

The Impact of Joint Participation on Liquidity in Equity and Syndicated Bank Loan Markets*

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Abstract

We examine the impact on market liquidity of the presence of financial intermediaries that are informed and active participants in both the equity and the syndicated bank loan markets. We identify the presence of informationally advantaged lead arrangers of syndicated bank loans that simultaneously act as equity market makers, denoted dual market makers. By employing a two-stage procedure with instrumental variables, we identify the simultaneous equations model of liquidity and dual market maker decisions. We find empirical support for our theoretical model's predictions that the presence of dual market makers improves the liquidity of more competitive equity markets but widens the spread in the less competitive loan market.

JEL Classification: G14, G24

Key Words: syndicated bank loans, joint participation, market liquidity

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Abstract

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1. Introduction

The interconnectedness of global financial markets has been clearly demonstrated during the 2007-2009 financial crisis by the transmission of market turmoil from the market for US subprime mortgages to credit markets around the world. The glue that connects markets is the financial intermediary. Financial intermediaries are information companies. In order to be considered a major player, a financial intermediary maintains a market presence in all of the major financial markets in the world. Participating in multiple financial markets can be particularly lucrative if information obtained in one market is useful in other, related, markets. For example, information about fundamental firm value obtained in debt and derivatives markets may be reusable in equity markets. Conversely, information about equity market order flow may be reusable in debt and derivatives markets. The reusability of information has motivated the potentially synergistic combination of commercial and investment banking activities into large complex financial institutions. When information is used effectively, these institutions can be net liquidity providers to global financial markets. However, large complex financial institutions can sometimes blockade market liquidity, thereby reducing trading efficiency. Indeed, the crisis of 2007-2009 demonstrates the crucial role financial institutions play in the liquidity of these markets.

In this paper, we examine how the simultaneous trading by global financial institutions across financial markets impacts the liquidity and informational efficiency of asset prices across markets.¹ In particular, we focus on financial intermediaries that are informed and active participants in both the syndicated bank loan and the equity markets. We define financial intermediaries that are simultaneously lead arrangers of the bank loan syndicate and equity market makers as dual market makers. In our formulation, these dual market makers are among the most informed participants in the market, because they can extract information from both the syndicated loan market and the equity market. The lead arranger, in contrast to other loan syndicate participants, is typically a bank with a

¹ For example, Madureira and Underwood (2008), Schultz (2003) and Chung and Cho (2005) document the interaction between equity market maker and investment banking services, such as equity research, underwriting and analyst coverage. While we focus on the role of informed market makers on market liquidity and especially bid-ask spreads, common players across multiple markets or assets can also cause contagion (for example, Allen and Gale, 2000, Kyle and Xiong, 2001, and Peng and Xiong, 2006), as well as commonality in liquidity (Coughenour and Saad, 2004) through various mechanisms.

prior lending relationship with the borrower. In the course of a long-term banking relationship that includes the provision of a myriad of deposit, cash-management and lending services, the relationship bank gathers private information about the borrower.² There is an extensive literature describing the private information generated in the course of a long-term bank-borrower relationship; see Boot (2000) for a survey of relationship lending.³ By virtue of its access to this private information, the lead arranger screens the loan on behalf of all lenders in the syndicate.

Moreover, as a result of concern about a potential lemons problem in the presence of these informational asymmetries, the lead arranger precommits to the other (less informed) syndicate members by holding a large portion of the loan until maturity.⁴ The lead bank's stake (and the accounting requirement that this position is generally marked to market) therefore provides it with strong incentives for market making in the secondary loan market, as well as ongoing monitoring during the life of the loan. Gande and Saunders (2006) show that monitoring and secondary market activity are complements in the syndicated loan market, such that the relationship bank profits from its informational advantage in all aspects of its role as lead arranger -- monitoring the borrower, managing the syndicate, and providing liquidity to the secondary market when needed. Indeed, it is understood that the lead arranger will manage secondary market trading, for example, by facilitating price discovery or by enforcing covenants requiring prior consent by the lead arranger (and/or the borrower) for secondary market

² Banks obtain private information about their customers by observing a history of customer information such as the flow of funds through customer checking accounts, past repayment history, customer use of commercial banking products such as letters of credit, firm hedging activities, etc. For example, Mester, Nakamura and Renault (2002) find that banks can use checking account activity to monitor borrower creditworthiness on a real time basis. Thus, lead arrangers tend to have informational advantages over other less informed, members of the loan syndicate. See Ivashina (2006) for a discussion of information asymmetries between the lead arranger and participants in loan syndications.

³ James (1987), Lummer and McConnell (1989), and Billet, Flannery and Garfinkel (1995) show that bank loans contain private information as measured by the bank loan's positive announcement effect in equity markets. Dahiya, Puri and Saunders (2003) find a negative impact on equity returns upon the announcement of loan sales. Moreover, Allen, Guo and Weintrop (2005) show that negative earnings announcements are reflected in loan prices a month prior to the stock market reaction on announcement date.

⁴ Allen and Gottesman (2006) show that the average share of the syndicated bank loan facility held by the lead arranger is 27% (median 16%). In contrast, the average share of syndicate participants is less than 3% (median 1.88%).

transactions.⁵ Given the repetitive nature of the syndication process, the failure of a lead arranger to provide market making services in the secondary loan market when required would likely impact that bank's ability to create syndicates in the future.⁶

The financial intermediary that syndicated a bank loan may also have incentive to become a market maker for the borrowing company's stock (thereby becoming a dual market maker). While the private information generated from the loan market will impact the bank's trading activity in the equity market, the same financial institution can also extract valuable information from the equity market order flow that is not shared by other traders in the loan market.⁷ Equity market making may produce information that complements the information about fundamental firm value obtained from the loan market. That is, while the loan syndicate has more micro-level information about the firm's fundamental value, equity market traders may have more macro-level information, e.g., regarding the general macroeconomic environment that is relevant to the firm, industry growth perspectives, the company's competitors, suppliers and the demand for its products.⁸

The identification of dual market makers as traders with an information advantage allows us to investigate both the role of informed financial institutions on market liquidity and the informativeness of asset prices. We hypothesize that information asymmetry in the relatively competitive equity markets may provide incentives for the informed lead arrangers to become natural liquidity providers – i.e., market makers - and benefit from their ability to set the price more efficiently. This is because in a more competitive equity market, when the degree of information asymmetry between the informed market makers (the lead arrangers of the bank loan syndicate) and other informed traders is low, the informed market makers are more willing to quote narrower

⁵ Pyles and Mullineax (2008) show that such restrictions are used particularly for small, informationally opaque borrowers in order to reduce the likelihood of strategic default, increase the chance of successful restructuring in the event of financial distress and foster relationships among syndicate members. Thus, the lead arranger has an incentive to manage the composition of the syndicate (both upon initiation of the deal and in the secondary market) so as to prevent failed restructurings or strategic default, which can harm the lead bank's reputation.

⁶ Drucker and Puri (2008) show that loans originated by top-10 market share banks tend to be more likely to trade in secondary markets, and find that relationships are more durable in the presence of secondary market loan trading.

⁷ In our conclusion, we address the issue of insider trading violations.

⁸ For example, Allen and Gottesman (2006) show that information contained in a firm's equity returns impacts returns on that firm's syndicated bank loan returns, and vice versa.

spreads and play a liquidity-provision role (see, for example, experimental evidence provided by Bloomfield and O'Hara, 2000). We denote this as the *liquidity enhancement effect*.

Alternatively, in a less competitive market such as the syndicated loan market, the information advantage possessed by the dual market maker can give them market power. Their presence may induce other, less informed, market makers to react defensively and be reluctant to provide liquidity. In this setting, the dual market maker may choose to widen spreads in order to extract information rents. We hypothesize that the activities of dual market makers may increase information asymmetries, widen spreads and lower market liquidity in such markets. We denote this process the *negative liquidity effect*. In Section 2, we analyze the market maker's inference problem, based on an extension of the Glosten and Milgrom (1985) model, to motivate the two hypotheses.

The presence of a dual market maker is not exogenously determined. Loan syndicate arrangers will have a greater incentive to become equity market makers when the profit opportunities are high. This will be the case when there is a large and active equity market with profitable spread levels, and when the degree of information asymmetry in the equity market is large. Formal tests for endogeneity reject the null hypothesis of no endogeneity and affirm the need to control for the endogenous decision to become a dual market maker. We explicitly model the dual market maker decision in the empirical analysis by using a simultaneous equation model.

Specifically, we estimate the impact of the dual market maker's presence on market liquidity using a two-stage procedure that permits simultaneous multivariate estimation of one continuous dependent variable and one discrete dependent variable, corresponding to the technique detailed in Maddala (1983). We employ the Sargen test, the Anderson underidentification test and the Cragg-Donald test to confirm the selection of our instruments and the identification of our equation systems. After accounting for the endogeneity of the dual market maker decision, we find a significant increase in equity market liquidity in the presence of dual market makers. The presence of the dual market makers reduced the equity spread by 39.5 basis points, about 35% of the mean equity spread, consistent with the *liquidity enhancement effect* for the more competitive equity market. In contrast, we find a significant increase in loan spreads in the presence of these

dual market makers, with an increase of 25.3 basis points (21% of the mean loan spread), consistent with the *negative liquidity effect* for the less competitive loan market. In addition, we find that the lead arranger of a syndicated bank loan has more of an incentive to become an equity market maker when the profit opportunity of market making is high. This occurs when the equity market is large, when the dual market maker has a greater informational advantage over other equity market makers, and when the dual market maker has more market power.

Our model focuses on the lead arranger's decision to become an equity market maker, rather than the equity market maker's decision to become a lead arranger in the syndicated loan market, because it is well established in both the academic literature and among practitioners that the borrower typically chooses the lead arranger on the basis of a prior banking relationship.⁹ The syndicate is then formed by the lead arranger. This is consistent with our hypothesis in that it is the private information about fundamental firm value obtained in the course of relationship banking that is the source of the lead arranger's informational advantage. In contrast, the equity market maker has superior information about market liquidity and order flow, but not necessarily about fundamental firm value. Moreover, the lead arranger's substantial holding of the loan provides them with strong incentives to make markets in these loans, thereby alleviating the concern that the lead arranger's choice in marking markets in the loan market can be endogenous.

The paper is organized as follows. Section 2 presents a theoretical model of the informed market maker's inference problem to motivate our empirical hypothesis. The sample selection and data description appears in Section 3. Section 4 lays out the empirical methodology and the results of the empirical tests on the impact of the presence of a dual market maker on liquidity in the equity and loan markets. Section 5 offers policy implications and conclusions.

⁹ For example, see Ivashina (2006) and Allen and Gottesman (2006). Further, Dennis and Mullineaux (2000) find that the likelihood of successful syndication is a function of the prior banking relationship between the lead arranger and the borrower.

2. Theoretical Model

In this section, we derive an extension of the Glosten and Milgrom (1985) model to analyze the relation between the informativeness of the market makers and the bid-ask spread of the traded asset. We then use this model to motivate the empirical hypothesis.

There is a single asset to be traded in the market. The final payoff of the asset is given by the random variable V . For simplicity, V can take two possible values, \underline{V} and \bar{V} , with equal probability. There are three types of traders in the market, the informed trader (i), the uninformed liquidity trader (n) and the market maker (m). All the market participants are risk neutral. The informed trader and the liquidity trader trade with the market maker, buy at the ask price and sell at the bid price. The measures of the informed trader and the liquidity trader are γ and $1-\gamma$, respectively. In the model, traders arrive sequentially and only one share of the asset can be traded at a time.

The informed trader observes the true value of V perfectly and can trade on this perfect information. The liquidity trader does not have any information and trades for exogenous liquidity reasons. For simplicity, we assume that the liquidity trader is equally likely to buy or sell.

Different from the Glosten and Milgrom (1985) setting, in this model the market maker receives an imperfect signal (I) about V . I can take two possible values, \underline{V} and \bar{V} . Essentially the market maker receives a signal that tells whether the firm's payoff is \underline{V} or \bar{V} . The usefulness of the signal I is determined by a parameter k ($0.5 \leq k \leq 1$), the probability that the signal is the same as the true value of V . When k takes the minimal value of 0.5, the signal is uninformative; i.e., when I equals \underline{V} , the truth could be either \underline{V} or \bar{V} with equal probability. In this case, the market maker is equivalently uninformed and the model reduces to the standard Glosten and Milgrom (1985) setting. When k equals 1, the value of the signal is exactly the same as the true firm value; i.e., when I equals \underline{V} (\bar{V}), the truth is \underline{V} (\bar{V}). In this case, the market maker has perfect information about V and there is no information asymmetry between the market maker and the informed investors. Our discussion focuses on the case where k takes any intermediate values between 0.5 and 1; i.e., the market maker has useful, but imperfect information.

In a rational expectations equilibrium, the market maker makes correct inferences about the probability that a trade comes from an informed trader based on his prior knowledge, the signal I , and the direction of the trade. The bid and ask prices are set in a way that reflects the market maker's expectation about the value of the asset. The following proposition describes the market maker's conditional expectation based on the order flow and his own information. The derivations are presented in Appendix 1.

Proposition 1. *The market maker's expected values of the asset when he receives a signal of low value are:*

$$E[V | B, I = \underline{V}] = \underline{V} + \frac{(1-k)(1+\gamma)}{k(1-\gamma) + (1-k)(1+\gamma)} (\bar{V} - \underline{V}) \quad (1)$$

$$E[V | S, I = \underline{V}] = \underline{V} + \frac{(1-k)(1-\gamma)}{k(1+\gamma) + (1-k)(1-\gamma)} (\bar{V} - \underline{V}) \quad (2)$$

The market maker's expected values of the asset when he receives a signal of high value are:

$$E[V | B, I = \bar{V}] = \underline{V} + \frac{k(1+\gamma)}{(1-k)(1-\gamma) + k(1+\gamma)} (\bar{V} - \underline{V}) \quad (3)$$

$$E[V | S, I = \bar{V}] = \underline{V} + \frac{k(1-\gamma)}{(1-k)(1+\gamma) + k(1-\gamma)} (\bar{V} - \underline{V}), \quad (4)$$

where B and S represent whether the trade is a buy (B) or a sell (S).

Consider a simple numerical example. Suppose $\underline{V} = 0$ and $\bar{V} = 1$. The measures of the informed investor and the liquidity trader are both set to 0.5 ($\gamma = 0.5$). In the baseline model where the market maker does not have information, $k = 0.5$, the market maker ignores the information signal and bases his expectation of the asset value only on the direction of the orders. Thus, $E[V | B] = 0.75$ and $E[V | S] = 0.25$. Therefore, the market maker's maximum bid is 0.25 and minimal offer is 0.75, with a minimum spread of 0.5.

Next, consider a case where the market maker receives valuable information ($k > 0.5$) about the final realization of the asset. When the information indicates low value, the expectations of the market maker are

$$E[V | B, I = \underline{V}] = \frac{3(1-k)}{3-2k} \quad \text{and} \quad E[V | S, I = \underline{V}] = \frac{1-k}{1+2k}.$$

When the information indicates high value, the expectations of the market maker are

$$E[V | B, I = \bar{V}] = \frac{3k}{1+2k} \text{ and } E[V | S, I = \bar{V}] = \frac{k}{3-2k}.$$

For example, consider the case where $k = 0.9$. When the information indicates low value, the expectations of the market maker are $E[V | B, I = \underline{V}] = 1/4$ and $E[V | S, I = \underline{V}] = 1/28$. Therefore, upon observing a low value signal, the market maker's maximum bid is $1/28$ and minimal offer is $1/4$. When the information indicates high value, the market maker's maximum bid and minimal offer is determined by $E[V | B, I = \bar{V}] = 27/28$ and $E[V | S, I = \bar{V}] = 3/4$. The minimum spread that the market maker charges (whether the signal is high or low) is $3/14$, smaller than the $1/2$ spread that he would charge in the benchmark case when the market maker has no information.

If the market is competitive, the spread set by the informed market maker is equal to the minimum spread:

$$E[V | B, I = \underline{V}] - E[V | S, I = \underline{V}] = E[V | B, I = \bar{V}] - E[V | S, I = \bar{V}]. \quad (5)$$

It is easy to demonstrate that, everything else equal, this spread is decreasing in k which indicates that as the market maker's information gets better, the competitive spread he charges becomes narrower. Although financial markets in reality may not be perfectly competitive all the time, for those that are reasonably competitive, we expect the spreads in these markets to be close to the competitive spreads. This suggests the following hypothesis:

Hypothesis 1 (Liquidity Enhancement): *In a relatively competitive market, an informed market maker is faced with less information asymmetry. He becomes a natural liquidity provider in the market and sets a narrower bid-ask spread.*

However, in a less competitive market, if the joint participation in both the equity and the loan markets gives rise to a dual market maker with an information monopoly in a market, the spreads could be higher for that market. In the most extreme case, the super-informed market makers can drive out the other uninformed market makers and become the monopolists in the market. In this case, the monopolist market maker can potentially capture the whole spread of $(\bar{V} - \underline{V})$. In the intermediate case, the spread will be between the minimum spread in equation (5) and the maximum spread of $(\bar{V} - \underline{V})$, and

will increase in the information advantage and the market power of the market maker.¹⁰ In this setting, we have the following hypothesis:

Hypothesis 2 (Negative Liquidity): *In a less competitive market, the informed market maker can extract information rents by setting a wider spread, resulting in reduced liquidity.*

Empirically, the effect of a more-informed market maker on liquidity depends on the degree of competitiveness of the market. The equity market, where NYSE specialists, floor brokers, institutions who place limit orders, and NASDAQ market makers function as financial intermediaries, is substantially more competitive than the loan market.¹¹ Therefore, we expect that the participation of the more-informed lead arranger as an equity market maker decreases the bid-ask spread in the equity market. The loan market, on the other hand, is generally less competitive, with far less transparency than in equity markets. We expect that the participation of the more-informed dual market maker will widen the bid-ask loan spreads when the informed traders have excessive market power.

In general, we expect that the lead arranger of a syndicated bank loan has greater incentive to become an equity market maker when the profit opportunity of market making is high. That is, the likelihood of entrance of a dual market maker increases when (1) the potential profit from equity trading is high (high equity spreads and/or large equity markets where market making activity generates large volume); (2) there is large uncertainty about the company and the lead arranger has a greater informational advantage over other equity market makers; (3) when the information extracted from

¹⁰ A theoretical model of an informed market maker among uninformed market makers in a non-competitive setting is beyond the focus of this paper. Strategic behaviors involving the interaction between uninformed and informed market makers greatly complicate the model. Uninformed market makers may try to infer information from the quotes of informed market makers. Informed market makers would then have an incentive to manipulate their quotes through, for example, adding random noise, or only providing wide quotes without the intention of actually trading. The repeated nature of this market would tend to reduce, but not eliminate, such opportunistic behaviors. We are currently unaware of any theoretical model that analyzes the effect of strategic interaction of differentially informed market makers on market liquidity.

¹¹ In addition, the presence of informed market makers that set prices more efficiently reduces the information disadvantage faced by liquidity traders whose trading is driven by portfolio rebalancing and hedging needs. Thus, the existence of informed market makers encourages more liquidity-based trading volume and improves stock market liquidity. Furthermore, the participation of dual market makers in trading increases the number of informed traders in equity markets. This increase can induce a “rat race” among the informed traders, causing them to compete aggressively, revealing information into prices rapidly and improving the informational efficiency of the price (see, for example, Holden and Subrahmanyam, 1992, and Foster and Viswanathan, 1993), thereby reducing equity market spread.

equity trading is more profitable in the loan market, i.e., when the lead arranger has more market power in the loan market.

In the remainder of the paper, we empirically test these hypotheses and implications. In particular, we examine the effect of the presence of a dual market maker on the bid-ask spreads in the equity and syndicated bank loan markets (Hypotheses 1 and 2) while controlling for the endogeneity of the decision to become a dual market maker.

3. Sample Selection and Variable Descriptions

To empirically test the implications of the model presented in Section 2, we obtain data on pricing in both the equity and syndicated bank loan markets. Our initial sample is obtained from the Loan Pricing Corporation (LPC) and consists of 129,172 daily secondary loan market quotations, observed on a weekly basis, for which at least two quotes are available for the date of the observation during the sample period January 1999 through May 2003.¹² These observations are associated with 1,621 individual loan facilities to 763 individual borrowers.¹³ The database provides the mean bid and mean ask quotation for each observation.¹⁴ The number of loan quotes for the day of the observation, LOANNBA, is calculated as the sum of the bid and ask quotations for each loan observation. The loan return, LOANRETURN, is calculated as the weekly loan return, where the average of the mean bid and mean ask quotation (denoted the mean of the mean) is a proxy for loan transaction price. The relative loan spread, LOANSPRD, is calculated as the difference between the mean bid and the mean ask divided by the transaction price proxy.

¹² Although the two quote minimum was imposed by the data provider, the impact is to limit our sample to the more liquid loan syndications that trade in the secondary market. These are relevant to the role of the lead arranger as loan market maker since there the presence of several quotes can be viewed as evidence of secondary market trading activity.

¹³ Loan deals to individual borrowers consist of multiple loan facilities that differ in characteristics such as spread, maturity, security, covenants, etc.

¹⁴ There is no “tape” in the syndicated bank loan market that records transaction prices. LPC data consist of quotations obtained from market makers (although the identity of the quoting market maker and individual quotes are not provided). LPC’s internal studies suggest that the average of the mean bid and ask quotes is very close to actual transaction prices for a subsample of par loan transactions. In contrast, transaction prices for distressed loans may trade outside of the bid/ask spread. Other recent papers that have used the LPC database include: Bharath, et al. (2007) and Sufi (2007), the winner of Brattle Prize for Distinguished Paper published in the *Journal of Finance*. Other papers that use the secondary market database are Altman, et al. (2006) and Gande and Saunders (2006).

Using primary loan market data from the *LPC DealScan* database, we extract control variables associated with the given facility at loan initiation. Dennis, Nandy and Sharpe (2000) show that collateral is an important loan contracting feature. Thus, we define SECURED as a dummy variable that is equal to one if the loan is secured, and zero otherwise. To control for credit risk at loan initiation, RATEAISD is the basis point loan spread at initiation over LIBOR. FACILITYSIZE is the facility size at initiation. NUMBSYN is the number of syndicate members at initiation. LFACILITYSIZE and LNUMBSYN are the corresponding logarithmic values of the two variables. LEADSHARE is the lead arranger's market share (in percentage), estimated using the LPC historical league tables.

We next merge the above sample with CRSP by comparing the borrower's ticker and name provided by LPC with the tickers and names specified on CRSP.¹⁵ Of the 763 borrowers, we identify 357 on CRSP, and extract a number of variables, as follows. EQUITYRETURN is the one-week equity return, calculated using the equity price standardized by the cumulative factor to adjust for splits and dividends. LMV is the logarithmic market value, where market value is defined as the number of shares outstanding multiplied by the equity price on the day of the observation. We calculate a return volatility measure based on monthly equity returns designated EQSTDEV. This volatility measure is calculated for observations for which at least 17 of the past 24 months of return data are available.

We obtain a number of additional control variables from COMPUSTAT's North America Fundamental Annual dataset for the end of the year that precedes the weekly secondary loan market observation. LEVERAGE is the borrower's total debt divided by total assets. INCOMETOA is the borrower's operating income before depreciation divided by total assets. EPS is earnings per share. TANGIBLE is gross property, plant and equipment divided by the firm's total assets. FRENCH1-12 are indicator variables that are equal to unity if the firm's industry, as defined by the firm's 4-digit SIC, falls into one of 12 categories as categorized by Kenneth French.¹⁶ From the TAQ database, we extract data that allows us to identify the market makers in the equity market on the

¹⁵ In twelve cases the borrowing entity's ticker and name could not be identified on CRSP but its parent company could be identified. In these cases the parent company's CRSP data was extracted.

¹⁶ See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

date of the observation specified by the LPC secondary loan market database, and use this information to calculate a number of variables. DUALMM is a dummy variable that is equal to one if the lead arranger on the syndicated bank loan is also a NASDAQ market maker for the firm's equity, and zero otherwise.¹⁷ A syndicate member is considered to be a lead arranger as long as the LPC *DealScan* database specifies a role designation other than "participant." Thus, the lead arranger can have the legal titles of administrative agent, documentation agent, arranger, lead manager, etc. TAQSPRD is the time-weighted relative equity spread, where the relative equity spread is calculated as the national best bid and offer (NBBO) spread divided by the average of the best bid and the best ask, measured in percentages. The NBBO is the best bid and offer at each moment in time, aggregated from NYSE, NASDAQ and AMEX. We also extract two market variables that we use in the tests. EQUITYINDEXRETURN is the weekly return on the S&P 500 Composite Index, extracted from CRSP. LOANINDEXRETURN is the weekly return on the S&P/LSTA syndicated bank loan index.

Using return and accounting data from COMPUSTAT and CRSP, we calculate the implied probability of default (denoted PD) using a Merton options-theoretic model.¹⁸ The variable PD is used to examine the relationship between the level of default risk and market liquidity (see Allen and Peristiani (2007)). However, we are also interested in how changes in default risk interact with liquidity measures and with the dual market maker decision. That is, large changes in default risk may trigger uncertainty about the loan's future value and thereby impact liquidity. Thus, we define two variables, DPD and

¹⁷ In order to construct strict tests of our hypotheses, we restricted our definition of dual market maker status to those financial intermediaries that are both lead arrangers and equity market makers on the same day. This definition may exclude some cases where the dual market maker does not immediately trade on information, but instead trades in subsequent days. To test for this, we examine whether the dual market maker status changes from week to week; if the designation of dual market maker status changes from week to week, it may be an indication that our definition is overly restrictive. We find that in 99.14% of the observations in our sample the dual market maker status does not change from week to week, and therefore we utilize the more restrictive, less noisy designation of dual market maker status if the lead arranger acts on the same day as an equity market maker.

¹⁸The model that we use to estimate the implied probability of default is described in Appendix 2. This implied measure of default does not exactly represent the true probability of default because it assumes normality. In contrast, Moody's/KMV uses a large proprietary database of defaults to calibrate the distance-to-default to the actual experience. For our purpose, however, the probability of default provides a time-consistent indicator that allows us to measure variations in the solvency of the firm. For a discussion of the options-theoretic approach to credit risk measurement, see Chapter 4 of Saunders and Allen (2002).

LAGDPD, that measure the one-week change in the implied default probability for weeks t and $t-1$.

Finally, we eliminate any observation for which the following key variables are missing: LOANNBA, LOANRETURN, LOANSPRD, TAQSPRD, EQUITYRETURN, DUALMM, and PD. After eliminating the observations for which the key variables are missing, we are left with 22,826 secondary market observations, associated with 384 individual loan facilities to 165 individual borrowers. Table 1 presents descriptive statistics for our sample and Table 2 presents the correlation matrix.

Table 1 shows that the firms in our sample tend to be smaller firms, with median stock market capitalization of 1.123 billion.¹⁹ In addition, more than 22% of our observations have dual market makers that simultaneously arrange loan syndications and act as equity market makers.

4. Empirical Methodology and Results

The focus of our analysis is the impact on market liquidity of the private information generated by the presence of financial intermediaries that are active participants in both the equity and the syndicated bank loan markets. However, the decision to participate both in the equity and the syndicated loan market may itself be determined by the liquidity of the loan and the equity markets. In Section 4.1 we begin our estimation using OLS regressions and test for endogeneity. In Section 4.2 we describe the simultaneous equation systems. We present the results of our simultaneous equation systems and test the validity of the proposed instruments in Section 4.3.

4.1 OLS Results

We perform OLS regressions of loan liquidity measures (LOANSPRD) on dual market participation. Table 3 summarizes the coefficient estimates and robust standard errors, adjusted for possible firm clustering (the latter are shown in parentheses). The coefficient of DUALMM is positive and statistically significant. This result seems to be

¹⁹ In the life cycle hypothesis, firms progress from private sources of funds (including bank loans) to publicly traded debt and equity as they grow and become more well-known to the market. Thus, in general, firms relying on syndicated bank loans will tend to be smaller and less likely to be publicly traded (and included on CRSP and COMPUSTAT databases) than firms issuing publicly traded debt. See Carey, Prowse, Rea and Udell (1993).

consistent with the negative liquidity hypothesis that the presence of dual market maker increases the loan spreads. However, as suggested earlier, the OLS results could be misleading since the explanatory variable, DUALMM, is endogenous. It is possible that it is the reverse causality – that the lead arrangers are more likely to trade in the equity market when the loan spreads are large. An OLS regression can not disentangle the causality.

Similarly, we perform OLS regressions of loan market liquidity (TAQSPRD) on dual market participation. Table 4 summarizes the coefficient estimates and robust standard errors, adjusted for possible loan clustering (the latter are shown in parentheses). The coefficient of DUALMM is insignificant in both equations. Again, the OLS results could be misleading since the explanatory variable, DUALMM, is endogenous. One possibility is that while the participation of dual market makers improves the liquidity and reduces the spread in the equity market, the decision of lead arrangers to participate in the equity market increases with the spreads, and therefore profit opportunities, in the equity market. An OLS regression cannot capture these two opposite effects.

We formally test for endogeneity in our OLS estimation, using the Durbin-Wu-Hausman (DWH) test (See Davidson and MacKinnon, 1993, Durbin, 1954, Hausman, 1978 and Wu, 1973). Our tests reject the null hypothesis of no endogeneity and affirm the need to control for the endogenous DUALMM decision.

4.2 Simultaneous Equation System Methodology

To formally account for the endogeneity between the liquidity of the equity and loan markets, and the decision of dual market makers to participate in both equity and loan markets, we utilize a two-stage probit least squares estimation method corresponding to Maddala (1983) that permits simultaneous multivariate estimation when one of the endogenous variables is continuous and the other endogenous variable is discrete.²⁰

We first test the relation between $DUALMM_t$ and $LOANSPRD_t$. We estimate the following simultaneous regression model:

$$LOANSPRD_t = \gamma_1 DUALMM_t + \beta_1' X_1 + e_1 \quad (6)$$

²⁰ The simultaneous estimation results presented in this paper are qualitatively similar to the results that we find when we implement standard 2SLS estimation, that does not formally account for discrete endogenous variables.

and

$$\text{DUALMM}_t = \gamma_2 \text{TAQSPRD}_t + \beta_2' \mathbf{X}_2 + e_2, \quad (7)$$

The coefficients associated with the simultaneously estimated variables are γ_1 and γ_2 ; e_1 and e_2 are the residuals; and \mathbf{X}_1 and \mathbf{X}_2 are vectors of other independent variables, including the instruments and the control variables, with coefficients β_1' and β_2' .

The simultaneous estimation of equations (6) and (7) is complicated by the fact that one dependent variable is continuous (LOANSPRD_t), whereas the other is discrete (DUALMM_t). Our estimation technique corresponds to the two-stage procedure detailed in Maddala (1983, p. 242). In the first stage, we estimate the following reduced form models:

$$\text{LOANSPRD}_t = \Pi_1 \mathbf{X} + v_1 \quad (8)$$

and

$$\text{DUALMM}_t = \Pi_2 \mathbf{X} + v_2, \quad (9)$$

where v_1 and v_2 are the residuals associated with the reduced form models and \mathbf{X} is a vector of all variables in \mathbf{X}_1 and \mathbf{X}_2 . Because DUALMM_t is a dichotomous variable, we estimate Π_2 / σ_2 , where $\sigma_2^2 = \text{Var}(v_2)$. We therefore rewrite the reduced form model (9) as:

$$\text{DUALMM}_t^* = \frac{\text{DUALMM}_t}{\sigma_2} = \frac{\Pi_2}{\sigma_2} \mathbf{X} + \frac{v_2}{\sigma_2} = \Pi_2^* \mathbf{X} + v_2^*, \quad (10)$$

and rewrite the structural equations (6) and (7) by substituting $\frac{\text{DUALMM}_t}{\sigma_2}$ for DUALMM_t^* as:

$$\text{LOANSPRD}_t = \gamma_1 \sigma_2 \text{DUALMM}_t^* + \beta_1' \mathbf{X}_1 + e_1 \quad (11)$$

and

$$\text{DUALMM}_t^* = \frac{\gamma_2}{\sigma_2} \text{LOANSPRD}_t + \frac{\beta_2'}{\sigma_2} \mathbf{X}_2 + \frac{e_2}{\sigma_2}, \quad (12)$$

We then estimate equations (11) and (12) using a two-stage procedure. In the first stage, we estimate Π_1 through ordinary least squares estimation of the reduced form

model (8), and estimate Π_2^* through probit maximum likelihood estimation of the reduced form model (10). This results in the estimates $\hat{\Pi}_1$ and $\hat{\Pi}_2^*$. In the second stage, we substitute $DUALMM_t^*$ with $\hat{\Pi}_2^* X$ in the structural equation (11) and estimate the equation using ordinary least squares estimation. We then substitute $LOANSPRD_t$ with $\hat{\Pi}_1 X$ in structural equation (12) and estimate the equation using probit maximum likelihood estimation. The corrected variances associated with this methodology are presented in Appendix 3.

To implement the econometric model, we define X_1 and X_2 as:

$$X_1 = [\text{CONSTANT, EQUITYRETURN, LOANRETURN, RATEAISD, SECURED, LFACILITYSIZE, LNUMBSYN, EQUITYINDEXRETURN, LOANINDEXRETURN, PD, DPD, LAGDPD, EQSTDEV, LEVERAGE, EPS, LMV, TANGIBLE, INDUSTRY}] \quad (13)$$

$$X_2 = [\text{CONSTANT, LEADSHARE, INCOMETOA, RATEAISD, SECURED, LFACILITYSIZE, LNUMBSYN, EQUITYINDEXRETURN, LOANINDEXRETURN, PD, DPD, LAGDPD, EQSTDEV, LEVERAGE, EPS, LMV, TANGIBLE, INDUSTRY}] \quad (14)$$

where INDUSTRY represent the industry dummy variables FRENCH1-FRENCH12, excluding the base case reference dummies FRENCH4 and FRENCH12. All other variables are defined in the previous section.

The instruments we use to identify loan market liquidity are EQUITYRETURN and LOANRETURN. Equity return and loan return can impact liquidity since liquidity tends to improve and spreads narrow in an upmarket where the equity and loan returns are positive. However, equity return and loan return per se are unlikely to have direct impact on the decision of becoming a dual market maker.

The instruments used to identify the dual market maker decision are the loan market characteristics – LEADSHARE and INCOMETOA. LEADSHARE is the percentage of the syndicated bank loan that is held by the lead arranger at the initiation of the deal. Since the LEADSHARE reflects the market power of the lead arranger, we expect that the higher the LEADSHARE, the more likely the lead arranger becomes an equity market maker so that information collected from the equity market is more

beneficial for its loan market activities. However, since this variable does not change over time, it is not expected to be directly related to either loan or equity market spreads that are measured over time. INCOMETOA is expected to be positively related to the likelihood that the lead arranger will become an equity market maker, but not directly related to equity or loan spreads. INCOMETOA is a measure of the asset turnover ratio of the borrowing firm. Firms with high asset turnover tend to generate high amounts of income (sales) for a given asset base, *ceteris paribus*, making information on firm operations useful in equity trading. Thus, all else equal, the lead arranger would be more likely to reuse its private information about firm operations and choose DUALMM status. Spreads would not be expected to be directly related to the level of operational profitability.

The control variables in both equations are: SECURED, LFACILITYSIZE, LNUMBSYN, EQUITYINDEXRETURN, LOANINDEXRETURN, PD, DPD, LAGDPD, EQSTDEV, LEVERAGE, EPS, LMV, TANGIBLE, and INDUSTRY.

For the equity market, we jointly estimate the following equations:

$$TAQSPRD_t = \gamma_1 \sigma_2 DUALMM_t^* + \beta_1' X_1 + e_1 \quad (15)$$

and

$$DUALMM_t^* = \frac{\gamma_2}{\sigma_2} TAQSPRD_t + \frac{\beta_2'}{\sigma_2} X_2 + \frac{e_2}{\sigma_2}, \quad (16)$$

where

$$X_1 = [\text{CONSTANT, EQUITYRETURN, LOANRETURN, SECURED, LFACILITYSIZE, LNUMBSYN, EQUITYINDEXRETURN, LOANINDEXRETURN, PD, DPD, LAGDPD, EQSTDEV, LEVERAGE, EPS, LMV, TANGIBLE, INDUSTRY}] \quad (17)$$

$$X_2 = [\text{CONSTANT, INCOMETOA, RATEAID, SECURED, LFACILITYSIZE, LNUMBSYN, EQUITYINDEXRETURN, LOANINDEXRETURN, PD, DPD, LAGDPD, EQSTDEV, LEVERAGE, EPS, LMV, TANGIBLE, INDUSTRY}], \quad (18)$$

Similar to equation (13), the instruments we use in equation (15) to identify equity market liquidity measures are EQUITYRETURN and LOANRETURN. The instruments we use in equation (16) to identify the decision of becoming dual market makers are

INCOMETOA and RATEAISD. For reasons explained previously, we expect INCOMETOA to affect the DUALMM decisions, but not influence the equity market liquidity measures. RATEAISD is a measure of the borrower's credit risk exposure and is expected to be positively related to the DUALMM variable. The lead arranger generates private information about the borrower's creditworthiness, which can be reused when the lead arranger chooses to act as an equity market maker. This information is more useful, the greater the risk of insolvency and the higher the RATEAISD. However, the credit spread would not directly impact equity spreads, which are determined by the structure and the interaction of informed traders, noise traders and market makers in the equity market.

Note that the DUALMM equation specification in equation (16) is identical to the one in equation (12), except for the endogenous TAQSPREAD variable and the LEADSHARE variable.²¹

4.3 Simultaneous Equation System Results

4.3.1 Loan Market Liquidity Effects

Table 5, Panel A presents the effect of dual market maker on loan market liquidity estimated from equation (11). The joint participation of lead arrangers in both the loan and the equity market significantly increases the loan spread (LOANSPRD). The statistically significant (at the 1% level) coefficient on DUALMM takes a value of 0.253, suggesting that having a dual market maker in both the equity and loan market increases the loan spreads by 25.3 basis points. This effect is economically significant compared to the average loan spread of 121 basis points (see Table 1), which represents an increase of 21%. This finding is consistent with *Hypothesis 2*, suggesting that by participating in the equity market the lead arranger learns valuable information from the equity market order flows that gives it monopolist power in the loan market, which in turn increases the overall loan spread. The significant difference in the role of dual market maker in the

²¹ Although LEADSHARE can be an economically appealing instrument for TAQSPREAD, our statistical tests can not strongly reject that LEADSHARE is uncorrelated with the residuals in the TAQSPRD regression. To be conservative, we did not use LEADSHARE as an instrument to identify TAQSPRD. Our results remain robust if we include LEADSHARE as an instrument for the TAQSPRD regression.

equity and loan markets underscores the importance of the different competitive structure of these two markets.

Several other variables also contribute to the loan market liquidity. Loan spreads decrease significantly with increases in the loan prices (LOANRETURN), and increase when the default probability (PD and LAGDPD) is high. Loan spread are lower for firms with more earnings per share (EPS), firms with less leverage (LEVERAGE), and secured loans (SECURED). The firm's equity return volatility (EQSTDEV) is positively related to the loan spread. The loan market is more liquid (loan spreads are narrower) for a company with a more transparent information environment; i.e., loan spreads tend to be smaller for larger firms (LMV). Loan spread also increases with facility size (LFACILITYSIZE) and number of syndicate participants (LNUMBSYN), indicating that our sample of larger deals may more likely include risky, leveraged loans with wider spreads. The adjusted R^2 values show that our specifications are able to explain 36.8% of the variation in the loan spreads.

Table 5, Panel B describes the determinants of the dual market maker decision from the loan market perspective estimation of equation (12). Lead arrangers are more likely to trade in the equity market if they have larger market share in the loan market (LEADSHARE) and therefore can take more advantage of the information extracted from equity trading. The dual market maker probability is higher the more profitable the equity trading opportunities using the lead arranger's information advantage; i.e., the higher the stock return volatility (EQSTDEV) and the larger the equity size (LMV). Lead arrangers are more likely to trade in the equity market if they can profitably use the information they extract from the equity market, for example, when they have more market power in the loan market, as captured by LEADSHARE. Moreover, the likelihood of a dual market maker increases the riskier the loan, as indicated by the positive coefficients on the basis point loan spread at initiation (RATEAISD) variable, lagged change in default probability (LAGDPD), and the secured dummy variable (SECURED).

4.3.2 Equity Market Liquidity Effects

To examine how the participation of dual market makers who have private information about the company affect the structure of the equity market, we jointly

estimate equations (15) and (16) by regressing the equity illiquidity measure on a dummy variable indicating whether the equity market maker is the lead syndicate, while simultaneously controlling for the determinants of the syndicate's decision of becoming an equity market maker.

Table 6, Panel A presents the results for the equity illiquidity equation (15). In contrast to the loan market liquidity case, The presence of a dual market maker significantly decreases the equity spread (TAQSPRD). After controlling for firm-specific and industry effects, the DUALMM variable has a statistically significant (at the 1% level) coefficient of -0.395. That is, the presence of an equity market maker that is also the lead arranger of a bank loan syndicate decreases the equity spread by 39.5 basis points. Given that the average equity spread is approximately 111 basis points (see Table 1), the effect of the dual market maker on spread reduction is economically important at 35%. This result confirms *Hypothesis 1* that the loan syndicate lead arranger with an information advantage becomes a natural liquidity provider in the more competitive equity market and, therefore, the presence of a dual market maker decreases overall equity spreads.

In addition, Table 6, Panel A shows that the equity spread narrows when the equity and loan return (EQUITYRETURN and LOANRETURN) is positive or when the loan is secured (SECURED) and widens when the default probability (PD) is high. The spread also correlates positively with equity volatility (EQSTDEV), consistent with the idea that risk averse market makers set a higher spreads for riskier stocks (see, for example, Ho and Stoll, 1981). Equity spreads are also wider the greater the firm's leverage (as shown by the positive coefficient on the LEVERAGE variable), due to the greater market maker inventory holding costs associated with risky, relatively high cost stocks. The equity of firms with larger market capitalization (LMV) is more liquid, but the spread increases with the loan facility size (LFACILITYSIZE), suggesting that our sample of larger loan syndications may more likely include risky, leveraged loans. The adjusted R^2 values show that our specifications are able to explain 42.2% of the variation in the equity spreads.

Table 6, Panel B describes the determinants of decision to become a dual market maker, as estimated in equation (16). There is no evidence of a statistically significant

relation between measures of equity market liquidity and DUALMM. The likelihood of having a dual market maker is higher if trading in stocks based on the lead arranger's information advantage is more profitable; that is, when the stock return volatility (EQSTDEV) is high and when the equity market is large (LMV). The lead arrangers are more likely to trade in the equity market when there is greater uncertainty about the value of the company, which gives the lead arrangers more information advantage relative to other equity market makers. Thus, as the loan becomes riskier (RATEAISD), the likelihood of a dual market maker increases.

4.3.3 Tests of Instrumental Variables

In this subsection, we perform statistical tests based on a two-stage least squares regression of liquidity variables on the instrumented DUALMM variable.²² The results in Table 7 suggest that our instruments are valid and the system is well-identified.

We first implemented the Sargan test to ascertain that the instruments are exogenous to the structural equation.²³ To implement this test, we first extract the residuals from the instrumental variable regression of the original models. These extracted residuals were then regressed on a set of variables including a constant, the instruments, and all the control variables in the regression. The uncentered R^2 associated with this estimation was then extracted, and the Sargan statistic was estimated as the number of observations multiplied by R^2 , which follows a chi-square distribution. The null hypothesis is that the Sargan statistic is not statistically different from zero. The intuition is that when the instrumental variables are orthogonal to the residuals, the regression R^2 will be low. Failure to reject the null suggests that the instruments are orthogonal to the residuals and, therefore, the overidentifying restrictions are valid. Rejection of the null hypothesis would raise questions about the validity of some of the instruments. Our estimation of the Sargan statistic fails to reject the null.

²² As argued by Angrist and Kruger (2001), the two state least squares regression method is robust and generates consistent estimates even with a dummy endogenous variable. See also Angrist and Imbens (1995), Card (1995), Heckman and Vytlačil (1998). We are not aware of any similar statistics for testing instruments that explicitly account for a dummy endogenous variable.

²³ See Sargan (1964) and Gujarati (2003, pg. 713).

We also investigate whether our systems of equations are underidentified and whether our instruments are irrelevant in model identification.²⁴ To determine whether the system is underidentified we estimate the Anderson underidentification test.²⁵ The Anderson canonical correlation LR statistics are all significantly different from zero (at the 1% confidence level or better). We therefore reject the null of underidentification. To determine whether the instruments are relevant for model identification, we estimate the Cragg-Donald statistic.²⁶ The null is that the system of equation is underidentified. Our test statistics are all well above the associated critical values, which indicates the rejection of the null. These results suggest that our systems of equations are well-identified.²⁷

5. Conclusions and Policy Implications

This paper is the first to study the role of a financial intermediary that simultaneously serves as a lead arranger for a syndicated bank loan and acts as an equity market maker for the borrowing firm's stock, denoted a dual market maker. The lead arranger of a syndicated bank loan possesses private information about the borrowing firm, typically obtained over the course of a long-term lending relationship. In addition, participating in the equity market allows the lead arranger to gain valuable and complementary information from the order flows. We extend the Glosten and Milgrom (1985) model to consider the impact on market liquidity of the presence of such an informed market maker. We hypothesize that in a competitive market such as the equity market, the informed dual market maker becomes a natural liquidity provider and helps to reduce the bid-ask spread in both the equity and the loan market. However, in a less competitive market such as the syndicated loan market, the dual market maker can exploit their informational advantage and extract rents by imposing a higher spread.

Empirically, we analyze the equity and loan market liquidity in the presence of a dual market maker while accounting for the endogeneity of the choice to become a dual market maker. We employ instrumental variables and apply Maddala's (1983) two-stage

²⁴ See Hall (1996).

²⁵ See Anderson (1951).

²⁶ See Cragg-Donald (1993).

²⁷ Rejection of the null is based on the critical values based on TSLS size at the 5% significance level presented in Table 2 of Stock and Yogo (2003).

procedure that permits simultaneous multivariate estimation of dependent variables that are both continuous (liquidity measures) and discrete (the decision to become a dual market maker. We find support for the theoretical proposition that the participation of a dual market maker decreases the degree of information asymmetry in the competitive equity market and, therefore, narrows the bid-ask spread and improves liquidity in the equity market. In contrast, the presence of a dual market maker is found to increase spreads in the less competitive secondary market for syndicated bank loans.

In addition, we find that the lead arranger of a syndicated bank loan has more of an incentive to become an equity market maker when the profit opportunities of market making are high. This occurs when the dual market maker has a greater informational advantage over other equity market makers, when the equity market capitalization is large, and when the lead arranger has a larger market share in the loan market.

Our analysis has two major policy implications. The gradual relaxation and the eventual repeal of the Glass-Steagall Act in 1999 expanded banking powers to include a broad range of banking, securities underwriting and dealing, and insurance activities. However, there is a growing debate whether the benefits of such expansions outweigh the costs.²⁸ Berger and Bouwman (2008) show that large banks contributed most to the creation of liquidity in the economy over the period from 1993-2003. However, this liquidity increase may have been obtained at the cost of financial market fragility, as the reach of global financial institutions contagiously spread risk throughout the financial

²⁸Kanatas and Qi (2003) describe possible conflicts of interest between lending and underwriting, and claim that specialized financial intermediaries are more innovative than universal banks. However, Saunders and Stover (2004) find evidence of economies of scope between underwriting and commercial banking when the same bank serves as underwriter and as credit guarantor. Moreover, Drucker and Puri (2005) find evidence of information economies of scope between lending and equity underwriting. Ljungqvist, Marston and Wilhelm (2006) find that the strength of a prior banking relationship is an important determinant in the award of underwriting contracts. Bharath et al. (2007) also find that banks are more likely to win underwriting engagements if they have established prior lending relationships. Moreover, although these relationship loan rates are, on average, lower than the rate on non-relationship bank lending, underwriting fees are significantly higher for relationship banks. A study documenting the “dark role of investment banks in the market for corporate control” was highlighted on the front page of the *Wall Street Journal* (January 14, 2008), and shows that bank advisors to acquirers in mergers and acquisitions take positions in the target company’s stock prior to the announcement of the merger. The bank advisor appears to exploit its informational advantage in order to obtain substantial positive abnormal returns from the bank’s investment in target firm stock, but its actions harm its client by reducing the returns to the acquirer. See Bodnaruk, et al. (2008). Moreover, Keys et al. (2008) show that securitized debt was 20% more likely to default than debt held on the lending banks’ books, suggesting that combining securitization and lending undermines the banks’ incentives to screen and monitor borrowers.

system (highlighted by the financial crisis of 2007-2008). Our analysis contributes to this debate on the benefits and costs of expanding the role of financial intermediaries by examining the impact on informational efficiency and market liquidity of combining lending with equity market making activities.

The second set of policy implications associated with this paper is related to regulations on information flows within financial intermediaries – in particular, the possibility that dual market making violates insider trading laws. This is a murky area, in part, because “securities laws neither provide a definition of ‘insider trading’ nor expressly forbid it.” (Eads (1991), p. 1457). Indeed, Congress may have deliberately refused to precisely define insider trading so as to give the SEC more flexibility in enforcement. Recent court cases have developed the theory that insider trading involves misappropriation. “‘Misappropriation trading’ results when a trader exploits material, non-public information to trade securities and breaches a duty owed to the source of such information.” (Prakash (1999), p. 1493). However, where the divider lies between legal and illegal activity is murky. It is unclear whether members of a loan syndicate owe a fiduciary duty to the borrower or even if they are privy to “material” information in a legal sense.²⁹ Although this paper does not address the question of whether illegal trading activity is taking place, we demonstrate that the presence of global financial institutions, simultaneously trading in many financial markets, affects the liquidity and information efficiency of asset prices in these markets. Hence, we demonstrate that policy proposals regarding “Chinese” and “ethical” walls restricting the reusability of information within financial institutions should consider the potential impact on market efficiency.

²⁹ Upon extensive interviews with regulators (at the SEC and the Federal Reserve) and trade organizations (the Loan Syndications and Trading Association, the LSTA), no clear consensus arose regarding the legality of the reusability of borrower information provided to the loan syndicate. What can loan syndicate members do with information obtained in the course of a loan syndication? Can they engage in proprietary equity trading (most state emphatically, “no”), credit default swaps (“maybe”), syndicate participations (“yes”). As yet, however, there has been no legal resolution to this uncertainty.

Appendix 1: Derivation of Proposition 1

Due to the presence of the noise trader and the imperfect information available to the market makers, the market maker's expectation about the value of the asset (and therefore the price he sets) only partially incorporates the asset's true value; i.e., it is below the true value if the true value is \bar{V} and above the true value if the true value is \underline{V} . Therefore, when trading against such a market maker, the informed trader's trading rule is simple: he always buys when the true value is \bar{V} and sells when the true value is \underline{V} .

The market maker's conditional expectation of the asset value based on the signal I and the direction of the order is:

$$E[V | S, I] = \underline{V} \Pr\{V = \underline{V} | S, I\} + \bar{V} \Pr\{V = \bar{V} | S, I\} \quad (\text{A1})$$

and

$$E[V | B, I] = \underline{V} \Pr\{V = \underline{V} | B, I\} + \bar{V} \Pr\{V = \bar{V} | B, I\}, \quad (\text{A2})$$

where B and S represent whether the trade is a buy or a sell, and the signal I can take a value of either \underline{V} or \bar{V} .

To solve for $\Pr\{V = \underline{V} | S, I\}$, we first consider the case where the market maker's signal indicates that the asset is of low value: $I = \underline{V}$. Following Bayes rule, the conditional probability is given by

$$\Pr\{V = \underline{V} | S, I = \underline{V}\} = \frac{\Pr\{S, I = \underline{V} | V = \underline{V}\} \Pr\{V = \underline{V}\}}{\Pr\{S, I = \underline{V} | V = \underline{V}\} \Pr\{V = \underline{V}\} + \Pr\{S, I = \underline{V} | V = \bar{V}\} \Pr\{V = \bar{V}\}} \quad (\text{A3})$$

If $V = \underline{V}$, the informed investor will sell with probability 1 and the uninformed investor will sell with probability 0.5. The probability of seeing a sale and receiving a low signal if $V = \underline{V}$ is:

$$\begin{aligned} & \Pr\{S, I = \underline{V} | V = \underline{V}\} \\ &= \Pr\{S^i, I = \underline{V} | V = \underline{V}\} \Pr\{\text{informed}\} + \Pr\{S^n, I = \underline{V} | V = \underline{V}\} \Pr\{\text{liquidity}\}, \quad (\text{A4}) \\ &= k\gamma + 0.5k(1 - \gamma) = 0.5k(1 + \gamma) \end{aligned}$$

where S^i indicates that the sell order is from the informed investor and S^n indicates that the sell order is from the liquidity trader.

Similarly,

$$\begin{aligned}
& \Pr\{S, I = \underline{V} \mid V = \bar{V}\} \\
&= \Pr\{S^i, I = \underline{V} \mid V = \bar{V}\} \Pr\{\text{informed}\} + \Pr\{S^n, I = \underline{V} \mid V = \bar{V}\} \Pr\{\text{liquidity}\} \quad (\text{A5}) \\
&= 0 + 0.5(1-k)(1-\gamma) = 0.5(1-k)(1-\gamma)
\end{aligned}$$

Using equation (A4) and (A5), we can solve for the probability of seeing a sale and receiving a low signal if $V = \underline{V}$ in equation (A3) as:

$$\Pr\{V = \underline{V} \mid S, I = \underline{V}\} = \frac{k(1+\gamma)\delta}{k(1+\gamma)\delta + (1-k)(1-\gamma)(1-\delta)} \quad (\text{A6})$$

The probability of seeing a sale and receiving a low signal if $V = \bar{V}$ is simply $\Pr\{V = \bar{V} \mid S, I = \underline{V}\} = 1 - \Pr\{V = \underline{V} \mid S, I = \underline{V}\}$.

Consider the second scenario, when the market maker receives a low value signal and a buy order, the probability that the true value is low is

$$\Pr\{V = \underline{V} \mid B, I = \underline{V}\} = \frac{\Pr\{B, I = \underline{V} \mid V = \underline{V}\} \Pr\{V = \underline{V}\}}{\Pr\{B, I = \underline{V} \mid V = \underline{V}\} \Pr\{V = \underline{V}\} + \Pr\{B, I = \underline{V} \mid V = \bar{V}\} \Pr\{V = \bar{V}\}} \quad (\text{A7})$$

Solving for the two conditional probabilities, we have:

$$\begin{aligned}
\Pr\{B, I = \underline{V} \mid V = \underline{V}\} &= \Pr\{B^i, I = \underline{V} \mid V = \underline{V}\} \gamma + \Pr\{B^n, I = \underline{V} \mid V = \underline{V}\} (1-\gamma) \\
&= 0 + 0.5k(1-\gamma) = 0.5k(1-\gamma)
\end{aligned}$$

and

$$\begin{aligned}
\Pr\{B, I = \underline{V} \mid V = \bar{V}\} &= \Pr\{B^i, I = \underline{V} \mid V = \bar{V}\} \gamma + \Pr\{B^n, I = \underline{V} \mid V = \bar{V}\} (1-\gamma) \\
&= (1-k)\gamma + 0.5(1-k)(1-\gamma) = 0.5(1-k)(1+\gamma)
\end{aligned}$$

Therefore, equation (A7) becomes

$$\Pr\{V = \underline{V} \mid B, I = \underline{V}\} = \frac{k(1-\gamma)\delta}{k(1-\gamma)\delta + (1-k)(1+\gamma)(1-\delta)} \quad (\text{A8})$$

In the third scenario, the market maker receives a high value signal and a sell order, the probability that the true value is low is

$$\begin{aligned}
& \Pr\{V = \underline{V} \mid S, I = \bar{V}\} = \\
& \frac{\Pr\{S, I = \bar{V} \mid V = \underline{V}\} \Pr\{V = \underline{V}\}}{\Pr\{S, I = \bar{V} \mid V = \underline{V}\} \Pr\{V = \underline{V}\} + \Pr\{S, I = \bar{V} \mid V = \bar{V}\} \Pr\{V = \bar{V}\}} \quad (\text{A9})
\end{aligned}$$

Solving for the two conditional probabilities in equation (A9), we have:

$$\begin{aligned}
\Pr\{S, I = \bar{V} \mid V = \underline{V}\} &= \Pr\{S^i, I = \bar{V} \mid V = \underline{V}\} \gamma + \Pr\{S^n, I = \bar{V} \mid V = \underline{V}\} (1-\gamma) \\
&= (1-k)\gamma + 0.5(1-k)(1-\gamma) = 0.5(1-k)(1+\gamma)
\end{aligned}$$

and

$$\begin{aligned}\Pr\{S, I = \bar{V} \mid V = \underline{V}\} &= \Pr\{S^i, I = \bar{V} \mid V = \underline{V}\}\gamma + \Pr\{S^n, I = \bar{V} \mid V = \underline{V}\}(1-\gamma) \\ &= 0 + 0.5k(1-\gamma) = 0.5k(1-\gamma)\end{aligned}$$

Therefore, equation (A9) becomes

$$\Pr\{V = \underline{V} \mid S, I = \bar{V}\} = \frac{(1-k)(1+\gamma)\delta}{(1-k)(1+\gamma)\delta + k(1-\gamma)(1-\delta)} \quad (\text{A10})$$

In the fourth scenario, the market maker received a high value signal and a buy order, the probability that the true value is low is

$$\begin{aligned}\Pr\{V = \underline{V} \mid B, I = \bar{V}\} &= \\ &= \frac{\Pr\{B, I = \bar{V} \mid V = \underline{V}\}\Pr\{V = \underline{V}\}}{\Pr\{B, I = \bar{V} \mid V = \underline{V}\}\Pr\{V = \underline{V}\} + \Pr\{B, I = \bar{V} \mid V = \bar{V}\}\Pr\{V = \bar{V}\}}\end{aligned} \quad (\text{A11})$$

Solving for the two conditional probabilities, we have:

$$\begin{aligned}\Pr\{B, I = \bar{V} \mid V = \underline{V}\} &= \Pr\{B^i, I = \bar{V} \mid V = \underline{V}\}\gamma + \Pr\{B^n, I = \bar{V} \mid V = \underline{V}\}(1-\gamma) \\ &= 0 + 0.5(1-k)(1-\gamma) = 0.5(1-k)(1-\gamma)\end{aligned}$$

and

$$\begin{aligned}\Pr\{B, I = \bar{V} \mid V = \bar{V}\} &= \Pr\{B^i, I = \bar{V} \mid V = \bar{V}\}\gamma + \Pr\{B^n, I = \bar{V} \mid V = \bar{V}\}(1-\gamma) \\ &= k\gamma + 0.5k(1-\gamma) = 0.5k(1+\gamma)\end{aligned}$$

Therefore, equation (A11) becomes

$$\Pr\{V = \underline{V} \mid B, I = \bar{V}\} = \frac{(1-k)(1-\gamma)\delta}{(1-k)(1-\gamma)\delta + k(1+\gamma)(1-\delta)} \quad (\text{A12})$$

With the conditional probability for these four scenarios determined, we can calculate the market maker's expected value of the asset when he receives a signal of low value:

$$\begin{aligned}E[V \mid B, I = \underline{V}] &= \underline{V} \Pr\{V = \underline{V} \mid B, I = \underline{V}\} + \bar{V} \Pr\{V = \bar{V} \mid B, I = \underline{V}\} \\ &= \underline{V} + \frac{(1-k)(1+\gamma)(1-\delta)}{k(1-\gamma)\delta + (1-k)(1+\gamma)(1-\delta)}(\bar{V} - \underline{V})\end{aligned} \quad (\text{A13})$$

and

$$\begin{aligned}E[V \mid S, I = \underline{V}] &= \underline{V} \Pr\{V = \underline{V} \mid S, I = \underline{V}\} + \bar{V} \Pr\{V = \bar{V} \mid S, I = \underline{V}\} \\ &= \underline{V} + \frac{(1-k)(1-\gamma)(1-\delta)}{k(1+\gamma)\delta + (1-k)(1-\gamma)(1-\delta)}(\bar{V} - \underline{V})\end{aligned} \quad (\text{A14})$$

Similarly, the market maker's expected value of the asset when he receives a signal of high value is:

$$\begin{aligned} E[V | B, I = \bar{V}] &= \underline{V} \Pr\{V = \underline{V} | B, I = \bar{V}\} + \bar{V} \Pr\{V = \bar{V} | B, I = \bar{V}\} \\ &= \underline{V} + \frac{k(1+\gamma)(1-\delta)}{(1-k)(1-\gamma)\delta + k(1+\gamma)(1-\delta)} (\bar{V} - \underline{V}) \end{aligned} \quad (A15)$$

and

$$\begin{aligned} E[V | S, I = \bar{V}] &= \underline{V} \Pr\{V = \underline{V} | S, I = \bar{V}\} + \bar{V} \Pr\{V = \bar{V} | S, I = \bar{V}\} \\ &= \underline{V} + \frac{k(1-\gamma)(1-\delta)}{(1-k)(1+\gamma)\delta + k(1-\gamma)(1-\delta)} (\bar{V} - \underline{V}) \end{aligned} \quad (A16)$$

Appendix 2: Estimation of the Implied Probability of Default

The contingent claims indicator of default is backed out from a nonlinear system of two equations:

$$V_{Eit} = V_{Ait} N(D_{1it}) - e^{-rT} L_{it} N(D_{2it}), \quad (A17)$$

$$\sigma_{Eit} = \frac{V_{Ait}}{V_{Eit}} N(D_{1it}) \sigma_{Ait}, \quad (A18)$$

where

$$D_{1it} = [\ln(V_{Ait}/L_{it}) + T(r_t + 0.5\sigma_{Ait}^2)] / \sigma_{Ait} \sqrt{T}, \quad (A19)$$

$$D_{2it} = D_{1it} - \sigma_{Ait} \sqrt{T} \quad (A20)$$

and $N(\cdot)$ is the normal distribution. The variables V_{Eit} (market value equity of firm (i) at time (t)), σ_{Eit} (volatility of firm's equity), L_{it} (firm's total debt), and r_t (risk free rate of return) are all known or estimated from a firm's equity price over the period T (in our monthly framework $T = 1/12$). Estimates for the firm's asset value (\tilde{V}_{Ait}) and volatility ($\tilde{\sigma}_{Ait}$) can be solved using Newton's nonlinear approximation technique. The market variables V_{Eit} and σ_{Eit} were computed monthly using daily stock return information from CRSP (to obtain a more stable measure of volatility, we used a rolling 6-month horizon). The risk-free rate is measured by the 1-year Treasury bill rate. We use COMPUSTAT

information on long-term debt to measure L_{it} as the total debt obligations with maturity greater than one year (primarily, outstanding bonds and loans). The implied default probability is $IDP_{it} = N(-DD_{it})$ where $DD_{it} = [\ln(V_{Ati}/D_{it}) + T(\mu - 0.5\sigma_{Ati}^2)]/\sigma_{Ati}\sqrt{T}$. The parameter μ representing the instantaneous drift of V_A can be estimated by calculating the average change in $\log(\tilde{V}_{Ati})$.

Appendix 3: Corrected Variances Used in the Two Stage Procedure

Following a procedure similar to Amemiya (1979), Maddala (1983) derives the following asymptotic covariance matrix. Define $\alpha'_1 = (\gamma_1\sigma_2, \beta'_1)$ and $\alpha'_2 = (\gamma_2/\sigma_2, \beta'_2/\sigma_2)$. The corrected variances are

$$\text{Var}(\hat{\alpha}_1) = c(H'X'XH)^{-1} + (\gamma_1\sigma_2)^2(H'X'XH)^{-1}H'X'XV_0X'XH(H'X'XH)^{-1} \quad (\text{A21})$$

and

$$\text{Var}(\hat{\alpha}_2) = (G'V_0^{-1}G)^{-1} + d(G'V_0^{-1}G)^{-1}G'V_0^{-1}(X'X)^{-1}V_0^{-1}G(G'V_0^{-1}G)^{-1}, \quad (\text{A22})$$

where

$$c = \sigma_1^2 - 2\gamma_1\sigma_{12},$$

$$d = (\gamma_2/\sigma_2)^2\sigma_1^2 - 2(\gamma_2/\sigma_2)(\sigma_{12}/\sigma_2),$$

$$H = (\Pi_2, J_1),$$

$$G = (\Pi_2, J_2),$$

$$V_0 = \text{Var}(\hat{\Pi}_2),$$

and J_1 and J_2 are matrices of ones and zeros such that $XJ_1 = X_1$ and $XJ_2 = X_2$.

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Table 1: Descriptive statistics.

Variables, variable descriptions, number of observations, mean, median and standard deviation are reported for a sample of syndicated bank loans that had at least two quotes from loan dealers on a given date between January 1999 and May 2003.

Variable	Variable Description	Number	Mean	Median	Standard Dev.
DUALMM	Dual market maker dummy	22,826	0.2244	0.0000	0.4172
LOANSPRD	Relative loan spread (%)	22,826	1.2109	0.6609	2.1054
LOANRETURN	Loan return	22,826	-0.0001	0.0000	0.0106
LOANINDEXRETURN	Loan index return	22,698	-0.0002	0.0002	0.0032
LOANNBA	Sum of loan bid and ask quotations	22,826	8.0191	6.0000	5.6000
LEADSHARE	Lead arranger's market share (%)	19,618	17.1927	18.0000	14.2534
TAQSPRD	Relative equity spread (%)	22,826	1.1139	0.4363	2.2897
EQUITYRETURN	Equity return	22,826	0.0027	0.0000	0.0991
EQUITYINDEXRETURN	Equity index return	22,826	-0.0024	-0.0026	0.0307
EQSTDEV	Monthly equity volatility	21,602	0.1599	0.1448	0.0670
PD	Implied probability of default	22,826	0.0367	0.0012	0.0971
DPD	Change in implied probability of default	21,826	0.0004	0.0000	0.0124
LAGDPD	Lagged change in implied probability of default	20,726	0.0004	0.0000	0.0123
SECURED	Collateralization dummy	22,826	0.8408	1.0000	0.3658
RATEAISD	Basis point loan spread at initiation	22,826	266.0756	275.0000	105.8605
FACILITYSIZE	Loan facility size	22,826	479.3394	285.0000	579.0908
NUMBSYN	Number of syndicate members at initiation	22,595	17.5789	15.0000	14.6432
LEVERAGE	Total debt/total assets	22,826	0.5277	0.5207	0.2120
INCOMETOA	Operating income before depreciation/total assets	21,645	0.1264	0.1149	0.0785
EPS	Earnings per share	22,771	0.2791	0.4900	6.5365
TANGIBLE	Gross property, plant and equipment/total assets	21,742	0.5002	0.3945	0.3294
MV	Market value (Million \$)	22,826	2,704.1882	1,122.9224	6,614.6769

Table 2: Correlations.

Correlations between the variables in our sample. Correlations in bold are statistically significant at the 10% level or better.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	
DUALMM	(1)																					
LOANSPRD	(2)	0.09																				
LOANRETURN	(3)	0.01	-0.08																			
LOANINDEXRETURN	(4)	-0.02	-0.03	0.10																		
LOANNBA	(5)	0.17	-0.08	0.00	0.00																	
LEADSHARE	(6)	0.34	0.12	0.01	-0.02	0.21																
TAQSPRD	(7)	-0.07	0.22	-0.06	-0.06	-0.08	-0.05															
EQUITYRETURN	(8)	0.00	-0.02	0.12	0.07	0.01	0.01	-0.05														
EQUITYINDEXRETURN	(9)	-0.04	0.01	-0.03	0.00	0.00	0.00	0.01	0.25													
EQSTDEV	(10)	0.12	0.30	0.02	-0.01	0.03	0.05	0.30	0.02	0.00												
PD	(11)	0.00	0.30	-0.07	0.00	0.03	0.03	0.48	-0.01	0.01	0.45											
DPD	(12)	0.00	0.08	-0.19	-0.07	0.00	0.00	0.10	-0.23	-0.03	0.01	0.17										
LAGDPD	(13)	-0.01	0.10	-0.17	-0.06	0.00	0.00	0.11	-0.02	0.04	0.01	0.21	0.19									
SECURED	(14)	0.06	-0.01	-0.02	0.00	0.17	-0.05	0.03	-0.01	0.00	-0.01	0.08	0.01	0.01								
RATEAID	(15)	0.02	0.10	-0.02	-0.01	0.12	-0.11	0.21	-0.01	0.01	0.27	0.33	0.02	0.02	0.46							
FACILITYSIZE	(16)	0.07	-0.03	0.01	0.00	0.28	0.14	-0.10	0.00	0.00	0.01	-0.03	-0.01	-0.01	-0.25	-0.22						
NUMBSYN	(17)	0.07	0.01	0.00	-0.02	0.15	0.33	-0.06	0.00	0.00	-0.02	-0.01	0.00	0.00	-0.06	-0.08	0.24					
LEVERAGE	(18)	0.02	0.05	-0.01	-0.03	0.04	0.15	0.27	-0.01	0.01	0.26	0.20	0.01	0.02	0.09	0.16	-0.08	-0.05				
INCOMETOA	(19)	0.10	-0.06	-0.01	0.00	-0.05	-0.03	-0.07	0.00	0.00	-0.27	-0.16	-0.01	-0.01	0.07	-0.21	-0.12	-0.07	0.13			
EPS	(20)	0.01	-0.05	-0.01	0.00	-0.01	-0.02	-0.07	0.00	0.00	-0.17	-0.08	0.00	0.00	0.02	-0.08	-0.03	0.01	-0.06	0.21		
TANGIBLE	(21)	-0.05	0.00	0.01	0.00	-0.03	0.01	0.14	0.00	0.00	-0.09	0.07	0.00	0.00	0.01	0.02	-0.01	-0.08	0.16	0.07	-0.04	
MV	(22)	0.03	-0.04	0.02	0.00	-0.02	0.03	-0.13	0.01	0.00	-0.14	-0.11	-0.02	-0.02	-0.27	-0.21	0.49	0.04	-0.17	0.04	0.03	0.03

Table 3: OLS regressions of loan market liquidity.

We perform OLS regression of LOANSPRD on DUALMM. DUALMM is the dual market maker dummy. LOANSPRD is the relative loan spread. EQUITYRETURN is the equity return. EQUITYINDEXRETURN is the equity index return. LOANRETURN is the loan return. LOANINDEXRETURN is the loan index return. PD is the implied probability of default. DPD is the change in implied probability of default. LAGDPD is the lagged change in implied probability of default. SECURED is the collateralization dummy. LFACILITYSIZE is the logarithmic value of the loan facility size. LNUMBSYN is the logarithmic value of the number of syndicate members at initiation. LEVERAGE is the ratio of total debt to total assets. EPS is the earnings per share. TANGIBLE is the ratio of gross property, plant and equipment to total assets. LMV is the logarithmic value of the market value. The standard errors are shown in the parenthesis and the significance levels are indicated by *, ** and *** that represent 10%, 5% and 1% level, respectively.

	LOANSPRD
DUALMM	0.340** (0.154)
EQUITYRETURN	0.278** (0.117)
LOANRETURN	-13.877*** (3.625)
SECURED	-0.455*** (0.111)
LFACILITYSIZE	0.105 (0.069)
LNUMBSYN	0.048 (0.046)
EQUITYINDEXRETURN	0.089 (0.178)
LOANINDEXRETURN	-7.239** (2.951)
PD	4.184*** (0.887)
DPD	1.708 (1.530)
LAGDPD	3.347** (1.315)
EQSTDEV	1.889*** (0.675)
LEVERAGE	(0.452) (0.398)
EPS	0.002 (0.002)
LMV	-0.303*** (0.059)
TANGIBLE	0.120 (0.132)
INDUSTRY	YES
CONSTANT	YES
Adj. R ²	0.370
N	17,664

Table 4: OLS regressions of equity market liquidity.

We perform OLS regression of the equity liquidity measure (TAQSPRD) on DUALMM. DUALMM is the dual market maker dummy. TAQSPRD is the relative equity spread. EQUITYRETURN is the equity return. EQUITYINDEXRETURN is the equity index return. LOANRETURN is the loan return. LOANINDEXRETURN is the loan index return. EQSTDEV is the monthly equity volatility. PD is the implied probability of default. DPD is the change in implied probability of default. LAGDPD is the lagged change in implied probability of default. SECURED is the collateralization dummy. LFACILITYSIZE is the logarithmic value of the loan facility size. LNUMBSYN is the logarithmic value of the number of syndicate members at initiation. LEVERAGE is the ratio of total debt to total assets. EPS is the earnings per share. TANGIBLE is the ratio of gross property, plant and equipment to total assets. LMV is the logarithmic value of the market value. The standard errors are shown in the parenthesis and the significance levels are indicated by *, ** and *** that represent 10%, 5% and 1% level, respectively.

	TAQSPRD
DUALMM	0.074 (0.093)
EQUITYRETURN	-0.514** (0.249)
LOANRETURN	-3.904*** (1.449)
SECURED	-0.586* (0.325)
LFACILITYSIZE	0.079 (0.078)
LNUMBSYN	(0.081) (0.061)
EQUITYINDEXRETURN	0.536 (0.451)
LOANINDEXRETURN	-23.610*** (4.202)
PD	5.930*** (1.866)
DPD	1.608 (2.592)
LAGDPD	(0.311) (2.655)
EQSTDEV	1.286 (1.066)
LEVERAGE	0.851** (0.367)
EPS	0.000 (0.003)
LMV	-0.699*** (0.103)
TANGIBLE	1.128*** (0.303)
INDUSTRY	YES
CONSTANT	YES
Adj. R ²	0.420
N	17,664

Table 5: Joint multivariate estimation of loan spreads and dual market maker decision.

We utilize a two-stage probit least squares estimation method corresponding to Maddala (1983) to simultaneously estimate LOANSPRD and DUALMM. Panel A presents the result of the LOANSPRD equation. Panel B presents the result of the DUALMM equation. DUALMM is the dual market maker dummy. LOANSPRD is the relative loan spread. LOANRETURN is the loan return. LOANINDEXRETURN is the loan index return. LOANNBA is the sum of loan bid and ask quotations. LEADSHARE is the lead arranger's market share. TAQSPRD is the relative equity spread. EQUITYRETURN is the equity return. EQUITYINDEXRETURN is the equity index return. EQSTDEV is the monthly equity volatility. PD is the implied probability of default. DPD is the change in implied probability of default. LAGDPD is the lagged change in implied probability of default. SECURED is the collateralization dummy. RATEAISD is the basis point loan spread at initiation. LFACILITYSIZE is the logarithmic value of the loan facility size. LNUMBSYN is the logarithmic value of the number of syndicate members at initiation. LEVERAGE is the ratio of total debt to total assets. INCOMETOA is the ratio of operating income before depreciation to total assets. EPS is the earnings per share. TANGIBLE is the ratio of gross property, plant and equipment to total assets. LMV is the logarithmic value of the market value. The standard errors are shown in the parenthesis and the significance levels are indicated by *, ** and *** that represent 10%, 5% and 1% level, respectively.

Panel A: Estimation of the loan spread equation.

	LOANSPRD
DUALMM	0.253*** (0.016)
LOANRETURN	-13.206*** (0.935)
EQUITYRETURN	0.319*** (0.097)
RATEAISD	-0.002*** 0.000
SECURED	-0.228*** (0.030)
LFACILITYSIZE	0.099*** (0.013)
LNUMBSYN	0.018* (0.010)
LOANINDEXRETURN	-1.941 (2.832)
EQUITYINDEXRETURN	0.650** (0.299)
PD	4.113*** (0.128)
DPD	-0.299 (0.806)
LAGDPD	2.152*** (0.804)
EQSTDEV	1.317*** (0.188)
LEVERAGE	-0.464*** (0.052)
EPS	-0.005* (0.003)
LMV	-0.448*** (0.012)
TANGIBLE	0.025 (0.034)
INDUSTRY	YES
CONSTANT	YES
Adj. R ²	0.368
N	15,404

Panel B: Estimation of the dual market maker equation.

	DUALMM
LOANSPRD	0.007 (0.108)
LEADSHARE	0.039*** (0.001)
INCOMETOA	4.420*** (0.258)
RATEAISD	0.002*** (0.000)
SECURED	0.334*** (0.046)
LFACILITYSIZE	0.095*** (0.023)
LNUMBSYN	0.003 (0.016)
LOANINDEXRETURN	-18.831*** (4.132)
EQUITYINDEXRETURN	-3.487*** (0.407)
PD	0.425 (0.494)
DPD	1.925 (1.179)
LAGDPD	4.269*** (1.299)
EQSTDEV	5.206*** (0.387)
LEVERAGE	-0.336*** (0.101)
EPS	0.016*** (0.004)
LMV	0.415*** (0.041)
TANGIBLE	-0.289*** (0.051)
INDUSTRY	YES
CONSTANT	YES
Chi ²	4,721.541
N	15,404

Table 6: Joint multivariate estimation of equity spreads and dual market maker decision.

We utilize a two-stage probit least squares estimation method corresponding to Maddala (1983) to simultaneously estimate the equity liquidity measure (TAQSPRD) and DUALMM. Panel A presents the results of the TAQSPRD equation. Panel B presents the results of the DUALMM equation. DUALMM is the dual market maker dummy. LOANSPRD is the relative loan spread. LOANRETURN is the loan return. LOANINDEXRETURN is the loan index return. LEADSHARE is the lead arranger's market share. TAQSPRD is the relative equity spread. EQUITYRETURN is the equity return. EQUITYINDEXRETURN is the equity index return. EQSTDEV is the monthly equity volatility. PD is the implied probability of default. DPD is the change in implied probability of default. LAGDPD is the lagged change in implied probability of default. SECURED is the collateralization dummy. RATEAISD is the basis point loan spread at initiation. LFACILITYSIZE is the logarithmic value of the loan facility size. LNUMBSYN is the logarithmic value of the number of syndicate members at initiation. LEVERAGE is the ratio of total debt to total assets. INCOMETOA is the ratio of operating income before depreciation to total assets. EPS is the earnings per share. TANGIBLE is the ratio of gross property, plant and equipment to total assets. LMV is the logarithmic value of the market value. The standard errors are shown in the parenthesis and the significance levels are indicated by *, ** and *** that represent 10%, 5% and 1% level, respectively.

Panel A: Estimation of the equity spread equation.

	TAQSPRD
DUALMM	-0.395*** (0.050)
LOANRETURN	-4.132*** (1.480)
EQUITYRETURN	-0.543*** (0.151)
SECURED	-0.358*** (0.049)
LFACILITYSIZE	0.120*** (0.021)
LNUMBSYN	-0.019 (0.018)
LOANINDEXRETURN	-30.565*** (4.610)
EQUITYINDEXRETURN	-0.721 (0.496)
PD	6.086*** (0.193)
DPD	1.800 (1.251)
LAGDPD	1.105 (1.254)
EQSTDEV	3.262*** (0.356)
LEVERAGE	1.066*** (0.085)
EPS	0.004 (0.005)
LMV	-0.550*** (0.024)
TANGIBLE	0.983*** (0.055)
INDUSTRY	YES
CONSTANT	YES
Adj. R ²	0.422
N	17,578

Panel B: Estimation of the dual market maker equation.

	DUALMM
TAQSPRD	0.101 (0.181)
INCOMETOA	4.387*** (0.349)
RATEAISD	0.001*** (0.000)
SECURED	0.401*** (0.095)
LFACILITYSIZE	0.129*** (0.021)
LNUMBSYN	0.168*** (0.020)
LOANINDEXRETURN	-13.583** (5.955)
EQUITYINDEXRETURN	-3.008*** (0.373)
PD	-0.299 (1.086)
DPD	0.831 (1.139)
LAGDPD	3.671*** (0.999)
EQSTDEV	5.048*** (0.316)
LEVERAGE	0.152 (0.189)
EPS	-0.009* (0.005)
LMV	0.422*** (0.127)
TANGIBLE	-0.706*** (0.222)
INDUSTRY	YES
CONSTANT	YES
Chi ²	3,273.334
N	17,578

Table 7: Tests for the instruments.

The statistical tests are performed using a two-stage least squares regression of liquidity variables (TAQSPRD and LOANSPRD) on the instrumented DUALMM variables. The Sargan test checks for the validity of instruments. The Anderson underidentification test and the Cragg-Donald statistic investigate whether our system of equations are underidentified and whether our instruments are irrelevant in model identification. The test-statistic and the P-values are reported for the Sargan statistic and the Anderson underidentification tests. For the Cragg Donald statistic, we report critical values based on TSLS size at the 5% significance level of a Wald test for the desired maximal size of 10, as presented in Table 2 of Stock and Yogo (2005).

	LOANSPRD	TAQSPRD
Sargan statistic	1.720	1.561
P-value	0.1897	0.2115
Anderson canonical correlation LR statistic	1,858.792	541.362
P-value	0.00	0.00
Cragg-Donald Wald F statistic	1,054.946	278.837
Stock Yogo critical values, maximal size of 10, of a 5% Wald test	19.93	19.93