield determination to default frequency ignores the lessons of state pricing— that the state of nature in which a loan defaults should also dictate its expected return. Thus, rather than trying to project firm characteristics onto spreads in an effort to control for risk, the second half of Table 2 instead uses a measure of risk premium taken from another market to capture a more complete picture of borrower risk.

In particular, we focus on firms for which credit default swaps are traded (and spreads reported) in the month in which each loan in our sample is issued and use the reported CDS spread as a control for borrower risk. CDS spreads provide a useful alternative to ratings in that the spread on credit default swaps should impound any information the market, and thus bankers, have about the borrower. Moreover, because CDS spreads are themselves risk premia, they control for the probability of default as well as the covariance of expected cash flows on borrower loans/bonds with stochastic discount rates. Finally, after controlling for CDS spreads, we can dismiss the notion that, more broadly, risk premia follow a predictable seasonal pattern, or at least that seasonal risky premia drive seasonal loan spreads.

We use Markit data to match the merged DealScan/Compustat database to CDS spreads. Matching is based on borrower name, where we accept only exact or very close matches where there is no ambiguity about the identity of the firms. We end up with 2,064 loan transactions for which the borrower had a quoted CDS spread in the closing month for the loan. Markit reports quoted spreads for various maturities. We use the average 5 year spread reported during the closing month. In the rare event that the 5 year spread is missing, we default to reported 3 or 7 year spreads. With CDS spreads in place, we replace the model in equation (1) with the following specification:

$$AllinSpread_{i,t} = \delta_t + \gamma_{industry} + \lambda Seasonal_t + \theta_1 CDS + \theta_2 CDS^2 + \beta X_{i,t} + \varepsilon_{i,t} \quad (1)$$

We allow for a flexible functional form for the relationship between loan spreads and CDS spreads, including both the level and the squared CDS spreads as controls in our regression. This nonlinear functional form is supported by our regression results, as well as visual inspection, which suggest the relationship between loan spreads and CDS spreads is concave. Finally, because borrowers with traded CDS have substantially different transaction timelines than firms in the holdout sample (typically smaller, privately owned firms), the time between rate setting and loan closing will impact the timing of the observed seasonality. To account for this, we adjust the dates for the CDS sample back by 2 weeks so that the CDS spreads will better reflect firm circumstances as of the original negotiations dates. The 2-week adjustment is based on the mean difference in closing speed for borrowers in the CDS and holdout samples, estimated from the subsample of loans for which facility start date and mandate date are both reported in DealScan.

Due to the limited availability of the CDS spread data, our sample shrinks appreciably when we condition on its existence. However, replacing the rating dummies (column 3) with the

CDS spread and its square (column 7) again produces a similar estimate for the seasonal difference – 7 basis points. Finally, in column 8, the effect of the coefficient on the out of sample seasonal effect is larger than before (0.73 versus 0.51) but not significantly so, and still notably smaller than one. As before, the coefficient estimates and R^2 are almost identical across the two ways to measure seasonality.

Our interest in the reported results is twofold. First, note that loan seasonality is not solely a product of variation in borrower risk. Rather, the evidence suggests that even using a variety of controls for the market price of a borrower's risk, lenders mark-up loans priced during the winter and summer, and provide discounted borrowings in the fall and late spring. Given that CDS spreads represent a natural baseline cost of credit for the borrower, the first result suggests that lenders' ability to generate rents from their specialized services varies within the calendar year.[10]

Second, the attenuation in the seasonal effect after appropriately controlling for borrower risk implies that borrowers respond to seasonal lender markups by sorting into different periods in ways that are correlated with their risk. Table 3 makes this point directly by estimating an ordered probit model of the season in which a borrower times its issuance, using logged CDS spreads as the right hand side variable of interest. Season of issuance are coded as a -1 for cheap issuance seasons (low spreads), 1 for the expensive issuance season (high spreads), and 0 for the

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[10] After controlling for ratings-based, accounting-based, and even market-based measures of borrower risk, we've interpreted the residual spread between expensive and cheap seasons as a non-risk markup charged by lenders, making borrowing in January and February more expensive for the average borrower. The alternative explanation is that loans issued in these months are riskier in ways that we have not controlled for. Although we can never be certain we have the same information about risk that the borrowers and lenders have, we can take an alternative approach to answering this question. If the spread we find in Table 2 is unmeasured risk, then borrowing in January and February is not more expensive for borrowers, nor is it more lucrative for lenders. In this case, there is no incentive for borrowers to move their borrowing away from the expensive months. Nor is there any incentive for lender to try and poach loans in the expensive (more lucrative months). We find evidence of both behaviors and both are consistent with the spread we find being a differential markup opposed to a difference in unmeasured risk. We examine the behavior of borrowers at the end of this section and the behavior of lenders in Section IV.

rest of the year. We also include controls for the fiscal year end of the borrower and industry fixed effects, both of which may determine the choice of issuance season, as well as year dummies. The marginal effects reported in column 1 under the coefficient estimates suggest that a one standard deviation move in CDS spreads reduces the probability of issuing during the cheap season by 2.6% and increases the probability of an issuance during an expensive month by 2.0%.[11]

The evidence of seasonality in issuer quality is open to a few alternative interpretations. The first interpretation is that, given the coordinated reduction in lending and borrowing during expensive periods, only borrowers in desperate need will seek financing. Thus, the act of borrowing itself may serve as a strong signal of the severity of borrower need, causing the lender to rationally update his belief about borrower risk.[12] A related interpretation would be that the borrower has received a severe liquidity shock which was completely observable and caused the both the urgent borrowing need and the deterioration in CDS spreads.

Either of the above interpretations would suggest that changes to borrower CDS, rather than the level of the CDS, should be linked to borrowing in expensive months. Column 2 of Table 3 finds very weak evidence of this. In column 2, we replace logged CDS spreads with the change in logged CDS spreads, where the difference in spreads is measured between the month of issuances and 6 months prior, we find the coefficient on CDS changes is positive, but not significant. Meanwhile, in column 3, we find that controlling for both the level and the change in spreads in the same specification, only the level effect is correlated with issuance season.

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[11] Logged CDS spreads and changes in logged CDS spreads in Table 3 are standardized (demeaned and given unit variance) such that the marginal effect can be interpreted as the effect of a one standard deviation change in the variable of interest on the probability of issuance in a given season.
[12] This explanation does not explain seasonality. The presumed new information about borrower risk revealed by the borrowing season should be reflected in CDS spreads. Table 2 showed that, even controlling for all priced information regarding the borrower's condition, banks charge a markup for their services during summer and winter.

Replacing the backwards looking change in CDS spreads with a forward looking measure (the change in spreads from 6 months prior to six months after issuance) in column 4 leaves the results largely unchanged.

Thus, while we can clearly say that borrowers who tap the markets during expensive months tend to be riskier borrowers than those who take advantage of fall and late spring discounts, there is no evidence that the act of borrowing coincides with or signals credit deterioration. Rather, it seems that there is a fixed component of borrower risk which plays a role in the timing of issuance.

This leads us to a second interpretation of the selection effects in which firms facing low costs of financing arrange for precautionary financing during "sales" in anticipation of potential borrowing need during the high priced seasons. The precautionary borrowing in the seasonal context is a straightforward extension of the literature on the use of lines of credit and excess cash to provide for unexpected investment opportunities. Lins, Servaes, and Tufano (2010), for example, suggest firms may pre-arrange lines of credit in order to make acquisitions on short notice. In the seasonal setting, we can imagine firms reserving their funding during cheap periods in order to lock-in rates in the event an investment opportunity arises.

However, there may be substantial variability in the cost of the option embedded in a line of credit (or alternatively, a funded loan invested in cash or liquid securities). Whereas in a Modigliani-Miller world, the discount rate for holding cash is the same for a risky or riskless firm, when cash or lines of credit are retained for the purpose of making risky investment in the future, conditional on the investment opportunity arising, then the discount rate will depend on the riskiness of the universe of possible opportunities and the probability of each arising. Martin and Santomero (1997) show that firms with a high variance associated with their investment

opportunities face higher costs of securing precautionary funding and therefore are more likely to rely on spot borrowing markets as opportunities arise. If we think firms with higher CDS spreads face more uncertain growth paths, then we would expect to see low risk firms issuing more in the late spring and fall, thereby leaving winter and summer for weaker credit funding themselves in the spot market. Alternatively, firms with higher CDS spreads may face more severe hidden information or hidden action problems and therefore pay a larger dead weight cost of arranging precautionary financing than a firm which could more easily be trusted to serve as a good steward of cash until the arrival of such a project. Either case will generate the variation in borrower quality we observe over the cycle.

Evidence on the precautionary nature of seasonal borrowing comes in two flavors. First, we can look at transactions during "sales" and see if borrower behavior—in particular, the use of credit lines and investment patterns— fit a model of precautionary issuance. Second, we want to examine borrowings done in expensive periods and question the extent to which these borrowers appear as if they are responding to unanticipated investment opportunities. We do this by looking at the drawdown and investment behavior of borrowers, as well the types of loans and the use of proceeds reported for borrowings over the course of different issuing seasons. [13]

Table 4 returns to the full linked DealScan-Compustat sample and reports on the sources and uses of cash associated with new financings as a proportion of DealScan issuance activity during that quarter. Of interest is the extent to which firms actually borrow the funds available to them under new loan facilities, and how that depends on the season of loan issuance. For each borrower x quarter observations, we sum up the total volume of DealScan issuance reported and

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[13] An additional way to examine the motivations of firms in our sample is to examine individual cases. We thus searched the financial press and analysts reports of firms in our sample who borrowed in the expensive months. In the vast majority of cases, firms do not publicly disclose the reasons for their financing. In a few cases we were able to determine the motivation for the financing and why the firms were unable to predict their financial needs or postpone the investment project. Four examples are contained in the appendix.

note the season of issuance. *CheapSeason* refers to issuers who arranged their financing during May, June, and October. *ExpensiveSeason* refers to January, February, and August, and the base category reflects issuers who arranged financing during the rest of the year. Non-issuers or issuers who spread their borrowings across multiple seasons are then excluded from the sample. Also excluded from the sample are small borrowings (those which constitute less than 5% of the firm's total assets) and are therefore unlikely to be systematically related to changes in cash flows.

In columns 1 and 2, we focus on the change in cash attributable to new financing from the firm's statement of cash flows, scaled by the total volume of DealScan facilities closed during the quarter. Note, we only observe loan commitments made in DealScan and not the extent to which borrowers actually borrowed from their facilities. Thus, cash flow from financing scaled by total issuance suggests the extent to which borrowers actually drew down on the funding sources they arranged, during the quarter in which they arranged it. Said otherwise, we track variation in the extent to which firms exercise the call option on funding embedded in a line of credit and how that depends on season of issuance. In columns 3 and 4, we then look to the percentage of funding reserved which was allocated in new investments, again using net investment variables from the statement of cash flows.

In each case, the coefficient estimates reported for the variable *CheapSeason* (*ExpensiveSeason*) represent the mean difference in drawdown/investment activity observed for firms who issue during the cheap (expensive) season, relative to those issuing during the rest of the year. As controls, we include the percentage of issuance which appears to be new issuance activity, defined as 1 minus the percentage of issuance flagged as a refinancing in DealScan or for which the primary purpose was flagged as debt repayment. We also control for cash flows

from operations, derived from the borrower's statement of cash-flows. Finally, in addition to year dummies, we also include dummies for the fiscal quarter in which the issuance (and related cash flow from financing/investment) occurred to account for the fact that firms may have seasonality in their fiscal reporting cycle which coincides with the loan market seasons. Columns 2, 4, 6, and 8 also include borrower fixed effects.

Focusing first on the results from columns 1 and 2, we immediately see a consistent pattern tying the extent to which funds are drawn to seasonal cost. Compared to the rest of the year, cheap season borrowers use 0.4% less of the financing they raise in syndicated lending markets, whereas those issuing during the expensive season drawdown 2.5% more. This 3% difference in cash from financings is significant at the 1% level. The effect is unchanged when borrower fixed effects are included as controls. Thus, a given borrower will draw down more of the cash raised via a loan when the loan is completed during an expensive period than a cheap period.

A similar result obtains when comparing the investment activities of borrowers based on issuance season. Specifically, borrowers who borrow during discount periods spend 2-3% less of the commitments raised on investment than when they borrower during expensive months. This post-issuance behavior is consistent with high quality spring and fall issuers responding to cheap funds by raising precautionary credit in case financing needs arise, and lower quality issuers deferring borrowings until a clear need for disbursement and spending is identified, even if it means borrowing at higher rates.

The results presented in columns 1 through 4 would seem to suggest that demand does move in response to season price variation. In particular, firms seem to take advantage of sales periods by issuing, even when their apparent need (at least their ex-post realized need) for

funding is low. Meanwhile, the selection effects apparent in Tables 2 and 3 suggest that the sales periods are populated by firms which enjoy low cost of credit regardless of season. Putting these two effects together, it's tempting to think that the precautionary borrowing motive is stronger for firms with lower borrowing costs, or rather less enticing for firms facing high costs. Returning to the commodities examples from the introduction, commodity buyers need to have access to efficient "storage" for the commodity to arbitrage seasonal spot prices. By way of analogy, if weaker credits are less efficient at storing capital because their net cost of carry is higher, then their ability to move their demand may be limited.

To verify this, we not only need to see that high credit quality firms are more prevalent issuers during cheap periods (as shown in Tables 2 and 3) and that issuance during sales tends to be more precautionary in nature (columns 1-4 of Table 4), but we also need the interaction of the two effects. That is, low interest rate firms will take advantage of sales with precautionary issuance while high interest rate firms ignore sales and issue on as-needed basis. Columns 5 through 8 test exactly this with the inclusion of interaction terms between issuance season and a dummy for low vs. high interest rate borrowers. We classify high interest rate borrowers as those in the top quartile of firms based on the average interest rate spread paid over the DealScan-Compustat linked sample and low interest rate borrowers as their complement (for clarity of presentation, we report our regression results based on interactions with low interest rate dummy).

The evidence appears consistent with precautionary motives being substantially weaker for high interest rate borrowers. Specifically, with either cash flow from financing or investment/issuance amount on the left hand side, there is no difference in drawdown or investment behavior across seasons for high interest rate borrowers. *ExpensiveSeason -*

CheapSeason estimates are not statistically or economically distinct from zero. Instead, it is low-rate borrowers that drive the average effects reported in columns 1-4. The interaction of season of issuance effects and funding cost— *(ExpensiveSeason -CheapSeason) X LowRateBorrower*—represents the differential sensitivity to issuance season effects between high and low rate borrowers. We find the interactions range from 3.8%-5.3% for drawdown behavior and 3.2-3.4% for investment behavior, and are significant at the 5-10% level, depending on the specification. Thus, the precautionary issuance behavior is significantly different (in fact, not evident at all) for firms which live with high costs of capital throughout the year. This suggests that a "storage cost" hypothesis may be at least one mechanism at work which prevents borrowers from fully moving their demand to low cost periods.[14]

Even with some firms issuing on a precautionary basis, some non-deferrable and unanticipated projects will fall into high interest rate periods. In Table 4, we showed these loans were associated with higher level of drawdown and investment. To get a clearer sense of the types of non-deferrable projects being funded during expensive seasons, Table 5 reports the use of proceeds and deal types for the different periods. The top panel tabulates the number of deals by time of issuance (rows) and the use of proceeds (columns) variable reported in DealScan. We also report the percentage of deals linked to each use of proceeds within a given season. Meanwhile, the final row reports an overall chi-squared test of the null hypothesis that the distribution of deal purpose is independent of issuance season, as well as each column's contribution to that statistic. To narrow our discussion, we'll focus on relatively large

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[14] Regressions without borrower fixed effects also report the coefficient on the indicator for high interest rate borrowers (otherwise absorbed by fixed effects). That coefficient is positive and significant for cash flows from financing, consistent with high interest rate borrowers being unconditionally less likely to engage in precautionary borrowing, regardless of season. The result for investment is substantially weaker and is not significant.

contributors to the overall differences in the distribution of deal type over different seasons—commercial paper backups, takeover and LBO deals, and debt repayment.[15]

Not surprisingly, we see that regular, anticipatable financing needs are more typically taken care of during sales periods. Specifically, commercial paper back-up lines used to support the issuance of short-term notes by highly rated borrowers tend to happen during the cheap season. Debt repayments or refinancing also tend to happen during cheap seasons. In each case, the financing need is easy to anticipate and scheduled in advance. In contrast, the table shows that takeovers and targeted acquisition activity seem to be concentrated during expensive months. Unlike investment in new equipment or inventory, acquisition financings are likely to be time-sensitive and non-deferrable. They also may arise unexpectedly, as rival firms may put a target "in play" at any time, forcing bidders to arrange financing on short notice (see the appendix for examples).

The second half of Table 5 repeats the analysis based on the loan type variable reported in DealScan. Consistent with precautionary borrowing, we see that the season of cheap issuance are more frequently populated by short-term revolvers which charge only a commitment fee if the facility is unused. In contrast, during the expensive season, term loans, which are typically funded immediately at deal closing, are more likely. While a small percentage of total financings, the significant increase in bridge financing is also consistent with an urgency of need during more costly months.[16]

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[15] The Chi-squared test statistic in the Table 5 references a Pearson chi-squared test of row-column independence. It is calculated by summing the squared deviations of actual frequency counts for each column x row cell from its expected frequency under column-row independence, in each case scaled by the same expected frequency. The degrees of freedom for the resulting statistic are equal to (number of rows minus 1) x (number of columns minus 1). The numbers at the bottom of each column represent the contribution of the column to the overall Chi-squared statistic. The superscript associated with that number references the p-value of a test that the seasonal distribution for that Deal Purpose is equal to the seasonal distribution for all other Deal Purposes.

[16] Bridge loans refer to short-term loans designed to be refinanced with longer term debt when market conditions improve, in order to fund longer term projects.

Returning to the question of why rationally shifting demand is insufficient to quash the documented variation in credit cost, we've suggested two possible costs of adjustment. First, we documented that only firms with already low interest rates seem to take advantage of the sales, perhaps because cost of storing capital is too high for riskier credits. Second, even with some firms arranging precautionary financing during sales, some high value, non-deferrable projects beyond the scope of pre-arrange lines of credit and cash may still arise during high cost periods.

Before continuing with the next obvious question (why doesn't supply move), it's worth foreshadowing our proposed response by pointing out that the borrower reaction to cyclical variation effectively sorts firms into two periods based on their degree and urgency of their funding needs—low need precautionary issuance during sales and higher need/higher urgency issuance during the rest of the year.[17] In the next section, we'll consider the possible usefulness of this equilibrium sorting mechanism to banks who would optimally like to set an interest rate schedule which charges each borrower exactly based on their willingness to pay, and the resulting disincentives to compete the pattern away.

IV. The supply side of seasonality

In the prior section we showed, even after benchmarking borrowers during high and low priced seasons against firms of equivalent creditworthiness, lending spreads are considerably more favorable to banks during certain times of the year (see Table 2). Having documented the borrower response to these seasonal fluctuations, we now consider why lenders don't simply shift their production into periods of higher markups until the seasonal pattern disappears.

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[17] The firms that borrow in the expensive months do so for less predictable and less deferrable needs. Firms whose projects let them plan ahead or defer their projects and borrow when rates are low do so. This only makes sense if the firms perceive the debt to be more costly in the expensive months compared to the cheap months. This behavior is inconsistent with the loans being correctly priced and the spread we find in Table 2 being due solely to risk.

A possible explanation is that the cost, or possibly the efficiency of labor, varies enough across the seasons so even though prices fluctuate, lender profits are constant, dissuading further lender entry into summer and winter months.[18] This labor cost hypothesis posits that summer/winter loans are more expensive because loan officers' marginal cost of being in the office is higher during these periods and these costs are passed on to the borrower. The intuitive appeal of this argument is bolstered by the close correspondence between peak pricing periods and traditional vacation periods for workers in the financial sector. It is tempting, for example, to imagine a banker works over Christmas break to close a loan in January or forgoes a scheduled trip to the Grand Canyon with her family during July or August might be entitled to additional bonus compensation. Alternatively, labor may simply be less productive during summer months and thus require more labor input on a per deal basis. If, for example, it takes the lead arranger of a syndicated loan twice as long to coordinate participant banks as a result of heavy vacationing, the cost per loan will rise, even though the cost per unit of labor is constant.

The labor costs hypothesis, however, seems less plausible when we hold it up against the magnitude of the seasonal component of spreads. If we attribute the differential spread between peak pricing months and the cheapest months to variation in costs, then the difference in spreads during these months multiplied times the volume of peak pricing issuance delivers a lower bound on the dollar value of the increase in labor costs.[19] Making a similar calculation for each month and summing up, we obtain an aggregate estimate of labor's seasonal component. This number

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[18] We showed in Table 1 that there is little evidence in support of seasonality in base rates like LIBOR, suggesting the other non-labor input in the bank's production function does not drive seasonality in loan rates.

[19] This is a lower bound because it assumes the supply curve facing borrowers is perfectly inelastic due to competition. Under an elastic supply curve, price movement would only reflect a portion of the total increase in costs.

is large $7 billion per annum on average during the period 2000-2011 (excluding crisis years, when new lending was scant).[20]

In particular, the $7 billion number is large when benchmarked against estimates of the total compensation of commercial bankers active in this market. As an example, consider that JP Morgan—easily the dominant lender in this market— arranged 30% of all transactions in 2011. If we conservatively assume JPMorgan bankers are paid comparably to lenders at other banks, then their share of the $7BN seasonal labor costs would be 2.1BN. Yet conversations with employees there suggest roughly 175 bankers work on JPMorgan's syndicated loan desk. Thus, for seasonal labor costs to drive rate seasonality, each worker would need to be paid a $12 million dollar seasonal bonus (2.1 billion divided by 175), in addition to their standard compensation. Even dividing that number by 3 vastly overstates the total compensation of a typical loan officer. So while it is difficult to completely rule out that the cost of bank labor has a seasonal component, the magnitude of variation in spreads makes this an unlikely stand-alone explanation for our findings.

Instead, we'll focus on mechanisms from the supply side which we find more consistent with the magnitudes documented. In particular, consider a setting in which a monopolist lender faces demand from firms with different preferences, unobservable to the lender. While some firms may be willing to pay a great deal for financing, others will be more indifferent. In a perfectly competitive equilibrium, these preferences are irrelevant to the price charged, as competitive lenders will offer loans at their cost. For the monopolist bank, however, its goal will be to price discriminate, charging each borrower exactly their willingness to pay, and thereby collecting the entire consumer surplus associated with the transaction.

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[20] The appendix presents the details of this calculation, which includes not just the seasonal variation in spreads, but also in upfront and commitment fees.

The typical solutions to the monopolist's problem involve generating variation in prices which induce borrowers to reveal their true willingness to pay (WTP), either completely, or at least partially. Salop and Stiglitz (1977), for example, proposed a model of spatial variation in prices, where low WTP purchasers search until they find a bargain, but high WTP purchasers forego search costs and buy at the first store they find. In at least some of the cases, the seller will then be able to capture the high WTP buyers at their reservation price. Varian (1980) extends the model to allow for intertemporal price discrimination in which prices vary randomly in time. Low WTP purchasers wait for sales, while high WTP purchasers buy immediately.

Our setting most closely resembles Conlisk, Gerstner, and Sobel (1984), in which prospective purchasers (borrowers) arrive continuously, have correct beliefs about the temporal pricing schedule set by the seller (the bank) and can either make a purchase of a durable good (borrow) immediately, or wait for lower prices. The equilibrium has the banks initially setting prices high—just high enough to capture rents from high WTP borrowers (but who also anticipate the forthcoming sale)— followed by sales periods which clear the accumulated demand from borrowers with low WTP, who either just arrived to the market or have been waiting for the sale. Once the market is cleared, the bank faces an identical problem with a repetition of the same strategy, thus driving a cyclical pattern in prices. Central to the intuition is the fact that the good being purchased is durable, and therefore gives utility in each period, such that the cost of waiting is higher for high WTP customers. While this certainly might apply to our setting where the cost of waiting will be higher for firms with better projects, we can imagine variation on this theme in which a borrower's reservation rate may be otherwise positively related to its urgency of need. As long as it is more costly for high WTP borrowers to wait, the proposed schedule of intertemporal price variation will yield rents to the lender.

The cyclical pricing solution presented in Conlisk, Gerstner, and Sobel also predicts a matching variation in volumes, consistent with our findings in the loan market. Even with uniform arrival rates of borrowers, low WTP firms will accumulate into sales periods after saving up demand from high priced periods. Finally, a third prediction of the model is that the mix of firms borrowing during "sales" will have lower need for funding. In the prior section, we showed that borrowers coming to market during sales tend to have less ex-post use for the funds raised, drawing-down less of the their loan facilities immediately and investing less in the quarter of issuance.

The evidence on price, volume, and borrower behavior all line up closely with the predictions of a model of a monopolist bank's optimal seasonal pricing schedule designed to price discriminate. This suggests an answer to the question of why supply does not move to take advantage of, and ultimately quash the predictable price variation.

At the same time, if lenders were to devise the optimal seasonal pricing schedule as a manner of achieving third degree price discrimination, their ability to sustain it would depend critically upon the nature of lender competition. While the models described above assume a monopolist price setter, in practice, the syndicated loan market is better characterized as an oligopoly of ten or so banks which set terms for the majority of transactions, and a competitive fringe of outsider banks arranging the occasional deal. Sustaining any pricing schedule which deviates from marginal cost, therefore will depends on lenders' ability to uphold a cooperative equilibrium.

To test this, we'll look at variation in conditions which might reasonably impact the feasibility of cooperative pricing in the bank market. In particular, we'll focus on two basic

facilitating conditions: market concentration and the ability to punish lenders which deviate from the cooperative equilibrium.

Unconditionally, the syndicated loan market appears to support both conditions with a handful of large lead arrangers interacting frequently. The concentration of lead arrangers over time, however, has been subject to variation, as large bank mergers in the 1990's consolidated the market share of the top banks. The dashed line in Figure 4 plots the percentage of loan market volume which was led by a lead arranger who was among the top ten lead arrangers from the prior year (lenders are ranked in terms of the dollar volume of transactions arranged). A few noteworthy periods of consolidation are apparent. From 1991-1993, the top two lead arrangers, Chemical Bank and Citibank, nearly doubled their market share, partly driven by Chemical's acquisition of Manufacturers Hanovers Trust (an independently important player in this market at the time). Similarly, from 1998-2001, Bank of America's merger with NationsBank and the merger of JPMorgan and Chase consolidated the volume of deals arranged by the top banks considerably. The reverse trend from 2002-2009 meanwhile is less obvious, but generally appears to be driven by increased transaction flows to smaller non-US, and in particular, European banks.

To the extent that market concentration facilitates cooperative behavior among lenders, a first test of the supply side roots of seasonality is to link the degree of seasonality to market concentration over time. Our hypothesis is that as the market becomes more dispersed, coordination will become more difficult and opportunistic lenders will move capital to high priced seasons, reducing the seasonal effect.

Continuing with Figure 4, the solid line reports the magnitude of seasonality on an annual basis, estimated by regressing individual loan spreads on the seasonal effect variable (described

in Table 2), year dummies, and the interaction of each year's dummy with the seasonal effect. The seasonal magnitude, captured by the coefficient on the year dummy times the seasonal effect variable, appears to follow lead arranger market concentration, as predicted. Table 6 formalizes this test, first presenting the actual seasonal interactions by year, along with standard errors and significance levels. We see that the seasonality's strength varies substantially by year. Meanwhile, panel B links that annual variation to the percentage of loan volume arranged by the top 10 banks in the prior year. Column 1 includes only time dummies as controls, while column 2 adds controls used in Table 2 to partial-out firm creditworthiness. The interaction between market concentration and seasonal effect captures the covariance between the strength of the "pure" seasonal effect (after conditioning out borrower risk) and market concentration. We present the results with market concentration demeaned and divided by its standard deviation, such that the economic interpretation of the interaction term refers to the variation in the strength of the seasonal effect related to a one standard deviation move in market concentration. With or without controls, seasonality appears to depend on the prevailing market structure, with a one standard deviation increase in concentration, nearly doubling the range of spreads from peak to trough. It shouldn't be surprising that the effect becomes smaller and less significant after controlling for firm and deal characteristics, as the sorting effects described in Section III should be expected to strengthen and weaken together with the "pure" seasonal effect. Meanwhile, in column 3 we add separate interactions for the level and volatility of spreads. The variable *mean spreads* reflects the average loan spread during each calendar year, while *std. deviation monthly spreads* is calculated based on the annual standard deviation of the 12 monthly average spreads during that year. Neither interaction drives out the seasonal variation, allowing us to reject this

notion that seasonality is simply proxying for either market volatility or time variation in risk premia which might plausibly be linked to lender consolidation or entry.[21]

A second way to examine the effect of concentration on seasonality is to exploit the cross-sectional variation in lender concentration across industries. Banks which specialize in oil and gas may be less active in telecom and *vice-versa*, for instance, allowing for industry-by-industry variation in market structure and concentration. While we won't claim that lender concentration is random or unrelated to other market characteristics, it is a necessary facilitation condition for seasonality to sustain itself under the price discrimination mechanism described, and thus it provides a sensible test of the theory. Whereas the time series tests focused on the yearly sensitivity to an established pattern of sensitivity—something we might think of as the average seasonality across markets— there is nothing guaranteeing that different segments of the loan market will coordinate on the same seasonal pattern. Moreover, even if they did, variation in the timing of transactions (the time between loan negotiation and closing) might drive some industries to look as though they had limited seasonality because transaction cycles were longer or shorter than average. As a result, we instead characterize highly seasonal industries as those with a high seasonal R-squared—the R-squared from a regression of loan level spreads on 12

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[21] Since bank loans are not the only source of debt capital for the firms in our sample, it is not enough that banks successfully coordinate among themselves. Bond investors, which can be thought of as an uncoordinated mass of lenders, would have similar effects on seasonality as an influx of new bank entrants. In Panel C, we replace bank market concentration with a measure of flows into corporate bond mutual funds. Flows are estimated using CRSP data as the change in total net assets for corporate bond funds, less year-end returns on the prior year's total net assets and are standardized to have mean zero and unit standard deviation. Corporate bond funds are flagged as those funds with CRSP mutual find style codes ICQH (high quality corporate bonds), ICQM (medium quality corporate bonds), and ICQY (high yield corporate bonds). Our time series starts in 1993, the first year Strategic Insight Objective codes used to construct CRSP fund objective codes are reported.

Focusing on the interaction between seasonal sensitivity and bond fund flows, we see that in periods of strong inflows (more competition) seasonality is attenuated (see Table 6 – Panel C). The coefficient on the interaction term between seasonality and fund flows of 1.09 in column 1. This means that a 1.6 standard deviation increase in fund flows is needed to completely remove the aggregate seasonal effect from our pricing regressions. These levels of flows occur only twice during our sample period. So while competition from the bond market affects seasonality in a manner similar to competition within the bank market, only in periods of extreme bond market liquidity is seasonality eliminated.

calendar month dummies (this approach follows Miron's (1996) measure of industry level seasonality). Consistent with the rest of the paper, we identify industries using Fama and French's classification, this time splitting the loan market into 49 industry segments of the loan market. To measure market concentration, each year and for each industry, we calculate the percent of the loan market volume led by the top ten banks in that industry and average that number overall years in the sample.

Figure 5 plots the log of each industry's seasonal R-squared against the proposed measure of market concentration. Similar to the time series relationship between the bank market structure and seasonality, we find industries with concentrated bank groups tend to exhibit more seasonality in interest rates. The correlation between the two measures is 71%, significant at the 1% level. Table 7 extends the analysis by adding controls for industry size (average log dollar volume of issuance), the average level of loan spreads, and volatility of annual mean loan spreads over the sample period. While ex-ante, we're agnostic about the predicted signs from these controls, we might worry that seasonality simply captures other statistical or economic properties in these markets. Even with these controls, a 10% level increase in market share of the top 10 banks increases seasonality by roughly 40%.

Table 8 considers the second facilitating condition for a cooperative pricing strategy, which is the ability to punish rogue lenders who undermine the optimal pattern of sales and pricing. In our view, the obvious mechanism for punishment relates to a shirking bank's ability to syndicate transactions in the future to their peers. The punishment mechanism, however, depends on the frequency of interaction with other banks. The implication is that banks which are less central and therefore have less frequent interactions with other banks in the loan market as lead arrangers will have more incentive to undermine the equilibrium and increase market

share during high priced periods. We test this prediction by looking at the seasonal variation in the probability of a bank from outside the top-ten (ranked by lead arranger volume from the prior year) leading a transaction for an investment grade rated borrower. We focus on the subsample of investment grade borrowers because these transactions are unconditionally less likely to be led by the smaller banks, absent the advantage they are ceded by the larger banks committed to maintain "cost plus" pricing during the summer and winter periods. Columns 1 through 3 report the marginal impact of the seasonal pricing effect (reported as a percentage) on the probability of a non-top 10 bank serving as the lead arranger (or lead arrangers in the case of jointly lead deals) for investment grade borrowers. The key control in column 2 is the inclusion of borrower size, which, even within investment grade borrowers, may be correlated with the probability of an outsider bank leading the transaction. We also include other firm controls including ratings, as well as deal characteristics. Finally, in column 3 we add firm fixed effects (and replace the probit specification with a linear probability model) to isolate the impact of issuance season on lender choice for a given borrower. In each case, the effect is statistically and economically significant. The smallest estimates imply that the peak to trough variation in seasonal spreads of 20bps (0.2%) drives a 3.7% increase in the likelihood a given borrower will tap an outsider bank to lead its transaction. This is a large effect, especially considering the unconditional probability of an outsider bank leading an investment grade deal of just 16%.

Figure 6, meanwhile presents the corresponding visual evidence, with side-by-side plots of the seasonal effect for investment grade rated borrowers and the percentage of transactions led by banks outside the top 10. From the seasonal trough prices in June to the peak in February, the probability of a smaller, outsider bank successfully winning a mandate from a top borrower increases from 12.9% to 17.3%.

The entry of fringe banks during expensive periods provides the counterintuitive result, albeit consistent with the model of price discrimination presented above, that markets appear more competitive during periods of high prices. In this case, the high prices attract competition via the entry of smaller players.[22] Meanwhile, because of their size and limited capacity, we think that the smaller players are unable to sufficiently compete away the lender rents, although this remains an area for further exploration.

V. Discussion

The patterns we've documented of recurring periods of significant markups and discounts in the market for corporate debt raise questions about both the dynamic nature of borrower demand over relatively short horizons and the rate setting behavior of large banks. The evidence presented suggests that firms with already low costs of funds are prone to time the market when sales occur, and then store liquidity in anticipation of future funding needs. High costs borrowers, meanwhile, appear less prone to precautionary borrowings during cheap periods and instead tend to fund themselves, sometimes during predictably high cost periods, as needs arise. Given the anticipation of loan sales in the future, the financings raised during high costs periods appear to be driven by unpredictable and non-deferrable capital needs.

On the supply side, we have argued that this predictable fluctuation in costs of funds fit the patterns of intertemporal price discrimination described in the industrial organization literature. The evidence we've presented on the plausibility of cooperative rate setting by lenders is open to a range of interpretations. An extreme interpretation would imagine lenders are

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[22] Just as we argued that firms will only move their borrowing out of the expensive months if they perceive these months as being more expensive, a similar argument works on the supply side. If the risk-adjusted return is the same across the year, there are no incentives for the competitive fringe to poach transactions during the more "expensive" months. Thus, the behavioral response of outsider banks seems to further bolster evidence for an economically significant seasonal markup as opposed to seasonal risk factors or compositional effects completely driving the seasonal pattern we document in Table 2.

explicit in forming a cartel, deriving the optimal price schedule, and designing and implementing explicit modes of punishment for those who break rank. A more nuanced, and we believe a more plausible, interpretation requires neither a strong statement about the origins of seasonality, nor lender intent. It instead asks, given the presence of a pricing pattern which is ex-post optimal for the group, what are the incentives to compete it away. In this context, seasonality exists as a fortunate anomaly which less than perfectly competitive lenders are more than happy to preserve.

This argument matches well with one suggested source of the seasonality which is centered around US winter and summer vacation schedules, both typically expensive seasons. While we argued that seasonal labor costs can't plausibly explain the magnitude of the seasonal effect we observe, they might provide a plausible focal point around which banks could naturally coordinate softer competition.[23] Consider for example that bankers have incentives to be out of the office during holidays, perhaps pricing bids on new deals less aggressively to preserve family vacations. Yet from a governance perspective, shareholders have limited incentives to correct this if it achieves, as we've argued, the effects of third degree price discrimination. Thus, allowing loan officers to accrue rents in the form of more relaxed summers and winter holidays is optimal for bank shareholders, as long as other bank shareholders allow the same.[24]

Meanwhile, note that we've also made no statements regarding the welfare implications of this behavior. Third degree price discrimination may be strictly preferable in the aggregate to Cournot competition among a handful of lenders, to the extent that banks are less prone to under produce credit when they capture the entire surplus from a given transaction. Moreover, if lender rents mitigate excess risk taking, as has been suggested by some in the bank competition

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[23] In theory, seasonal price discrimination could focus on any calendar date. GE and Westinghouse famously used the phase of the moon to coordinate pricing of turbines used for electrical generation (see Lewis and McAfee (2009)).

[24] Thanks to for Chris Parsons for helping guide us to this intuition.

literature, then seasonality and the related rents may also generate positive externalities for the broader economy.

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Table 1: Season Variation in Loan Spreads and Volumes. The table contains tests of seasonality across the calendar year for the average loan spreads and volumes from our sample as well as a set of market interest rates. Loan spreads (volumes) are averaged (summed up) for each month times year and thus the unit of observation is a month-year. Tests of seasonality of average loan spreads and logged dollar volumes of issuance are reported in Columns 1 and 2. Both regressions include monthly and yearly dummies. The F-statistics test the hypothesis that the monthly dummies are jointly zero (i.e. there is no seasonality in the data). The year dummies are replaced with autoregressive lags of the dependent variable in Columns 3 and 4. The test from column 1 is repeated on 3-month LIBOR (Column 5), the spread between Baa and Aaa rated bonds (Column 6), and the average monthly quoted CDS spreads for dollar denominated contracts on non-Government names covered in the Markit CDS database (Column 7). With the exception of the data on CDS spreads, the sample period is January 1987-December 2012. For sample for the CDS spreads is 2001-2010. Loan dates are based on effective date—the date on which loan documents become effective and typically the first date the borrower can draw down. Newey-West standard errors with a lag length of 12 months are reported in parentheses. Statistical significance at the 1, 5, or 10% levels is reported as superscripts. Constants are excluded from all models.

	(1) Mean Monthly Spread	(2) Monthly Volume	(3) Mean Monthly Spread	(4) Monthly Volume	(5) 3 Month LIBOR	(6) Baa-Aaa Spread	(7) CDS spread
Lag1 (dependent variable)			0.58^{1}	0.47^{1}			
			(0.08)	(0.07)			
Lag2 (dependent variable)			0.30^{1}	0.16^{1}			
			(0.07)	(0.06)			
Lag3 (dependent variable)			0.07	0.23^{1}			
			(0.10)	(0.08)			
Lag4 (dependent variable)			0.09	0.10^{10}			
			(0.06)	(0.06)			
Lag12 (dependent variable)			-0.03	0.01			
			(0.04)	(0.04)			
Month Dummies	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	NO	NO	YES	YES	YES
Observations	312	312	300	300	312	312	109
F-Test of equality of monthly	3.13^{1}	19.86^{1}	5.55^{1}	17.33^{1}	0.46	0.57	0.28

Table 2: Loan Level Seasonality. Table 2 estimates regressions of loan spread on seasonal variables and controls, including long term debt ratings and prevailing credit default swaps spreads for the borrower in the month of issuance and loan characteristics. *Cheap Season* and *Expensive Season* dummies denote the month in which the deal was closed. *Expensive–Cheap* at the bottom of the table reports the spread difference between issuance in January, February, and August (expensive) and issuance in May, June, and October (cheap). Seasonal effect is the monthly/seasonal prediction in loan spread from the holdout sample of non-Compustat firms. Standard errors clustered by firm and month are reported in parentheses. Statistical significance at the 1, 5, or 10% levels is reported as superscripts.

				Rated Sample		
Loan Spread (in basis points)	(1)	(2)	(3)	(4)	(5)	(6)
Seasonal Effect (holdout sample)					0.60^1	0.51^5
					(0.21)	(0.21)
Cheap Season (May, June, Oct)	-4.02	-0.08	-1.80	-0.51		
	(3.10)	(2.37)	(1.84)	(1.91)		
Expensive Season (Jan, Feb, Aug)	14.96^1	10.91^1	5.51^5	5.31^5		
	(4.20)	(3.07)	(2.37)	(2.46)		
ln(Maturity)		-3.03	-4.24^1	-2.86^{10}	-4.23^1	-2.86^{10}
		(2.17)	(1.60)	(1.55)	(1.60)	(1.55)
Secured		119.13^1	30.98^1	24.04^1	30.87^1	23.93^1
		(3.32)	(3.47)	(3.46)	(3.47)	(3.45)
ln(Assets)			-1.48	0.93	-1.53	1.02
			(1.17)	(2.86)	(1.17)	(2.85)
Operating Profit/Assets			-152.89^1	-195.77^1	-152.73^1	-195.88^1
			(16.78)	(23.72)	(16.77)	(23.69)
Total Debt/Assets			37.54^1	35.71^1	37.39^1	35.46^1
			(5.31)	(9.86)	(5.31)	(9.84)
PP&E/Assets			1.75	15.55	1.50	15.71
			(5.73)	(14.14)	(5.73)	(14.14)
Time Fixed Effects	YES	YES	YES	YES	YES	YES
Deal Purpose Fixed Effects	NO	YES	YES	YES	YES	YES
Industry Fixed Effects	NO	NO	YES	-	YES	-
Ratings Fixed Effects	NO	NO	YES	YES	YES	YES
Firm Fixed Effects	NO	NO	NO	YES	NO	YES
Observations	12,087	12,087	12,087	11,414	12,087	11,414
R-squared	0.12	0.41	0.63	0.77	0.63	0.77
Expensive-Cheap	18.98^1	10.99^1	7.31^1	5.82^5		
	(4.66)	(3.28)	(2.38)	(2.53)		

Table 2: Loan Level Seasonality (cont).

Loan Spread (in basis points)	CDS Sample	
	(7)	(8)
Seasonal Effect (holdout sample)		0.73[5]
		(0.29)
Cheap Season (May, June, Oct)	-2.42	
	(2.78)	
Expensive Season (Jan, Feb, Aug)	4.97	
	(3.62)	
ln(Maturity)	0.82	1.34
	(2.02)	(1.93)
Secured	23.53[1]	23.24[1]
	(5.70)	(5.73)
CDS Spread	0.30[1]	0.29[1]
	(0.03)	(0.03)
$(CDS\ Spread/100)^2$	-1.04[1]	-1.02[1]
	(0.15)	(0.15)
ln(Assets)	-2.00	-2.09
	(1.80)	(1.79)
Operating Profit/Assets	-48.34	-53.39[10]
	(30.76)	(30.99)
Total Debt/Assets	17.12	19.66[10]
	(11.58)	(11.64)
PP&E/Assets	-21.97[5]	-19.13[5]
	(9.01)	(8.90)
Time Fixed Effects	YES	YES
Deal Purpose Fixed Effects	YES	YES
Industry Fixed Effects	YES	YES
Ratings Fixed Effects	YES	YES
Observations	2,064	2,064
R-squared	0.78	0.78
Expensive-Cheap	7.39[5]	
	(3.67)	

Table 3: Loan Issuance Timing: The Seasonal Effect. Table 3 estimates an ordered probit model of the decision to issue during the cheap season (-1) vs. the expensive season (1) vs. the rest of year (0). The ordering goes from cheap, to rest of year, to expensive. Below the model estimates, we report the marginal effect of the log CDS spread (or the change in the log CDS spread) on the probability of issuing during each season. Independent variables are standardized (zero mean and unit variance) such that the marginal effect can be interpreted as the effect of a one standard deviation change in the variable of interest on the probability of issuance in a given season. Standard errors clustered by firm are reported in parentheses. Statistical significance at the 1, 5, or 10% levels is reported as superscripts.

Issuance Season (order from cheap to expensive)	(1)	(2)	(3)	(4)
ln(CDS Spread)	0.08^{5}		0.07^{10}	0.08^{5}
	(0.03)		(0.03)	(0.04)
Δln(CDS Spread)$_{t,t-6}$		0.05	0.03	
		(0.03)	(0.03)	
Δln(CDS Spread)$_{t+6,t-6}$				0.01
				(0.05)
$\dfrac{\partial\mathrm{Pr}\,(Cheap\ Season)}{\partial x}$	-0.026^{5}	-0.016		
	$(.011)$	(0.010)		
$\dfrac{\partial\mathrm{Pr}\,(Rest\ of\ Year)}{\partial x}$	0.006^{5}	0.004		
	(0.003)	(0.003)		
$\dfrac{\partial\mathrm{Pr}\,(Expensive\ Season)}{\partial x}$	0.020^{5}	0.012		
	(0.008)	$(.007)$		
Time Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES
Observations	2,064	1,772	1,772	1,687

Table 4: Uses of funding in the quarter of issuance. Table 4 compares changes in various sources and uses of cash around the time of loan issuance for cheap and expensive season issuers. Cheap season issuers are borrowers whose loans closes in May, June, or October, and expensive season borrowers had loans close in January, February, and August. In each case, changes in cash flow are scaled by the total volume of issuance from the DealScan sample by that borrower over the quarter. Repeat borrowers within a fiscal quarter whose borrowings happened over different seasons were excluded from the sample. Columns 5-8 test the differential effect for high and low rate borrowers, which are defined as the firms with average interest rate spreads which place them above (below) the 75th percentile of observations respectively. Standard errors are clustered by firm and quarter and are reported in parentheses. Statistical significance at the 1, 5, or 10% levels is reported as superscripts.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cash flow from financings/ Issuance Size		Investment / Issuance Size		Cash flow from financings/ Issuance Size		Investment / Issuance Size	
Cheap Season (May, Jun, Oct)	-0.004	-0.006	-0.008	-0.011^{10}	0.010	0.008	-0.001	-0.010
	(0.006)	(0.008)	(0.006)	(0.006)	(0.014)	(0.016)	(0.012)	(0.014)
Expensive Season (Jan, Feb, Aug)	0.025^{1}	0.023^{1}	0.016^{5}	0.017^{5}	0.009	-0.004	-0.000	-0.009
	(0.008)	(0.008)	(0.007)	(0.007)	(0.017)	(0.018)	(0.014)	(0.015)
Cheap Season X Low Rate Borrower					-0.017	-0.018	-0.010	-0.001
					(0.014)	(0.017)	(0.014)	(0.015)
Expensive Season X Low Rate Borrower					0.021	0.035^{10}	0.022	0.033^{5}
					(0.017)	(0.020)	(0.014)	(0.016)
Low Rate Borrower					-0.025^{5}		-0.004	
					(0.010)		(0.009)	
Cash Flow from Operations	-0.479^{1}	-0.506^{1}	0.256^{1}	0.189^{1}	-0.472^{1}	-0.506^{1}	0.256^{1}	0.188^{1}
	(0.017)	(0.020)	(0.014)	(0.016)	(0.017)	(0.020)	(0.014)	(0.016)
% New Issuance	0.110^{1}	0.109^{1}	0.111^{1}	0.106^{1}	0.109^{1}	0.109^{1}	0.111^{1}	0.106^{1}
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
Borrower Fixed Effects	NO	YES	NO	YES	NO	YES	NO	YES
Fiscal Quarter Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	20,129	18,100	20,129	18,100	20,129	18,100	20,129	18,100
R-squared	0.125	0.446	0.065	0.421	0.126	0.446	0.065	0.421
Expensive-Cheap	0.029^{1}	0.029^{1}	0.024^{1}	0.028^{1}	-0.001	-0.012	0.001	0.001
(Expensive-Cheap) x Low Rate Borrower					0.038^{5}	0.053^{5}	0.032^{10}	0.034^{10}

Table 5: Deal Type. Table 5 reports the two way tabulation of deal purpose and loan type by issuance season, along with test of row/column independence. Issuance date is based on facility effective date. We aggregate deal purpose and loan type for transaction types with less than 1,000 observations in the merged DealScan-Compustat sample in the "other" category.

	CP Backup	Working Capital	Corp. Purposes	Debt Repay.	Acquis. Line	LBO	Take-over	Other	Total
Cheap Season (May, Jun, Oct)	938	2,361	6,838	3,001	716	562	1,462	1,390	17,268
	5.43%	13.67%	39.60%	17.38%	4.15%	3.25%	8.47%	8.05%	100
Expensive Season (Jan, Feb, Aug)	439	1,776	4,626	2,046	556	516	1,346	1,037	12,342
	3.56%	14.39%	37.48%	16.58%	4.50%	4.18%	10.91%	8.40%	100
Rest of Year	1,346	4,566	11,935	5,706	1,416	1,061	2,796	2,603	31,429
	4.28%	14.53%	37.97%	18.16%	4.51%	3.38%	8.90%	8.28%	100
TOTAL	2,723	8,703	23,399	10,753	2,688	2,139	5,604	5,030	61,039
	4.46%	14.26%	38.33%	17.62%	4.40%	3.50%	9.18%	8.24%	100
χ2 test of rows column independence	61.3[1]	5.9[5]	10.6[1]	13.3[1]	3.6	20.7[1]	52.4[1]	1.2	**169.0[1]**

	Bridge Loan	Note	Revolver < 1 Year	Revolver > 1 Year	Revolver /Term Loan	Standby LC	Term Loan	Other	Total
Cheap Season (May, Jun, Oct)	336	611	2,612	7,848	354	352	3,930	1,225	17,268
	1.95%	3.54%	15.13%	45.45%	2.05%	2.04%	22.76%	7.09%	100%
Expensive Season (Jan, Feb, Aug)	297	482	1,552	5,367	255	243	3,054	1,092	12,342
	2.41%	3.91%	12.57%	43.49%	2.07%	1.97%	24.74%	8.85%	100%
Rest of Year	582	1,119	4,493	13,988	661	661	7,588	2,336	31,428
	1.85%	3.56%	14.3%	44.51%	2.1%	2.1%	24.14%	7.43%	100%
TOTAL	1,215	2,212	8,657	27,203	1,270	1,256	14,572	4,653	61,038
	1.99	3.62	14.18	44.57	2.08	2.06	23.87	7.62%	100%
χ2 test of rows column independence	13.9[1]	3.4	33.6[1]	6.3[1]	0.2	0.8	13.9[1]	32.1[1]	**104.2[1]**

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Table 6: Seasonality by year. In Panel A, we estimate a regression of loan spreads on year fixed effects and the seasonal effect variable (predicted monthly spreads estimated from the holdout sample of non-Compustat firms) interacted with each year's dummy. Reported below are the interaction terms, representing the year-to-year sensitivity to seasonal pricing. Panel B reports the results from a regression of loan spreads on the seasonal effect interacted with the percent of loan volume originated by the top 10 lead banks in the prior year's lead arranger league tables (*Loan Market Concentration*). Column 3 adds interactions with the mean level of annual spreads and the yearly volatility of monthly mean spreads, both estimated from the holdout sample. Unreported controls include ln(Maturity), Secured, ln(Assets), Operating Profit/Assets, Total Debt/Assets, PP&E/Assets, plus 17 Fama-French Industry dummies, deal purpose, and ratings dummies. Standard errors are clustered over firm and month and are reported in parentheses. Statistical significance at the 1, 5, or 10% levels is reported as superscripts.

Panel A: Seasonal Effect (holdout sample) X Year

1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
-0.25	0.75	0.31	2.50^{10}	2.32^5	-0.72	-0.60	1.62^1	-0.28	1.67^5	2.41^1
(1.55)	(1.87)	(0.93)	(1.31)	(1.06)	(0.51)	(1.11)	(0.52)	(0.72)	(0.75)	(0.72)

2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
1.94^1	2.76^1	4.46^1	4.44^1	2.14	0.13	0.54	-2.71	-1.03	2.12^1	4.61^1
(0.58)	(0.82)	(0.55)	(1.33)	(1.52)	(0.71)	(0.80)	(2.20)	(1.12)	(0.74)	(1.22)

Panel B: Seasonal Effect (holdout sample) X Bank Market Concentration

Loan Spread (in basis points)	(1)	(2)	(3)
Seasonal Effect (holdout sample)	1.74^1	0.63^1	0.66^1
	(0.38)	(0.21)	(0.20)
Seasonal Effect (holdout sample) X % Loan Market Concentration	0.94^1	0.43^5	0.73^1
	(0.36)	(0.21)	(0.26)
Seasonal Effect (holdout sample) X % Mean Spreads			0.61^5
			(0.27)
Seasonal Effect (holdout sample) X % Std. Dev Monthly Spreads			-0.12
			(0.20)
Time Dummies	YES	YES	YES
Deal Purpose Dummies	NO	YES	YES
Industry Dummies	NO	YES	YES
Ratings Dummies	NO	YES	YES
Other Controls	NO	YES	YES
Observations	11,738	11,738	11,738
R-squared	0.13	0.64	0.64

Table 6: Seasonality by year (cont). Panel C repeats the exercise from Panel B, replacing bank market concentration with the dollar volume of flows to mutual funds investing in corporate bonds. Flows are estimated as the change in total net assets, less year-end returns on the prior year's total net assets and are standardized to have mean zero and unit standard deviation. Corporate bond funds are flagged as those funds with CRSP mutual find style codes ICQH (high quality corporate bonds), ICQM (medium quality corporate bonds), and ICQY (high yield corporate bonds). Other controls are the same as those reported in Panel B.

Panel C: Seasonal Effect (holdout sample) X Corporate Bond Fund Flows

| Loan Spread (in basis points)	(1)	(2)	(3)
Seasonal Effect (holdout sample)	1.75[1]	0.57[1]	-1.35
	(0.39)	(0.21)	(1.27)
Seasonal Effect (holdout sample) X % Corporate Bond Fund Flows	-1.09[1]	-0.41[5]	-0.49[5]
	(0.33)	(0.21)	(0.22)
Seasonal Effect (holdout sample) X % Mean Spreads			0.01
			(0.01)
Seasonal Effect (holdout sample) X % Std. Dev Monthly Spreads			-0.02
			(0.02)
Time Dummies	YES	YES	YES
Deal Purpose Dummies	NO	YES	YES
Industry Dummies	NO	YES	YES
Ratings Dummies	NO	YES	YES
Other Controls	NO	YES	YES
Observations	11,164	11,164	11,164
R-squared	0.14	0.65	0.65

Table 7: Seasonality and industry concentration. We estimate the seasonal R-squared from a regression of loan spreads on 12 monthly dummies for 49 Fama-French industries and regress this logged R-squared on an industry level measure of bank concentration. The measure consists of the percentage of loan volume led by the top ten banks in a given industry each year, estimated yearly and averaged from 1990-2012. Controls for the mean loan spread and the volatility of annual mean loan spreads in that industry are also included. Standard errors are robust to heteroskedasticity and are reported in parentheses. Statistical significance at the 1, 5, or 10% levels is reported as superscripts.

log(Seasonal R-squared by industry)	(1)	(2)
% volume of loans led by the top 10 banks	0.037^1	0.020^5
	(0.012)	(0.010)
Industry size	-0.553^1	-0.738^1
	(0.119)	(0.126)
Industry mean loan spread		-0.010^1
		(0.002)
Industry volatility loan spread		0.006
		(0.005)
Observations	49	49
R-squared	0.64	0.76

Table 8: Seasonal poaching of borrowers by outsider banks. We report probit regressions of whether a loan to an investment grade rated borrower was arranged by a bank (or banks) outside of the prior year's top 10 league table (a volume weighted ranking of lead arranger activity). The seasonal effect on loan spreads is the predicted seasonal loan spread using average monthly spreads from the holdout sample. Spreads are reported in percentages here, so the marginal effect denotes the change in probability of a non-top-ten bank leading a loan based on a 1 percentage point change in spread. Column 3 estimates a linear probability model with firm fixed effects. Standard errors clustered by firm and month are reported in parentheses. Statistical significance at the 1, 5, or 10% levels is reported as superscripts.

| Non top 10 bank served as lead arranger(s)	(1)	(2)	(3)
Seasonal Effect on Loan Spreads (%)	1.30[5]	0.90[10]	0.22[5]
	(0.54)	(0.53)	(0.11)
Marginal Effect	**0.30**	**0.19**	
ln(Assets)		-0.20[1]	-0.03[10]
		(0.03)	(0.02)
Operating Profit/Assets		-1.82[1]	-0.08
		(0.54)	(0.14)
Total Debt/Assets		-0.00	0.08
		(0.21)	(0.07)
PP&E/Assets		0.36[5]	-0.18[10]
		(0.18)	(0.10)
ln(Maturity)		-0.04	0.00
		(0.04)	(0.01)
Secured		0.29[1]	0.08[1]
		(0.08)	(0.02)
Time Dummies	YES	YES	YES
Deal Purpose Dummies	NO	YES	YES
Industry Dummies	NO	YES	YES
Ratings Dummies	NO	YES	YES
Firm Fixed Effects	NO	NO	YES
Observations	6,256	6,256	6,256
(Pseudo) R-squared	0.06	0.14	0.48

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Figure 1: Seasonal Commodity Prices. The top picture graphs the average price of electricity for each of the 12 months using a sample from 1995 to 2000. The numbers are constructed by taking the average of weekly on-peak (6am to 10pm PST) electricity prices from the Dow Jones California/Oregon Border Electricity Price Index. Below, we reproduce a plot from Meinken (1955) showing seasonal wheat prices. Wheat prices from 1922-1941 are divided by a 12-month moving average and centered to 100 before being averaged by month.
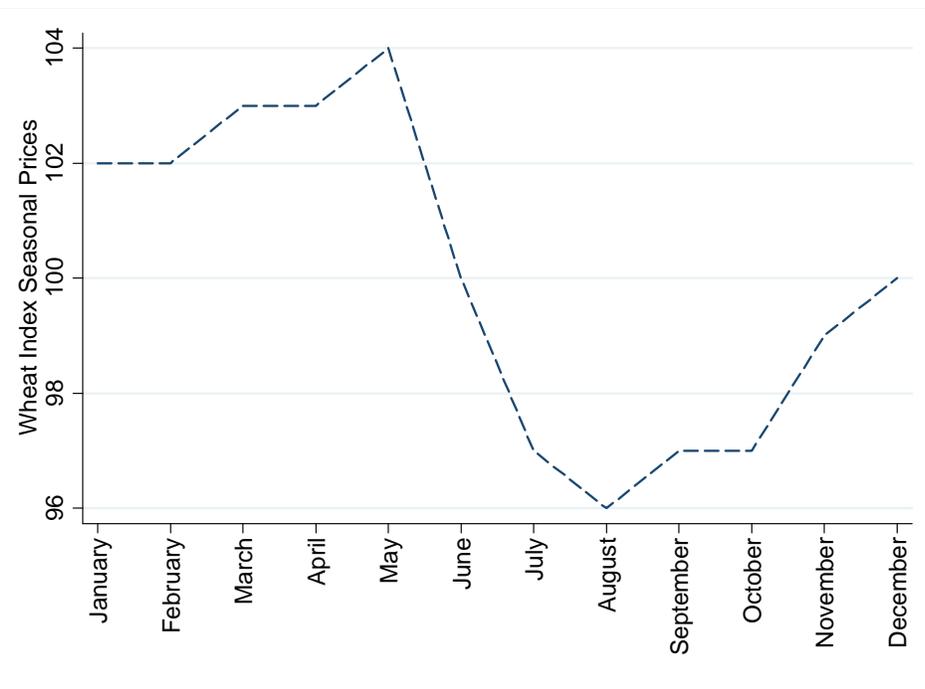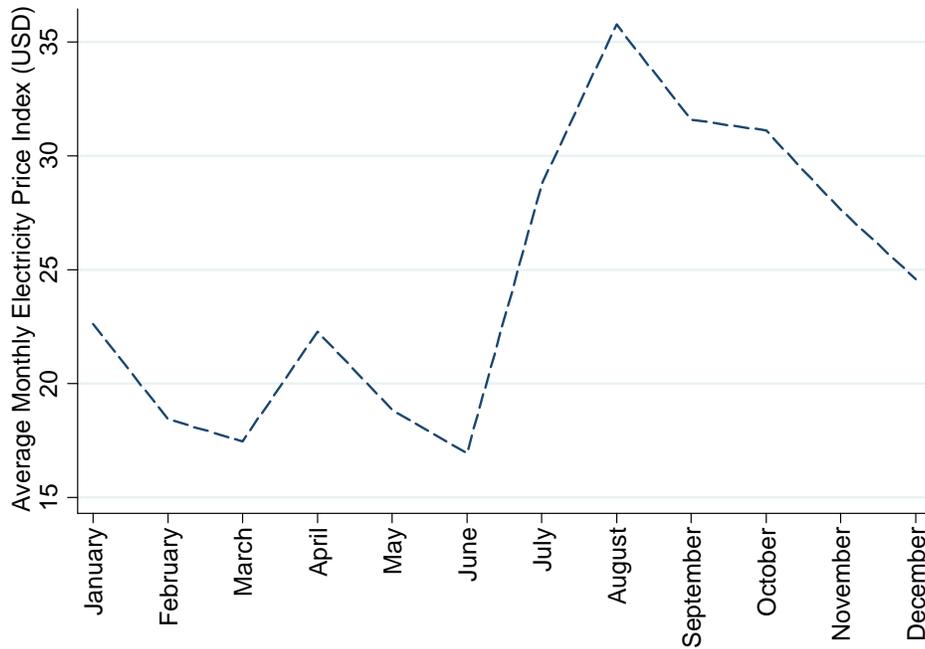
Figure 2a: Loan Spread Seasonality. The solid line in Figure 2 depicts average monthly spreads over base rate for new issue loans from 1999-2007, where the month represents the loan's effective date. The dashed line represents a simple out-of-sample seasonal prediction based on the average spread for each calendar month from 1987 to 1998.
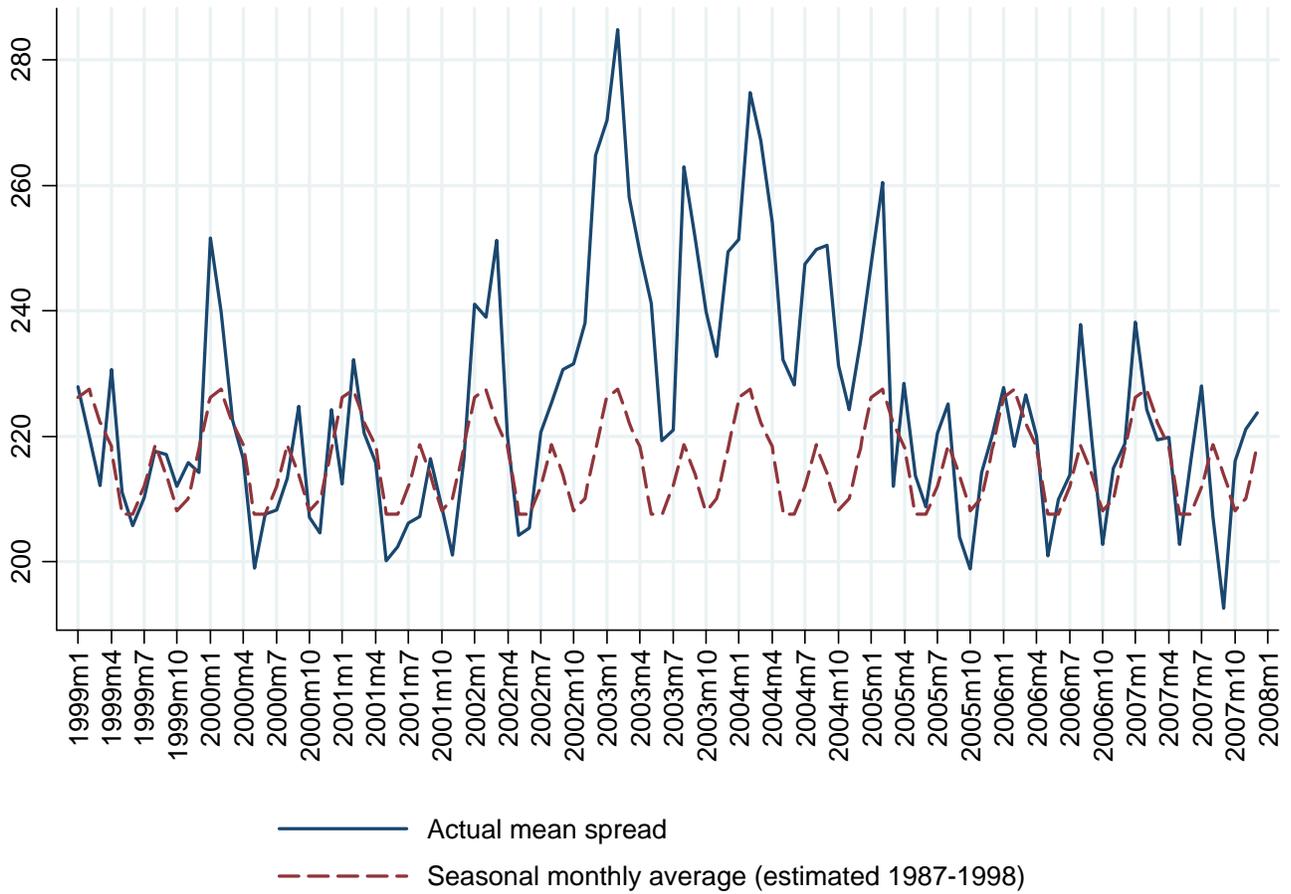
Figure 2b: Loan Spread Seasonality. The dashed line in Figure 2b depicts average monthly spreads over base rate for new issue loans from 1987-2012, where the month represents the loan's effective date.
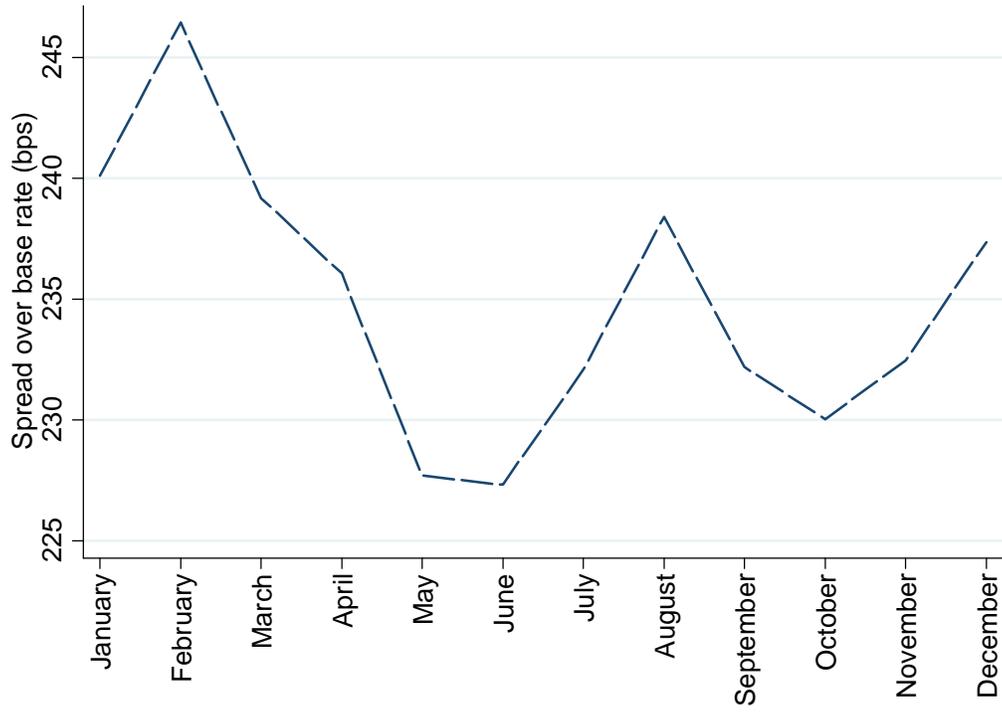
Figure 3: Seasonal spreads and loan supply. Figure 3a reports the average spreads on new issue loans and average monthly loan volumes for each calendar month for DealScan sample from 1987-2012 based on the loan effective date. Figure 3b replaces the x-axis with the average number of loans issued per month.
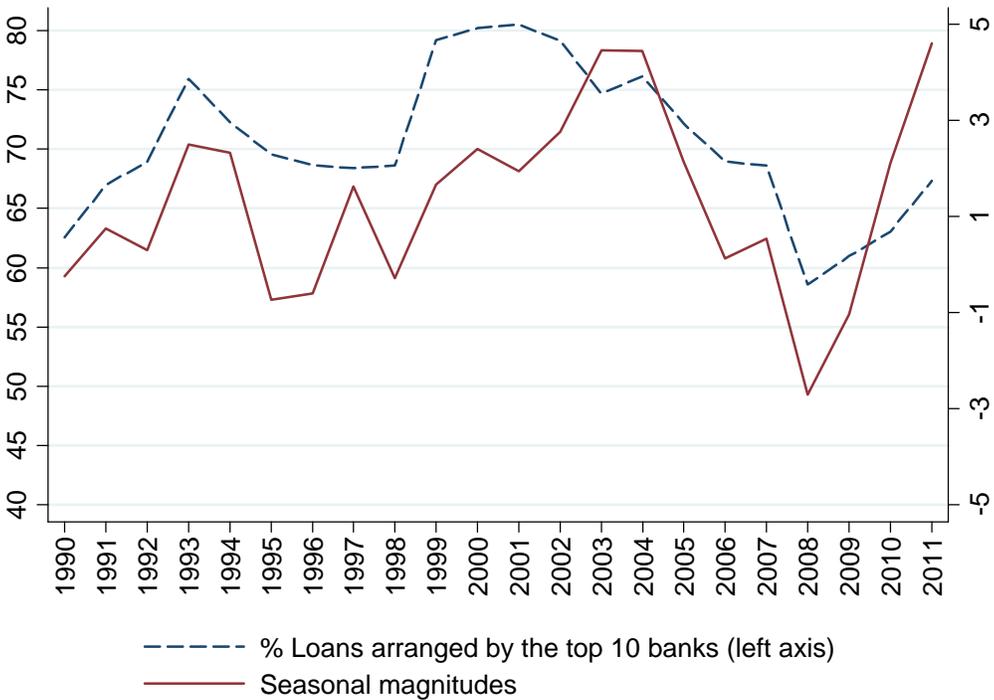
Figure 3a
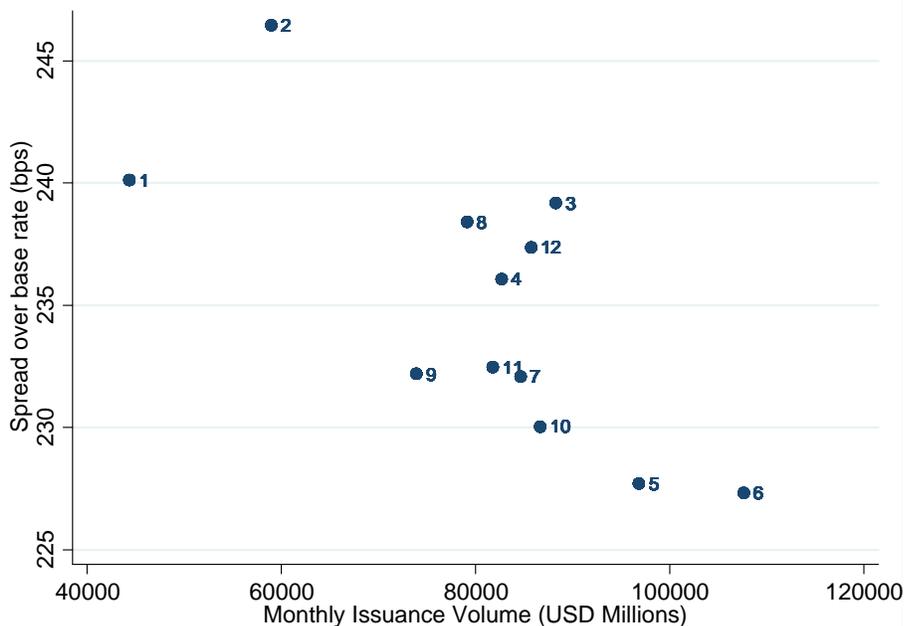
Figure 3b
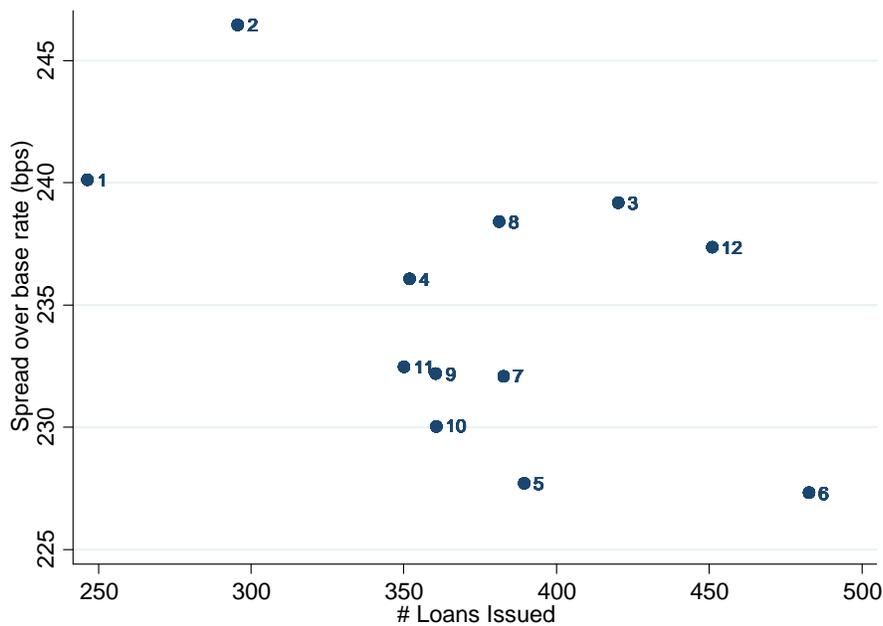
Figure 4: Seasonality by year and lender competition. We plot the sensitivity to seasonal patterns estimated in Table 6 against the percentage of loan volume arranged by the top ten lead arrangers in the prior year.

Figure 5: Seasonality by industry and lender competition. We plot the seasonal R-squared for 49 Fama-French industries against the average yearly percentage loan volume in that industry led by the top ten banks in that industry.
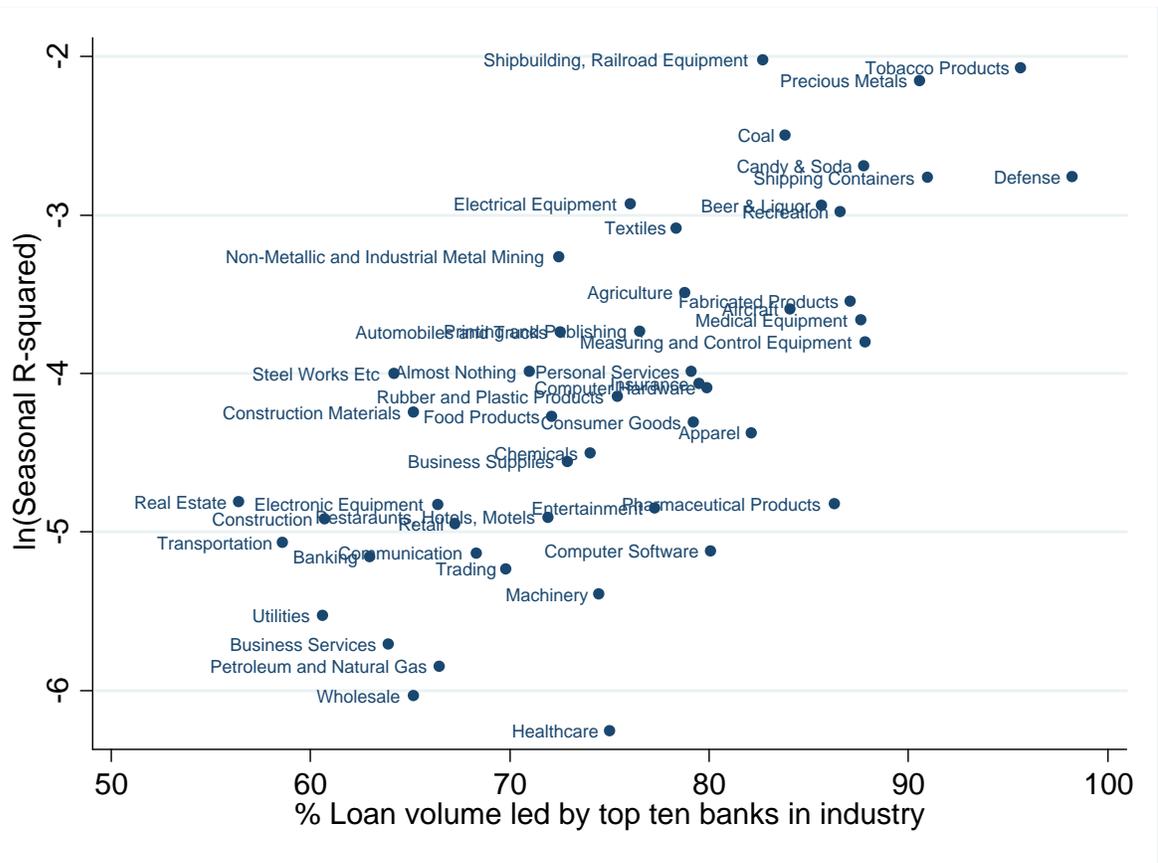
Figure 6: Seasonal market structure and loan spreads. Figure 6 plots the percentage of loans to investment grade rated borrowers which were arranged by a bank that was not ranked in the top ten of prior year's lead arranger league tables (left axis) and the average seasonal loan spread by calendar month (in basis points) (right axis).

Average seasonal spread
% investment grade loans led by banks outside the top 10
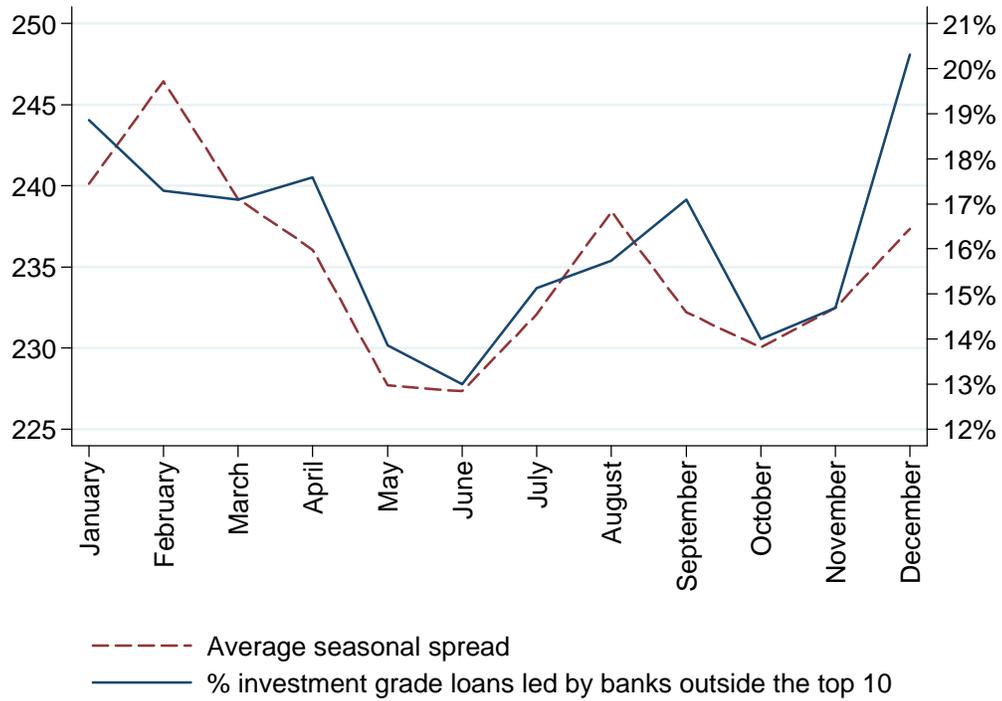
Appendix

Appendix I: Fee Seasonality. We note that fees follow similar seasonal patterns to all-in-drawn spreads. Below, we plot the average monthly fees of loan facilities by month. Averages are constructed first at the facility level, where we include the most common fee types-- facility fees, upfront fees, commitment fees, annual fees, and standby letter of credit fees. After calculating the average fees per transaction, we take the monthly average across the 12 calendar months. The second plot captures the average undrawn fee—annual fees plus any commitment fees on transactions with a revolving loan component.
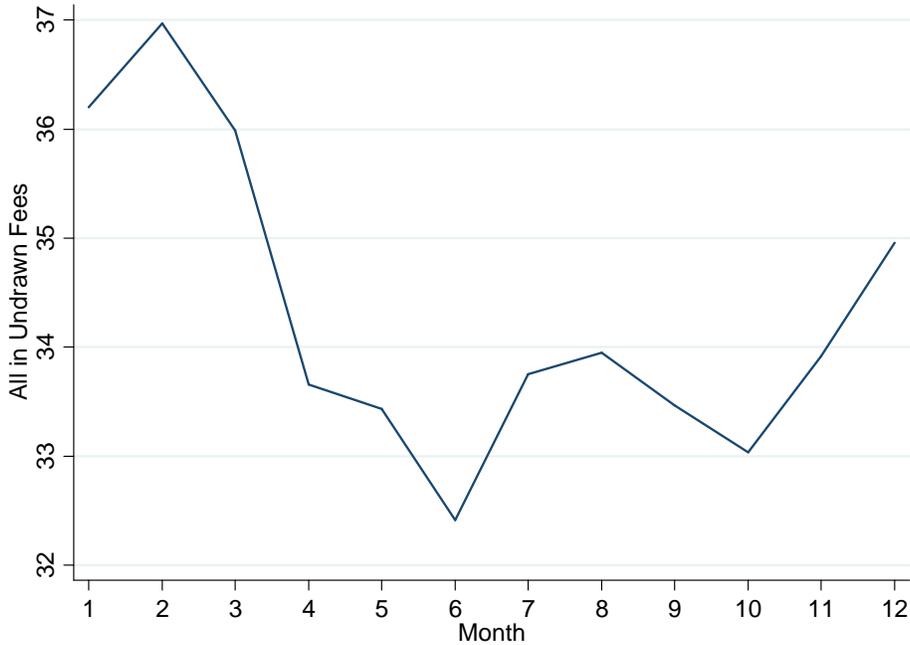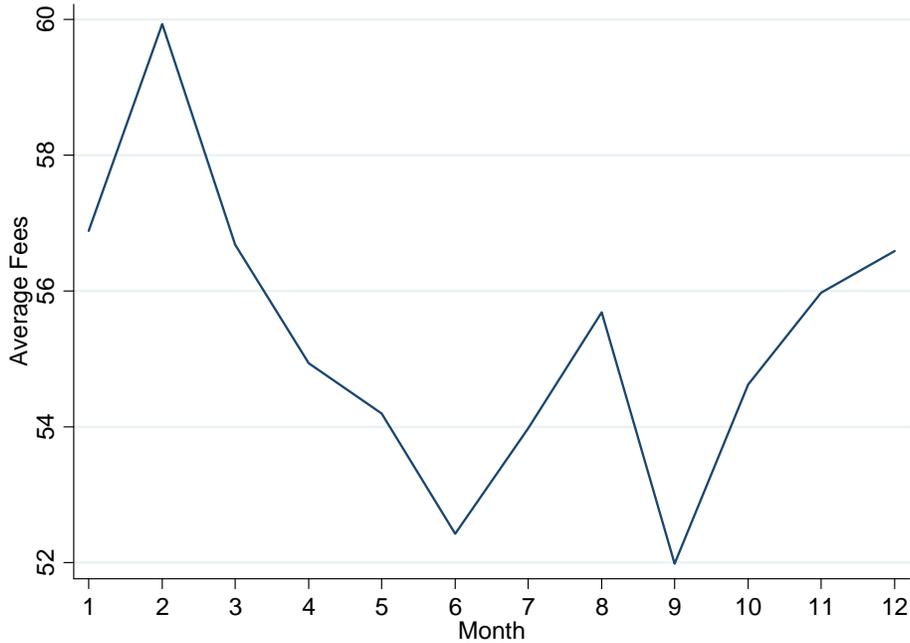
Appendix II: Robustness: Loan Level Seasonality. We re-estimate the regressions from Table 2, column (4) under a variety of subsamples and variants of seasonality for robustness. Column 1 subsamples among just packages that include revolving credit facilities (column 1 below). Column 2 restricts loans to just those with use of proceeds reported as "general corporate purposes" or "working capital". Column 3 adjusts the seasons so the expensive season better matches the global maximum average spreads seen in Figure 2b (January, February, and March) as opposed to the local peaks in pricing (January, February, and August). Column 4 excludes repeat issuers from the sample, focusing only on each borrower's first DealScan transaction in order to ensure that transactions reflect new deals and not just amendments or refinancings of existing transactions. Standard errors clustered by firm and month are reported in parentheses. Statistical significance at the 1, 5, or 10% levels is reported as superscripts.

Loan Spread (in basis points)	(1)	(2)	(3)	(4)
Cheap Season	0.88	-0.16	-0.47	-7.75**
	(1.92)	(2.47)	(1.85)	(3.92)
Expensive Season	8.11***	8.70***	5.46**	3.32
	(2.52)	(3.30)	(2.75)	(4.30)
ln(Maturity)	-10.91***	-2.90	-2.80*	-13.25***
	(2.42)	(2.13)	(1.55)	(3.22)
Secured	32.53***	16.90***	23.93***	28.40***
	(3.38)	(4.50)	(3.45)	(5.52)
ln(Assets)	-0.86	4.88	1.10	-6.07***
	(2.75)	(3.53)	(2.85)	(1.71)
Operating Profit/Assets	-203.10***	-195.79***	-195.61***	-150.10***
	(22.98)	(33.76)	(23.68)	(28.04)
Total Debt/Assets	50.64***	62.12***	35.76***	43.61***
	(9.82)	(14.32)	(9.87)	(9.04)
PP&E/Assets	15.26	4.45	15.17	-0.02
	(14.11)	(21.94)	(14.16)	(8.35)
Time Fixed Effects	YES	YES	YES	YES
Deal Purpose Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects	-	-	-	YES
Ratings Fixed Effects	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	NO
Observations	7,863	5,892	11,414	2,642
R-squared	0.82	0.82	0.77	0.61
Expensive-Cheap	7.23***	8.87**	5.93**	11.07**
	(2.73)	(3.45)	(2.85)	(4.65)

Appendix III: Examples of Firms that Borrow in the Expensive Periods

Finish Line signed a new $60M loan agreement with lenders on February 21, 2003 to allow for increased capital expenditures.[25] The Finish Line, Inc. is a mall-based specialty retailer which operates under the Finish Line and Running Specialty brand names. They are retailers of athletic shoes, apparel and accessories. Sales were up 40% for the year on a comparable store basis, while the sales forecast for the next year was raised by 31% (from $640M to $837M).[26] This growth was considerably above other athletic specialty retailers and was surprising given the "geopolitical and macroeconomic conditions in the United States, which have negatively impacted many other specialty retailers."[27] The growth in sales and the subsequent decision to expand capacity significantly was driven in part by Nike's decision to move more of its high-end shoes to Finish Line after the relationship between Nike and Foot Locker, a competitor of Finish Line deteriorated.[28] Nike reduced shipments to Foot Locker by 40% over the firms' dispute over selection and price of shoes which Nike sold to Foot Locker.[29] Finish Line Inc. announced that 2004 capital expenditures was projected to be $48M (an 85% increase over the prior year) to fund the build out of 50 new stores in the next year (which was greater than earlier plans) and the remodeling of 15-20 existing stores.

RWE AG closed on a 9B Euro loan on January 12, 2009.[30] The purpose of the loan was to finance the takeover of Essent Network. RWE AG is a German electric utility that supplies electricity and gas principally in Europe. Essent Network is a Dutch utility company that distributed electricity and natural gas and also provides related services to both industrial and private customers. Essent announced that they were looking for a new partner in June 2008. RWE's interest in Essent was reported by the financial daily Boersen-Zeitung on November 12, 2008.[31] Essent Networks provided RWE an entry into a new market and helped their carbon profile. The cost of CO_2 emission certificates are a significant burden for RWE.[32] On January 8th, 2009 the Dutch newspaper *Het Financieele Dagblad* said RWE AG "is the most serious candidate to take over Dutch peer Essent N.V." The firms announced they had reached an all-cash agreement on January 12, 2009. As Leonard Birnbaum, RWE's Chief Strategy Officer said, they "waited for the right opportunity to arise".[33] The unpredictability of the opportunity made it difficult to plan financing for such a large transaction until a deal was certain. RWE did not want to delay the transaction either, but instead wanted to take advantage of the difficulty created for competing bidders by the financial market conditions.[34] RWE announced lower earnings for the second quarter due in part to the "upfront costs of financing the Essent acquisition."[35]

W-H Energy Services signed a new $375M loan agreement on February 6, 2006. W-H Energy Services, Inc. is an oil field services company that provides products and services for use in the drilling, completion, and

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[25] Finish Line Inc. repurchased no shares in the prior quarter even though they had repurchased shares in quarters. [25] Shanley, John, and Christopher Svezia, March 31, 2014, "The Finish Line Inc." Wells Fargo Securities, Inc.

[26] Finish Line Inc. Q4 2002 Financial Release Conference Call, March 28, 2003.

[27] Shanley, John, and Christopher Svezia, March 31, 2014, "The Finish Line Inc." Wells Fargo Securities, Inc.

[28] "Indianapolis-Based Finish Line Posts Robust Results during Fourth Quarter" *Indianapolis Star*, March 28, 2014.

[29] "…management noted that it believes its store traffic levels have improved considerably as a direct result of increased elite launch product now found in The Finish Line and the exclusive footwear items from its largest vendor (Nike)." Shanley, John, and Christopher Svezia, March 31, 2014, "The Finish Line Inc." Wells Fargo Securities, Inc. Inventory also rose significantly with the greater sales expectations and store openings. Finish Line Inc. Q4 2002 Financial Release Conference Call, March 28, 2003.

[30] RWE AG Earnings Presentation, February 26, 2009.

[31] Dow Jones Newswire, November 12, 2008.

[32] RWE AG Earnings Presentation, February 26, 2009.

[33] RWE AG Earnings Presentation, August 13, 2009.

[34] "We're determined to benefit from the crisis," executive board member Leonhard Birnbaum told reporters in December, *Wall Street Journal online edition,* January 9th, 2009.

[35] RWE AG Earnings Presentation, August 13, 2009.

production of oil and natural gas wells. Demand for the completion and production products and services depend upon the success of the first stage: drilling. It is thus volatile and unpredictable. Their business had been focused in off-shore drilling (the Gulf region), but they planned to expand into land based business (the Rockies region). Then demand for their products and services increased dramatically at the end of 2005. "Completion and Workover had an outstanding quarter and the largest variance versus our forecast".[36] Revenues in this division grew 45% on an annualized basis.[37] The unexpectedly high growth in this sector lead to "very, very high utilization rates".[38] This led to a planned increase in capital expenditure for 2006 due to the greater customer demand, forcing the client to restructure their existing credit which limited capital expenditure below now necessary levels.[39]

Eaton Corporation closed a $3B loan on January 25, 2008. The purpose of the loan was to finance Eaton's $2.23B acquisition of Moeller Group, the largest acquisition in Eaton's history.[40] Eaton announced the acquisition of Phoenixtec Power Company for $565M on the same day.[41] Eaton is a diversified industrial manufacturer and the Moeller Group is a leading supplier of components for commercial and residential building applications, and industrial controls for industrial equipment applications. The Moeller acquisition expanded Eaton's production and distribution assets in Eastern and Western Europe as well as reduced Eaton's dependence on the automotive and truck markets.[42] With the acquisition, Eaton's assets are better balanced between early and late-cycle business and thus better able to absorb the reduction in demand for automotive and construction equipment.[43]

Neither Eaton nor Doughty Hanson & Co (a private equity firm) made any public announcement about the planned merger until December 20th, 2007. Under Doughty Hanson & Co.'s ownership, the Moeller Group had increased their core revenues by 26% in two years, but the private equity firm felt now was the right time to exit.[44] Since there were no public announcements or leaks prior to Eaton announcing they had signed a deal, Eaton's management may have wanted to wrap the negotiations up quickly before other bidders appeared, especially given the price they paid as favorable by equity analysts.[45]

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[36] Credit Suisse Equity Research Report on W-H Energy Services, January 31, 2006.

[37] "First Read: W-H Energy Services, UBS Investment Research, January 30, 2006.

[38] Ken White (President & CEO, W-H Energy Services) W-H Energy Services earnings conference call, April 27, 2006.

[39] "WHQ introduced its 2006 capex guidance of $150M, up 60% from 2005… in response to strong customer demand." Credit Suisse Equity Research Report on W-H Energy Services, January 31, 2006.

[40] "Eaton makes $2.8B buys in Asia-Europe" Associated Press, December 20th, 2007.

[41] The acquisitions were financed with a combination of debt, equity, and cash. "Eaton Agrees To Acquire The Moeller Group And Launches Tender Offer To Acquire Phoenixtec Power Company Ltd." Eaton Press Release, December 20th, 2007.

[42] "Eaton makes $2.8B buys in Asia-Europe" Associated Press, December 20th, 2007.

[43] Nigel Coe and Nicole DeBalse, "Electrifying the Revenue Base", Deutsche Bank, December 21st, 2007.

[44] "Now is the right time for Moeller to enter the next phase of growth by becoming a part of a major global industrial group with a compelling strategic and geographic fit." Claus Felder, Managing Partner of Doughty Hanson & Co as quoted in "Doughty Hanson Sells Moeller Group to Eaton Corporation" Doughty Hanson & Co Press Release, December 20th, 2007.

[45] "We were also pleased with the pricing of the transactions… for Moeller… and… Phoenixtec – both at the lower end of comparables, which is surprising given the highly strategic nature of the deals." Nigel Coe and Nicole DeBalse, "Electrifying the Revenue Base", Deutsche Bank, December 21st, 2007.

Appendix IV: Estimating labor costs.

In Section IV, we argue that seasonal variation in the cost of loan officer labor cannot drive the magnitude of seasonal effects observed. To do this, we estimate the seasonal variation in labor costs that would be necessary to drive the observed seasonal magnitudes, and then show that the implied seasonal variation is likely to exceed total compensation for lenders.

In order to calculate aggregate season costs implied by a season cost shifter, we aggregate pricing details, including upfront fees, all-in-drawn spread, and, when present, commitment fees paid on undrawn commitments. We assume seasonal costs will be earned by the bank for one year on all facilities, allowing for that fact that although the average loan maturity is 4.5 years, loans are typically renegotiated at more frequent intervals, especially those priced at unattractive terms.[46] We further assume that committed lines of credit are on average 33% drawn. Although these number vary from year to year, a sampling of the Federal Reserve's Shared National Credit Reports suggest outstanding loans represent 30-50% of total commitments. Thus, we calculate the cost of a committed line of credit as the upfront fee plus 33% the all-in-drawn spread plus 66% the commitment fee (or upfront fee plus 100% the all-in-drawn spread for term loans) for one year.

We calculate this cost on a deal-by-deal basis from 2000-2011, excluding the period of acute crisis from September 2008-June 2009. We averaging these costs for each of 12 calendar months, and then subtract off the cost for the cheapest month (May), giving us an estimate of the hypothetical seasonal supply shifter. This is multiplied by monthly loan volumes to give a month-by-month dollar value of the potential supply shifter, which we can then benchmark against plausible labor costs in the commercial lending market.

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[46] Note that the presence of upfront fees (akin to original issue discounts in the bond market) make it costly for firms to renegotiate down seasonally expensive loans immediately, as those fees will need to be paid again at the new loan's closing.