Essays in Financial Intermediation

by

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For my parents, Huanwei and Yanwei. This work is made possible by your love, nurturing and guidance over the years. For my wife, Jia. This work is made possible by your love, help, tolerance, and unrelenting positivity. For my children, Alexander and Arianna. This work is made possible by your love and smiles.

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ABSTRACT

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This dissertation includes three essays about different aspects of financial intermediation. The first two essays look into bank risk-taking and risk reporting. The third essay studies the merits of market making contracts.

The first essay examines how banks react differently to an increase in banking market competition conditional on their ex ante capital ratio. Low equity capital and credit market competition have been viewed as the main driving factors of bank risk taking. To understand risk taking by banks, however, we need to understand the interaction between the competition and the capital ratio. This essay studies the impact of the capital (leverage) ratio on a bank's risk-taking behavior. Using deregulation in the 1980s as a shock to competition, I find that low-capital banks, compared with their high-capital peers, significantly reduce their risk when facing increased competition. This difference in risk-taking behavior between high- and low-capital banks is a crucial factor to take into account when considering bank capital requirements.

While the first essay focuses on the risk-taking behavior of banks conditional on their capital ratio, the second one looks into the reporting of risk by financial institutions. Current financial regulation requires banks to self-report the level of risk, namely their Value-at-Risk (VaR), in their trading portfolio. This self-reported VaR is linked to their capital requirements. If banks under-report their risk in the current period, they are more likely to violate the self-reported risk levels and face the penalty of higher capital requirements in future periods. In this essay, we show that banks significantly under-report the risk in their trading book when they have lower equity capital. Specifically, a decrease in a bank's equity capital results in substantially more violations of its self-reported risk levels in the following quarter. The under-reporting is especially high during the critical periods of high systemic risk and for banks with larger trading operations. We exploit a discontinuity in the expected benefit of under-reporting present in Basel regulations to provide a causal link between capital-saving incentives and under-reporting. Our results provide evidence that banks' self-reported risk measures become least informative precisely when they may matter the most.

Besides banks, market makers are another kind of financial intermediary, which provide liquidity in the secondary stock market. The third essay uses a simple model to examine the effects of secondary market liquidity on firm value and the decision to conduct an Initial Public Offering (IPO). Competitive liquidity provision can lead to market failure as the IPO either does not occur or its price is discounted to reflect that some welfare-enhancing secondary trades do not occur. Market failure arises when uncertainty regarding fundamental value and asymmetric information are both large. In these cases, firm value and social welfare are improved by a contract where the firm engages a Designated Market Maker (DMM) to enhance liquidity. Our model implies that such contracts represent a market solution to the market imperfection in the IPO market due to information asymmetry in the secondary stock market, particularly for small growth firms. In contrast, proposals to encourage IPOs by use of a larger tick size are likely to be counterproductive.

CHAPTER I

Bank Equity Capital and Risk-taking Behavior: The Effect of Competition

1.1 Introduction

How does a bank's equity capital affect its risk-taking behavior? This is a fundamental question in financial economics, with significant implications for ongoing policy debates.[1] It is argued that higher equity capital can limit excessive risk-taking behavior by banks, which in turn can have positive effects on corporate borrowers and the economy as a whole.[2] While a number of research papers in the prior literature investigate the link between equity capital and risk-taking behavior, there is scant evidence in the literature on how this relationship changes in the presence of other potential risk-mitigating devices such as increased competition in the banking industry. Competition, by itself, has been shown to alter the risk-taking behavior of firms in both banking and non-banking industries. In fact, the role of competition in banking has been studied extensively by earlier papers.[3] But does higher competition attenuate or exacerbate the risk-mitigating effect of higher capital? I answer this question in my paper.

[1]See *Admati et al.* (2011), *Thakor* (2014), for example.

[2]See *Bernanke and Blinder* (1989) for theoretical evidence, and *Chava and Purnanandam* (2011) for empirical evidence.

[3]See *Jayaratne and Strahan* (1998), *Dick* (2006), for example.

The difficulty of studying the impact of competition on the relationship between capital ratio and risk-taking is that competition and capital ratio are likely to be endogenously related (*Bolton and Scharfstein* (1990)). To avoid this endogeneity problem, I exploit the plausible exogenous changes in competition in the banking industry caused by deregulations in the 1980s. I find that increased competition can dampen the relationship between capital ratio and risk-taking. Said differently, the negative relationship between capital ratio and risk-taking is weaker when the banking industry is more competitive. This implies that raising the minimum capital ratio requirement is more likely to have significant impact on risk-taking behavior in a concentrated banking market.

Similar to bank capital ratio, competition is one of the important levers that have been used to regulate the banking industry.[4] It has been argued in the literature that higher competition can lead to higher risk-taking by firms. In a competitive banking market, banks may lose a part of their franchise value, which in turn can increase their risk-taking incentive (*Keeley* (1990)). The franchise values can come in the form of access to subsidized deposits or to profitable lending opportunities. Banks are more likely to lose these rents in competitive markets, and hence their risk-taking incentives may be higher. Alternatively, competition may work as a disciplining device. For example, in a competitive market, banks need to be more prudent in their risk-taking behavior in order to stay competitive in the long run. In fact, competition, as shown in *Boyd and De Nicolo* (2005), reduces the risk-taking incentive of banks in the presence of agency problems between banks and their borrowers. Thus, the effect of competition on the bank's risk-taking behavior remains an empirical issue.

[4]For example, BASEL I, II, III, and the interstate banking and intrastate branching deregulations mentioned in this paper.

Related to my work, there are a number of earlier theoretical papers that highlight the intricate connections between competition, corporate leverage, and the firm's behavior in different settings. A general theme of this literature is that the firm's product market strategy is jointly shaped by the competitive environments it faces and its leverage ratio.[5] In a recent paper, directly related to my work, *Opp et al.* (2014) analyze the efficacy of bank capital regulation in a competitive environment. They derive predictions relating the level of competition to the effect of capital structure on a bank's risk-taking behavior. They show that it is not obvious that higher capital requirements will limit the risk-taking behavior of banks. Depending on the nature of competition the effect of capital structure on risk-taking behavior can go either way. They argue that increased competition not only renders previously optimal bank capital regulations ineffective but also implies that, over some ranges, increases in capital requirements cause more banks in the economy to engage in value-destroying risk-shifting.

Overall, it can be argued that higher competition can work as either a substitute or a complement for bank capital. Which force is at play and how much does it matter? To answer this question, I empirically analyze the effect of equity capital on risk-taking behavior of banks subsequent to the changes in the level of product market competition in the 1980s. My empirical setting is based on the exogenous variation in competition created by interstate and intrastate banking deregulations. It is important to note the identification challenge faced by a study of this type. Bank capital is likely to be determined jointly with the level of competition they face. Hence my setting, which exploits a reasonable exogenous variation in competition,

[5]For example, *Maksimovic* (1988) shows that high leverage leads to more aggressive competition in the product market, which is in line with the risk-shifting argument by *Jensen and Meckling* (1976). In contrast, *Bolton and Scharfstein* (1990) argue that low leverage firms, with their "deep pockets", are the ones who compete more aggressively (high production and low markup) to deter entry.

provides several advantages for identification.

The banking deregulations that occurred between 1977 and 1994 significantly enhanced the openness and competitiveness of the banking market (*Black and Strahan* (2002)). For example, after these deregulations, there were significant entries into local banking markets (*Amel and Liang* (1992)), which led to a sharp increase (from 2% to 28% in a typical state) in the percentage of deposits held by subsidiaries of out-of-state bank holding companies (*Berger et al.* (1995)). Besides leading to reasonable exogenous change in competition, staggered implementation of deregulation in different states in different years implies a reduced likelihood that comparisons before and after deregulation are influenced by contemporaneous changes in market-wide factors affecting the inferences of the relationship between the variables that I study.

Under the assumption that deregulation causes an exogenous change in competition, I analyze the dynamics of bank risk-taking. More specifically, I focus on the risk on the asset side, of which lending risk is the main component.[6] Following the literature, I use loan loss provision, charge-off, and non-performing loan ratios as lending risk measures. I first confirm that, on average, lending risk significantly decreases after deregulation, consistent with *Jayaratne and Strahan* (1998). I then show that low-capital banks, compared with their high-capital peers, significantly lower their lending risk after deregulation. They do so primarily by shifting to loans with lower risk. This difference between high- and low-capital banks in risk-taking behavior cannot be explained by pre-existing trends, geographical location, or other bank characteristics, such as size, that may influence bank risk-taking. This result is consistent with the argument that increased competition makes banks more prudent in risk-taking. When competition is increased by the deregulation, the smaller capital

[6] The median ratio of total lending to total assets in my sample is 60%. The remaining 40% is mainly consist of cash and treasure bonds and bills.

buffer makes low-capital banks more likely to fail compared with their high-capital peers. To stay alive, one effective strategy is to reduce risk.

Instead of low-capital banks being prudent in a competitive environment, an alternative explanation of their larger reduction in risk could be that low-capital banks are out-competed by high-capital banks in the high risk lending market after deregulation. Hence, the larger reduction in risk by low-capital banks results from their larger loss in lending market share. To rule out this possibility, I look into the dynamics of total lending volume and the ratio of total lending to total assets. I find that changes in the total lending of low-capital banks are not significantly different from those of high-capital banks. I also find, after controlling for the change in the ratio of total lending to total assets, low-capital banks still have larger reductions in risk. Hence, my results cannot be explained by changes in total lending or asset re-allocation across loans and other assets.

To verify the robustness of my empirical finding, I use lending interest rate as an alternative measure of risk. One of the important components of the lending interest rate is the underlying project risk. If low-capital banks have a larger reduction in lending risk, they should also have a larger reduction in the lending interest rate, which is exactly what I find when analyzing the changes in lending interest rates. Further, to rule out another potential alternative explanation that the larger reduction in risk is driven by low-capital banks' underestimation of lending risk, I show low-capital banks have larger improvements in future performance relative to their high-capital peers.

In summary, the overall decrease in risk-taking documented in this paper suggests high competition leads to low risk-taking, which is consistent with the hypothesis that high competition in the banking industry makes banks more prudent in their risk-taking behavior. More notably, the larger reductions in risk-taking by low-capital banks when facing increased competition suggest that competition can dampen the relationship between bank capital ratio and risk-taking. This implies that, in a competitive banking environment, the marginal effect of increasing capital ratio requirement might be less significant than that in a monopolistic banking environment. Therefore, when considering changes in the capital requirement, regulators should take into account the competitive landscape in the banking industry.

The empirical findings in this paper also speak to the debate about risk-shifting versus risk management. On one hand, the theory of asset substitution (*Jensen and Meckling* (1976)) suggests that firms with low equity ratios have stronger risk-taking incentives. On the other hand, it is also argued (*Mayers and Smith Jr* (1987) and *Froot et al.* (1993)) that future funding and investment opportunities give low-equity firms incentives to engage in risk management and risk reduction. In line with the risk management argument, I show that low-capital banks reduce their risk-taking when facing increased competition, suggesting that the incentive of risk management outweighs that of risk shifting. This finding is consistent with the empirical evidence documented in *Rauh* (2009) that firms with poorly-funded pension plans and weak credit ratings allocate a greater share of pension fund assets to safer securities (see also *Purnanandam* (2008)).

While the main analysis focuses on risk on the asset side, I do briefly look into changes on the liability side. After both interstate and intrastate deregulations, on average, banks have reductions in their equity ratios. However, these reductions are mainly driven by banks with high capital before deregulation. Banks with low capital ratios do not have significant change in their capital ratios. Since the decrease in risk after deregulation is mainly contributed by low-capital banks, changes in the capital ratio in high-capital banks are unlikely to be the driving force of this decrease in risk.

The remainder of this chapter is organized into five sections. Section 1.2 reviews the history of bank deregulations in the 1980s and their effect on local economies and the banking industry. Section 1.3 describes the data and provides descriptive statistics. Section 1.4 discusses empirical methods and presents empirical results. Section 1.5 discusses how banks reduce their risk when facing increased competition. Section 1.6 concludes.

1.2 Banking deregulations

1.2.1 History of Banking Deregulations

From the 1950s to the early 1970s, state statutes in the United States severely restricted the ability of banks to expand across state borders or to branch within a state. Beginning with the 1956 Douglas Amendment to the Bank Holding Company Act, bank holding companies were prohibited from acquiring banks in other states unless state regulations permitted such transactions. This amendment effectively prohibited interstate bank mergers and acquisitions because no state allowed such cross-state transactions.

Twenty-two years later, in 1978, Maine permitted out-of-state bank holding companies (BHCs) to buy Maine banks. Following Maine, by 1992, all states but Hawaii (Hawaii opted-in in June, 1997) had entered into interstate banking agreements with other states. This period comprises the first wave of interstate banking deregulation. However, under this deregulation, out-of-state banks still were not allowed to open *de novo* branches (establish new branches) or convert acquired in-state banks into branches.

Another type of deregulation, intrastate branching deregulation, occurred at about the same time as the first wave of interstate banking deregulations. In 1970 only 12 states allowed unrestricted intrastate branching. In the other 38 states, banks could have either only branches within a 100-mile radius from their headquarters or no branch at all. By 1994, all these 38 states and Washington, D.C. substantially eliminated restrictions on intrastate branching. These branching deregulations led to significant entries into local markets via *de novo* branching (*Amel and Liang* (1992), *Calem* (1994), and *McLaughlin* (1995)).

The second wave of the interstate deregulation was triggered by the Interstate Banking and Branching Efficiency Act 1994 (IBBEA), which allows banks and BHCs to (i) acquire out-of-state banks and convert them into branches of the acquiring bank (rather than holding the out-of-state bank as a separately chartered entity), (ii) acquire a single branch or portions of an out-of-state institution to convert into branches of the acquiring bank, and (iii) open *de novo* branches across state borders. By the end of 1997 all states allowed interstate banking and branching.

Before IBBEA, most states allowed intrastate branching via merger and acquisition and/or via *de novo* branch creation. The important change to emerge from the IBBEA is permission for interstate branching. It is unclear how much marginal effect is created by this interstate branching deregulation after the first wave of interstate banking deregulation and the intrastate branching deregulation. Adoption of the interstate branching deregulation occurred in a two-year window (from June 1995 to June 1997), in contrast to two earlier deregulations that spread over a long time period. This difference makes it hard to disentangle the impacts of changes in competition and changes in macroeconomic environments.[7] Therefore, in this paper, I do not include the interstate branching deregulation, but focus on the first wave of interstate banking deregulation and the intrastate branching deregulation in the period between 1976 and 1994.

The interstate banking and intrastate branching deregulations, as discussed in *Jayaratne and Strahan* (1996, 1998) and *Kroszner and Strahan* (1999), are mainly driven by national and local forces. One force is the lobbying pressure from large banks. These large banks asked for deregulation so that they can compete with national banks. To mitigate this endogeneity issue and avoid the possible large money-centric bank effect, I exclude banks in the top 5% of total assets before the deregulations.[8]

1.2.2 Effect of Banking Deregulations

Deregulating interstate banking, interstate branching, and intrastate branching leads to significant changes in the banking industry, especially in credit market competition. After deregulation, on one hand high rates of failures and mergers reduced the number of stand-alone banks and bank holding companies. On the other hand, high rates of *de novo* entries increased the number of local banks. *Berger et al.* (1999) document the number of US banks and banking organizations (stand-alone banks and top-tier BHCs) fell almost 30% between 1988 and 1997. During this period, the share of total nationwide assets held by the largest eight banking organizations rose from 22.3% to 35.5%. Despite the failures and consolidation activities, the average local market deposit Herfindahl index (HHI) declined slightly over the period, falling about 4% for MSAs and about 5% for non-MSA counties. Total number of bank offices rose

[7] However, when using this interstate branching deregulation for robustness checks, I find weaker but similar results.

[8] Please see Appendix for more discussion about the possible drivers of the deregulations and potential endogeneity problems

by 16.8%. Similarly, *Jayaratne and Strahan* (1998) show that banking assets' concentration decreased after deregulation.

In terms of the effect of deregulation on the lending market, *Black and Strahan* (2002) argue that regulatory changes in the banking industry enhanced the openness and competitiveness of banking markets, which led to increases in efficiency and new incorporations in local markets. Supporting this argument, *Rice and Strahan* (2010) show stricter branching rules lead to higher lending interest rates. Furthermore, *Jayaratne and Strahan* (1996) document that although loan growth does not change after deregulation, loan quality improves. For example, non-performing loans decrease as much as 38% and as little as 12% of the unconditional mean after the intrastate branching deregulation. Similarly, *Jayaratne and Strahan* (1998) show that, after the interstate banking is permitted, operating costs significantly decrease. Most of the reduction in cost is passed along to the borrowers, indicated by a lower lending interest rate.

In summary, the consensus in the literature is that deregulations led to an increase in competitiveness within the banking industry. My findings support this consensus.

1.3 Data

The timings of interstate banking and intrastate branching deregulations since 1970 are listed in Table A1.1 in the Appendix.[9] As shown in the table, depending on the state, intrastate branching deregulations happened before or after the interstate banking deregulations. The gap between the two deregulations varies from zero (Tennessee) to more than 18 years (Vermont). This makes it possible to disentangle

[9]This time table is from *Jayaratne and Strahan* (1998).

the effects of the two deregulations.

All financial characteristics of banks in this study are from the Commercial Bank Reports of Income and Condition (Call Reports). Chartered commercial banks must file these public reports with bank regulators on a quarterly basis.[10] The reports contain bank balance sheets, income statements (including loan loss provisions), and other information. As mentioned in the last section, I exclude banks with total assets in the top 5%[11] to avoid a possible lobbying effect. By removing these large banks, I also alleviate the concern that large money-centric banks might have a different business model than regional and local banks. After excluding the top 5% banks, the full sample contains over 260,000 bank-year observations from 1976 to 1994. Table 1.1 Panel A reports the summary statistics of bank characteristics. The mean equity-to-asset ratio is 8.12%. The 25th and 75th percentile book equity-to-asset ratios are 7.0% and 9.9%, respectively. Table 1.1 Panel B reports the average risk measures before and after deregulations. Consistent with *Jayaratne and Strahan* (1998), the mean and loan loss ratios after deregulation are about 20% lower than those before deregulation, while non-performing loan ratios are more than 50% smaller.

Bank Failures and Assistance Transactions (BFAT) data is from the FDIC's Historical Statistics on Banking (HSOB). The HSOB provides bank failures and assistance transactions data including event date, total deposits and total assets prior to the event date, and estimated loss. Bank merger data is from the Bank Regulatory Database in WRDS. This database covers all of the historical bank mergers in the US. It provides not only the information about the surviving and non-surviving entities of each merger, but also the reason for termination of the non-surviving entity. The

[10]Since all risk measures are based on variables reported as a year-to-date aggregation, I use annual data in this study for convenience of analysis.

[11]This 5% will be analyzed separately in Section 1.5.1.

bank failure and merger data is used in regressions with duration models to address potential survivorship bias.

I use the state coincident index provided by the Federal Reserve Bank of Philadelphia as a measure of the state economic environment in each state.[12] The coincident index combines four state-level indicators, which include non-farm payroll employment, average hours worked in manufacturing, the unemployment rate, and wage and salary disbursements deflated by the consumer price index (U.S. city average), to summarize current economic conditions in a single statistic.

1.4 Empirical Results and Discussions

1.4.1 Realized and Expected Risk

In this paper, my main task is to identify the change of the relationship between bank capital ratio and risk-taking behavior when competition in the banking sector is increased. The null hypothesis is that there is no interactive effect of bank capital ratio and competition on the risk-taking behavior of banks. In other words, the correlation between bank capital ratio and risk-taking should not change when competition in the banking sector changes. My main alternative hypothesis is that the effect of equity capital on risk-taking behavior changes when competition changes in the banking market. More specifically, low-capital banks, relative to their high-capital peers, either decrease or increase risk-taking when facing increased competition. As mentioned earlier, theoretical models provide arguments for both an increase or a decrease in risk-taking when facing increased competition.

[12] https://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/

Since bank capital and competition are likely to be jointly determined, estimates from a naive regression of risk on the capital ratio, competition, and their interaction suffer from an endogeneity problem. To properly identify the effect of competition on the relationship between equity capital and risk-taking, I examine how banks with different equity capital ratios react to changes in interstate banking and intrastate branching deregulations by comparing their lending portfolio risk before and after deregulation. I analyze the data with the following model:

$$\begin{aligned} Riskiness_{i,t} =& \lambda\, Post_{i,t} + \gamma\, Equity\ Ratio_i + \theta\, (Post_{i,t} \times Equity\ Ratio_i) \\ & + \beta\, X_{i,t} + \alpha_i + \nu_t + \epsilon_{i,t}. \end{aligned} \tag{1.1}$$

The dependent variable of this model, $Riskiness_{i,t}$, measures the lending risk of bank i in year t. I use three measures of lending risk: net charge-offs, non-performing loans, and loan loss provisions scaled by the corresponding total loans and leases. Charge-offs are the amount of un-collectable debt of a bank due to borrower defaults. This can be taken as a realized risk measure. Instead of the total level of charge-offs, I use net charge-offs to reflect the actual loss caused by defaults in a year. Non-performing loans is also a realized risk measure. It is the sum of borrowed money upon which the debtor has not made his or her scheduled payments for at least 90 days. In contrast, loan loss provisions are the expense set aside as an allowance for expected bad loans (e.g., customer defaults or renegotiated loan terms). Being set aside, loan loss provisions can be viewed as the *ex ante* expected risk of the lending portfolio.[13]

$Post_{i,t}$ is an indicator variable that equals one for all the years after deregulation of the state in which bank i operates, and zero otherwise. The coefficient on this

[13]Because the non-performing loan measure is not available before 1983, the discussion in the rest of the paper will focus on charge-offs and loan loss provisions because they can be dated back to 1977. However, the coefficient estimates (as reported in Table 1.3) from the analysis on non-performing loans are consistent with those from analysis on charge-offs and loan loss provision.

variable, λ, captures the overall difference in bank riskiness before and after deregulation. $Equity\,Ratio_i$ is a time-invariant variable that measures the book equity ratio of bank i in the year immediately before the deregulation. This variable is absorbed by the bank fixed effects because there is only one equity ratio before the deregulation for each bank. $Equity\ Ratio_i$, however, is included in the interaction term $Post_{i,t} \times Equity\ Ratio_i$ because I am interested in how banks with different equity capital ratios before deregulation react to the deregulation. Using this equity ratio before deregulation, I avoid the impact from possible endogenous change in current period lagged equity ratio (equity ratio at the end of period *t-1*) on the estimates of the interaction term. However, I do include current period lagged equity ratio as a control variable (included in $X_{i,t}$) to capture the effect of lagged equity ratio on risk-taking behavior. The coefficient, θ, on the interaction term $Post_{i,t} \times Equity\,Ratio_i$ is the estimate of interest. θ measures the marginal effect of the *ex ante* capital ratio on the *ex post* change in lending risk. A positive θ indicates that, compared with their high-capital peers, low-capital banks reduce their lending risk after the deregulation.

Besides lagged equity ratio, lagged total assets (logged), and the state coincident index are also included in $X_{i,t}$. They account for the impact of bank size and state economic environment, respectively. α_i and ν_t are bank fixed effects and year fixed effects, respectively. The fixed effects capture the impacts from unobserved time-invariant firm characteristics and unobserved macroeconomic factors. I also cluster standard errors at the bank level to address both heteroskedasticity and non-independence of errors within firms across time.[14]

Results are provided in Tables 1.2 and 1.3. The dependent variables in Table

[14]In an unreported regression, I cluster at the state level to alleviate the concern about non-independence of errors within states across time. And this state level clustering does not change the results.

1.2 are loan loss provisions to total loans and leases ratio. In models (1) and (2), I examine the effect of either the interstate banking deregulation or the intrastate branching deregulation, which means only one deregulation dummy and its interaction with equity ratio before the deregulation are included. In model (3), dummies and their interaction terms of both deregulations are included. The dependent variables in Table 1.3 are charge-offs to total loans and leases ratio and non-performing loans to total loans and leases ratio. In Table 1.3, similar to those in Table 1.2, there is only one deregulation dummy and its interaction term in models (1) to (4), while both dummies and their interaction terms are included in models (5) and (6).

As shown in Tables 1.2 and 1.3, the coefficient estimates on total assets are negative, which is consistent with the fact that larger banks are riskier because they can diversify better. The coefficient estimates on the deregulation dummies are significant and negative. This indicates that banks, regardless of their equity capital ratios, reduce risk after the deregulation. More importantly, I find that the change in competition has a significant impact on the relationship between a bank's equity capital ratio and its risk-taking behavior. In all the regressions reported in Tables 1.2 and 1.3, coefficients on the interaction terms between deregulation and bank equity ratio are positive and significant, regardless of the choice of risk measure.

The positive significant estimates on the interaction terms, together with the negative estimates on the dummies, indicate low-capital banks have larger reductions in lending risk when facing increased competition. This is consistent with the hypothesis that low-capital banks become less risky when facing increased competition. Besides being statistically significant, these effects are also economically significant. For example, based on the estimates of the model (3) in Table 1.2, the coefficient on intrastate branching dummy is -0.00479 and the coefficient on interaction term between this dummy and equity capital is 0.0298. This result implies that after the intrastate branching deregulation, the loan loss ratio decreases by 27 basis points (34% of the pre-deregulation mean, and 34% of the mean return-on-asset) for a bank with a capital ratio at the 25th percentile (with capital ratio equal to 0.07), while the loan loss ratio decreases by only 18 basis points (23% of the pre-deregulation mean, and 23% of the mean return-on-asset) for a bank with a capital ratio at the 75th percentile (with capital ratio equals to 0.10). Similarly, a bank with a capital ratio at the 25th percentile has six basis points (8% of the mean) more decrease in loan loss ratio than a bank with a capital ratio at the 75th percentile after the interstate banking deregulation.

Overall, Tables 1.2 and 1.3 show significant reductions in mean charge-off ratio and mean loan loss ratio after both deregulations; and the decreases are mostly driven by banks with low capital ratios. For instance, the charge-off ratio and the loan loss ratio of a bank with a capital ratio at the 25th percentile decrease by 23 and 27 basis points (both are about 34% of their pre-deregulation means) after the intrastate branching deregulation, respectively. The decrease in lending risk after the interstate banking deregulation of a 25th-percentile bank is less but remains significant. In contrast, the behavior of high-capital banks is ambiguous. The charge-off ratio and loan loss ratio of a bank with capital ratio at the 75th percentile decrease after the intrastate branching deregulation but remain unchanged after the interstate banking deregulation.

1.4.2 Cause of Risk Reduction: Risk Preference or Lending Size?

In the previous section, I show the lending risk of low-capital banks, compared with that of high-capital banks, significantly decreases after deregulation. While these results are consistent with the hypothesis that competition and low capital ratio make banks less risky, there are a few alternative explanations. One is that the reduction in risk of low-capital banks results from losing market share when facing increased competition, as explained in the following paragraph. Another alternative explanation is that banks are just re-allocating their assets into different categories without changing their risk preference. More specifically, if low-capital banks want to increase their loan-to-asset ratio while keeping their total asset risk unchanged, they need to reduce lending risk because most non-loan assets are mainly low-risk assets, e.g. cash and treasury bills.

To understand the first alternative explanation, let's assume that banks carry out their safest projects before moving on to riskier projects. Based on this assumption, there would be a mechanical effect from change in total lending on lending risk. That is, the larger the total lending, the higher the charge-off and loan loss ratios would be. If low-capital banks are doing poorly and losing their shares in the risky loan market after deregulation (as predicted in *Allen et al.* (2011)), these low-capital banks should suffer a reduction in total lending. Because of the reduction in lending, despite unchanged risk preference of banks, the riskiness still decreases. Therefore, a decrease in charge-offs or loan loss provisions along with a reduction in total lending could be the result of a loss in the lending market, and cannot be solely interpreted as a decrease in risk preference.

To address this concern, I look into the dynamics of total lending of all banks. I run regressions with the same setup as equation (1) with the level of total lending and the lending-to-asset ratio as dependent variables. Results are shown in Table 1.4, columns (1) and (2). The coefficient estimate on the interaction term between the interstate banking dummy and equity to asset ratio in column (1) is negative and significant, implying that low-capital banks have relative increases, instead of decreases, in their total lending level after the interstate banking deregulation. However, all other coefficient estimates on the interaction terms suggest that there is no significant difference between high- and low-capital banks in their changes of total lending level and lending to total assets ratio. Therefore, my finding of a larger decrease in lending risk of low-capital banks cannot be driven by a relative reduction in their total lending because, as shown in Table 1.4, this relative reduction in lending does not exist.

The second alternative explanation is that the larger risk reduction by low-capital banks is driven by asset re-allocation among different asset categories, rather than a change of their risk preference. If high-capital banks decrease their lending fraction in total assets but want to maintain the total asset risk at the same level, they can increase their lending risk. Or, if low-capital banks increase their lending fraction but want to maintain the same asset risk level, they can reduce lending risk. One implicit assumption of this alternative explanation is that the risk of the non-loan assets is less than the loan-and-lease asset. Another assumption is that the risk of the non-loan assets is more uniform across banks when compared with that of the loan-and-lease assets. These assumptions are reasonable because cash and treasury bills are the main components of the non-loan assets and they have low and similar levels of risk across banks.[15]

To rule out this alternative explanation, I investigate changes in total asset risk. If the total asset risk of the low-capital banks does not change or increase after deregulation, I cannot argue that they reduce their risk-taking. Because the risk of the non-loan assets is not observable, based on the two implicit assumptions of this al-

[15]Most of the banks in my sample are small to medium banks that do not have any trading assets, which are considered risky.

ternative explanation, I measure total asset risk with charge-off-to-total-asset ratio and loan-loss-provision-to-total-asset ratio. With these ratios scaled by total assets as proxies for asset risk, I use equation (1) to measure the changes in total asset risk. Regression results are presented in Table 1.4, columns (3) and (4), which show that low-capital banks have a larger reduction in charge-off-to-total-asset ratio and loan-loss-provision-to-total-asset ratio than high-capital banks after deregulation. This not only rules out the second alternative explanation, but also suggests that the purpose of lending risk reduction is to decrease asset risk and improve survival probability.

In summary, regression results in Tables 1.2, 1.3, and 1.4 show that after taking the dynamics of total lending and lending ratios into account, the risk of low-capital banks decreases more than that of high-capital banks. I argue that this decrease in risk can be attributed to a reduction in risk preference of low-capital banks when facing increased competition.

1.4.3 Lending Interest Rate

In this section, using lending interest rate as an alternative measure of risk, I provide additional direct evidence in support of the hypothesis that low-capital banks reduce risk-taking more when facing increased competition. This provides additional evidence that my results are robust to different measures of risk.

Lending interest rate is defined as a bank's interest income divided by its total loans and leases net of its bad loans. I remove the bad loans from total loans and leases because non-performing loans do not generate interest income.[16] Even though

[16] This method is similar to that used in *Jayaratne and Strahan* (1998), except I remove the non-performing loans from total loans and leases. However, regression results are similar if I keep the bad loans.

the interest rate is calculated from realized interest income, the interest rate is determined when a bank enters a lending contract with a borrower. A risky borrower is more likely to get a higher lending interest rate *ceteris paribus*. Therefore, similar to loan loss provisions, lending interest rate can be viewed as expected lending risk.

Again, I use equation (1) with lending interest rate as the dependent variable to examine the *ex post* change in lending risk, conditional on the *ex ante* capital ratio. The result is provided in Table 1.5, column (1). Similar to the main findings in Tables 1.2 and 1.3, there is an overall reduction in lending interest rate. And consistent with my findings in earlier sections, the reduction is mainly driven by low-capital banks. For instance, a 25th percentile capital bank, compared with its 75th percentile peer, lowers its interest rate by 4 basis points more after the interstate banking deregulation.

While the results from the lending interest rate study are consistent with the hypothesis that low-capital banks reduce their risk-taking when faced with increased competition, perhaps the decrease in the interest rate is a result of an underestimation of lending risk. If a low-capital bank underestimates the risk of its borrowers' projects, we should observe low loan loss provisions and low interest rates from this bank. Since the bank underestimates its lending risk, its realized lending risk should be high unless its true lending risk is lower than that of other banks that do not underestimate their lending risk. What the data show, however, is that low-capital banks have larger reductions in both expected risk (loan loss ratio and lending interest rate) and realized risk (charge-off ratio and non-performing ratio) after deregulation, suggesting that the reduction in lending interest rate is driven by either a reduction in risk alone, or a reduction in risk together with an underestimation of lending risk; both are consistent with the hypothesis that low-capital banks reduce their risk more when facing increased competition.

To further investigate whether underestimation of risk leads to low interest rates, I examine the changes in return-on-asset (ROA) and return-on-equity (ROE) of banks. If a bank routinely underestimates its lending risk, it should have lower ROA and ROE. When a bank underestimates its lending risk and charges low interest rates, it is actually taking a lot of negative NPV projects because the risk adjustment is too small due to the underestimation of risk. Table 1.5, columns (2) and (3) provide regression results from equation (1) with ROA and ROE as dependent variables. The negative coefficient estimates on the interaction terms indicate that low-capital banks have better improvement in performance, compared with high-capital banks, ruling out the alternative explanation that the larger decrease in loan loss provisions and lending interest rates of low-capital banks results from underestimation of their lending risk. To avoid the mechanical effects of loan loss provisions on net income,[17] I also examine gross return-on-asset (GROA) and gross return-on-equity (GROE). The regression results are shown in Table 1.5, columns (4) and (5). Consistent with those in columns (2) and (3), the coefficient estimates on the interaction terms are negative.

As shown in Table 1.5, there is a relative improvement in performance by the low-capital banks. At first glance, this seems to contradict the larger reduction in risk-taking by low-capital banks shown in Tables 1.2 and 1.3. Larger reductions in risk-taking should also lead to larger reductions in performance *ceteris paribus*. However, when a bank is reducing risk to survive, it is likely that this bank is also taking other actions to improve its survival probability (for example, estimate lending risk correctly and improve efficiency). These actions could be the drivers of the better performance of low-capital banks. In fact, in Section 1.5.3, I find that low-capital banks have a relative improvement in their efficiency.

[17] Net income is defined as gross income less loan loss provision

1.4.4 Survivorship Bias

Based on the evidence presented in Tables 1.2 to 1.5, I argue that low-capital banks reduce their risk when facing increased competition after deregulation. The intuition of this argument is that the competition and low capital ratio together lead to a higher probability of failure for low-capital banks. This threat of failure pressures bank managers reduce their lending risk, which is a major component of the asset risk, to increase the probability of survival. This intuition raises a natural concern about survivorship bias. Because I can observe the behavior only of banks that survive, the risk measures of both high- and low-capital banks are subject to survivorship bias. If low-capital banks compared to high-capital banks are more likely to fail because of their low capital ratio, the observed risk of low-capital banks suffers a more severe survivorship bias than that of high-capital banks.

The survivorship bias, however, can be either downward or upward. On one hand, if failed banks increase their risk after deregulation compared to the surviving ones, actual risk should be higher than observed risk. In this case, survivorship leads to a downward bias on the risk measures of low-capital banks. With the bias in the same direction as the results in Tables 1.2 to 1.5, I would not be able to disentangle the effect of risk reduction and the effect of survivorship bias. On the other hand, if the failed banks relatively decrease their risk compared with the surviving ones, the risk measures are biased upward. In this case, the survivorship bias goes against the results in Tables 1.2 to 1.5.

In order to find out the direction of the survivorship bias, I use the following regression model.

$$Riskiness_{i,t} = \lambda \, Post_{i,t} + \beta \, X_{i,t} + \alpha_i + \nu_t + \epsilon_{i,t}. \tag{1.2}$$

In this model, equity ratio and its interactions with deregulation dummies are excluded because, as mentioned earlier, I focus on the lowest equity quartile. The regressions are run separately on the surviving and failed banks to find out whether their behaviors are different. The estimate of interest is λ. The regression results are presented in Table 1.6, which show that the failed banks do not increase their risk compared with the surviving banks. This suggests that the survivorship bias is at least not in the same direction as that of the results shown in Tables 1.2 to 1.5. In other words, survivorship bias is not the reason we observe a larger reduction in risk by low-capital banks.

1.5 How to Reduce Risk?

1.5.1 Raise More Capital: Large Banks vs. Small Banks

In previous sections, I show that low-capital banks reduce their lending risk when competition is intensified after deregulation. I argue that this reduction is to counter the increase in failure probability due to competition. Besides reducing lending risk, another way to reduce failure probability is to increase the capital ratio. Even though the literature documents that bank capital ratios are sticky,[18] the ability to raise capital is heterogeneous across banks. It is usually relatively easier for large banks to raise capital. With better ability to raise capital, large low-capital banks, compared with small low-capital banks, are less likely to reduce lending risk because they can raise capital instead, when having the incentive to reduce risk. To demonstrate this difference, I perform the same risk analysis on the top 5% banks excluded in earlier analysis. Table 1.7 shows a comparison of changes in lending risk between the top 5% banks (columns (4) to (6)) and all other banks (columns (1) to (3)). The re-

[18] See *Adrian and Shin* (2010) and *Gropp and Heider* (2010), for example.

gression results show that, among large banks, the difference in changes in lending risk between high- and low-capital banks is not significant. This suggests small- and medium-sized low-capital banks reduce their lending risk to counter the increase in failure probability, while large low-capital banks can choose other mechanisms, e.g., increasing their capital ratio.

1.5.2 Commercial and Industrial Loans

So far I show that low-capital banks reduce their risk-taking when facing increased competition. Going forward, it is important to understand how they reduce their risk and improve their survival probability. I analyze the changes in the ratios of commercial and industrial (C&I) loans and real estate loans to total loans and leases to examine this problem.

C&I and real estate loans make up the majority (more than 60%) of the total loans and leases of a bank. C&I loans, in general, are more risky than other loans. In contrast, real estate loans are less risky because the underlying properties are held as collateral.[19] To analyze the dynamics of these loans, I use equation (1) with C&I loans and real estate loans to total loans and leases ratios as dependent variables. The regression results are presented in Table 1.8, columns (1) and (2). They show that low-capital banks reduce their C&I loan fraction but raise their real estate loan fraction; low-capital banks shift their focus toward real estate loans, while high-capital banks shift toward C&I lending. This difference in changes in lending focus is an important driver for the larger reduction in lending risk of low-capital banks after deregulations.

[19] According to data from Federal Reserve, the aggregate charge-off ratio of C&I loans in the US is almost twice that of real estate loans during the period from 1985 to 1994 (data from pre-1985 is not available).

1.5.3 Improve Efficiency

Besides looking into changes in lending portfolios, I examine the changes in efficiency (proxied by expenditure-to-asset ratio). Because improving efficiency is another mechanism to increase probability of survival, I conjecture that low-capital banks should become relatively more efficient when facing increased competition. The regression result shown in Table 1.8, column (3) supports this conjecture. For example, the coefficient estimate on the interaction between equity capital ratio and the interstate banking deregulation dummy is 0.0762, indicating that the decrease in the expenditure-to-asset ratio of a bank with a capital ratio at the 25th percentile is 3% (of the mean) more than that of a bank with a 75th percentile capital ratio. And this 3% is also economically significant because it is equivalent to 28% of the mean ROA, which explains why low-capital banks have larger improvement in performance after deregulation as shown in Table 1.5.

1.5.4 Robustness Checks

Two of the risk measures I use in this paper are the charge-off ratio and the non-performing loan ratio, which are based on the loan defaults in the current year. Since the defaulted loans can be granted in the previous years, charge-off and non-performing loan ratios are actually moving averages of the realized risk in all previous years and the current year, instead of just the current year. Similarly, the loan loss ratio and the lending interest rate include the risk of all existing loans instead of loans issued in the current year only. To address this issue, I use bank fixed effects in my regressions, which gives me changes in risk measures. The changes in risk measures should be driven predominantly by the loans in the current year, which are better representatives of the risk in the current year. To further address this problem, I remove observations from the year of and one year after deregulation in the analysis.

By creating this two-year gap, I reduce the fraction of risk from the pre-deregulation period in the post deregulation observations, while keeping the majority (70%) of the sample. Besides this two-year gap, I also use gaps of zero, one, and three years for robustness checks. The outcomes remain the same as those with a two-year gap.

When using capital ratio as an independent variable, one assumption I make is that equity capital cannot be immediately changed in response to the deregulation shock. For example, let us assume low-capital banks increase their capital ratio and become high-capital banks in response to deregulation, while high-capital banks do not change their capital ratio. Following the assumption that high capital banks take less risk than low-capital banks, we should observe that low-capital banks have a larger reduction in risk after deregulation, and that the reduction is not driven by their low capital before deregulation, but by their post-deregulation high capital ratio.

If the increased capital ratio after deregulation is the main driver of my findings, we should observe a quick increase in the capital ratio of low-capital banks. However, this kind of rapid change in capital ratio is inconsistent with the empirical facts documented in the existing literature. For example, *Adrian and Shin* (2010) and *Gropp and Heider* (2010) show that bank capital ratios are sticky, and it is expensive for banks to raise new capital.[20] In addition, with lagged equity ratio as a control variable in the regressions, if my finding is actually driven by post-deregulation high capital ratio, the estimates on the interactions would not be significant because the reduction would be captured by the lagged equity ratio.

To further address this concern, I use a difference-in-difference model, similar to

[20] Various frictions can cause cost associated with raising equity. For example, *Gennaioli et al.* (2013), attribute these costs to risk aversion on the part of households (while bankers are risk-neutral). *Baker and Wurgler* (2013) find empirical evidence for the high cost of raising equity as reflected in the low risk anomaly of banks' stock returns.

the one in Table 1.2, to determine the change in capital ratios after deregulation. The dependent variable is equity capital ratio. Besides total assets, other possible determinants of capital ratio (lagged ROA and collateral) are included as independent variables.[21] Lagged capital ratio is excluded because it can lead to inconsistent estimates. The regression results are presented in Table 1.9, column (1). The estimates show there is a reduction in capital ratio after the intrastate deregulation. The mean of the reduction is $0.183 \times 0.0877 - 0.0122 = 0.0038$, where 0.0877 is the mean capital ratio before the intrastate deregulation. However, this reduction is mainly driven by high-capital banks. A bank with a capital ratio of 10% (75th percentile) has a reduction of 0.61%, while a bank with a capital ratio of 7% (25 percentile) has a reduction of 0.06%. Similarly, after the interstate deregulation, a bank with a capital ratio of 10% (75th percentile) has a reduction of 0.20%, while a bank with a capital ratio of 7% (25 percentile) has a reduction of 0.04%.

These results suggest that the larger reduction in risk by low-capital banks is unlikely to be driven by changes in capital ratio, which are economically insignificant. These results are also consistent with findings in the earlier analysis that low-capital banks become more conservative than high-capital banks. Table 1.9 column (2) also presents the regression result with dividend-to-asset ratio as the dependent variable. Even though most estimates are not significant, the positive estimates on deregulation dummies and negative estimates on the interaction dummies suggest there is a reduction in dividend after both deregulations mainly driven by low-capital banks.[22] This, again, suggests that low-capital banks become more conservative after deregulation.

[21] Possible determinants of capital ratio mentioned in the finance literature include market-to-book ratio, size, profit, collateral, and dividend (*Gropp and Heider* (2010)). Since more than 95% of the banks in my sample are private banks, market-to-book ratio and dividend of these banks are not available. Therefore, I include size, profit (proxied by return on assets), and collateral as control variables in the regressions.

[22] The dividend reduction after the interstate deregulation is not significant.

Another robustness check I perform is to examine whether the larger reduction by low-capital banks is driven by a reduction of capital ratio before deregulation. If a bank planned to reduce risk-taking after deregulation, it could start lowering its capital ratio before deregulation because it does not need that much buffer after deregulation. To rule out this possibility, I redo the analysis with equity ratios two or three years before the deregulation. I find similar results.

One more robustness check I do is to examine whether the observed larger reduction in risk-taking by low-capital banks is driven by the interaction between competition and a factor that determines the capital ratio, instead of that between competition and the capital ratio itself. Due to variable availability mentioned in footnote 21, I include size, profit (proxied by ROA), collateral, and their interactions with deregulation dummies in my regressions.

The regression results are presented in Table 1.10. With all the possible determinants of capital ratio and their interactions with deregulation dummies, the coefficient estimates continue to indicate that low-capital banks exhibit a larger reduction in risk when facing increased competition. In fact, the coefficient estimates on the interactions between the capital ratio and the two deregulation dummies are both positive and significant, while most of the estimates on other interactions are inconsistent. For example, the coefficient estimates on the interactions between size and the deregulation dummies are positive, while only one of them is significant in each regression. Similarly, the estimates on the interactions between collateral and the deregulation dummies have opposite signs. The only possible determinant with consistent estimates on both interactions is ROA. The estimates on the interactions of ROA and the deregulations are both positive and significant, suggesting that when past performance is good, banks are likely to take on more risk. This, again, is consistent with the risk management argument in the literature and my argument about why low-capital banks have larger reduction in risk after deregulation.

One limitation of the analysis in this paper is that it relies on banks' self-reported risk measures. The inaccuracy of the risk measures can invalidate interpretation of the results. For example, a reduction in reported risk from a bank can be due to the bank's under-reporting instead of a change in its risk preference. This concern is mitigated to some extent by the non-performing loan measure, which accounting literature shows is hard to manipulate. Further, since I am using a difference-in-difference method, my interpretation that low-capital banks have a larger risk reduction is still valid unless low-capital banks under-report more than high-capital banks after deregulation.

Another limitation of this paper is that the analysis focuses on and speaks to medium and small banks. Large banks (e.g., Citibank, Wells Fargo) not only have much more complicated asset compositions, but also have different incentives when facing competition because they are "too-big-to-fail." However, medium and small banks account for more than 40% of the assets in the banking industry. Therefore, it is important to understand their risk-taking behavior.

‘

1.6 Conclusion

A number of theoretical models and empirical papers explore the linkage between equity capital and risk-taking. It has been argued that lower levels of bank capital can lead to increased risk-taking behavior (*Jensen and Meckling* (1976)). However, the prior literature and recent policy debates in this area ignore the effect of other risk-mitigating devices (e.g., increased competition in the banking industry) on this relationship. In this paper, I empirically study how competition alters the relationship between bank capital ratio and risk-taking behavior. By using banking deregulations in the 1980s as shocks to competition, I document that low-capital banks, relative to their high-capital peers, significantly reduce their lending risk (reflected by lower loan loss provision, charge-offs, non-performing loans, and lending interest rates) when facing increased competition. Based on this empirical evidence, I argue that high competition in the banking industry induces banks more prudent in their risk-taking behavior. Low-capital banks engage in more risk reduction than their high-capital peers because they are more likely to fail (*Schmidt* (1997)) in a competitive environment.

The empirical evidence presented in this paper shows that low-capital banks take significantly more risk when competition is absent, which implies competition can be another mechanism to mitigate risk-taking. The empirical evidence also suggests that competition can alter the relationship between bank capital ratio and risk-taking. When regulators consider a higher minimum bank-capital requirement to mitigate risk-taking, they should take into account the competitiveness of the banking sector and how it changes the efficacy of bank capital ratio on risk-taking.

Table 1.1: **Summary Statistics**

This table presents summary statistics of bank characteristics in the sample. All summary statistics in Panel A are calculated with all bank-year observations available between 1976 and 1994. The risk measures (loan loss provision ratio, charge-off ratio, non-performing loan ratio, and lending interest rate) before any deregulation and after both deregulations are presented in Panel B to show the difference in lending risk before and after the deregulations.

Panel A: Bank Characteristics

Bank Characteristics	Mean	St. Dev.	Min	Max	25%	75%
Total Assets (M)	57.9	253	1.42	37100	19.1	95.0
Total Loans & Leases (M)	34.7	164	0.987	28100	10.0	57.5
Equity / Total Assets (%)	9.0	4.13	2.46	48.9	7.0	9.9
Charge-offs/Total Loans & Leases (%)	0.56	1.40	0	16.2	0.03	0.58
Loan Loss/Total Loans & Leases (%)	0.69	1.54	0	17.5	0.11	0.71
Non-Performing/Total Loans & Leases (%)	1.74	2.60	0	100	0.29	2.10
Lending Interest Rate (%)	9.93	2.55	0.18	23.1	8.3	11.5
Return on Assets (%)	0.80	1.18	-10.9	10.8	0.66	1.32
Return on Equity (%)	8.08	30.2	-505	220	7.5	15.0

Panel B: Risk Measures pre- and post-Deregulation

Risk Measures	Before Any Deregulation	After Both Deregulations
Charge-offs / Total Loans & Leases (%)	0.66	0.56
Loan Loss Provisions / Total Loans & Leases (%)	0.79	0.63
Non-performing Loans / Total Loans & Leases (%)	2.90	1.35
Lending Interest Rate (%)	10.9	9.9

Table 1.2: **Changes in Expected Lending Risk**

This table presents estimates from a difference-in-difference regression model:

$Riskiness_{i,t} = \lambda\, Post_{i,t} + \gamma\, Equity\ Ratio_i + \theta\,(Post_{i,t} \times Equity\ Ratio_i) + \beta\, X_{i,t} + \alpha_i + \nu_t + \epsilon_{i,t}$.

The dependent variable, $Riskiness_{i,t}$, is lending risk measured by loan loss provisions to total lending ratio, which can be viewed as expected lending risk. $Equity\ Ratio_i$ is a time-invariant variable that measures the equity ratio of bank i in the year before the deregulation. This variable is absorbed by the bank fixed effects because there is only one equity ratio before deregulation for each bank; it is not shown in the table. $Post_{i,t}$ is an indicator variable that equals one for the year after the deregulation of the state where bank i is located, and 0 otherwise. $Post_{i,t} \times Equity\ Ratio_i$ is the interaction term between deregulation dummy and equity ratio. $X_{i,t}$ stands for a set of control variables. They include lagged total assets (logged), lagged equity-to-asset ratio, and state coincident index. α_i and ν_t are bank fixed effects and year fixed effects, respectively. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	Loan Loss (1)	Loan Loss (2)	Loan Loss (3)
Total Assets ($t-1$)	0.00749***	0.00701***	0.00704***
	(21.72)	(19.72)	(19.86)
Equity-to-Asset Ratio ($t-1$)	0.0206***	0.0207***	0.0211***
	(7.09)	(6.94)	(7.07)
Interstate Banking Dummy (IBK)	-0.00467***		-0.00229***
	(-7.65)		(-3.79)
IBK $\times$ Equity-to-Asset Ratio before Deregulation	0.0379***		0.0193***
	(6.72)		(3.60)
Intrastate Branching Dummy (IBH)		-0.00599***	-0.00479***
		(-7.12)	(-5.42)
IBH $\times$ Equity-to-Asset Ratio before Deregulation		0.0424***	0.0298***
		(4.85)	(3.24)
Control Variables	Y	Y	Y
Bank Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Clustered at Bank Level	Y	Y	Y
N	106780	96495	96495
adj. R^2	0.218	0.216	0.216

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: **Changes in Realized Lending Risk**

This table presents estimates from a difference-in-difference model similar to the one in Table 1.2, except that the risk measures are charge-offs to total lending ratio and non-performing loans to total lending ratio, which can be viewed as realized lending risk. Independent variables include lagged total assets (logged), lagged equity-to-asset ratio, intrastate branching dummy, interaction of intrastate branching dummy and equity-to-asset ratio before the intrastate branching deregulation, interstate banking dummy, interaction of interstate banking dummy and equity-to-asset ratio before the interstate banking deregulation, and state coincident index. The equity-to-asset ratios before the intrastate and interstate deregulations are omitted in the regressions because their effects are absorbed by bank fixed effects. Besides bank fixed effects, year fixed effects are also included. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	Charge-off (1)	Charge-off (2)	Non-performing (3)	Non-performing (4)	Charge-off (5)	Non-performing (6)
Total Assets ($t-1$)	0.00460***	0.00420***	0.0145***	0.0130***	0.00421***	0.0111***
	(14.07)	(13.45)	(17.52)	(14.54)	(13.54)	(11.54)
Equity-to-Asset Ratio ($t-1$)	-0.0118***	-0.0117***	-0.0389***	-0.0410***	-0.0114***	-0.0191**
	(-3.87)	(-4.25)	(-4.93)	(-4.64)	(-4.16)	(-2.38)
Interstate Banking Dummy (IBK)	-0.00386***		-0.00755***		-0.00184***	-0.00885***
	(-7.12)		(-7.68)		(-3.24)	(-6.18)
IBK × Equity-to-Asset Ratio before Deregulation	0.0321***		0.0651***		0.0179***	0.0750***
	(6.60)		(6.88)		(3.59)	(5.88)
Intrastate Branching Dummy (IBH)		-0.00504***		-0.00646***	-0.00393***	-0.00572***
		(-7.09)		(-5.29)	(-5.18)	(-3.58)
IBH × Equity-to-Asset Ratio before Deregulation		0.0356***		0.0766***	0.0240***	0.0704***
		(4.93)		(6.19)	(3.11)	(4.55)
Control Variables	Y	Y	Y	Y	Y	Y
Bank Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Clustered at Bank Level	Y	Y	Y	Y	Y	Y
N	106780	96495	94832	86228	96495	61066
adj. R^2	0.218	0.217	0.218	0.216	0.217	0.216

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: **Changes in Total Lending and Asset Risk**

This table presents estimates from a difference-in-difference model similar to the one in Table 1.2, except that the dependent variables are level of total loans and leases, fraction of total loans, charge-offs to total assets ratio, and loan loss provisions to total assets ratio. Independent variables include lagged total assets, lagged equity-to-asset ratio, intrastate branching dummy, interaction of intrastate branching dummy and equity-to-asset ratio before the intrastate branching deregulation, interstate banking dummy, interaction of interstate banking dummy and equity-to-asset ratio before the interstate banking deregulation, and state coincident index. The equity-to-asset ratios before the intrastate branching and interstate banking deregulation are omitted in the regressions because their effects are absorbed by bank fixed effects. Besides bank fixed effects, year fixed effects are also included. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	Total Loans and Leases (1)	Total Loans and Leases to Total Assets (2)	Charge-offs to Assets Ratio (3)	Loan Loss to Assets Ratio (4)
Equity-to-Asset Ratio ($t-1$)	-2.690***	-0.429***	-0.00708***	0.00771***
	(-24.11)	(-5.31)	(-5.10)	(4.83)
Interstate Banking Dummy (IBK)	0.178***	0.0663***	-0.00161***	-0.00161***
	(6.55)	(3.92)	(-5.60)	(-5.14)
IBK× Equity-to-Asset Ratio before Deregulation	-0.585**	-0.240	0.0134***	0.0128***
	(-2.17)	(-1.37)	(5.22)	(4.54)
Intrastate Branching Dummy (IBH)	-0.0552	-0.0114	-0.00208***	-0.00260***
	(-1.55)	(-0.45)	(-6.53)	(-7.17)
IBH× Equity-to-Asset Ratio before Deregulation	0.555	-0.226	0.0113***	0.0151***
	(1.50)	(-0.81)	(3.65)	(4.21)
Control Variables	Y	Y	Y	Y
Bank Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Clustered at Bank Level	Y	Y	Y	Y
N	93545	93537	111119	111119
adj. R^2	0.929	0.709	0.217	0.214

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: **Lending Interest Rate and Bank Performance**

This table presents estimates from a difference-in-difference model similar to the one in Table 1.2, except that the dependent variables are lending interest rate, return on asset (ROA), return on equity (ROE), gross return on asset (GROA), gross return on equity (GROE). Independent variables include lagged total assets, lagged equity-to-asset ratio, intrastate branching dummy, interaction of intrastate branching dummy and equity-to-asset ratio before the intrastate branching deregulation, interstate banking dummy, interaction of interstate banking dummy and equity-to-asset ratio before the interstate banking deregulation, and state coincident index. The equity-to-asset ratios before the intrastate branching and interstate banking deregulation are omitted in the regressions because their effects are absorbed by bank fixed effects. Besides bank fixed effects, year fixed effects are also included. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	Lending Interest Rate (1)	Return on Assets (2)	Return on Equity (3)	Gross Return on Assets (4)	Gross Return on Equity (5)
Total Assets ($t-1$)	0.00390***	-0.000382	-0.0140*	0.00390***	0.0445***
	(11.95)	(-1.32)	(-1.72)	(17.99)	(12.62)
Equity-to-Asset Ratio ($t-1$)	-0.0430***	0.00288	-0.0632	0.0150***	-0.277***
	(-14.63)	(0.75)	(-0.91)	(4.05)	(-8.39)
Interstate Banking Dummy (IBK)	-0.000212	0.00531***	0.0532***	0.00390***	0.0223***
	(-0.32)	(9.21)	(4.32)	(8.25)	(4.20)
IBK× Equity-to-Asset Ratio before Deregulation	0.0214***	-0.0482***	-0.467***	-0.0365***	-0.144***
	(3.33)	(-8.48)	(-4.32)	(-7.50)	(-3.13)
Intrastate Branching Dummy (IBH)	-0.00173**	0.00382***	0.0473***	0.000913**	0.00451
	(-2.30)	(6.69)	(3.90)	(2.10)	(0.87)
IBH× Equity-to-Asset Ratio before Deregulation	0.0118	-0.0351***	-0.391***	-0.0165***	-0.0925**
	(1.49)	(-6.13)	(-3.64)	(-3.62)	(-1.98)
Control Variables	Y	Y	Y	Y	Y
Bank Fixed Effects	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y
Clustered at Bank Level	Y	Y	Y	Y	Y
N	115051	96505	96505	96505	96505
adj. R^2	0.752	0.312	0.127	0.416	0.275

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: **Surviving and Failed Low-capital Banks**

This table presents estimates from a difference-in-difference model similar to the one in Table 1.2. The observations are from banks in the lowest equity quartile only. The dependent variables are loan loss and charge-off ratios. Independent variables include lagged total assets, intrastate branching dummy, interstate banking dummy, and state coincident index. The equity-to-asset ratios and their interaction terms are excluded because all the observations are from banks in the lowest equity quartile. Besides bank fixed effects, year fixed effects are also included. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	Loan Loss (Surviving)	Loan Loss (Failed)	Charge-off (Surviving)	Charge-off (Failed)
Total Assets $(t-1)$	0.00596***	0.00607***	0.00444***	0.00388***
	(9.07)	(2.99)	(7.86)	(2.28)
Intrastate Branching	-0.00676***	-0.0135***	-0.00592***	-0.0134***
Dummy (IBH)	(-6.74)	(-2.84)	(-6.81)	(-2.84)
Interstate Banking	-0.00600***	-0.0118 ***	-0.00577***	-0.0124***
Dummy (IBK)	(-4.37)	(-2.03)	(-4.77)	(-2.37)
Bank Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Clustered at Bank Level	Y	Y	Y	Y
N	13224	1776	13224	1776
adj. R^2	0.226	0.235	0.227	0.232

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: **Comparison of Large Banks to All Others**

This table presents estimates from a difference-in-difference model similar to the one in Tables 1.2 and 1.3. Columns (1) to (3) are the same as column (5) in Table 1.3, column (3) in Table 1.2, and (6) in Table 1.3, respectively. These columns present the regression results of small (with assets in bottom 95%) banks. Columns (4) to (6) in this table present regression results of large banks (with assets in top 5%). The dependent variables are charge-off ratio, loan loss ratio, and non-performing loan ratio of large banks, respectively. Independent variables include lagged total assets, lagged equity-to-asset ratio, intrastate branching dummy, interaction of intrastate branching dummy and equity-to-asset ratio before the intrastate branching deregulation, interstate banking dummy, interaction of interstate banking dummy and equity-to-asset ratio before the interstate banking deregulation, and state coincident index. The equity-to-asset ratios before the intrastate branching and interstate banking deregulation are omitted in the regressions because their effects are absorbed by bank fixed effects. Besides bank fixed effects, year fixed effects are also included. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	Non-large Banks (bottom 95%)			Large Banks (top 5%)		
	Loan Loss	Charge-off	Non-performing	Loan Loss	Charge-off	Non-performing
	(1)	(2)	(3)	(4)	(5)	(6)
Total Assets ($t-1$)	0.00704***	0.00421***	0.0111***	0.00333	0.00141	0.00145
	(19.86)	(13.54)	(11.54)	(0.85)	(0.40)	(0.30)
Equity-to-Asset Ratio ($t-1$)	0.0211***	-0.0114***	-0.0191**	0.0237	-0.0163	-0.198
	(7.07)	(-4.16)	(-2.38)	(0.77)	(-0.50)	(-1.40)
Interstate Banking Dummy (IBK)	-0.00229***	-0.00184***	-0.00885***	0.000774	0.000649	0.0089
	(-3.79)	(-3.24)	(-6.18)	(0.12)	(0.11)	(0.43)
IBK $\times$ Equity-to-Asset	0.0193***	0.0179***	0.0750***	-0.0600	-0.0394	-0.239
Ratio before Deregulation	(3.60)	(3.59)	(5.88)	(-0.69)	(-0.47)	(0.89)
Intrastate Branching Dummy (IBH)	-0.00479***	-0.00393***	-0.00572***	-0.00916	-0.00514	-0.034
	(-5.42)	(-5.18)	(-3.58)	(-1.53)	(-0.91)	(-1.30)
IBH $\times$ Equity-to-Asset	0.0298***	0.0240***	0.0704***	0.0999	0.0558	0.233
Ratio before Deregulation	(3.24)	(3.11)	(4.55)	(1.12)	(0.63)	(0.71)
Control Variables	Y	Y	Y	Y	Y	Y
Bank Fixed Effects	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Clustered at Bank Level	Y	Y	Y	Y	Y	Y
N	96495	96495	61066	1582	1582	708
adj. R^2	0.217	0.216	0.216	0.178	0.214	0.405

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: **Commercial and Industry Loans, Real Estate Loans and Operating Expense**

This table presents estimates from a difference-in-difference model similar to the one in Table 1.2. The dependent variables are commercial and industrial (C&I) loans to total loans ratio, real estate loans to total loans ratio, and expenditure to total assets ratio. Independent variables include lagged total assets, lagged equity-to-asset ratio, intrastate branching dummy, interaction of intrastate branching dummy and equity-to-asset ratio before the intrastate branching deregulation, interstate banking dummy, interaction of interstate banking dummy and equity-to-asset ratio before the interstate banking deregulation, and state coincident index. The regression of expenditure to total assets ratio also includes fractions of C&I loans and real estate loans as control variables to account for different expenses on different categories of loans. The equity-to-asset ratios before the intrastate branching and interstate banking deregulation are omitted in the regressions because their effects are absorbed by bank fixed effects. Besides bank fixed effects, year fixed effects are also included. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	C & I Loans	Real Estate Loans	Expenditure
	(1)	(2)	(3)
Total Assets $(t-1)$	0.00931***	0.0248***	0.00165***
	(2.77)	(6.92)	(3.99)
Equity-to-Asset Ratio $(t-1)$	0.221***	-0.241***	-0.0450***
	(8.66)	(-8.94)	(-8.27)
Intrastate Branching Dummy (IBH)	-0.0299***	0.0307***	-0.00351***
	(-5.64)	(4.36)	(-5.14)
IBH $\times$ Equity-to-Asset	0.160***	-0.307***	0.0264***
Ratio before Deregulation	(3.13)	(-4.42)	(3.79)
Interstate Banking Dummy (IBK)	-0.0199***	0.00638	-0.00695***
	(-3.71)	(1.00)	(-10.19)
IBK $\times$ Equity-to-Asset	0.169***	-0.353***	0.0762***
Ratio before Deregulation	(3.38)	(-5.82)	(11.22)
Control Variables	Y	Y	Y
Bank Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Clustered at Bank Level	Y	Y	Y
N	96496	96496	96505
adj. R^2	0.692	0.831	0.794

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: **Changes in Capital Ratio and Dividend**
This table presents estimates from a difference-in-difference model similar to the one in Table 1.2. The dependent variables are equity capital ratio and dividend-to-asset ratio. Independent variables include lagged total assets, lagged equity-to-asset ratio (only in the regression with dividend ratio as dependent variable), lagged return-on-asset ratio, lagged collateral-to-asset ratio, intrastate branching dummy, interaction of intrastate branching dummy and equity-to-asset ratio before the intrastate branching deregulation, interstate banking dummy, interaction of interstate banking dummy and equity-to-asset ratio before the interstate banking deregulation, and state coincident index. The equity-to-asset ratios before the intrastate branching and interstate banking deregulation are omitted in the regressions because their effects are absorbed by bank fixed effects. Besides bank fixed effects, year fixed effects are also included. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	Equity Capital Ratio	Dividend-to-asset Ratio
	(1)	(2)
Total Assets (lagged)	-0.0122***	0.00111***
	(-11.09)	(3.37)
Intrastate Branching Dummy (IBH)	0.0122***	-0.00163*
	(3.03)	(-1.81)
IBH× Equity-to-Asset Ratio before Deregulation	-0.183***	0.0165
	(-3.79)	(1.53)
Interstate Banking Dummy (IBK)	0.00337	-0.000772
	(1.32)	(-0.82)
IBK× Equity-to-Asset Ratio before Deregulation	-0.0532*	0.00599
	(-1.80)	(0.54)
Control Variables	Y	Y
Bank Fixed Effects	Y	Y
Year Fixed Effects	Y	Y
N	25888	25888
adj. R^2	0.847	0.379

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: **Changes in Lending Risk (with Determinants of Capital Ratio as Control Variables)**

This table presents estimates from a difference-in-difference regression model with similar regression setup as in Table 1.2, except that the possible determinants of capital ratio and their interaction with deregulation dummies are included as independent variables. The dependent variables are loan loss provision to total assets ratio, charge-offs to total assets ratio, and non-performing loan to total assets ratio. Independent variables include lagged total assets, lagged equity-to-asset ratio, intrastate branching dummy and its interaction with equity-to-asset ratio before the intrastate branching deregulation, interstate banking dummy and its interaction with equity-to-asset ratio before the interstate banking deregulation, ROAs (as a measure of profitability) before both deregulations and their interactions with both deregulation dummies, total assets before both deregulations and their interactions with both deregulation dummies, collateral (measured by cash plus investment security on balance sheet) before both deregulations and its interactions with both deregulation dummies, and state coincident index. The equity-to-asset ratios before the intrastate branching and interstate banking deregulations are omitted in the regressions because their effects are absorbed by bank fixed effects. Similarly, ROAs, total assets, and collateral before both deregulations are absorbed by bank fixed effects. Besides bank fixed effects, year fixed effects are also included. Adjusted R-squared and number of observations are provided in the bottom rows. All standard errors are clustered at the bank level.

	Loan Loss	Charge-off	Non-performing
	(1)	(2)	(3)
Total Assets ($t-1$)	0.0067 ***	0.0038***	0.0104***
	(18.88)	(12.25)	(10.93)
Equity-to-Asset Ratio	0.0176***	-0.0143***	-0.0244***
($t-1$)	(5.83)	(-5.11)	(3.02)
Interstate Banking	-0.0041**	-0.0046***	-.0351***
Dummy (IBK)	(-2.06)	(-2.50)	(-6.13)
IBK × Equity-to-Asset	0.0224***	0.0226***	0.0889***
Ratio before Deregulation	(4.07)	(4.40)	(6.47)
Intrastate Branching	-0.0189***	-0.0188***	-0.0106*
Dummy (IBH)	(-7.12)	(-7.81)	(-1.67)
IBH × Equity-to-Asset	0.0397***	0.0351***	0.0851***
Ratio before Deregulation	(4.28)	(4.46)	(5.27)
IBK × ROA	0.116***	0.0899***	-0.246***
before Deregulation	(4.92)	(3.98)	(4.02)
IBH × ROA	0.153***	0.0951***	0.300***
before Deregulation	(5.52)	(3.67)	(4.34)
IBK × Total Assets	0.0000	0.0002	0.0021***
before Deregulation	(0.12)	(1.01)	(4.14)
IBH × Total Assets	0.0013***	0.0014***	0.0007
before Deregulation	(5.88)	(6.86)	(1.26)
IBK × Collateral	0.0017**	0.0001	0.0063**
before Deregulation	(2.07)	(0.10)	(2.54)
IBH × Collateral	-0.0024***	-0.0026***	-0.0118***
before Deregulation	(-3.06)	(-3.45)	(-3.64)
Control Variables	Y	Y	Y
Bank Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
N	96495	96495	61066
adj. R^2	0.219	0.218	0.418

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER II

The Strategic Under-Reporting of Bank Risk

2.1 Introduction

Accurate and timely measurement of risk is crucial for assessing the soundness of financial institutions and the stability of the financial system and economy as a whole. The complexity of a large bank's business model makes it difficult for regulators and market participants to observe the bank's true risks at a reasonable cost. As a result, outsiders depend on information from the bank itself to judge its riskiness. These self-reported risk levels then heavily influence both regulatory treatment of the banks and market participants' investment decisions. Riskier banks face higher capital charges and pay more for deposit insurance. Such banks are also likely to face more risk in the stability of their funding during periods of banking crisis. These consequences have the potential to create an important problem: they give banks incentives to under-report their risk. Do banks engage in such behavior? What are the implications of this behavior on the usefulness of risk measurement for the financial system as a whole, particularly in times of systemic stress? We empirically address these policy relevant questions by examining the accuracy of self-reported risk measures in banks' trading books.

While accurate risk reporting is important for the entire business of large financial institutions (banks), we focus on the trading book because it allows us to cleanly tease out the under-reporting incentives. A typical trading portfolio consists of marketable financial instruments linked to interest rates, exchange rates, commodities, and equity prices. The trading desks of large banks have significant risks and have been the subject of many recent policy debates and discussions on risk-management failures within a bank.[1] Basel rules allow banks to measure the risk of their trading portfolio with internal Value-at-Risk (VaR) models. Broadly, VaR is a statistical measure of risk that estimates the dollar amount of potential losses from adverse market moves. Regulators around the world use these numbers to determine capital requirements for market risk. The use of an internal risk model leaves a great deal of discretion with the reporting bank. For example, banks can vary assumptions about asset volatilities, correlations between asset classes, or alter the length and weighting of the historical period used to estimate these quantities, all of which significantly affect the output of their models (*BIS*, 2013). This discretion gives banks a significant ability to under-report their trading risks, which directly lowers their current capital requirements. Thus, the incentives to under-report is especially strong when capital is dear (e.g.,when they have lower equity capital). The combination of ability and incentive to under-report risk has the potential to compromise the integrity of the risk management system and risk-based regulations.

To mitigate the under-reporting incentive, regulators use a "backtesting" procedure to evaluate banks' self-reported VaR, and impose a penalty on institutions with models that have proven inaccurate. As per the recommendations of Basel committee, a bank's market-risk capital requirement is set at its 99% VaR number over a 10-day horizon multiplied by a capital multiplier k, which is initially set to three.[2]

[1]See, for example, the enactment of "Volcker Rule," (under Title VI of the Dodd-Frank Wall Street Reform and Consumer Protection Act) which restricts the trading activity of depository institutions. Recent scandals include "London Whale" Bruno Iksil at J.P. Morgan in 2012 and Kweku Adoboli at UBS in 2011. These events cost their banks about $6.2 billion and $2.2 billion in trading losses, respectively.

[2]VaR is computed at a certain confidence interval for a fixed horizon of time. A 10-day 99% VaR estimates the dollar amount of loss that the portfolio should not exceed more than 1% of time over the next 10 trading days. See *Jorion* (2007) for a comprehensive treatment of VaR models.

However, if a bank breaches its self-reported VaR level too often, it faces higher capital requirement in future periods. For example, the Office of the Comptroller of the Currency (OCC) examines the number of times a bank breaches its self-reported VaR – which we refer to as *exceptions* or *violations* – every quarter.[3] If a bank has more than four exceptions during the trailing four quarters, the regulators assume that the bank is more likely to have under-reported in the past, and its capital multiplier is increased for the subsequent periods for a charge of up to four-times their VaR level.[4] However, there is also some probability that the under-reporting does not get detected depending on future asset price movements. In such a scenario, the under-reporting bank avoids detection and penalties altogether. Even if the bank does experience VaR exceptions, the potentially significant time delay in detection and punishment may be sufficient to allow the offending bank to raise capital at a time when market conditions are more favorable. This regulatory structure therefore leads to the fundamental tradeoff we examine in this paper: a bank can under-report its risk to save capital today in exchange for the potential for a higher capital charge in the future.[5]

A bank's incentive to under-report its VaR depends on a trade-off between the shadow price of capital today versus the shadow price of capital in the future, which can be several quarters away. All else equal, raising capital is more costly when a bank has a very low capital base. In these cases, the trade-off is more likely to tilt the bank's incentive in favor of saving capital today at the expense of possibly a higher

[3]See **?** for further details on backtesting and statistical methods for assessing the accuracy of VaR models.

[4]The multiplier ranges from 3.0 (four or fewer exceptions) to 4.0 (ten or greater exceptions). The purpose of this increasing penalty is in "maintaining the appropriate structure of incentives applicable to the internal models approach" and to "generally support the notion that nine exceptions is a more troubling result than five exceptions" (*BIS*, 1996). We later exploit the shape of this institutional feature in our empirical tests.

[5]In addition to regulatory forces, the under-reporting incentives can also arise from a desire to understate risk measures to other market participants. For example, a bank that is concerned about large outflows of liabilities can resort to the under-reporting of risk to try to avoid such outflows. Again the basic tradeoff remains the same: benefits from under-reporting risk in the short-run with potential costs in the long-run.

capital charge in future quarters. After all, the bank's capital position may improve in the intervening time, there may be a shift in the supply of bank capital that lowers issuance costs, or prices may move in favorable directions so that outsiders fail to detect the under-reporting.

We assemble a detailed quarterly data set of self-reported trading book VaR and number of VaR exceptions for a sample of 18 very large financial institutions (banks) from the U.S., Europe, and Canada from 2002-2012. These cover a significant fraction of the global banking assets, and an even larger fraction of trading assets. A VaR exception occurs when a bank's realized losses exceed its self-reported VaR number. More specifically, VaR numbers are computed and reported at the end of the day for the bank's trading portfolio. Holding fixed that portfolio, gains or losses are measured over the next trading day and compared to the reported number.

Our first contribution is descriptive in nature. We provide the first detailed summary statistics on exceptions across banks and over this time period. Our main tests focus on commercial banks' VaR reporting at the 99% confidence level. We find 0.62 average quarterly exceptions per bank for this sample, which is approximately equal to the statistical benchmark for a 99% VaR model over roughly 63 trading days per quarter. This average, however, masks an important time-series variation. The average exceptions per quarter is below the statistical benchmark during 2002-2006 at 0.08 per bank-quarter, and increases considerably thereafter. During 2007-2009, we find average exceptions per bank-quarter of 1.64, which is greater than 2.5-times the statistical benchmark.

In our main empirical test, we show that when banks have lower equity capital at the beginning of a quarter, they have significantly more VaR exceptions in the following quarter. One standard deviation decrease in a bank's equity capital results in an increase of 1.32 exceptions in the following quarter, which is roughly twice the sample average of 0.62. Put differently, banks' future losses exceed their own risk assessment significantly more frequently in periods immediately following a decline in their equity capital (i.e., when they have higher capital-saving incentives). Our empirical design is powerful because exceptions occur when the losses exceed the bank's self-reported level of VaR, *not* simply when the level of VaR is high. Regardless of a given bank's level of riskiness or equity capital, the expectation of VaR exceptions should be identical: 1 in 100 trading days. Therefore, we do not suffer from any biases due to the endogenous determination of equity capital and the level of risk assumed by the bank. Further, our model includes both bank and year-quarter fixed effects, which ensures that our results are not driven by differences in bank-specific risk-modeling skills or market-wide shocks. Our design, therefore, relates within-bank variation in the level of equity capital to future VaR exceptions to identify the under-reporting behavior. A remaining identification concern is as follows: if a bank's VaR-model quality deteriorates precisely following quarters when it has low equity capital, then the negative association between equity capital and VaR exceptions might not reflect under-reporting incentives, but simply a systematic deterioration in model quality right after a negative shock to equity capital.

Given that our sample comprises some of the largest and most sophisticated financial institutions of the world, it is unlikely that the bank's modeling quality changes precisely *after* a period when the bank has lower equity capital. However, we directly address this concern by exploiting a regulation-driven discontinuity in the costs and benefits of under-reporting from the Basel Committee guidelines on market risk. Based on the number of exceptions experienced by a bank in the past year, bank regulators classify banks into three categories or zones: Green (0-4 exceptions), Yellow (5-9), and Red (≥ 10). These classifications, in turn, determine the supervisory pressure and increased scrutiny that the banks face in subsequent quarters. Banks in the Green zone have strong incentives to stay within this zone to avoid both the higher compliance costs and higher capital multiplier incurred by banks in the Yellow zone. Thus, banks on differing sides of the Green-Yellow threshold face sharply different under-reporting incentives. While there is a stark change in incentives at this point, it is unlikely that the quality of a bank's risk model changes sharply at this threshold. Under this identifying assumption, we first compare the number of future exceptions around the Green-Yellow threshold, and show that banks just above the threshold have almost 5-times as many exceptions in the following quarter compared to banks just below it. Further, in a difference-in-differences specification, we show that the relationship between equity capital and future exceptions is stronger and more negative for bank-quarter observations that are above the Green-Yellow threshold, compared to observations that fall just below. This difference increases as we limit our sample to observations that are closer to the threshold, providing further confidence in the empirical validity of our research design.

We conduct a series of tests to exploit the cross-sectional and time-series variation in under-reporting incentives to gain a better understanding of the economic channels behind the main findings. First, we show that the effect is stronger when the trading business represents a relatively larger portion of the bank's business. For such banks, under-reporting can be economically more beneficial, and our results confirm that. We next show that the relationship between equity capital and VaR exceptions is stronger when banks have recently experienced a decrease in market equity (low stock returns). Raising external equity capital is even more difficult in such situations, and thus the incentives to under-report risk even stronger.

While it is important to understand the risk reporting dynamics for a given bank over time, from a systemic perspective, it is even more important to understand how banks report their risk when the entire financial sector is under stress. These are the periods when the shadow cost of capital is likely to be high across all banks. Thus, a bank's private marginal benefit from under-reporting is likely to be higher precisely when the social cost of bank failure is high. Using different measures of systemic stress, we show that the relationship between equity capital and under-reporting is stronger during these periods. These results show that the self-reported risk measures become least informative in periods when understanding financial sector risk is likely to be most important.

We conduct a number of tests to ensure the robustness of our results. First, we exploit the panel data dynamics of exceptions to further rule out the "bad model" alternative discussed earlier. We consider the previous quarter's exceptions as a proxy for the quality of the bank's VaR model, and re-estimate our main specification including the lagged exceptions as an explanatory variable. Our results continue to hold. Among other tests, we also show that our results remain strong after controlling for a bank's time-varying exposure to market and mortgage-backed securities risk, and the asset class composition of the bank's trading book.

Finally we shed some light on a possible mechanism through which banks could be under-reporting their risk. Banks have a great deal of discretion in their modeling choices on a variety of dimensions. Properly used discretion should improve the quality of the reported levels of risk exposures. On the other hand, if discretion is used to under-estimate risk exposure, then this should lead to a greater number of future VaR exceptions. We estimate the relationship between past stock market volatility and the reported *level* of VaR. Ceteris paribus, the higher the volatility of a risk factor, the higher the level of VaR. We find that the relationship between past market volatility and reported VaR levels to be weaker when banks have lower equity capital. This is consistent with the notion that banks use more discretion when they have low equity capital. Combined with the main results above, this suggests that firms may be using their discretion in the choice of volatility parameters to under-report their risk.

Our paper relates to the literature on bank risk models and a recently growing literature on the implications of risk-management practices in banking (see *Ellul and Yerramilli* (2013)). *Jorion* (2002) and *Berkowitz and OBrien* (2002) analyze the informativeness and statistical accuracy of VaR models.[6] Recent work by *Behn et al.* (2014) examines the efficacy of model based regulation for the banking book of German banks around the introduction of Basel II. They find that banks' internal model-based risk estimates systematically underestimated the level of credit risk in banks' loan portfolios. Our work is consistent with their evidence highlighting the shortcomings of internal model-based regulations. While they focus on the accuracy of model-based regulation compared to standardized approach, our focus is on the relationship between equity capital and risk under-reporting. In summary, our paper contributes to this growing literature by being the first to directly analyze the effect of capital saving incentives on risk under-reporting.

This work is also related to the literature on the effect of risk-based capital requirements on the lending and risk-taking behavior of banks (e.g., see *Acharya et al.* (2013) and **?**), and the ongoing policy discussions and research work on capital regulations and risk-taking behavior in the financial sector (e.g., see *Admati et al.* (2011), *Brunnermeier and Pedersen* (2009), *Kashyap et al.* (2008), and **?**). At a broad level, our work is related to the literature on the economics of self-reporting behavior and probabilistic punishment mechanisms (e.g., *Becker*, 1968). *Kaplow and Shavell* (1994) show that self-reporting followed by a probabilistic audit and punishment for violation can be an optimal mechanism in several settings. These models, however, do not consider the differences in the shadow price of capital at the time of reporting compared to the time of (potential) punishment. Our work shows that in such settings, the probabilistic punishment mechanism that ignores state prices may have negative systemic consequences.

The rest of the paper is as follows. In Section 2.2 we present our hypothesis and

[6] *Basak and Shapiro* (2001) and *Cuoco and Liu* (2006) analyze VaR-based constraints and capital requirements, and theoretically analyze the optimality of this mechanism.

research design, Section 2.3 describes the data, Section 2.4 presents the results, and Section 2.5 concludes.

2.2 Research Design and Identification Strategy

VaR is a statistical measure of risk that estimates a dollar amount of potential loss from adverse market moves over a fixed time-horizon and at a given confidence interval (see *Jorion* (2007) for a comprehensive treatment of VaR models). For example, a 99% confidence interval, 10-day holding period VaR of $100 million for a portfolio means that over the next 10 days, this portfolio will lose less than $100 million with 99% probability. Due to pure statistical chance, we would expect to see one exception (i.e., losses exceeding $100 million) every 100 trading days. Absent any incentive conflict, the number of exceptions should be unrelated to the bank's prior equity capital. Alternatively, we should observe more frequent exceptions for banks following quarters with lower equity capital if banks strategically under-report their risk to save capital. Note that a bank may change its risk-taking behavior in response to changes in its equity capital position, but these changes should only affect the *level* of VaR, *not* the frequency of exceptions. This distinction highlights a key strength of our empirical setting: we relate capital-saving incentives to deviation from self-reported VaR numbers, which is independent of the scale of risk-taking.

To develop the intuition behind our empirical test, consider the VaR of a single unit of a risky asset i at time t. Denote this portfolio's reported and actual VaR by $Reported_{it}$ and $Actual_{it}$, respectively. Assume that $\sigma_{predicted}$ is the volatility estimate used by the bank in estimating its reported VaR. Banks typically develop their own internal model for VaR based on one of three approaches: (a) variance-covariance method, (b) historical simulation, or (c) Monte Carlo simulation. Although these approaches differ in their implementation approach, they all require the modeler to take a stand on the volatility of the assets, and covariances between securities and asset classes to estimate the potential loss of the portfolio.[7] Further assume that the realized volatility of the asset is denoted by $\sigma_{realized}$. We can express the reported VaR as a function G of risk ($\sigma_{predicted}$) at a confidence interval (α) with residual (η_{it}) as follows:[8]

$$\begin{aligned} Reported_{it} &= G(\alpha, \sigma_{predicted}) - \eta_{it} \\ \eta_{it} &= \phi(Incentives_{it}) + u_{it} \end{aligned}$$

The key term in the equation is the residual term η_{it}. In our model, this captures the extent of under-reporting and is driven by incentive effects and pure noise (u_{it}). The actual VaR, if the analyst had a perfect foresight of future volatility, can be expressed as $G(\alpha, \sigma_{realized})$. Our goal is to identify the incentive effects in VaR reporting using the following framework:

$$Actual_{it} - Reported_{it} = \{G(\alpha, \sigma_{realized}) - G(\alpha, \sigma_{predicted})\} + \phi(Incentives_{it}) + u_{it} \quad (2.1)$$

We use the frequency of VaR exceptions for bank i in a given quarter t ($Exceptions_{i,t+1}$) as an empirical proxy for the difference between actual (or realized) and reported risk numbers ($Actual_{it} - Reported_{it}$) in (2.1). To ensure comparability across observations, we focus on VaR reported at a 99% confidence interval in all of our main specifications.[9] The distribution of $\{G(\alpha, \sigma_{realized}) - G(\alpha, \sigma_{predicted})\}$ measures the quality of

[7] Banks typically use the past one to three years of data as an estimate of the underlying asset's historical volatility. For example, Bank of America state in their 2008 10-K, "Our VaR model uses a historical simulation approach based on three years of historical data and assumes a 99 percent confidence level. Statistically, this means that the losses will exceed VaR, on average, one out of 100 trading days, or two to three times each year."

[8] For example, $G(\alpha, \sigma_{predicted}) = 2.33 \times \sigma_{predicted}$ for a normally distributed asset at a 99% confidence level. For a normally distributed changes in asset value, $VaR = \mathcal{N}^{-1}(\alpha) \times \sigma$, where $\mathcal{N}^{-1}()$ is the inverse normal CDF. -2.33 is the point at which 1% of the mass of the distribution lies below (to the left). The corresponding number for a 95% confidence level is -1.65. Note, however, that we do not rely on normality assumptions for developing our empirical model.

[9] In a robustness test, we expand the sample and reconstruct the test to include observations where VaR is reported at 95% confidence level.

risk model – for a good model, this difference should be close to zero and uncorrelated with the incentive variable. We refer to this difference as the "model quality" in the rest of the paper. Thus, our model can be rewritten as follows:

$$Exceptions_{i,t+1} = ModelQuality_{it} + \phi(Incentives_{it}) + u_{it} \tag{2.2}$$

where $Exceptions_{i,t+1}$ measures the number of VaR exceptions over the next period.

If $ModelQuality_{it}$ were perfectly observable, we could identify the effect of under-reporting incentives on the frequency of exceptions by directly controlling for it in the regressions. In the absence of a precise measure of model quality, we confront three primary challenges in identifying the incentive effects on under-reporting. First, banks may have different modelling skills. Differences in risk-management skills, organizational structure, risk culture, and the importance of risk controls within the firm can have significant influence on the level of risk-taking by banks (see **?***Ellul and Yerramilli* (2013)). *Kashyap et al.* (2008) discuss the effects of internal controls and traders' incentives on risk-taking behavior. If these persistent unobserved modelling skills correlate with equity capital, then our estimates will be inconsistent. We include bank fixed-effect in the empirical specification to address this concern. Second, during periods of large fluctuations in market prices, the realized volatility may be significantly higher than the predicted volatility used in the VaR model, leading to general failures in VaR models across banks during these times. We include year-quarter fixed effect in the empirical specification to address this concern. Thus, our baseline model that addresses these two concerns can be expressed as below, where λ_i and δ_t are bank and year-quarter fixed effects, and X_{it} is a vector of further control variables including the size and profitability of the bank:

$$Exceptions_{i,t+1} = \beta(Incentives_{it}) + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \tag{2.3}$$

Our main measure of $Incentives_{it}$ is the bank's equity capital ratio ($Equity_{it}$). This measure directly maps to our economic argument that banks with stronger incentives to save equity capital are more likely to engage in under-reporting behavior. We also exploit an institutional feature that relates VaR model performance to punishment that alters the bank's under-reporting incentives based on the bank's number of exceptions during the trailing three quarters. We describe this approach in detail below.

The third primary identification challenge is related to concerns about potentially time-varying, bank-specific changes in model quality that correlates with their level of equity. The tests relate equity capital at the beginning of the quarter to the number of VaR exceptions during the next quarter. For the alternative explanation to hold, it must be the case that the VaR model becomes relatively more inaccurate during the quarter, for reasons unrelated to reporting incentives, only when banks have had low equity capital at the beginning of the quarter. Since banks are expected to update their VaR model periodically to better capture the changes in underlying volatilities, this explanation is unlikely to be true. It is also worth emphasizing that the inclusion of year-quarter fixed effects in the model removes the effect of economy-wide deterioration in model quality. However, to directly address this concern we exploit an institutional feature of the market risk capital regulation formulated by Basel Committee on Bank Supervision (*BIS*, 1996).

As mentioned earlier, bank regulators use a back-testing procedure to check the quality of a bank's risk model. Based on the bank's number of exceptions in the past four quarters, regulators categorize them into one of three zones: "Green," "Yellow," or "Red." Banks with four or fewer exceptions during the past year are categorized into the "Green" zone; those between five and nine are categorized into the "Yellow" zone; and those with ten or more exceptions are categorized into the "Red" zone. These zones, in turn, dictate both the level of regulatory scrutiny and capital charges that the bank faces in subsequent quarters. Banks in the Green zone do not face any special regulatory scrutiny of their risk model, as the lack of exceptions indicate a model that is likely to be more accurate or sufficiently conservative. As per the *BIS* (1996) policy document, "the green zone needs little explanation. Since a model that truly provides 99% coverage would be quite likely to produce as many as four exceptions in a sample of 250 outcomes, there is little reason for concern raised by backtesting results that fall in this range."

Banks in the Yellow zone automatically come under additional regulatory scrutiny and face significantly higher compliance costs. As stated by the BCBS guidelines: "the burden of proof in these situations should not be on the supervisor to prove that a problem exists, but rather should be on the bank to prove that their model is fundamentally sound. In such a situation, there are many different types of additional information that might be relevant to an assessment of the bank's model." As per the guidelines, such banks may be required to provide more granular data on trading risk exposure, intraday trading activities, and a number of other additional information. Finally, banks with ten or more exceptions fall into the Red zone. Their model is considered inaccurate by the regulators: in extreme cases the regulators can even suspend the bank's internal risk model, and subject it to a standardized model for risk assessment.

In addition to the changes in the level of regulatory scrutiny, banks in different zones face different levels of capital charge as well, which is a function of the bank's reported VaR and a regulatory capital charge multiplier (k). Banks in the Green zone face a capital charge multiplier of 3.0; those in Yellow zone face a multiplier between 3.0 and 4.0 depending on the number of past exceptions; and banks in the Red zone face a multiplier of 4.0. Figure 2.1 illustrates these classifications and the associated capital charge for the entire range of exceptions.[10]

[10]Specifically, the market risk charge C equals the greater of the previous day's reported VaR and the average of the prior 60 days' VaR multiplied by the regulatory multiplier k: $C = \max(VaR_{t-1}, k\times$

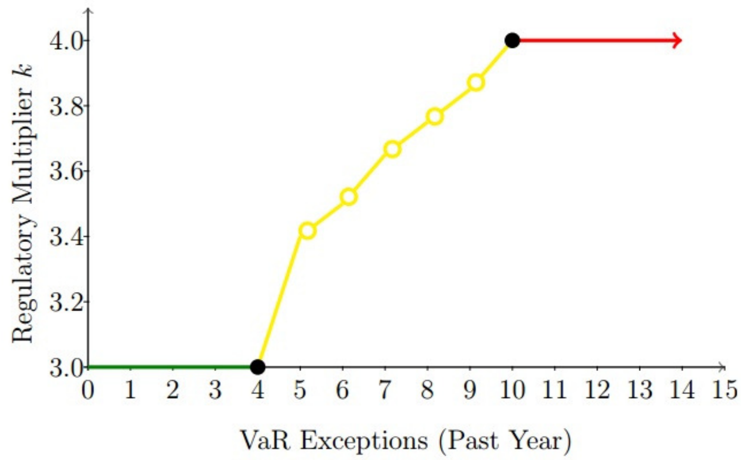

Figure 2.1: **The Shape of Penalties**
This figure presents the shape of regulatory capital multiplier k as a function of past exceptions (based on trailing 250 trading days).

Figure 2.1 makes clear that there are two prominent discontinuities in the relationship between past exceptions and resulting regulatory scrutiny and capital charges: the Green-Yellow threshold and the Yellow-Red threshold. The quality of banks' VaR model, however, is unlikely to be very different within a given neighborhood along the x-axis. For example, model quality of banks with four exceptions in the past year is likely quite similar to those with three or five exceptions, particularly since the occurrence of an exception is a probabilistic event. We use this similarity in model quality combined with the stark change in economic incentives around the threshold to tease out the causal effect of capital-saving incentives on risk-reporting.

In particular, we focus on the reporting incentive of banks that are around the Green-Yellow threshold. Since the zone assignment is based on the back-testing result of past one year, at the beginning of each quarter we first compute the number of exceptions that a bank had in the trailing three quarters. Absent any under-reporting incentives, banks expect to incur roughly one additional exception every quarter by

VaR^{ave}_{60-day}). Table B.1 in the appendix presents mapping from number of exceptions over the last 250 trading days to the corresponding supervisory zone and regulatory multiplier.

construction due to the 99% VaR confidence interval. For example, a bank that has two exceptions in the past 3 quarters will, in expectation, have an additional exception in the next quarter for annual total of three exceptions. Thus, banks with three or fewer exceptions in the past 3 quarters are expected to stay within the Green zone at the end of the quarter with a four-quarter total of four or fewer exceptions. We refer to these observations – which in expectation will avoid the additional scrutiny that faces those in the Yellow zone – as the Green group for the remainder of the paper. These observations can be thought of as a control group. Banks with four up to eight exceptions, on the other hand, will in expectation be in the Yellow zone in the next quarter even without any under-reporting. We refer to these observations as the Yellow group, and they can be thought of as a treatment group. Given the significantly higher costs and scrutiny incurred by banks in the Yellow zone relative to the Green zone, banks in the Green zone have incentives to be relatively more conservative in their risk reporting compared to banks in the treatment group. However, such incentives disappear for banks in the Yellow group who expect to face this scrutiny in any case. The remainder of the observations are in the Red group.

In addition to the changes in regulatory pressure around the threshold, the shape of the multiplier function provides further support to our identification strategy. There is a significant change from a flat multiplier charge of 3.0 to a sharp increase in capital charge as a bank moves from the Green to the Yellow zone, which makes Green zone banks face a convex penalty function. However, for banks in the Yellow zone, the multiplier increases broadly at a linear pace until it reaches a level of 4.0, after which it is capped. Therefore, the shape of penalty function is concave for banks in this region. This switch in the shape from a convex penalty function to a concave one further strengthens the relative under-reporting incentive of banks in the Yellow zone.

In summary, banks in the Yellow group are likely to have a stronger under-reporting incentive to save capital in the current quarter as compared to the Green group.[11] Also, the comparability of these two groups is likely to improve as we narrow the window around the threshold, where our assumption of similarity in unobserved model quality is most reasonable. Under the identifying assumption that banks in the neighborhood of the Green-Yellow threshold are likely to have similar model quality, we are able to identify the effect of the incentive to save capital on under-reporting by simply comparing the differences in exceptions around this threshold. Further, we interact the zone assignment variable with the level of equity capital to assess whether banks with lower equity capital in the Yellow group are more likely to under-report compared to their counterparts in the Green group. The identifying assumption here is that any potential correlation between equity capital and model quality does not change abruptly at the Green-Yellow threshold. For expositional clarity, we defer further details on the empirical implementation to the results sections.

While our tests focus on the threshold between the Green and Yellow zones, there is a second kink as a bank moves from the Yellow to Red zone. However, the underlying changes in incentives are not as clear at this threshold. On one hand, banks face a flat multiplier charge of $k = 4.0$ for any number of exceptions beyond ten, providing them with an incentive to be aggressive in risk reporting. On the other hand, such banks might also have concerns that their permission to use internal models may be revoked by the regulator. In such a situation, they face the risk of a much higher capital charge based on the standardized modelling approach of the regulator. Further, we have a very few observations in the Red group. Considering these factors, we do not exploit this threshold in our empirical tests.

Following our main empirical tests, we examine further cross-sectional and time series variation in the economic incentives to under-report. Cross-sectionally, we

[11] The combination of Green zone banks' desire to avoid additional regulatory scrutiny and the convex cost function may help explain the seemingly excessive conservatism in VaR reporting we see in the early periods. *Berkowitz and OBrien* (2002) also find that VaR estimates tended to be conservative relative to the 99% benchmark for six large U.S. banks during 1998-2000.

exploit variation across banks in the size of their trading books. Banks with larger trading books may have stronger incentive to under-report when capital is costly. We then exploit time series variation in financial system stress to examine the systemic implications of our study.

2.3 Data and Sample

We construct a sample of large financial institutions from U.S., Canada, and Europe that provide sufficient details in their quarterly filings about the extent of VaR during the quarter, and the number of exceptions over the same period. We collect quarterly data on aggregate VaR of the bank as well as the corresponding number across risk categories such as interest rates, and foreign exchange.[12] As mentioned earlier, banks are required to report their back-testing results to the regulators based on a quarterly basis. When losses exceed the self-reported VaR on a given day, an exception occurs. We collect all exceptions during the quarter for each bank, and use it as the key measure of reporting accuracy.

Our "base" sample includes large commercial banks that report their VaR at the 99% confidence level, and these observations are the subject of the bulk of our analysis. Our "expanded" sample adds broker-dealers and observations where VaR is reported at 95%. We do not include these observations in our base sample because it is not generally meaningful to compare the frequency of VaR exceptions across different confidence intervals. In addition to the consistency in reporting, commercial banks are also more homogenous in terms of their capital requirements. For robustness tests, we conduct our main tests on the expanded sample that includes VaR exceptions at the 95% level as well as VaR exceptions from broker-dealers.[13] Finally, we miss some

[12]Banks typically break down their overall VaR across these categories: interest rate, foreign exchange, equity, commodities, and others. In addition, often they provide the diversification benefit claimed across the asset classes. The total VaR is the sum of VaRs across all categories net of the diversification benefit.

[13]Broker-dealers also face capital requirements for market risks based on similar Basel Committee

banks altogether from our sample because they do not disclose their VaR exceptions in their quarterly filings at the 95% or 99% level.

Our sample period begins in 2002 since the required data on VaR are not available for most banks before this year. Our sample ends in 2012. The total sample comprises 15 commercial banks and 3 broker-dealers, which covers a large portion of assets in the global banking system. Commercial banks in our sample have about $14 trillion in assets. This compares well with the aggregate asset base of about $13-14 trillion for U.S. commercial banks, and about €30 trillion for banks covered by the ECB as of 2013. Even more important, these institutions cover a disproportionately large fraction of trading assets of the economy. Our base sample of commercial banks provides 424 bank-quarter observations over 2002-2012 for our main tests. The expanded sample contains 545 bank-quarter observations that we examine in robustness tests.

We also collect data on some measures of systemic stress. Our key measure of systemic stress is the Marginal Expected Shortfall (MES) of the banking sector, provided by the New York University's Volatility Lab (see *Acharya et al.* (2010)). We obtain this measure for all systemically important financial institutions of the world on a quarterly basis, and aggregate them to construct the systemic MES measure. The MES measure varies considerably over time, providing us with reasonable time-series variation in the extent of capital shortfall in the economy.

We collect balance sheet data on banks' equity capital, profitability, and asset base on a quarterly basis from the bank's quarterly filings and Bankscope. We also obtain their stock returns from CRSP and Datastream. Data on interest rate, foreign currency, equity, and commodity volatility come from the Federal Reserve Bank, CRSP, and Bloomberg. All data are winsorized at the 1% level to mitigate the effects

formula. Their net capital requirement is regulated by the Securities and Exchange Commission (SEC). SEC's formula for computing capital requirement for market risk is identical to the formula used by other banking regulators for commercial banks (*SEC*, 2004).

of any outliers. Continuous variables and the number of exceptions are standardized to have zero mean and unit standard deviation prior to the regression analysis for easier interpretation.

Table 2.1 provides summary statistics for the base sample. The sample banks have an average asset base of $901 billion. On average, they are profitable during our sample period, with a mean quarterly net-income-to-assets ratio of 0.17%. On average banks have 6.32% equity as a percentage of their asset base. This ranges from 4.06% for the 25th percentile bank to 9.01% for the 75th percentile. Following prior literature, most of our main tests will focus on the log of this ratio, which emphasizes the idea that the strength of incentives increase at an increasing rate as capital levels get lower. We use the book equity capital ratio instead of the regulatory capital ratio as the key variable for our tests to avoid measurement error problems. Regulatory capital ratios, such as the risk-weighted Tier-1 capital ratio, use the computed risk-weighted assets of the bank in the denominator. The VaR of the trading book is an important variable in the computation of the ratio, which then leads to a mechanical correlation between under-reporting and regulatory capital ratio. The use of book equity capital ratio avoids such a problem.

Turning to the VaR data, we find a wide variation in VaR exceptions, the level of VaR, and the composition of VaR in our sample. On average, interest rate risk forms the largest proportion of banks' trading book risk. They also have considerable exposure to foreign exchange, equities, and commodities risk. Overall, the pooled-sample statistics indicate that the sample comprises very large banks with a wide variation in equity capital, trading desk risk exposure, and VaR exceptions.

Table 2.2 provides a list of the financial institutions that enter our sample along with some key descriptive statistics for each. It is clear that there is a large cross-sectional variation in the level of VaR as well as exceptions across banks. Table 2.2 also highlights the substantial within-bank variation of VaR levels and exceptions that we exploit in our main tests.

2.4 Results

In addition to our main exercise that examines the under-reporting incentives, our paper makes an important contribution to the literature by documenting some key empirical facts about VaR and its exceptions. Therefore, we first present some descriptive statistics on aggregate VaR and overall exceptions in our sample. Following the research design discussed in Section 2.2, we next use regression analysis to examine the relationship between incentives to save equity and VaR exceptions. We then examine further cross-sectional and time series variation in the banks' economic incentives to under-report by looking at banks with larger trading exposures, and periods when the financial system is under stress.

2.4.1 Value-at-Risk Exceptions Over Time

Table 2.1 presents summary statistics on VaR exceptions for the sample. Since the VaR numbers that we consider in the base sample are based on 99% confidence interval, we expect to see one exception in every 100 days purely by chance. Hence on a quarterly basis, we expect to observe an average of about 0.63 exceptions based on roughly 63 trading days per quarter. Across banks and quarters, the average quarterly exceptions (*Exceptions*) is 0.62 for the base sample which is in line with the statistical expectation. Ranging from 0 to 13, there is substantial variation in the number of exceptions which is present both in the cross-section and the time-series.

Table 2.2 shows the variation in exception frequency across banks, while Figure 2.3 presents this variation over time by plotting the average number of exceptions per bank during each quarter in the sample. The average number of VaR exceptions are well below their statistical expectation during 2002-2006 at 0.08 per bank-quarter, but starting in 2007 the exceptions increase by a considerable amount. The spike in these exceptions coincide with a period of increased systemic risk in the economy of 2007-2009, where there are 1.64 exceptions per bank-quarter. From 2010-2012, we once again observe fewer VaR exceptions with an average of 0.18 per bank-quarter. This figure provides a clear insight: on average, the VaR models failed during periods of high systemic risk when timely and accurate risk measurement in the financial sector is likely most important. During these periods, the exceptions are far greater than what reliable risk-measurement reporting would predict. While this point has been argued by various market observers, our paper provides first systematic assessment of this issue. Was the VaR exception during this period simply an artifact of large changes in asset prices, or was it also related to capital-saving incentives? The following empirical analysis teases out these alternatives.

2.4.2 Value-at-Risk Exceptions and Equity Capital

We begin the regression analysis by estimating our base regression model relating capital-saving incentives to subsequent VaR exceptions. As mentioned earlier, the number of exceptions and all continuous variables are standardized to mean zero and unit standard deviation for ease of interpretation. Table 2.3 presents the baseline results along with several alternative specifications of the following model that differ in terms of control variables used and estimation approach:

$$Exceptions_{i,t+1} = \phi(Equity_{it}) + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \tag{2.4}$$

Column (1) reports the effect of equity capital, as measured by log(Equity/Assets), on exceptions without any control variables other than bank and year-quarter fixed effects.[14] We find a negative and statistically significant coefficient on the equity

[14] The log-transform of equity ratio follows the literature and assigns more weight on variation in equity capital at lower values. This is consistent with our key economic argument that incentives to under-report is higher when banks have lower levels of equity. We estimate our model with equity-to-asset ratio as well as other natural concave transformations of the ratio such as the square root and cubic root of equity ratio and discuss those later in the paper.

capital ratio: when banks have lower equity capital, they have more VaR exceptions in the following period. In terms of economic magnitude, one standard deviation (s.d.) decrease in equity capital results in approximately 0.70 s.d., or 1.40, more exceptions in the following quarter. With a sample average of 0.62 exceptions and s.d. of 2.00, this is an economically significant increase to over three times the average VaR exception frequency. In column (2), we include controls for bank size and profitability. Our main result are virtually unaffected, both statistically and economically. Also, including bank-specific controls explains little if any of the variation in exceptions, as the R^2 across the first three columns remains at 0.45. In column (3), we explicitly include measures of the volatility of underlying risk factors during the quarter in the regression model and drop year-quarter fixed effects. As expected, we find higher exceptions during quarter with high volatility in market returns, interest rates, and commodity prices. Our main result relating equity capital to exceptions remains similar.

The quarterly timing of reporting is not exactly the same for all banks in our sample. For example, some banks end their quarter in March, while others end in April. Therefore, the volatility measure computed during the quarter is not perfectly collinear with year-quarter fixed effects, and we can include year-quarter fixed effects in the model along with the volatility measures. Column (4) shows that our results are similar based on this full specification. We cluster the standard errors in our main specifications at the year-quarter level. In column (5), we compute standard errors clustered at the bank level and find that the results are statistically significant at the 3% level. Since we need a large number of clusters to ensure consistent estimates and bank clustering yields only 15 clusters, we focus on the estimates with year-quarter clustering in the rest of the paper. Overall, Table 2.3 documents a strong effect of equity capital on the accuracy of self-reported VaR measures.

In untabulated tests, we estimate the model with various other measures of equity capital ratio. We find a coefficient of -0.21 (p-value of 0.13) for the model that uses Eq/TA as the key explanatory variable. The coefficient is larger for the model that uses square root of Eq/TA (-0.41 with p-value of 0.01) and even larger for the model that uses cubic root of Eq/TA as the explanatory variable (-0.50 with p-value of 0.01). Overall, these results paint a clear picture. Banks with lower equity capital are more likely to under-report their risks, and the under-reporting mainly comes when banks have very low equity capital.

2.4.3 Identification Using the Shape of the Penalty Function

We now present the results of empirical tests based on the discontinuity in incentives around the Green-Yellow threshold highlighted earlier in Figure 2.1. At the beginning of each quarter, we first compute the number of exceptions reported by the bank in the prior three quarters. We call this number as "trailing exceptions." As discussed in Section 2.2, banks in the Yellow group are likely to have higher under-reporting incentives compared to similar banks in the Green group that fall just below this threshold.

In our first test, we compute the average exceptions in the next quarter for observations currently in the neighborhood of the Green-Yellow threshold. Figure 2.2 presents a plot of these averages for each trailing-exceptions bin from 0 to 8. Banks in the Yellow group have significantly higher exceptions than the banks in the Green group. For example, banks in the Green group have an average exceptions of 0.32 in the next quarter compared to the average exceptions of 2.38 for banks in the Yellow group. The average difference of 2.06 across the two groups is statistically significant at 1%. Narrowing the range of examination to [2-7] yields a similar difference of 1.96 (2.47 for Yellow observations versus 0.51 for Green). Table B.2 in the appendix presents this statistic along with other bank characteristics which shows the comparability of the two groups on observable dimensions. This finding is consistent

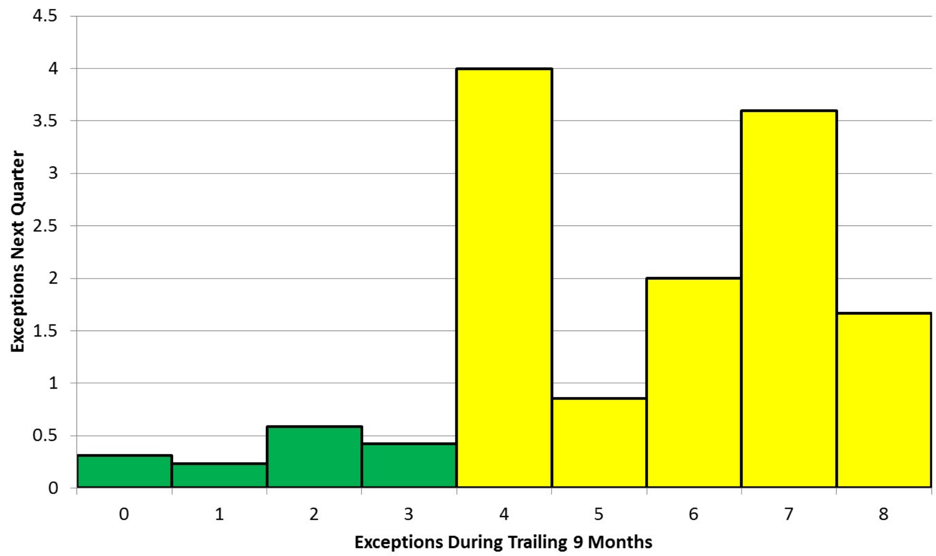

Figure 2.2: **Distribution of Value-at-Risk Exceptions**
This figure presents the average number of Var exceptions reported by a bank in quarter t across different groups of "trailing exceptions." "Trailing exceptions" measures the total number of VaR exceptions reported by the bank in trailing three quarters ($Exceptions_{t-1} + Exceptions_{t-2} + Exceptions_{t-3}$).

with our key assertion in the paper: when the under-reporting incentive increases discontinuously around the Green-Yellow threshold, we observe significantly higher VaR exceptions the following quarter.

We extend this analysis further in a regression framework by including an indicator *Yellow* to our base regression specification (2.4). Since we require data on trailing three quarters for this analysis, we lose a few observations for this regression. For easier interpretation of estimates that include interaction effect, we use the negative of *logEq/TA*, called *NegativeEquity*, as the measure of equity capital in this portion of the analysis. Table 2.4 presents the results.

Column (1) presents the base case analysis relating equity capital to future VaR exceptions for this sample. The estimated coefficient of 0.75 on *NegativeEquity* is almost identical to our full sample result. We next estimate the effect of *Yellow* for the full sample, and then progressively narrow down the sample by decreasing the window around the Green-Yellow threshold. In addition, we include an indicator variable *Red* for banks with ten or more trailing exceptions. Thus, the omitted category is the Green group that have three or fewer trailing exceptions. In column (2), we find a positive and significant coefficient of 0.59 (p-value=0.02) on *NegativeEquity* and 0.54 (p-value=0.02) for the Yellow group. This indicates that after controlling for bank characteristics, bank fixed effects, and year-quarter fixed effects, banks in the Yellow group have 0.54 s.d., or 1.08, more exception in the following quarter. Economically, column (2) suggests that when included independently, a one s.d. decrease in equity capital and being on the right-hand side of the Green-Yellow threshold have quantitatively similar incentive effects.

We now consider how the combination of the two incentive effects relates to future exceptions. In column (3), we interact the zone variable with *NegativeEquity.* This model allows us to compare the differential effect of equity capital on under-reporting incentives around the threshold. We find a positive and significant coefficient on the interaction term: banks with lower equity capital in the Yellow group have significantly more future exceptions. As argued earlier, while the benefit of under-reporting increases significantly above the Green-Yellow threshold, it is unlikely that the correlation between equity capital and any unobserved model quality also sharply changes around the same threshold. Hence, this empirical specification allows us to get closer to a causal interpretation of the effect of equity capital on risk under-reporting. The model also includes the indicator variable for *Red* zone and its interaction with *NegativeEquity.* The effect of equity capital on future exceptions is higher for banks in the Red zone as compared to the similar effects for banks in the Green group, however this effect is not statistically significant.

Our specifications so far include all observations for which we have data on trailing exceptions. In columns (4)-(6), we progressively tighten our window of investigation, limiting our sample to narrower bands around the Green-Yellow threshold. Column

(4) limits observations to banks that have trailing exceptions in [0,8], column (5) to [1,8], and column (6) to [2,7]. There is a standard trade-off in terms of bias and efficiency as we narrow the band: the unobserved characteristics such as model quality of banks in the treatment and control groups are likely to be more similar as we narrow the band, but the fewer observations results in a loss of statistical precision. Despite the loss in efficiency, we find stronger results as we narrow the band. The coefficient estimate on the interaction $Yellow \times NegativeEquity$ increases from about 0.8 to 1.5 as we narrow estimation window. These results provide strong support for the main hypothesis that capital-saving incentives drive banks' under-reporting behavior.

2.4.4 Cross-Sectional Variation in the Benefits of Under-Reporting

In the next set of tests, we focus attention on the effect of equity capital on under-reporting when banks are likely to obtain larger net benefits from doing so. We exploit variation along two important dimensions: (a) when trading represents a larger fraction of the bank's business, and (b) when the firm has recently experienced poor stock returns.

First, we exploit the cross-sectional variation in the importance of trading business to a bank's overall value. For this test, we first compute the ratio of self-reported VaR to equity capital as of 2006Q1 (called VE_2006_i) as a proxy for the importance of trading business for the bank. We compute and freeze this measure for each bank based on exposure at the beginning of 2006 to ensure that our measure is not affected by post-crisis changes in risk-taking behavior or equity capital. Using this variable, we estimate our model with data from 2006-2012 period to examine whether the effect of under-reporting during and in the aftermath of the crisis is larger for banks with larger trading business just before the crisis. The key idea behind our test is that under-reporting gives these banks significantly more capital relief as compared to banks with smaller trading operations. Table 2.5 presents the estimates from the following regression model:[15]

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \psi(Equity_{it} \times VE\_2006_i) + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \quad (2.5)$$

Column (1) presents an estimate of the base specification on this smaller subsample (2006-2012), and shows the similar result that low equity capital is strongly related to future exceptions. Column (2) shows that our main effects are concentrated within banks with larger trading exposure: the coefficient on *VE_2006* $\times$ *log(Eq/A)* is negative and statistically significant. In an alternative specification, we use an indicator variable $High(VE\_2006)_i$ that equals one for banks that have above-median trading exposure (*VE_2006*), and zero otherwise. Column (3) shows that the effect of equity capital on exceptions for high-trading-exposure banks is about twice as large as the base case. Overall, these results are consistent with the idea that the effect of equity capital on under-reporting is higher when banks have more to gain in economic terms.

Next, we consider the effect of a bank's recent stock market return on subsequent exception frequency. While our tests so far have shown the effects based on book equity capital, the incentive to save equity capital by under-reporting is likely to be even higher after a large decline in stock prices (i.e., market equity). In these quarters, banks are likely to have relatively higher reluctance and reduced ability to raise external equity capital. Based on this idea, we include the bank's equity capital, prior quarter's stock return, and the interaction of these terms in the regression model. Table 2.6 presents the results, with the baseline full specification reproduced in column (1). For easier economic interpretation, we divided all observations into two groups based on their prior quarter's stock returns. *LowRet* equals one for firms that whose stock price has declined by at least 5% (approximately 30% of observations). Without

[15] In this specification, the independent effect of the level of trading exposure on under-reporting cannot be estimated since it is subsumed by the bank fixed effects.

the interaction effect, column (3) shows that banks with lower equity capital as well as banks with poor stock returns have more exceptions, though the estimate on *LowRet* is statistically insignificant with p-value of 0.12. Column (4) includes the interactive effect and reveals that when banks have lower equity capital and lower stock returns, they have significantly higher future exceptions: we find a coefficient estimate of -0.41 (p-value=0.02) on *log(Eq/A)*, and -0.35 (p-value=0.03) on the interaction term. In economic terms, a low-equity-capital bank with lower recent stock returns has twice as many VaR exceptions as a low-equity-capital bank with higher recent stock returns.

2.4.5 Time Series Variation in the Benefits of Under-Reporting: Systemic Stress

Our results so far shed light on a individual bank's incentive in isolation. The informativeness of a bank's risk measures is important to understand because its failure can have severe negative consequences for the real economy (e.g., see *Khwaja and Mian* (2008), *Chava and Purnanandam* (2011), *Schnabl* (2012)). However, costs are likely to be even greater when the entire banking system in under stress. During these periods, the stability of the entire system depends crucially on a proper assessment of the banks' risk exposure. The risk measures form a key basis for policy responses such as requiring banks to raise additional capital. These are also times when the supply of capital to banks is likely to be most scarce and thus costly to raise. As a result, the incentive to under-report and save on capital is likely to be higher across all banks during these periods. With this in mind, we design our next test to investigate whether the cross-sectional variation in banks' under-reporting behavior documented in the main tests are stronger during periods of financial sector stress. We estimate the following empirical model to estimate this effect:

$$Exceptions_{i,t+1} = \phi(Equity_{it}) + \theta(System\ Stress_t) + \rho(Equity_{it} \times System\ Stress_t) \\ + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \quad (2.6)$$

System Stress is a measure of systemic stress in the economy. We interact this variable with *Equity* to estimate the effect of equity capital on under-reporting behavior during such periods. The parameter estimate $\hat{\rho}$ represents the effect of *Equity* during periods of financial system stress beyond its effect in normal times ($\hat{\phi}$), and beyond the level effect on VaR exceptions for all banks during that time period ($\hat{\theta}$). To empirically implement (2.6), we use two measures of $System\ Stress_t$: (a) an indicator variable for the quarter immediately after the collapse of Lehman Brothers (2008q4) and (b) the total marginal expected shortfall (MES) for the banking sector. Marginal Expected Shortfall measures expected capital shortfall faced by a firm in a potential future financial crisis (*Acharya et al.*, 2010). We use the MES for the aggregate banking sector in our empirical tests which provides a good proxy for economic construct we have in mind for our study.

Table 2.7 presents the results. The effect of equity capital on VaR exceptions increases by about three-fold for this quarter above the base effect. While a standard deviation decrease in equity capital is associated with more than one additional future exception outside of this period, the total effect is about 4.64 more exceptions during 2008q4.[16] Note that we are estimating the marginal effect of equity capital on VaR exceptions during this quarter. Thus, any unconditional increase in volatilities of the underlying risk factors during the quarter is absorbed in the year-quarter fixed effect. The result shows that the low-equity-capital banks breached their self-reported VaR levels considerably more often during this quarter than their high-equity-capital

[16] This is computed as the sum of the coefficients ($\hat{\phi}+\hat{\rho}$) times the standard deviation of exceptions: (0.57+1.75)*2.00=4.64.

counterparts.

While the Lehman Brothers failure provides a clearly identifiable period of stress in the market, a limitation of this measure is that it is based on just one quarter. To exploit time-varying changes in the level of systemic risks, we obtain the MES for the banking sector as a whole and divide all quarters into four groups based on this measure. Using the quarters that fall in top quartile of the MES measure as systemically stressful quarters (*HiMES*), we re-estimate our model and present results in Columns (3) and (4).[17] The effect of equity capital on VaR exceptions is primarily concentrated in these quarters.

These results paint a clear picture: in addition to banks breaching their self-reported VaR limits at a higher rate during periods when their level of capital is low, these effects are most pronounced in periods of systemic stress in the economy. Thus, the reported risk measures are least informative when accurate risk measurement is likely most important for regulators and policy-makers.

2.4.6 Bank Discretion and the Level of Reported Value-at-Risk

Banks have a great deal of discretion in constructing and implementing their VaR model. The choice of overall modeling technique (e.g., historical simulation versus Monte Carlo simulation), the length and weighting scheme of the data period for model calibration, risk factor volatilities, and correlations are just a few assumptions that can have substantial effects on banks' estimate of their risk for reporting purposes (*BIS*, 2013). Without the knowledge of precise modeling assumptions and inputs used in the model, we are limited in our ability to pin down the channels through which banks under-report their risk. However, we provide some suggestive evidence in this section to shed light on a channel of under-reporting.

[17] In unreported robustness tests, we use a continuous measure of MES, and also examine three additional financial stress indexes which are constructed by the Federal Reserve Banks of Cleveland, Kansas City, and St. Louis, respectively, and find similar results.

Two crucial inputs for a bank's VaR estimate are the level of exposure to a risk factor undertaken by the bank and assumptions about the risk factor's volatility, where the assumption on volatility is typically based on a trailing historical data period. Consider two banks: one bank uses discretion in making assumptions about volatility parameters versus another that follows a fixed policy based on past realized volatility. All else equal, the discretionary bank's reported level of VaR should be less sensitive than the rule-based bank's VaR to publicly observed realized volatility measures. Ex ante, the use of discretion can cause the models to be more or less accurate in capturing risk. However, if the discretionary bank is using its discretion to systematically lower their model's estimate relative to the true risk in the trading book, then their VaR exceptions should be higher than the rule-based bank ex post. Based on these ideas, we estimate the sensitivity of reported VaR level to past macro-economic volatility measures across high- and low-capital banks.

We use a simplified model to link these ideas to our empirical tests. For normally distributed changes in portfolio value,

$$VaR = \mathcal{N}^{-1}(\alpha) \times \sigma \tag{2.7}$$

where $\mathcal{N}^{-1}()$ is the inverse normal CDF, α is the confidence level, and σ is the underlying volatility. Taking logs and assuming a noise term ξ leads to the following linear relationship:

$$\log(VaR) = \log(\mathcal{N}^{-1}[\alpha]) + \log(\sigma) + \xi \tag{2.8}$$

where $\log(\mathcal{N}^{-1}[\alpha])$ is a constant. Using past one year's volatility in the returns to S&P 500 index as a measure of aggregate macro-economic volatility σ, we estimate the following model where we additionally control for the bank specific covariates X_{it}

and bank fixed effects (λ_i):

$$\log(VaR_{i,t}) = \phi(Equity_{it}) + \theta(\log[Vol_t]) + \rho(Equity_{it} \times \log[Vol_t]) + \lambda_i + \Gamma X_{it} + \epsilon_{it} \tag{2.9}$$

The dependent variable is the log of the reported level of VaR at the beginning of quarter t, and Vol_t is the market volatility over the past year as measured by S&P 500 volatility. We expect to find a positive relationship between past volatility and VaR ($\hat{\theta}$). However, if banks use more discretion in their VaR computation when they have low equity capital, we expect this the sensitivity of VaR to volatility to be weaker for such banks. In such a case, $\hat{\rho}$ should be positive and significant.

We estimate the regression model (2.9) and report the results in Table 2.8. As shown in column (1), the past year's market volatility significantly affects the reported VaR numbers. However, the full specification in column (3) shows that this relationship is significantly different across banks with varying degree of equity capital. The coefficient of interest ($\hat{\rho}$) is positive and significant. This suggests that when banks have relatively lower equity capital, the sensitivity of reported VaR to past market volatility is significantly lower. These findings, along with our earlier results that such banks have higher exceptions in future quarters, lend support to the hypothesis that banks are under-reporting their VaR by relying on their discretion in choosing volatility measures.

2.4.7 Alternative Explanations & Robustness Tests

2.4.7.1 Stale Model

Our main dependent variable is the number of exceptions with respect to self-reported VaR number. An alternative interpretation of our results is that the under-reporting is not due to incentives to save capital, but due to a poor-quality model that has not been updated. Our test based on the Green-Yellow zone threshold minimizes such concerns. We conduct two more tests to provide further evidence to rule out this alternative hypothesis.

Omitting Transition Periods

VaR models are estimated on a daily basis at large banks. They calibrate their model to historical data and therefore use inputs on volatilities and correlations across asset classes based on frequently updated historical data. When the economy transitions from a relatively stable state to a stressful one, VaR models based on historical data are more likely to be inaccurate. However, as banks learn about the risks and correlations over time, they update their models according to the new levels of risk.[18] For example, in their 10-K form, Bank of America state, "As such, from time to time, we update the assumptions and historical data underlying our VaR model. During the first quarter of 2008, we increased the frequency with which we updated the historical data to a weekly basis. Previously, this was updated on a quarterly basis." Hence, the initial inaccuracy of the model after a shock should have a short half-life.

In our sample, there is a large increase in the volatilities of the underlying risk measures in 2007 as compared to historical averages. Based on the idea that banks can update their model to reflect risk measures, we exclude the entire year of 2007 from our sample and re-estimate the base model. If some banks simply have poor-quality models, this gives them times to correct those models. We report the result from this test in column (2) of Table 2.9. Our results remain similar in both qualitative and quantitative sense: banks have more exceptions after low-equity quarters, even after leaving out the transition year from a stable to volatile period. These results show that our findings are not completely driven by periods following extreme shocks in the market conditions.

Lagged Exceptions as a Proxy for a Poor-Quality, Stale Model

[18] BIS standards require that banks update their model at a minimum of once per quarter *BIS* (2005).

If some firms are just better than the others in modelling their risk, then the inclusion of firm fixed effects in our base model separates out such differences. However, if the quality of risk-model is time varying, then the firm fixed effects might not be adequate to remove such effects. Specifically, if the quality of risk models deteriorates precisely when a bank enters a low-capital quarter and the poor quality of the bank's model is persistent (i.e., not updated), then our inference can be problematic. While such a time-varying difference in modelling skill seems unlikely and such concerns are mitigated by our tests that exploit the Green-Yellow threshold, we also exploit the dynamics of the panel data to further alleviate this concern. In our next test, we include the lagged exceptions as an explanatory variable in the model.

If the modelling skill is time-varying and correlated with lower equity capital quarters for a given bank, then our model takes the following form:

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \lambda_i + \delta_t + \Gamma X_{it} + \epsilon_{it} \tag{2.10}$$

where

$$\epsilon_{it} = ModelQuality_{it} + \eta_{it} \tag{2.11}$$

and

$$cov(Equity_{it}, \epsilon_{it}) = cov(Equity_{it}, ModelQuality_{it}) \neq 0 \tag{2.12}$$

If we can control for the time-varying nature of model quality in the above model and if η_{it} are serially uncorrelated, we can consistently estimate the coefficient of interest ($\hat{\beta}$). A natural candidate for the time-varying model quality is the number of exceptions in the past quarter. The key idea is that if a bank experiences a number of exception during a quarter, that could indicate that it has a relatively more inaccurate model for that quarter. We include lagged exceptions as a proxy for the potentially "stale model" for the next quarter to rewrite our regression model as follows:

$$Exceptions_{i,t+1} = \beta(Equity_{it}) + \alpha_i + \delta_t + \Gamma X_{it} + \theta Exceptions_{i,t} + \eta_{it} \tag{2.13}$$

The inclusion of lagged dependent variable in a fixed effect model, however, results in inconsistent estimates. To avoid this problem, we estimate our model using the GMM approach suggested by *Arellano and Bond* (1991). This estimator first transforms the equation using first-differences, and then uses lagged values of the dependent variable as instruments to consistently estimate the model parameters.

We estimate the model with both first and second lag of quarterly exceptions as instruments for lagged differences and present the results in columns (3) and (4) of Table 2.9. The coefficient on equity ratio remains negative and both economically and statistically significant for these specifications. We find a coefficient of -0.45 (p-value of 0.01) on *log(Eq/A)* in the model with one lag and -0.47 (p-value of 0.02) in the model with two lags as instruments. The table also reports the p-values for Sargan test and a test for second order autocorrelations in the residual term. Sargan test fails to reject the null hypothesis that the over-identifying restrictions are valid. Similarly, we fail to reject the null hypothesis of zero second-order correlation in the residual term, thus supporting the necessary assumptions for this estimation method.

The use of lagged exception as a proxy for the model quality is a strict specification for our empirical exercise. To the extent that lagged exceptions are also driven by incentives to save capital, we are underestimating the true effect of capital in the model. Despite this limitation, we find strong results. It is, therefore, unlikely that our results are driven by time varying skills of the bank or the stale model problem.

Other Robustness Tests

Table 2.10 presents results from a battery of additional robustness tests. As discussed earlier, one of the reasons we focus on the book equity-to-assets ratio in our empirical tests is because the reported VaR directly affects the computation of regulatory Tier 1 capital requirements, thus introducing measurement concerns.[19] Nevertheless, column (1) highlights that our results are robust to using Tier 1 capital as our measure of equity capital.

Banks have differing sensitivities to various risk factors depending on their business model. To ensure that our results are not driven by these differences, in a robustness test we control for differences in sensitivities to two major risk factors during our sample period, namely the exposure to the aggregate stock markets and mortgage-backed-securities. We first compute the sensitivity of each bank's stock returns to equity market returns (proxied by CRSP value-weighted index) and mortgage-backed securities returns (proxied by PIMCO's mortgage-backed securities index). Next we include the estimated sensitivity as control variables in the regression model. Column (2) shows that these two betas, called *Market Beta* and *MBS Beta*, do not explain our results.

We showed substantial variation in trading book risk composition in the summary statistics in Table 2.2. Some banks, for example, engage more in risks related to interest rates or equities. In column (3), we directly control for bank's VaR composition by including the fraction of total VaR from each exposure to each asset class, and our results remain virtually unaffected. Column (4) shows that our results remain similar after dropping observations from 2008q4, the quarter when Lehman Brothers collapsed and the most volatile quarter in our sample.

The number of exceptions is a count variable. We use fixed-effect linear regression models in the base case analyses since this specification allows us to consistently and efficiently estimate the coefficients of interest. We re-estimate our main regressions using a poisson count data model. This modelling approach explicitly recognizes the

[19]This regression can also be interpreted as exploiting variation in the within bank relative tightness of capital constraints.

fact that VaR exceptions only take non-negative integer values. However, the use of fixed effects in a nonlinear model suffers from the incidental parameter problem, which can result in inconsistent estimates. With these caveats in mind, column (5) presents the results from a poisson model regression estimation and shows that our main results do not change under the count model specifications. We find similar results using a negative binomial regression.

In the tests so far, we report our results based on 99% VaR measures of commercial banks. As mentioned earlier, this allows us to have sensible comparison across all observations. As a robustness exercise, we now repeat our main results by including observations where VaR exceptions are reported for the 95% level. This allows us to expand our sample to 545 observations.

For the empirical test, we use a measure called *Excess*, which compares the actual exceptions to the statistical benchmark based on the reporting confidence level of VaR. If the exceptions exceed the statistical benchmark, *Excess* is set to one and is zero otherwise. Thus, *Excess* takes a value of one if the reported exception in a quarter is greater than 0.63 for 99% VaR and greater than 3.15 for 95% VaR. Column (6) presents the estimation results, and confirms that banks are more likely to have future excess exceptions following quarters when they have low equity capital.

2.5 Conclusion

We show that banks are more likely to under-report their market risks when they have stronger incentives to save equity capital. Specifically, banks under-report their risk when they have lower equity capital, and during periods of high systemic stress. Regulators and investors rely on the bank's self-reported risk measures for a number of regulatory and investment decisions. The accuracy of these numbers assume special importance particularly when banks have lower levels of equity capital, and thus they are closer to failure. Moreover, accurate risk reporting is extremely valuable during periods of systemic crisis because the success of a number of policy responses depends crucially on a clear understanding of the level of risk undertaken by poorly capitalized financial institutions in the economy. Our results show that the integrity of self-reported measures becomes most questionable precisely when accurate risk measurement in the financial system is most important.

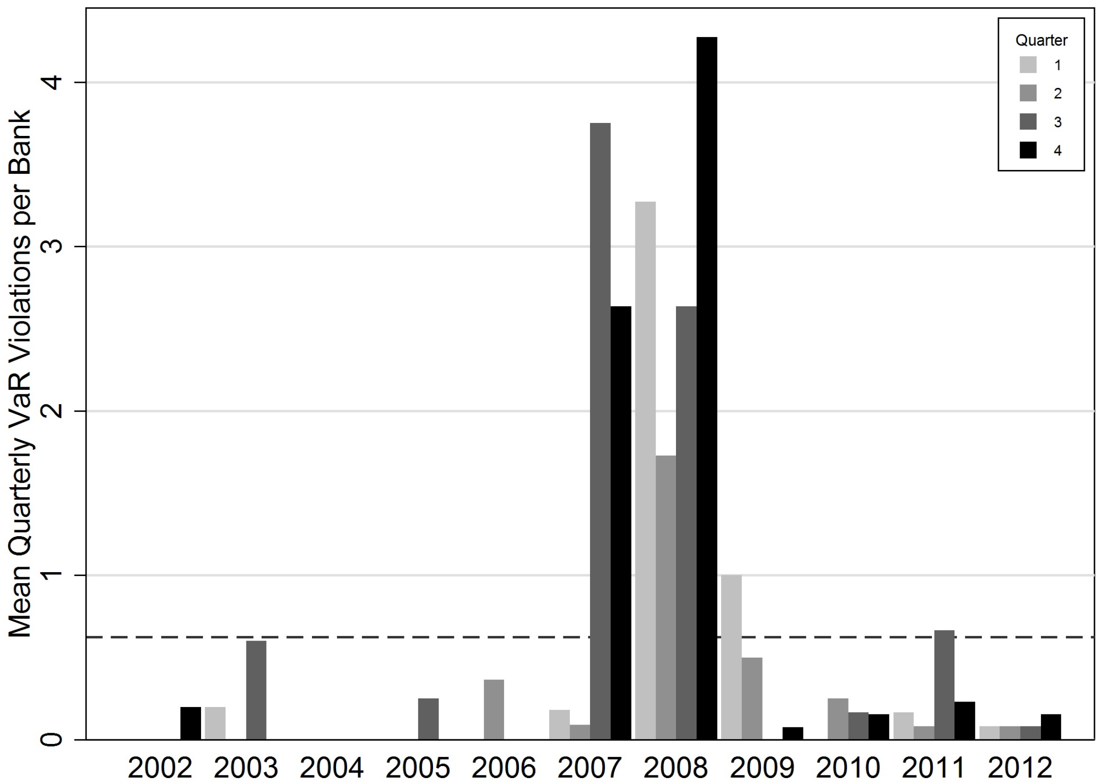

Figure 2.3: **Average Value-at-Risk Exceptions**
This figure presents the average frequency of Value-at-Risk (VaR) exceptions for banks each quarter during the 2002-2012 sample period. The dashed line at 0.63 represents the expected exception frequency based on at 99% VaR confidence interval and approximately 63 trading days per quarter.

Table 2.1: **Base Sample Summary Statistics**

This table presents summary statistics for our sample. These sample statistics are for the base sample of commercial banks reporting 99% Value-at-Risk during 2002-2012. Table 2.2 provides details of the specific banks in the sample. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *Value-at-Risk* is the reported level of future loss that should not be exceeded at the 99% confidence level, and *VaR-[Trading Desk]* variables are the reported value-at-risk for the various trading desks (interest rate, foreign exchange, equities, and commodities) with *Diversification Benefit* representing the claimed reduction in VaR due to less than perfect correlation across trading desks.

	Mean	SD	Min	P25	Median	P75	Max	N
Bank Characteristics:								
Total Assets ($Bn)	901.40	767.93	73.14	291.14	602.46	1428.16	3643.58	424
NI-to-Assets (%,Q)	0.17	0.20	-1.16	0.09	0.18	0.25	1.57	424
BookEq/AT (%)	6.32	3.15	1.69	4.06	5.14	9.01	13.84	424
log(Eq/A)	-2.89	0.51	-4.08	-3.20	-2.97	-2.41	-1.98	424
Value-at-Risk ($MM):								
Exceptions	0.62	2.00	0.00	0.00	0.00	0.00	13.00	424
Total Value-at-Risk	61.90	85.86	3.60	9.00	26.00	75.00	433.00	422
VaR-Interest Rate	46.42	73.39	0.00	4.40	15.28	60.80	430.58	422
VaR-Foreign Exchange	9.09	12.44	0.00	0.89	2.69	15.70	62.82	422
VaR-Equities	20.87	31.39	0.00	3.14	7.64	27.12	204.60	422
VaR-Commodities	7.49	10.80	0.00	0.29	2.08	10.50	52.31	422
VaR-Other	17.23	49.72	0.00	0.00	0.00	8.65	322.88	422
VaR-Diversification Benefit	40.89	54.01	0.00	4.86	11.70	59.60	241.67	422

Table 2.2: **Sample Composition and Value-at-Risk Statistics**

This table presents summary statistics for our sample. Panel A presents statistics for the "Base Sample," which comprises commercial banks reporting 99% Confidence Interval Value-at-Risk (VaR) during 2002-2012. Panel B presents statistics for observations that are added to form the "Expanded Sample," which also includes commercial bank observations reporting 95% VaR and observations from broker/dealers. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *Value-at-Risk* is the reported level of future loss that should not be exceeded at the defined confidence level (99% or 95%).

Panel A: Base Sample

	Exceptions (99% CI)			Value-at-Risk			
Bank	Mean	Min	Max	Mean	Min	Max	N
Bank of America Corporation	0.45	0.00	10.00	93.75	32.50	275.80	44
Bank of Montreal	0.73	0.00	5.00	25.00	11.00	46.00	33
Bank of New York Mellon	0.07	0.00	2.00	7.48	3.90	13.40	44
Canadian Imperial Bank of Commerce	0.14	0.00	3.00	8.67	3.60	18.70	44
Citi Group	0.22	0.00	1.00	167.22	109.00	224.00	9
Credit Suisse Group	1.39	0.00	11.00	119.18	44.00	243.00	28
Deutsche Bank	1.50	0.00	13.00	88.63	55.10	142.90	32
ING Group	0.00	0.00	0.00	20.62	11.80	39.00	13
JPMorgan Chase	0.38	0.00	5.00	113.34	53.70	289.00	32
PNC	0.44	0.00	5.00	7.39	4.70	11.70	27
Royal Bank of Canada	0.75	0.00	4.00	36.25	18.00	60.00	28
Scotia Bank	0.10	0.00	1.00	13.12	6.80	29.30	42
SunTrust Bank	0.00	0.00	0.00	11.40	4.00	28.00	17
UniCredit Group	0.00	0.00	0.00	33.43	28.80	39.80	3
UBS	2.61	0.00	13.00	244.68	24.00	433.00	28

Panel B: Additional Observations for Expanded Sample

	99% CI				95% CI			
	Exceptions				Exceptions			
Bank	Mean	Max	VaR	N	Mean	Max	VaR	N
Goldman Sachs	–	–	–	0	0.80	6.00	118.79	40
JPMorgan Chase	–	–	–	0	0.50	3.00	70.75	12
Lehman Brothers	4.50	9.00	126.50	2	0.33	3.00	45.09	15
Morgan Stanley	0.00	0.00	66.50	18	1.38	13.00	102.16	26
PNC	–	–	–	0	0.25	1.00	3.77	8

Table 2.3: **Equity Ratio and Future Value-at-Risk Exceptions**
This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/A)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/A)* is the log of the book equity-to-assets ratio, *log(Assets)* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance.

	(1) (z)Exceptions	(2) (z)Exceptions	(3) (z)Exceptions	(4) (z)Exceptions	(5) (z)Exceptions
(z)log(Eq/A)	-0.70***	-0.63***	-0.78***	-0.66***	-0.66**
	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)
(z)log(Assets)		0.51	0.35**	0.51	0.51**
		(0.16)	(0.02)	(0.14)	(0.04)
(z)NI-to-Assets		-0.03	-0.02	-0.04	-0.04
		(0.74)	(0.81)	(0.57)	(0.65)
(z)Vol-Commodities			0.11**	0.07	0.07
			(0.03)	(0.45)	(0.11)
(z)Vol-S&P 500			0.31***	0.37**	0.37**
			(0.00)	(0.02)	(0.03)
(z)Vol-Foreign Exchange			0.01	0.07	0.07
			(0.85)	(0.42)	(0.23)
(z)Vol-Interest Rate			0.13**	0.07	0.07
			(0.02)	(0.70)	(0.38)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	No	Yes	Yes
Observations	424	424	424	424	424
R^2	0.45	0.45	0.41	0.47	0.47
Clustered by	Y-Q	Y-Q	Y-Q	Y-Q	Bank

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: **The Shape of Penalties, Equity Ratio, and Future Violations**

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/A)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *Yellow* is an indicator variable equal to 1 when the bank has four to nine VaR exceptions in the past 3 quarters, *Red* is an indicator variable equal to 1 when the bank has ten or more VaR exceptions in the past 3 quarters, *NegativeEquity* is the negative of log of the book equity-to-assets ratio, *log(Assets)* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) Full	(2) Full	(3) Full	(4) [0-8]	(5) [1-8]	(6) [2-7]
(z)NegativeEquity	0.75***	0.59**	0.40*	0.26	-0.08	1.68
	(0.00)	(0.02)	(0.09)	(0.20)	(0.83)	(0.13)
Yellow		0.54**	0.45*	0.54**	0.61*	1.01
		(0.02)	(0.08)	(0.03)	(0.05)	(0.38)
(z)NegativeEquity * Yellow			0.79*	0.78*	1.47***	1.54**
			(0.06)	(0.06)	(0.00)	(0.04)
Red		0.83	0.54			
		(0.25)	(0.34)			
(z)NegativeEquity * Red			0.37			
			(0.24)			
(z)log(Assets)	0.80*	0.74	0.50	0.36	-0.57	-1.88
	(0.10)	(0.13)	(0.38)	(0.53)	(0.40)	(0.15)
(z)NI-to-Assets	-0.01	-0.00	0.00	0.07	0.19	-0.00
	(0.95)	(1.00)	(0.99)	(0.34)	(0.17)	(0.99)
(z)Vol-Commodities	0.07	0.04	0.06	0.12	0.17	0.22
	(0.56)	(0.68)	(0.56)	(0.14)	(0.22)	(0.44)
(z)Vol-S&P 500	0.40**	0.41**	0.40**	0.37**	0.42**	0.51*
	(0.03)	(0.02)	(0.01)	(0.02)	(0.04)	(0.06)
(z)Vol-Foreign Exchange	0.06	0.04	0.05	-0.03	0.09	0.18
	(0.58)	(0.64)	(0.57)	(0.59)	(0.57)	(0.58)
(z)Vol-Interest Rate	0.11	0.18	0.16	0.20	0.11	-0.12
	(0.61)	(0.35)	(0.44)	(0.29)	(0.51)	(0.72)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	378	378	378	349	119	64
R^2	0.50	0.52	0.55	0.58	0.77	0.85

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: **Future Exceptions when VaR is a larger portion of Equity Capital**

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/A)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/A)* is the log of the book equity-to-assets ratio, *VE_2006* is the ratio percentage of Value-at-Risk to Equity ($\frac{VaR}{Equity} * 100$) at the beginning of 2006, *High(VE_2006)* is an indicator equal to 1 for observations where *VE_2006* is above the sample median, *log(Assets)* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. With *VE_2006* measured as of 2006, all observations prior to 2006 are dropped from this subsample. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) (z)Exceptions	(2) (z)Exceptions	(3) (z)Exceptions
(z)log(Eq/A)	-0.92**	-0.50	0.35
	(0.01)	(0.15)	(0.45)
(z)VE_2006 * (z)log(Eq/A)		-0.48**	
		(0.02)	
High(VE_2006) * (z)log(Eq/A)			-1.92**
			(0.02)
(z)log(Assets)	0.31	-0.10	-0.08
	(0.46)	(0.80)	(0.85)
(z)NI-to-Assets	-0.05	0.00	-0.01
	(0.58)	(0.95)	(0.90)
(z)Vol-Commodities	0.08	0.09	0.05
	(0.53)	(0.44)	(0.70)
(z)Vol-S&P 500	0.37**	0.35**	0.39**
	(0.04)	(0.02)	(0.02)
(z)Vol-Foreign Exchange	0.08	0.08	0.07
	(0.49)	(0.49)	(0.50)
(z)Vol-Interest Rate	0.08	0.13	0.11
	(0.73)	(0.50)	(0.62)
Bank FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	330	330	330
R^2	0.47	0.50	0.51

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: **Equity Ratio, Recent Returns, and Future Value-at-Risk Exceptions**

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/A)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/A)* is the log of the book equity-to-assets ratio, *LowRet* is an indicator variable equal to 1 when the prior quarter's return is less than -5%, *log(Assets)* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1)	(2)	(3)	(4)
	(z)Exceptions	(z)Exceptions	(z)Exceptions	(z)Exceptions
(z)log(Eq/A)	-0.66***		-0.64***	-0.41**
	(0.00)		(0.01)	(0.02)
LowRet		0.23	0.19	0.18
		(0.12)	(0.19)	(0.16)
(z)log(Eq/A) * LowRet				-0.35**
				(0.03)
(z)log(Assets)	0.51	0.67*	0.50	0.66**
	(0.14)	(0.08)	(0.15)	(0.03)
(z)NI-to-Assets	-0.04	-0.03	-0.03	-0.02
	(0.57)	(0.68)	(0.65)	(0.74)
(z)Vol-Commodities	0.07	0.06	0.08	0.08
	(0.45)	(0.54)	(0.40)	(0.34)
(z)Vol-S&P 500	0.37**	0.32**	0.34**	0.32**
	(0.02)	(0.05)	(0.03)	(0.02)
(z)Vol-Foreign Exchange	0.07	0.07	0.08	0.07
	(0.42)	(0.44)	(0.38)	(0.36)
(z)Vol-Interest Rate	0.07	0.07	0.08	0.06
	(0.70)	(0.66)	(0.69)	(0.76)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	424	424	424	424
R^2	0.46	0.48	0.50	0.51

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: **Equity Ratio and Future Value-at-Risk Exceptions during Stress**

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/A)* and a vector of control variables. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/A)* is the log of the book equity-to-assets ratio, *2008q4* is an indicator variable equal to 1 for the quarter following Lehman Brothers' collapse, *HiMES* is an indicator variable equal to 1 for quarter when the Marginal Expected Shortfall of the financial sector is in the top quartile for the sample, *log(Assets)* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1)	(2)	(3)	(4)
	(z)Exceptions	(z)Exceptions	(z)Exceptions	(z)Exceptions
(z)log(Eq/A)	-0.66***	-0.57**	-0.66***	-0.26
	(0.00)	(0.01)	(0.01)	(0.18)
(z)log(Eq/A) * 2008q4		-1.75***		
		(0.00)		
HiMES			0.22	0.21
			(0.56)	(0.57)
(z)log(Eq/A) * HiMES				-0.42**
				(0.04)
(z)log(Assets)	0.51	0.58*	0.52	0.54*
	(0.14)	(0.09)	(0.14)	(0.09)
(z)NI-to-Assets	-0.04	-0.06	-0.04	-0.02
	(0.57)	(0.40)	(0.60)	(0.73)
(z)Vol-Commodities	0.07	0.06	0.08	0.09
	(0.45)	(0.50)	(0.39)	(0.35)
(z)Vol-S&P 500	0.37**	0.37**	0.32*	0.29*
	(0.02)	(0.02)	(0.07)	(0.09)
(z)Vol-Foreign Exchange	0.07	0.08	0.06	0.06
	(0.42)	(0.40)	(0.47)	(0.50)
(z)Vol-Interest Rate	0.07	0.08	0.10	0.08
	(0.70)	(0.68)	(0.60)	(0.67)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	424	424	424	424
R^2	0.47	0.56	0.48	0.51

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: **Explaining the Level of Reported VaR**

This table presents OLS estimates from a regression of *log(Value-at-Risk)* on banks' equity capital ratio *log(Eq/A)*, past stock market volatility, and a vector of control variables. *log(Eq/A)* is the log of the book equity-to-assets ratio, *L.log(1yr S&P vol)* is the log of the annualized volatility of daily S&P500 returns over the past year, *log(Assets)* is the log of total assets, and *NI-to-Assets* is the ratio of quarterly net income-to-assets. All continuous variables are standardized (denoted by "(z)") to have a mean of zero and unit variance.Standard errors are clustered by year-quarter.

	(1) (z)log(VaR)	(2) (z)log(VaR)	(3) (z)log(VaR)
L.(z)log(1yr S&P vol)	0.09***	0.01	0.02
	(0.00)	(0.66)	(0.54)
(z)log(Total Assets)		0.43***	0.41***
		(0.00)	(0.00)
(z)NI-to-Assets		-0.12***	-0.12***
		(0.00)	(0.00)
(z)log(Eq/A)		-0.30***	-0.31***
		(0.00)	(0.00)
(z)log(Eq/A) × L.log(1yr S&P vol)			0.03**
			(0.04)
Bank FE	Yes	Yes	Yes
Observations	405	405	405
R^2	0.86	0.89	0.89

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: **Stale Model – Omitting Periods and Arellano-Bond Estimates** This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio *log(Eq/A)* and a vector of control variables. Column (1) is the baseline specification for comparison. Column (2) presents estimates omitting observations in 2007. Columns (3) and (4) present estimates of panel estimates using Arellano-Bond (1991) estimation with one and two lags, respectively. *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Eq/A)* is the log of the book equity-to-assets ratio, *log(Assets)* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1) All	(2) drop2007	(3) AB1lag	(4) AB2lags
(z)log(Eq/A)	-0.66***	-0.65**	-0.45**	-0.47**
	(0.00)	(0.01)	(0.01)	(0.02)
L.(z)Exceptions			0.30***	0.31***
			(0.00)	(0.00)
L2.(z)Exceptions				-0.01
				(0.96)
(z)log(Assets)	0.51	0.40	0.75***	0.75**
	(0.14)	(0.13)	(0.01)	(0.01)
(z)NI-to-Assets	-0.04	-0.06	0.07**	0.07**
	(0.57)	(0.44)	(0.04)	(0.02)
(z)Vol-Commodities	0.07	0.09	0.09*	0.09
	(0.45)	(0.37)	(0.08)	(0.30)
(z)Vol-S&P 500	0.37**	0.30**	0.42***	0.43***
	(0.02)	(0.01)	(0.00)	(0.00)
(z)Vol-Foreign Exchange	0.07	0.06	0.05	0.04
	(0.42)	(0.46)	(0.37)	(0.46)
(z)Vol-Interest Rate	0.07	-0.05	0.21***	0.22***
	(0.70)	(0.63)	(0.00)	(0.00)
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	424	379	392	378
R^2	0.47	0.48		
2nd Order AR test p-value			0.94	1.00
Sargan Test p-value			0.49	0.52

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: **Robustness Tests**

This table presents OLS estimates from a regression of the number of VaR exceptions in the next quarter on banks' equity capital ratio and a vector of control variables. Columns (1)-(4) present OLS estimates of the base specification along with various control variables. Column (5) presents estimates from a poisson regression. Column (6) OLS regression estimates of a measure of excess future VaR exceptions in the next quarter on banks' equity capital ratio and a vector of control variables. *Excess* is an indicator variable equal to 1 when a bank's number of exceptions exceeds their expected number of exceptions based on the confidence level (i.e., *Exceptions* ≥ 0.6 for 99% CI and *Exceptions* ≥ 3.0 for 95% CI). *Exceptions* is the number of times the bank had losses that exceeded their self-reported Value-at-Risk during the next quarter, *log(Tier 1 Ratio)* is the log of the Tier 1 capital ratio, *log(Eq/A)* is the log of the book equity-to-assets ratio, *Market Beta* is the bank's regression market beta estimated using the banks' prior two years' stock returns against the CRSP value-weighted market portfolio, *Market Beta* is the bank's regression MBS beta estimated using the banks' prior two years' stock returns against the PIMCO mortgage-backed securities index, *log(Assets)* is the log of total assets, *NI-to-Assets* is the ratio of quarterly net income-to-assets, and *Vol* variables are the volatilities of commodity, S&P 500, Foreign Exchange, and Interest Rate indices. All continuous variables and *Exceptions* are standardized (denoted by "(z)") to have a mean of zero and unit variance. Standard errors are clustered by year-quarter.

	(1)	(2)	(3)	(4)	(5)	(6)
	Tier 1	Betas	VaR Mix	Drop 2008q4	Poisson	Excess
(z)log(Eq/A)		-0.59***	-0.67***	-0.59**	-1.08***	-0.30**
		(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
(z)log(Tier 1 Ratio)	-0.28**					
	(0.04)					
(z)Market Beta		-0.12				
		(0.34)				
(z)MBS Beta		0.04				
		(0.71)				
(z)log(Assets)	0.68*	0.55	0.53	0.59*	-0.86	-0.18
	(0.07)	(0.11)	(0.19)	(0.09)	(0.14)	(0.45)
(z)NI-to-Assets	-0.04	-0.06	-0.05	-0.05	0.04	0.01
	(0.62)	(0.44)	(0.62)	(0.48)	(0.70)	(0.81)
(z)Vol-Commodities	0.06	0.07	0.09	0.09	-0.12	0.02
	(0.51)	(0.43)	(0.38)	(0.30)	(0.48)	(0.78)
(z)Vol-S&P 500	0.34**	0.37**	0.39**	0.41***	1.50***	0.70***
	(0.02)	(0.03)	(0.03)	(0.01)	(0.00)	(0.00)
(z)Vol-Foreign Exchange	0.06	0.07	0.08	0.01	-0.10	-0.07
	(0.49)	(0.42)	(0.37)	(0.89)	(0.62)	(0.34)
(z)Vol-Interest Rate	0.10	0.07	0.09	0.06	-0.19	-0.07
	(0.52)	(0.69)	(0.68)	(0.76)	(0.35)	(0.48)
VaR Mix	No	No	Yes	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	420	424	422	413	391	545
R^2	0.46	0.48	0.49	0.47		0.48

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER III

Market Making Contracts, Firm Value, and the IPO Decision

3.1 Introduction

Modern stock markets rely on competing limit orders to supply liquidity. In contrast to the designated "specialists" who in past decades coordinated trading on the flagship New York Stock Exchange (NYSE), limit order traders are typically not obligated to supply liquidity or otherwise facilitate trading. The desirability of such endogenous liquidity provision has recently been questioned. As Mary L. Shapiro, former chair of the U.S. Securities and Exchange Commission (SEC) noted, "The issue is whether the firms that effectively act as market makers during normal times should have any obligation to support the market in reasonable ways in tough times."[1] A joint Commodity Futures Trading Commission (CFTC)-SEC advisory committee observed that "incentives to display liquidity may be deficient in normal markets, and are seriously deficient in turbulent markets."[2] The SEC Advisory Committee on Small and Emerging Companies recently recommended an increase in the minimum

[1]Speech to the Economic Club of New York, September 7, 2010. Available at http://www.sec.gov/news/speech/2010/spch090710mls.htm.

[2]Recommendations Regarding Regulatory Responses to the Market Events of May 6, 2010, Summary Report of the joint CFTC-SEC Advisory Committee on Emerging Regulatory Issues. Available at http://www.cftc.gov/ucm/groups/public/@aboutcftc/documents/file/jacreport_021811.pdf.

price increment or "tick size" for smaller exchange-listed companies to "increase their liquidity and facilitate IPOs and capital formation."[3] Such policy initiatives are predicated on the notion that competitive market forces do not always supply sufficient liquidity.

In this paper, we introduce a simple model of secondary market illiquidity and its effect on stock prices and incentives to conduct IPOs. Our model shows that competitive secondary market liquidity provision can indeed be inefficient, and can lead to market failure. Failure occurs particularly for those firms or at those times when the combination of uncertainty regarding asset value and the likelihood of information asymmetry is high.

As a potential cure, we focus on contracts where the firm hires a designated market maker (DMM) to enhance liquidity. Such contracts are observed on several stock markets, including the leading markets in Germany, France, Italy, the Netherlands, Sweden, and Norway.[4] The most frequently observed obligation is a "maximum spread" rule, which requires the DMM to keep the bid-ask spread (the difference between the lowest price for an unexecuted sell order and the highest price for an unexecuted buy order) within a specified width, in exchange for a periodic payment from the firm.[5] DMM contracts of this type are currently prohibited in the U.S. by FINRA Rule 5250, which "prohibits any payments by an issuer or an issuer's affiliates

[3]Recommendations Regarding Trading Spreads for Smaller Exchange-Listed Companies, U.S. SEC Advisory Committee on Small and Emerging Companies. Available at http://www.sec.gov/info/smallbus/acsec/acsec-recommendation-032113-spread-tick-size.pdf.

[4]See, for example, *Venkataraman and Waisburd* (2007), *Anand et al.* (2009), *Menkveld and Wang* (2013), *Skjeltorp and Odegaard* (2015), and *Nimalendran and Petrella* (2003).

[5]Such obligations typically bind. For example, *Anand et al.* (2009) study DMM agreements on the Stockholm Stock Exchange and document that the contracted maximum spreads are typically narrower than the average spread that prevailed prior to the introduction of DMMs. In contrast, the "supplemental liquidity suppliers" currently employed on the NYSE are only obligated to enter orders that match the best existing prices a certain percentage of the time, and are not required to improve on the best prices from public limit orders.

and promoters for publishing a quotation, acting as a market maker or submitting an application in connection therewith."[6] The NYSE and Nasdaq markets have both recently requested partial exemptions from Rule 5250, to allow DMM contracts for certain exchange traded funds.[7] Some commentators have criticized these proposals on the grounds that DMM contracts distort market forces.[8]

Our model shows that insufficient liquidity in competitive secondary markets can lead to complete market failure, where the firm chooses not to conduct the IPO even though social welfare would be enhanced by doing so, or partial market failure, where the IPO is completed at a price that is discounted to reflect the fact that secondary market illiquidity will dissuade some efficient trading. We show that a DMM contract, where the firm pays a market maker a fixed fee in exchange for narrowing the bid-ask spread can cure these market failures. Such a contract reduces market-maker trading profits and/or imposes expected trading losses, but also increases the equilibrium IPO price, as investors take into account the benefits of being able to subsequently trade at lower cost. Notably, the increase in the IPO price can exceed the requisite payment to compensate the DMM, thereby increasing the firm's net proceeds. The DMM contract thus represents a potential market solution to a potential market failure.

In our model, as in the classic analysis of *Glosten and Milgrom* (1985), illiquidity is attributable to information asymmetry. A key point of perspective is that, while informational losses entail a private cost to liquidity suppliers, these are zero-sum transfers rather than a cost when aggregated across all agents. Competitive bid-

[6]See FINRA Regulatory Notice 09-60.

[7]See SEC Release No. 34-67411, available at http://www.sec.gov/rules/sro/nasdaq/2012/34-67411.pdf. The proposals call for DMMs to match the best existing quotes at certain times, and thus are less aggressive than the obligations considered here.

[8]See SEC Release No. 34-67411, page 58.

ask spreads compensate liquidity suppliers for their private losses to better-informed traders, and are therefore wider than the net social cost of completing trades. A maximum spread rule can improve social welfare and firm value because more investors choose to trade when the spread is narrower. This increased trading enhances allocative efficiency and firm value.

The model generates cross-sectional predictions. First, it implies that the efficacy of DMM contracts depends on the interaction of uncertainty and asymmetric information regarding the fundamental value of the firm's assets. In the absence of asymmetric information, competitive liquidity provision is optimal, regardless of the degree of uncertainty regarding underlying value. In contrast, the combination of a high probability of information asymmetry and high uncertainty regarding fundamental value leads to potential market failure, and to improved firm value and social welfare from a DMM agreement. This combination is likely to be particularly relevant for smaller, younger, and growth-oriented firms. Further, the model implies that reductions in liquidity that are attributable to real or perceived increases in information asymmetry are economically inefficient, providing economic justification for a contractual requirement to enhance liquidity at times of high perceived information asymmetry.

The model also has regulatory implications. If the market for liquidity provision is competitive, then contracts that require further narrowing of bid-ask spreads will impose expected trading losses on and require side payments to the DMM. A regulatory requirement that certain liquidity suppliers provide liquidity beyond competitive levels without compensation could lead to exit from the industry and ultimately be counterproductive to the goal of enhancing liquidity.

Our analysis is also relevant to regulatory initiatives related to the minimum price increment. The U.S. Congress recently directed the SEC to reassess the effects of the 2001 decimalization of the U.S. equity markets, which reduced the minimum price increment to one cent.[9] The SEC's advisory committee has recommended larger tick sizes for smaller exchange-listed companies, to increase market- making profits, attract additional liquidity supply, and encourage IPOs.[10] Our model indicates that this approach is also likely to be counterproductive. Monopoly profits in liquidity provision reduce IPO prices as investors take into account increased secondary market trading costs. Lower IPO prices, in turn, can lead to market failure as firms elect to forgo the IPO entirely. In contrast, our model implies that the DMM contracts considered here can lead to higher IPO prices and facilitate IPOs.

3.2 The Related Literature

The literature on market making is vast. However, in most models the emphasis is on endogenous liquidity provision, that is, on dealer and trader behavior in the absence of any specific obligation to supply liquidity. Among the few exceptions, *Venkataraman and Waisburd* (2007) consider the effect of a DMM in a periodic auction market characterized by a finite number of investors. The DMM in their model is an additional trader present in every round of trading, thereby improving risk-sharing. *Sabourin* (2006) presents a model in which a noncompensated market maker is introduced to an imperfectly competitive limit order market. In her model, the continuous presence of a market maker causes some limit order traders to substitute to market orders, allowing the possibility of wider spreads with a market maker, for some parameters.

[9] The directive is contained in Section 106(b) of the 2012 Jumpstart Our Business Startups Act.

[10] See http://www.sec.gov/info/smallbus/acsec/acsec-recommendation-032113-spread-tick-size.pdf.

Among the empirical studies of DMMs, *Venkataraman and Waisburd* (2007), *Anand et al.* (2009), *Skjeltorp and Odegaard* (2015), and *Menkveld and Wang* (2013) study the introduction of DMMs on Euronext-Paris, the Stockholm Stock Exchange, the Oslo Stock Exchange, and Euronext-Amsterdam, respectively. In contrast to *Sabourin* (2006), each of these studies reports improvements in liquidity associated with DMM introduction, and each documents positive stock valuation effects on the announcement of the DMM introduction. *Anand and Venkataraman* (2013) and *Nimalendran and Petrella* (2003) study markets (the Toronto and Milan Stock Exchanges, respectively) in which DMMs operate in parallel with endogenous liquidity providers, and document improved market quality associated with the hybrid structure.

While the empirical evidence supports the view that DMMs enhance liquidity and firm value for at least some stocks, the evidence does not clarify the source of the value gain. The model in *Amihud and Mendelson* (1986) implies that improved liquidity reduces firms' cost of capital. However, providing enhanced liquidity is costly, and the DMMs must be compensated for these costs. Our analysis clarifies the economic mechanism through which firm value can be enhanced by more than the cost of compensating the DMM, and provides cross-sectional implications regarding the firms for which such an agreement will be value-enhancing.

3.3 The Model

We consider a simple three-date model. At t=0 the firm considers selling its existing asset to an investor in an IPO. Secondary market trading can occur at t=1. The asset is liquidated at t=2, paying $H = (1+\epsilon)\mu$ or $L = (1-\epsilon)\mu$ with equal probability, where $0 < \epsilon < 1$. All agents are risk-neutral and interest rates are zero, so $\mu > 0$ can be viewed as the fundamental value of the asset at t=0. At t=0, the firm can elect to (i) complete the IPO while also entering into a DMM contract through which the firm makes a fixed payment to market makers in exchange for a commitment to enhance secondary market liquidity, (ii) complete the IPO without entering into a DMM contract, or (iii) forgo the IPO.

To motivate the potential IPO, we assume that the firm needs cash. The t=0 value of the asset to the firm is $V_F = (1 - \delta)\mu$, where $0 < \delta < 1$. This discount can reflect the desire of the firm's owners to diversify their holdings, or the firms need for capital to invest in additional projects. If the investor acquires the asset in the IPO, with probability $\lambda > 0$ she will be subject to a liquidity shock that reduces her subjective valuation of the asset by $\rho\mu$, where $0 < \rho < 1$, and with probability p she will receive private information as to whether the t=2 liquidation value of the asset will be H or L.[11] The potential liquidity shock and information arrival both occur just prior to t=1 secondary market trading. Each random outcome is assumed to be statistically independent of the others.

We assume the presence of $N \geq 2$ risk-neutral market makers who are not subject to liquidity shocks and who engage in Bertrand competition.[12] The market makers set the t=1 bid quote, B, in the knowledge that the investor can be motivated to trade by either liquidity needs or private information. Let M(B) denote the investor's

[11]The two point distribution for liquidity shocks or "intrinsic preference" is for simplicity, and follows *Duffie et al.* (2007), as well as *Holmstrom and Tirole* (1996).

[12]Since the investor is subject to liquidity shocks while the market makers are not, it would be efficient in our simple setting for the firm to sell the asset directly to a market maker rather than the investor. In general, IPOs are used to raise cash while transferring ownership to a broad base of long-term investors. We assume that the IPO must be sold to investors, to incorporate in the simplest way possible the distinction between such long-term investors and market makers who typically tie up capital for only short periods of time. Related, we assume that the firm cannot repurchase the asset from the investor at t=1, to capture the notion that the firms initial need for cash is long lived.

expected monetary gain (or equivalently, the market makers' expected loss) from secondary market trading, conditional on the bid price, B. The expected monetary gain is zero with competitive market making, but could be positive if the firm contracts with a market maker to increase the bid price or negative if there were economic rents in market making. Let q(B) denote the probability that the investor will be dissuaded by a low bid price from selling her asset, conditional on a t=1 liquidity shock. The expected cost to the investor attributable to secondary market illiquidity is the product of the probability of a liquidity shock, λ, the probability that the investor does not sell conditional on the shock, $q(B)$, and the magnitude of the shock, $\rho\mu$. Hence, the value of the asset to the investor at t=0 is the expected cash flow μ minus the expected illiquidity cost, plus the expected monetary gain from trading:

$$V_I(B) = \mu - q(B)\lambda\rho\mu + M(B).^{13} \tag{3.1}$$

Aggregating across the firm, the investor, and market makers, and noting that monetary payments are zero-sum, the increase in social welfare from conducting the IPO can be stated as:

$$W(B) = (V_I(B) - V_F) - M(B) = \mu(\delta - q(B)\lambda\rho). \tag{3.2}$$

Welfare is improved by the IPO if the firm's need for cash, δ, is large relative to the costs attributable to secondary market illiquidity, $q(B)\lambda\rho$. The firm can potentially increase V_I by contracting with a market maker to increase the bid price, thereby decreasing $q(B)$. We initially consider model outcomes assuming that the firm has complete bargaining power, and is able to extract all investor surplus in the form of

[13] *Ellul and Pagano* (2006) develop a model of IPO pricing where the value of the asset to the investor is discounted to reflect both expected secondary market illiquidity and illiquidity risk. While the latter is not present in our model due to our assumption of risk neutrality, this result suggests that a DMM agreement (which Ellul and Pagano do not consider) could potentially also enhance value by reducing liquidity risk in the case of risk-averse investors.

an IPO price equal to V_I. In this case, firm value maximization and social welfare maximization coincide. In Section 3.5 we relax the assumption of complete bargaining power to consider model outcomes when gains are shared through an IPO price that is less than V_I. Table 3.1 summarizes the notation used in the model. All proofs not stated in the text are contained in the Appendix.

3.4 Model Outcomes with a Competitive IPO Market and Competitive Market Making

We first assess the model's implications when the IPO market and the market for secondary trading are both competitive. In particular, the firm is able to extract all of the investor's gains from trade in the form of an IPO price equal to the investor's valuation, V_I, and expected profits to market making in the absence of a DMM agreement are zero.

3.4.1 Outcomes with Perfect Secondary Market Liquidity

Consider as a benchmark the case in which the probability that the trader becomes privately informed regarding asset value, p, equals zero, implying that market makers suffer no losses due to information asymmetry. In the absence of any other market-making costs, the competitive bid quote in the secondary market is $B = \mu$. The investor's subjective t=1 valuation if she suffers a liquidity shock is $\mu(1 - \rho)$. Since this is less than the bid quote, the investor will always sell following a liquidity shock. Setting $q = 0$, we have $V_I = \mu$ and $W = \delta\mu$, which is the maximum welfare gain attainable in this model. That is, in the absence of illiquidity due to asymmetric information, the investor pays full value for the asset in the IPO, the firm completes the IPO for any positive δ, and the welfare gain is maximized.

3.4.2 Outcomes when the Secondary Market is Illiquid

We now consider a competitive secondary market in the presence of information asymmetry. The zero-expected-profit bid quote is the expected asset value conditional on a sale by the investor, which occurs if the investor's subjective t=1 valuation of the asset is less than the market bid quote, B. For some parameter ranges there are two bid quotes consistent with the zero-expected-profit condition, in which case we assume that competition leads to selection of the greater of the two in equilibrium. Outcomes in this model depend crucially on the interplay between the likelihood of information asymmetry, p, and the degree of uncertainty regarding the liquidation value of the asset, ϵ. We define "relative fundamental uncertainty" as follows.

DEFINITION 1: *Let* $\epsilon^* \equiv \frac{(2\lambda+(1-\lambda)p)}{(2(p+\lambda-p\lambda))}\rho$ *and* $\epsilon^{**} \equiv \frac{(p+2(1-p)\lambda)}{p}\rho$. Then,

(i) if $\epsilon \leq \epsilon^*$, relative fundamental uncertainty is low,

(ii) if $\epsilon^* < \epsilon \leq \epsilon^{**}$, relative fundamental uncertainty is intermediate,

(iii) if $\epsilon > \epsilon^{**}$, relative fundamental uncertainty is high.

We use the label relative fundamental uncertainty because the ranges of the equilibria in this model depend not only on ϵ, which is a measure of fundamental uncertainty, but also on liquidity shocks and the probability of information asymmetry. The two boundary points, ϵ^* and ϵ^{**}, increase with both the probability, λ, and magnitude, ρ, of liquidity shocks, while decreasing with the probability that the investor becomes privately informed. The relevance of the boundary points ϵ^* and ϵ^{**} can be attributed to shifts in investor behavior at these points, which lead in turn to discrete changes in the zero-profit bid quote, B.

LEMMA 1: *In competitive equilibrium, with* $p > 0$*:*

(i) Conditional on incurring a liquidity shock, the investor sells if relative fundamental uncertainty is low, if relative fundamental uncertainty is intermediate and she is uninformed or is informed that asset value is low, and if relative fundamental uncertainty is high and she is informed that asset value is low.

(ii) Conditional on not incurring a liquidity shock, the investor sells when she is informed that asset value is low, regardless of the level of relative fundamental uncertainty.

(iii) This trading behavior supports bid quotes, B, given by

$$B = \begin{cases} (1 - \frac{(1-\lambda)p}{(2\lambda+(1-\lambda)p)}\epsilon)\mu, & if \epsilon \leq \epsilon^* \\ (1 - \frac{p}{(p+2(1-p)\lambda)}\epsilon)\mu, & if \epsilon^* < \epsilon \leq \epsilon^{**} \\ (1-\epsilon)\mu, & if \epsilon > \epsilon^{**} \end{cases}$$

$$\textit{where } (1 - \frac{(1-\lambda)p}{(2\lambda+(1-\lambda)p}\epsilon)\mu > (1 - \frac{p}{(p+2(1-p)\lambda)}\epsilon)\mu > (1-\epsilon)\mu.$$

The bid quote is always discounted relative to the expected value of the asset, μ, when p is positive, to reflect the expected informational content of the sale. With high fundamental uncertainty, the investor sells in equilibrium whenever she is informed that asset value is low, while she retains her share if she is uniformed or informed that asset value is high. The discount in the bid quote, $\epsilon\mu$, is the value of bad news. With intermediate fundamental uncertainty the investor also sells in equilibrium in response to a liquidity shock when she is uninformed, and the possibility that the sale is uninformed allows a smaller discount, $\frac{p}{(p+2(1-p)\lambda)}\epsilon\mu$. With low fundamental uncertainty the investor will sell in equilibrium upon incurring a liquidity shock, even if privately informed that asset value is high, which supports a yet smaller discount, $\frac{(1-\lambda)p}{(2\lambda+(1-\lambda)p)}\epsilon\mu$. The bid quote always decreases with fundamental uncertainty, ϵ, and with the probability that the trader becomes privately informed, p, except when relative fundamental uncertainty is high (in which case the bid quote is already equal to the lowest possible asset value). The bid quote also increases with the probability of a liquidity shock, λ, except when fundamental uncertainty is high.

3.4.3 Firm Choice and Social Welfare with Competitive Markets

We next assess the firm's decision to conduct the IPO and the resulting social welfare with competitive market making. The firm will complete the IPO when V_I exceeds the value of the assets to the firm, V_F, which given M=0 requires $q\lambda\rho < \delta$. That is, the IPO occurs when the anticipated utility losses from secondary market illiquidity are sufficiently small relative to the firm's need for cash.

PROPOSITION 1: *Given competitive market making and the IPO price equals V_I:*

(i) If relative fundamental uncertainty is low, the IPO occurs at the price μ, and the improvement in social welfare is $W = \delta\mu$, the maximum attainable.

(ii) If relative fundamental uncertainty is intermediate, the IPO does not occur when $\delta < \frac{p}{2}\lambda\rho$. If the IPO occurs, the price is discounted to $V_I = (1 - \frac{p}{2}\lambda\rho)\mu$ and the improvement in social welfare is reduced to $W = (\delta - \frac{p}{2}\lambda\rho)\mu$.

(iii) If relative fundamental uncertainty is high, the IPO does not occur when $\delta < (1 - \frac{p}{2})\lambda p$. If the IPO occurs, the price is further discounted to $V_I = (1 - (1 - \frac{p}{2}\lambda\rho)\mu$, and the improvement in social welfare is further reduced to $W = (\delta - (1 - \frac{p}{2})\lambda\rho)$.

Proposition 1 implies that competitive market making can lead to a nondiscounted IPO and the largest possible improvement in welfare, but only when relative fundamental uncertainty is low. In contrast, markets will fail, either partially or completely, when relative fundamental uncertainty is intermediate or high. The range of parameters associated with market failure and the magnitude of the resulting welfare reduction are larger when relative fundamental uncertainty is high rather than intermediate. Market failure leads to Pareto-dominated outcomes, as discussed in Section 3.4.4.

3.4.4 Why The Competitive Market Can Fail

The potential market failure with competitive market making is attributable to an information-based externality. Efficiency gains occur in this model when the asset is sold to a party who values it more highly, that is, by the firm to the investor at t=0 or by the investor, should she suffer a liquidity shock, to the market makers at t=1. If the secondary market bid price is low enough that the investor will, in some states, be dissuaded from selling in the secondary market after a liquidity shock, then she will reduce the amount she is willing to pay at the IPO.[14] If the IPO price is reduced sufficiently the IPO does not occur.

The inefficiency arises because the competitive secondary market bid price is reduced to offset expected market-maker losses attributable to the possibility that the trader is privately informed regarding the asset's final value. A key point is that while trading losses due to asymmetric information are indeed a private cost from the viewpoint of a market maker, any loss to market makers is a gain to the investor, and the net social cost of informed trading is zero when aggregated across all agents. Since the private cost to market makers exceeds the social cost of completing trades, the competitive bid price is discounted by an amount greater than the net social

[14]Note that the discounting of the IPO price that arises in our model differs from the widely studied "underpricing" of IPOs. The latter refers to an IPO offer price that is less than the open market value of the share, while our model focuses on an illiquidity-induced reduction in the open market value of the share itself.

cost of providing liquidity. Social welfare is damaged if this discounting of the bid price potentially dissuades the trader from completing a secondary market trade that would have enhanced welfare.

The inefficiency arises only when the discounting of the bid price is sufficient to dissuade trading in response to liquidity shocks, at least in some states of the world. If fundamental uncertainty and the likelihood of private information shocks are sufficiently low, the discounting of the bid price is modest and efficiency is not damaged. With greater fundamental uncertainty and/or a higher likelihood of information asymmetry, the inefficiency becomes more severe and can dissuade the firm from conducting the IPO.

3.4.5 The Role of a DMM Contract

The preceding discussion of how the competitive market can fail provides background for the role played by a DMM agreement. In particular, efficiency is enhanced by avoiding possible outcomes in which the investor is dissuaded by a low bid price from selling in the secondary market after suffering a liquidity shock.

LEMMA 2: *Setting the bid quote to $B^* = (1 + \epsilon - \rho)\mu$ or higher is necessary and sufficient to ensure that q=0, that is that the investor will always sell in the t=1 secondary market after suffering a liquidity shock.*

Conditional on suffering a liquidity shock, the investor's possible subjective valuations are, in increasing order, $(1 - \epsilon - \rho)\mu$ if she is informed that the asset value is low, $(1 - \rho)\mu$ if she is uninformed, and $(1 + \epsilon - \rho)\mu$ if she is informed that the asset value is high. Thus, a bid quote of B^* or higher matches or exceeds the highest possible subjective valuation in the presence of a liquidity shock, implying that the investor will always sell conditional on a liquidity shock.[15]

We now consider the effect of a potential DMM contract that calls for a flat t=0 payment, C, from the firm to the DMM, in exchange for a commitment to maintain a minimum bid in the t=1 secondary market.[16] The contracted increase in the bid price beyond the competitive level implies that the DMM will on average suffer monetary losses in trading with the investor.

LEMMA 3: *When relative fundamental uncertainty is intermediate or high and the bid price is set to B^*, the DMM's expected trading loss $M(B^*)$ is given as*

$$\text{(i) if } \rho > \epsilon > \epsilon^*,\ M(B^*) = (\tfrac{p}{2}(1-\lambda)+\lambda)\rho(\tfrac{\epsilon}{\epsilon^*}-1)\mu > 0$$

$$\text{(ii) if } \rho < \epsilon,\ M(B^*) = (\epsilon - \rho + (1-\lambda)\tfrac{p}{2}\rho)\mu > 0.$$

The firm will enter into a DMM contract if its net gain $V_I - V_F - C$ is larger with the contract than without, and is positive, which implies the following central proposition.

PROPOSITION 2: *Given competitive market making and the IPO price equals V_I:*

(i) If relative fundamental uncertainty is low, the firm maximizes its value and also social welfare by completing the IPO without a DMM agreement.

[15] Note though that a bid quote of B^* does not ensure that the investor always sells, as the investors highest possible subjective valuation is $(1+\epsilon)\mu > B^*$, which is attained if she is privately informed that the asset value is high and does not suffer a liquidity shock. However, a sale motivated by information would create a market maker loss equivalent to the investor gain, with no net welfare gain.

[16] Given that the firm values cash more highly than the investor, it might appear efficient for the investor rather than the firm to contract with the DMM. In practice this alternative would lead to coordination issues across the multiple investors that typically participate in an IPO. Note also that in the present model investors effectively provide the cash that the firm uses to contract with the DMM, in the form of a higher IPO price.

(ii) If relative fundamental uncertainty is intermediate or high, the firm maximizes its value and social welfare by completing the IPO and entering into a DMM contract in which the firm pays the DMM the amount $C = M(B^*)$ in exchange for a commitment to maintain the bid price $B^* = (1 + \epsilon - \rho)\mu$.[17]

Proposition 2 follows immediately from the preceding discussions. When relative fundamental uncertainty is low, there is no market failure and no need for a DMM agreement. When relative fundamental uncertainty is intermediate or high. the competitive market fails either partially or completely. However, the marker failure can be cured by a DMM agreement that requires the bid price to be set high enough to ensure that the investor always sells following a liquidity shock. The DMM agreement leads to a Pareto improvement. The DMM is fully compensated in expectation for trading losses, the investor values the assets more highly and pays a correspondingly higher price to the firm, while the amount that the firm realizes in the IPO is increased by more than enough to pay the DMM.

3.4.6 Why the Increase in Value Exceeds the Required Payment

From expression (1), anticipated monetary trading gains increase the t=0 value of the asset to the investor. However, increasing the bid quote also increases the value of the asset to the investor by the amount $q\lambda\rho\mu$ as a consequence of reducing q, the probability of not trading after a liquidity shock, to zero. That is, asset value is increased both because the investor enjoys monetary trading gains and because she avoids utility losses due to nontrading after liquidity shocks. The DMM needs to be compensated for the former, but not the latter. Since monetary trading gains are

[17]Setting the contracted bid price higher than B^* would involve greater investor gains and market-maker losses, a higher IPO price, and a larger required payment from the firm, but these increased payments would be zero-sum.

zero-sum, the increase in value net of the DMM payment is entirely attributable to the avoidance of outcomes whereby the investor is dissuaded from trading in response to a liquidity shock.

3.4.7 Testable Implications and Discussion

Several aspects of this analysis deserve emphasis. Most importantly, Proposition 2 presents testable implications regarding the conditions under which DMM agreements are likely to be observed. Competitive liquidity provision is efficient if relative fundamental uncertainty is low, that is, if $\epsilon < \epsilon^*$, while DMM agreements will be efficient if relative fundamental uncertainty is intermediate or high, that is, if $\epsilon^* < \epsilon$. As previously noted, the boundary point ϵ^* increases with the probability, λ, and magnitude, ρ, of investor liquidity shocks, implying that larger and more frequent investor liquidity shocks reduce the need for DMMs, ceteris paribus. However, these liquidity shock parameters are investor characteristics that do not differ across firms if investors hold diversified portfolios.

The model implies that DMM agreements will be value enhancing for those firms and/or at those times when uncertainty regarding asset value, ϵ, and the probability, p, that private information is received, are high in combination. The relevance of fundamental uncertainty arises from the fact that our model implies that DMM contracts enhance value when $\epsilon > \epsilon^*$, while the relevance of the probability of private information being received arises because the threshold ϵ^* is lower for firms or at times when p is greater. The model therefore implies that DMM contracts are most likely to be value-enhancing for smaller and younger firms, to the extent these are characterized by more fundamental uncertainty and greater information asymmetry. This implication is generally consistent with the empirical evidence, see, for example, *Venkataraman and Waisburd* (2007), *Anand et al.* (2009), and *Menkveld and Wang* (2013).

The model further implies that DMM agreements that are voluntarily adopted should be observed more frequently for firms for which empirical measures of information asymmetry (e.g., the "PIN" measure attributable to *Easley et al.* (1996) or the price impact measure of *Huang and Stoll* (1996)) and fundamental volatility are large in combination. In light of our prediction that firms with high relative fundamental uncertainty will self-select to enter into DMM agreements, future researchers should consider the resulting endogeneity when interpreting any observed cross-sectional correlation between the existence of DMM agreements and empirical measures such as PIN or return volatility. In contrast, should DMM agreements ever be mandated based on an arbitrary threshold such as firm size, an appropriate research design (e.g., a regression discontinuity approach) may be able to estimate causal effects of the DMM agreement on market outcomes.
In addition to altering the breakpoint, ϵ^*, that defines the range of parameters over which a DMM contract is efficient, changes in the probability that private information is received, p, affect both the magnitude of the efficiency gain from a DMM contract and the size of the requisite payment to the market maker. Regarding the latter, Lemma 3 also implies testable implications. When a DMM contract is efficient, the required payment to the market maker is strictly increasing in uncertainty regarding fundamental value, ϵ, and in the probability that the trader is privately informed, p.

Our model explicitly considers only those liquidity shocks that reduce the investor's subjective valuation and induce a desire to sell. Of course investors may also experience liquidity shocks (e.g., a sudden cash inflow) that induce a desire to buy. The direct extension to a model with both positive and negative liquidity shocks is a contract calling for the DMM to both decrease the ask price and increase the bid price, that is, to narrow the bid-ask spread, relative to competitive levels. As noted above, DMM contracts that require the bid-ask spread to be kept within a narrow range are in fact observed on a number of markets, and are typically employed for less liquid stocks. Our model implies, however, that DMM contracts will enhance value and efficiency only when used to offset market-maker trading costs attributable to the information content of trades. Value is not enhanced by constraining bid-ask spreads to be narrower than the social cost (e.g., inventory carrying costs or order processing costs) of completing trades, which may also be greater for thinly traded securities.

Our model also helps rationalize the empirical observation (e.g., Schultz and Zaman (1994) and Ellis, Michaely, and O'Hara (2000)) that underwriters often act to support or stabilize post-IPO market prices. Such aftermarket support potentially complements a DMM contract, focusing particularly on the period immediately after the IPO when information asymmetry is potentially large. However, such stabilization activities are typically temporary, and therefore do not comprise a complete substitute for longer-term DMM contracts.

If the probability of informed trading is perceived by market participants to vary over time, relative fundamental uncertainty is dynamic. A firm that is typically characterized by low relative fundamental uncertainty may not always be so. While the model presented here is static, the economic reasoning suggests that in addition to contracts that require DMMs to routinely narrow spreads for smaller and younger firms, DMM contracts that impose a binding obligation during times of increased asymmetric information may be welfare- and value-enhancing for larger and better-known firms. To implement such a contractual obligation it would be useful to develop methods of detecting, on the basis of observable market data, periods of heightened information asymmetry.[18] One simple approach could be to contract for a maximum bid-ask spread that is sufficiently greater than the typical spread for the stock that the contract would be unlikely to bind except at times of heighted information asymmetry.

3.5 Partial Bargaining Power and Noncompetitive Market Making

The preceding section demonstrates that competitive market making need not lead to efficient outcomes, as the market may fail partially or fully when relative fundamental uncertainty exceeds a threshold. However, if the firm has complete bargaining power, in the sense that it captures through a higher IPO price any increase in the value of the asset attributable to better secondary market liquidity, then a value-maximizing firm will cure any market failure by contracting with a market maker to enhance secondary market liquidity.

3.5.1 Partial Bargaining Power in the IPO Market

In this section, we assess the effects of relaxing the assumption that the firm captures all of the benefits from enhanced liquidity. In practice, firms' proceeds from IPOs are typically less than the open market value of the shares issued, as some of the gains from trade are captured by intermediaries in the form of commissions and by investors in the form of the widely studied "underpricing" of shares.[19] A full model of the IPO process is beyond the scope of this paper. We instead assume that the bargaining game generates a parameter, β, which is the proportion of the improvement in t=0 value that is captured by the firm. In particular, the IPO price is

[18] See, for example, *Easley et al.* (2012) who present one such measure.

[19] See, for example, *Chen and Ritter* (2000) for analysis of investment bank commissions and *Ibbotson et al.* (1994) for evidence regarding underpricing.

$V_F + \beta(V_I - V_F)$. Stated alternatively, the improvement in firm value from completing the IPO, net of a possible payment to the DMM, C, is

$$\pi = \beta(V_I - V_F) - C. \tag{3.3}$$

Using expression (1) along with the definition of V_F in expression (3), the firm's net gain can also be expressed as

$$\pi = \beta\mu(\delta - q(B)\lambda\rho) + \beta M(B) - C. \tag{3.4}$$

If the firm conducts the IPO in the competitive market and chooses not to enter into a DMM agreement ($C = M = 0$), then the firm's net gain is $\pi = \beta\mu(\delta - q(B)\lambda\rho)$. The model therefore implies the following:

LEMMA 4: *The market will not fail if relative fundamental uncertainty is low, for any $\beta > 0$.*

Lemma 4 follows from the prior observation that when relative fundamental uncertainty is low, competitive market making without a DMM agreement leads to a bid price high enough that the investor always sells in response to a liquidity shock, which means $q(B) = 0$ and the firm's net gain is $\pi = \beta\delta\mu$. The firm will therefore conduct the IPO for any $\beta > 0$, that is, as long as it captures any positive portion of the benefit from doing so. Of course, this result would be changed if there was any fixed cost to completing the IPO, in which case the firm would choose not to proceed with the IPO for sufficiently small β, even with low relative fundamental uncertainty.

If the firm conducts the IPO and enters into a DMM agreement to set the bid price to B^* in exchange for a fixed payment $C^* = M(B^*)$, then $q(B^*) = 0$ and, from expression (4), the firm's net gain is $\pi = \beta\mu\delta - C^*(1 - \beta)$.[20] The market will fail

[20] We show in the Appendix that when $\beta < 1$ and relative fundamental uncertainty is high for some parameters the firm may prefer a DMM contract calling for a bid price lower than the welfare

completely if the firm's net gain is negative with or without a DMM agreement, while the market will fail partially if the firm's net gain is positive without a DMM agreement and is smaller with the optimal DMM agreement than without. This implies that, with intermediate or high relative fundamental uncertainty, the market will fail completely if

$$\delta < q(B)\lambda\rho \text{ and } \beta < \tfrac{C^*}{C^*+\mu\delta},$$

while the market will fail partially if

$$\delta \geq q(B)\lambda\rho \text{ and } \beta < \tfrac{C^*}{C^*+q(B)\lambda\rho\mu}.$$

Market failure occurs when the firm's bargaining power in the IPO market, β, is less than some critical level that depends on the payment to the market maker, C^*. Whether the potential market failure is partial or complete depends on the firm's need for cash, δ, relative to a critical level that depends on the probability, q, that the investor does not sell after suffering a liquidity shock.

The critical levels of δ and β can be stated in terms of the model's exogenous parameters, as summarized in Table 3.2.

The discussions above and the definitions in Table 3.2 allow us to state the following.

PROPOSITION 3: *Given competitive market making and the possibility of entering into a DMM agreement:*

(i) When relative fundamental uncertainty is intermediate or high, the firm completes the IPO and enters into the optimal DMM agreement only if the firm's bargaining power exceeds the threshold level, β^*. When $\beta < \beta^*$, the market fails. The failure is partial, as the firm completes the IPO but does not enter into the DMM contract, when δ exceeds the threshold level, δ^*, and is complete otherwise.

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maximizing level, B^*. As the general intuition of the firms decision is unchanged, for simplicity we continue to focus here on a DMM contract calling for the welfare-maximizing bid price.

(ii) The threshold level of bargaining power, β^*, decreases with the probability, λ, and magnitude, ρ, of investor liquidity shocks, and for most parameter values increases with the probability that private information is received.

The intuition for Proposition 3 is simply that the firm bears the full cost of compensating the DMM, while it captures only the proportion β of the resulting increase in value. The market fails if the firm's bargaining power, β, is sufficiently low. The failure is partial if the firm's need for cash is sufficiently strong, and is total otherwise.

We show in the Appendix that the threshold level β^* decreases, implying that efficient outcomes obtain for a broader range of β, when both the probability and magnitude of investor liquidity shocks are greater. This reflects the fact that more liquidity-motivated trading leads to smaller expected trading losses and a smaller required payment to market makers who have contracted to maintain a bid quote equal to B^*. Also, for most parameter values the firm's net gain with a DMM contract decreases with p, the probability that the trader becomes privately informed, due to greater expected market-maker trading losses that must be fully compensated by the firm. Thus, higher p leads to larger β^* and market failure occurs over a broader range of bargaining parameters.[21]

Chen and Ritter (2000) argue that investment bankers earn economic rents from conducting IPOs. Our analysis indicates that frictions such as investment bank commissions or market underpricing, which prevent firms from capturing the full market value of the assets they sell, can cause complete market failure in the sense that firms

[21]The exception arises in the range where $\rho < \epsilon \leq \epsilon^{**}$ and $\delta \geq \lambda \frac{p}{2} \rho$. Here, the net gain from the IPO is positive without a DMM contract, so the DMM decision depends on the comparison between net gains with and without the DMM contract. In this range the net gain to the firm decreases faster without than with the DMM contract, leading β^* to decrease with p.

choose not to proceed with efficiency-enhancing IPOs. Our model also produces the more subtle result that such frictions can lead to a partial market failure, where a firm with a strong need for cash conducts the IPO but does not enter into the efficient DMM contract. Market failure due to reduced firm market power is less likely if investors are more likely to be exposed to large liquidity shocks, but is more likely for firms with a higher likelihood of information asymmetry.

Outcomes characterized by full or partial market failure attributable to the firm's lack of bargaining power are Pareto-inefficient. Outcomes could be improved if the investor (or in more realistic settings, IPO investors acting collectively) were to sponsor a DMM. As noted, after-market support provided by underwriting firms can be interpreted as effectively reflecting a short-term DMM function. Our model implies that an implicit or formal agreement through which investors compensate the underwriter for enhancing secondary market liquidity can also be efficient and value enhancing.

Proposition 3 has the testable implication that firms with stronger bargaining power in the IPO process will be more likely to complete IPOs and to enter into DMM agreements when efficient. For example, *Jeon et al.* (2014) suggest that IPO firms backed by private equity or venture capital firms have greater negotiating power (higher β) because these firms have well-informed principals and repeat players in the IPO market. *Burch et al.* (2005) argue that investment banks with larger shares of IPO deals in an industry have a stronger bargaining position, implying lower firm β, while firms with larger offerings have greater negotiating power.

3.5.2 The Effect of Possible Monopoly Power in Liquidity Provision

Thus far, we have assumed that market makers engage in Bertrand competition, leading to zero expected market-making profits in the absence of a DMM contract. However, liquidity provision could be imperfectly competitive. *Glosten* (1989) models the case of a monopolist liquidity provider, and the model presented by *Bernhardt and Hughson* (1997) allows for positive expected market-making profits in equilibrium. In *Biais et al.* (2000), each liquidity supplier acts to maximize profits while taking as fixed the behavior of competitors, and economic profits persist in equilibrium as long as the number of competitors is finite. Depending on the degree of cross-market competition, a trading exchange may be able to extract monopoly rents in the form of trading fees, even if competition prevails among potential liquidity suppliers on the exchange. Monopoly rents may also arise if the tick size is large enough to constrain bid-ask spreads to be larger than the competitive level.

A full model of imperfect competition in market making is beyond the scope of this paper. To obtain insights into the potential role of market-maker rents that are as general as possible and in the simplest possible manner, we assume that market makers are able to extract an exogenously specified level of trading profits in the absence of a DMM agreement. We also assume that the potential DMM agreement would call for a bid price equal to B^*, in exchange for a payment from the firm to the DMM that is sufficient to compensate the DMM for boththeir anticipated trading losses as specified in Lemma 2 and forgone market-making rents. Let B' denote the secondary market bid price given market power, which is less than the competitive bid, and let $M(B')$ denote the trader's expected trading profit in the absence of a DMM agreement (so that $-M(B')$ is the market-making rent). The payment C from the firm to the DMM in exchange for maintaining a bid price equal to B^* is $M(B^*)-M(B')$.[22]

[22] In this setting, market makers are able to fully preserve the existing market-making rents upon

PROPOSITION 4: *Given the existence of rents in market making:*

(i) In contrast to outcomes with competitive market making, the market can fail completely as the firm choose not to complete the IPO, even if relative fundamental uncertainty is low and $\beta = 1$*.*

(ii) Larger market- making rents strictly increase the range of parameters that lead to market failure.

Monopoly rents in market-making affect outcomes in a manner that is similar to the effects of asymmetric information. Each leads to a reduction in the secondary market bid price relative to the fundamental value of the asset, μ. Monopoly rents, like market-making losses due to asymmetric information, are zero-sum transfers, not social costs of providing liquidity. Social welfare is reduced by market-making rents in the same manner as information asymmetry, that is, if the market-making rents lead to bid prices low, that the investor may be dissuaded from selling the asset after a liquidity shock.

However, the effects of market-making rents are not identical to those of asymmetric information, as the former can lead to market failure even when relative fundamental uncertainty is low, $\beta = 1$, and the firm has the option to enter into a DMM contract, while the latter cannot. Complete market failure occurs if the firm's net gains are negative with or without a DMM agreement. Given $M(B') < 0$, the market fails completely if

$$\delta < q(B')\lambda\rho - M(B')/\mu \text{ and } \beta < \tfrac{M(B^*)-M(B')}{M(B^*)+\mu\delta}.$$

entering into a DMM agreement. More broadly, the qualitative predictions of Proposition 4 will continue to hold if market makers retain any portion of their market-making rents. If market makers are not able to preserve any of their rents, that is, if the firms bargaining power versus market makers is complete, then C can be set to $M(B^*)$ and outcomes with a potential DMM agreement are identical to the competitive secondary market case.

The first of these conditions implies that the firm's net gain is negative if the firm completes the IPO without entering into a DMM agreement. This condition can be met even when relative fundamental uncertainty is low, because the investor reduces the price she is willing to pay for the assets in anticipation of trading losses attributable to market-maker rents, $-M(B')$, and because the bid price B' set in the presence of market-making rents is not necessarily high enough to ensure $q(B') = 0$, that is, that the investor always sells in response to a liquidity shock. The second condition implies that the firm's net gain is negative with the optimal DMM agreement. Even with $\beta = 1$ this condition can be met if $M(B') < -\mu\delta$. Further, increased market-maker rents strictly increase the range of β over which the IPO does not occur.

Partial market failure occurs if the firm completes the IPO, but the firm's net gain is lower with the optimal DMM agreement than without. The latter occurs if

$$\beta < \frac{M(B^*)-M(B')}{M(B^*)-M(B')+q(B')\lambda\rho\mu}.$$

Since the right-hand side of this expression increases with larger market-maker rents, the model also implies that partial market failure occurs for a broader range of firm bargaining power when market-making rents are greater.

An advisory panel to the U.S. SEC has recently recommended increases in the tick size for smaller exchange-traded companies. The intent appears to be to increase bid-ask spreads beyond competitive levels in the hopes that the resulting market-making rents will attract additional liquidity suppliers, who in turn may provide other services such as research reports. However, our model indicates that such a proposal will likely be counterproductive. In particular, the model implies that monopoly profits in secondary market liquidity provision reduce efficiency and in turn IPO prices, as investors take into account the higher costs of secondary market trading. Monopoly rents in secondary market liquidity provision can lead to complete market failure, where the firm chooses not to complete the IPO. In contrast, DMM contracts of the type considered here improve efficiency and facilitate the IPO process.

3.6 Conclusion and Extensions

We present a relatively simple model to assess the effects on firm value and social welfare of a contract through which a firm engages a DMM to improve secondary market liquidity. We show that a DMM contract can improve value and welfare because of an information-based externality. In particular, while market-maker losses from transactions with privately informed traders are a private cost of providing liquidity, they represent a zero-sum transfer rather than a cost when aggregated across all agents. Since the private costs of providing liquidity exceed the social costs, a competitive market provides less liquidity than the efficient level. DMM contracts comprise a potential market solution to this market imperfection. While contracts of the type modeled here are observed on some international markets, they are currently prohibited in the U.S. by FINRA Rule 5250.

Our analysis shows that the potential benefits of contracts that require enhanced liquidity supply are related to information, rather than illiquidity, per se. Our model's implications differ in an important but subtle way from the simple insight that enhancing liquidity is useful in otherwise illiquid stocks. If stocks are illiquid due to high real costs of competing trades, or example due to the inventory costs that *Demsetz* (1968) predicts will be high for thinly traded assets, then the marginal social cost of providing liquidity is high and it is efficient for spreads to be wide. Value will not be enhanced by contracts that reduce spreads below the real social costs of providing liquidity. Instead, our analysis implies that efficiency and firm value can be enhanced for those firms or at those times when markets are illiquid due to a combination of high fundamental uncertainty and information asymmetry. In the cross section, our analysis implies that DMM contracts are likely to be useful for smaller and younger firms, as opposed to larger firms with a high proportion of assets-in-place. In the time series, our analysis implies that DMM contracts may be useful if they require additional liquidity provision at times when perceived fundamental uncertainty and information asymmetry are temporarily elevated.

The model presented here has a number of implications for researchers and policy makers. First, and most important, our analysis shows that economic efficiency and firm value can be enhanced by contracts that require liquidity providers to supply more liquidity than they would otherwise choose. In the absence of barriers to entry in providing liquidity in electronic limit order markets, liquidity provision may well reflect competitive equilibrium. If so, side payments will be required to induce one or more DMMs to take on such affirmative obligations, and our model implies that affirmative obligations to provide liquidity should not be imposed in the absence of compensation to the DMMs. Our model also indicates that recent proposals to increase the minimum price increment for the trading of smaller stocks in order to attract additional liquidity providers and facilitate IPOs are also likely to be counterproductive, as investors will take into account wider bid-ask spreads in valuing shares. In contrast, contracts of the type studied here, between the listed firm and the DMM enhance liquidity, improve firm value, and facilitate IPOs. Our analysis also supports the intuition that IPOs can be facilitated by improving firms' bargaining power in the IPO process, for example, by measures that intensify competition among investment banks.

Several limitations of our analysis, each of which provides useful opportunities for future research, should be noted. For simplicity our model focuses on a single investor, a single round of secondary trading, and trades of fixed size. As such, we do not consider potential effects of market maker affirmative obligations on trade timing, trade size, repeat trading, or trading aggressiveness.

We also assume that the investor either transacts at the t=1 market-maker quote or does not trade, without allowing the trader the option to leave a limit order on the book. In a model extended to allow for multiple rounds of trading the trader might prefer to enter a limit order. While a formal analysis of a dynamic limit order book in the presence of a DMM is beyond the scope of this paper, we offer the following conjectures. First, as in *Sabourin* (2006), the introduction of a DMM will cause some traders who would have entered a limit order to submit a market order instead. Second, the t=1 seller will enter a limit order instead of transacting at the market bid quote only when her utility is increased by doing so. As a consequence, a contract calling for a given bid quote in a limit order market cannot be less valuable to the investor as compared to the same requirement in the absence of the option to enter limit orders. If the trader's option to enter a limit order benefits or at least does not harm the DMM, then the key implication of this model, that value and welfare are enhanced by a DMM agreement, will survive. Third, the t=1 seller will not consider entering a limit order unless it is sufficiently probable that another trader with a private valuation in excess of the t=1 bid will subsequently arrive. As in Kandel and Liu (2006), private information could motivate the use of a limit order. If the t=1 trader is privately informed that the asset value is high, then she can be more confident that the subsequent trader (who could also be informed) would also have a high valuation, and she will be more likely to enter a limit order with a price above the market maker's bid instead of selling to the market maker. If so, the market maker's adverse selection risk can be reduced by the trader's option to enter the limit order, potentially leading to a lower required DMM payment in equilibrium.

We also do not consider the full range of potential DMM agreements. For simplicity we focus for on a contract by which the listed firm pays a flat fee to a DMM to increase the market bid price, or by extension, to narrow the bid-ask spread. *Anand et al.* (2009) document two additional features of observed DMM contracts. First, in some cases DMM contracts call for a variable fee proportionate to the volume of trades accommodated, in addition to a fixed fee. Second, the obligation to narrow the spread can apply only a proportion (e.g., 90%) of the time. In the present model, the former modification is irrelevant, as given risk-neutrality, any combination of fixed and variable payments that are equal in expectation to market maker trading losses is equally satisfactory. The latter modification, implying that with some probability the DMM will not enhance secondary market liquidity, is potentially welfare-reducing in the present model. These features of actual DMM agreements likely reflect capital limitations, which are not considered in our model. A variable fee tied to the volume of DMM transactions can be viewed as a form of risk-sharing, with a portion of trading losses that are larger than anticipated passed from the DMM to the firm. Similarly, the option to temporarily cease enhancing liquidity will reduce the magnitude of market-maker losses during extreme events. Each provision therefore reduces the likelihood that the DMM will fail because it has exhausted its finite capital reserves.

Table 3.1: Notation

Symbol	Description	Algebraic Definition
μ	The unconditional expected value of the asset.	$\mu > 0$
ϵ	The uncertainty regarding asset value.	$0 < \epsilon < 1$
H	The high liquidation value.	$H = (1+\epsilon)\mu$
L	The low liquidation value.	$L = (1-\epsilon)\mu$
δ	The firms discount factor, reflecting its need for cash.	$0 < \delta < 1$
V_F	The t=0 value of the asset to the firm.	$V_F = (1-\delta)\mu$
λ	The probability that the investor incurs a liquidity shock.	$\lambda > 0$
ρ	The fraction by which the investors subjective valuation of the asset is reduced when she incurs a liquidity shock.	$0 < \rho < 1$
p	The probability that the investor will become privately informed as to whether the liquidation value of the asset will be H or L.	
B	The t=1 bid quote. B^* denotes the level that maximizes welfare.	$B^* = (1+\epsilon-\rho)\mu$
$M(B)$	The investors expected monetary gain, or equivalently, the market makers expected monetary loss, from t=1 secondary market trading.	
C	The payment from the firm to the market maker.	
$q(B)$	The probability that the investor will choose not to sell her asset, conditional on a t=1 liquidity shock.	
V_I	The t=0 value of the asset to the investor.	$V_I = \mu - q\lambda\rho\mu + M$
β	The firms bargaining power in the IPO market.	
W	The improvement in aggregate social welfare.	$W = \mu(\delta - q\lambda\rho)$
π	The firms net gain from conducting the IPO.	$\pi = \beta(V_I - V_F) - C$
$\epsilon < \epsilon^*$	Low relative fundamental uncertainty.	$\epsilon^* \equiv \frac{2\lambda+(1-\lambda)p}{2(p+\lambda-p\lambda)}\rho$
$\epsilon^* < \epsilon < \epsilon^{**}$	Intermediate relative fundamental uncertainty.	$\epsilon^{**} \equiv \frac{p+2(1-p)\lambda}{p}\rho$
$\epsilon > \epsilon^{**}$	High relative fundamental uncertainty.	

Table 3.2: Key Threshold Levels of δ and β

Range of ϵ	δ^*	β^*
$\epsilon^* < \epsilon \leq \rho$	$\delta^* = \lambda\frac{p}{2}\rho$	When $\delta < \delta^*$, $\beta^* = \frac{\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}{\delta+\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}$
		When $\delta \geq \delta^*$, $\beta^* = \frac{\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}{\lambda\frac{p}{2}\rho+\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}$
$\rho < \epsilon \leq \epsilon^{**}$	$\delta^* = \lambda\frac{p}{2}\rho$	When $\delta < \delta^*$, $\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\delta+\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}$
		When $\delta \geq \delta^*$, $\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\lambda\frac{p}{2}\rho+\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}$
$\epsilon > \epsilon^{**}$	$\delta^* = (1-\frac{p}{2})\lambda\rho$	When $\delta < \delta^*$, $\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\delta+\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}$
		When $\delta \geq \delta^*$, $\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho+\lambda\frac{p}{2}\rho+\lambda(1-p)\rho}$

APPENDICES

APPENDIX A

Bank Equity Capital and Risk-taking Behavior: The Effect of Competition

A.1 Timing of Banking Deregulations

Table A.1 shows the history of interstate banking and intrastate branching deregulation since 1970.[1] The second column shows the year that the state first entered an interstate banking agreement with a reciprocal state. The third column shows the year each state finished the transition to allow intrastate branching (both M&A branching and *de novo* branching).

A.2 Endogenous Deregulation?

Banking deregulations discussed in this paper were driven by several different factors as discussed in *Kane* (1996) and *Kroszner and Strahan* (1999). Regulatory

[1] As in *Jayaratne and Strahan* (1998), banks from Delaware and South Dakota are excluded in this paper. In the 1980s, Delaware and South Dakota experienced a surge in credit card operations because of their liberal usury laws. As a result, the health and profitability of the credit card industry became the dominating driver of performance of the local banking industry, which make it hard to identify the effect of deregulations.

changes adopted by regulators in the national level in the 1980s are important impetus to the deregulations. For example, the Office of the Comptroller of the Currency (OCC) allowed nationally chartered banks to branch freely in those states where savings institutions did not face branching restrictions. Also, federal legislators amended the Bank Holding Company Act to allow failed banks and thrifts to be acquired by any BHC, regardless of state laws. Besides regulatory changes, developments in technology and innovations in the banking industry are also important driving forces. For example, information and transportation technology eroded the geographic ties between customers and local banks, while checkable money market mutual funds and the Merrill Lynch Cash Management Account demonstrated that banking by mail and telephone provided a convenient alternative to local banks.

In addition to national forces, local political and economic factors are also found to be related to the deregulations. These factors include local economic development, market share of large banks, relative size of local insurance firms, number of small firms in each state, and the controlling party of the state government. These correlations can lead to misinterpretation if one uses these correlated factors as dependent variables. For example, if one regresses the market share of large banks on the deregulation dummies, it is very likely that the coefficient estimates on the dummies are positive. However, it is not proper to argue that deregulations lead to higher growth in market share by the large banks because it is likely that the positive estimates just capture the positive growth trend in the market share of large banks which leads to the deregulations.

In contrast, the coefficient estimates reported in this paper are not likely to be affected by the political economy factors. By including the firm fixed effects (α_i), which subsume state fixed effects, all of the cross-state variation is removed. This means that coefficients are driven by changes in variables after a state alters its regulations. Further, I am comparing banks based on their capital ratio before the deregulation. And there are both high and low capital banks in each state. Therefore, persistent differences across states do not affect the estimates in my study.

A.3 Variable Definitions

All variables are from Call reports.

Total Assets: rcfd2170

Total Loans and Leases: rcfd1400 (rcfd1400+rcfd2165 before 1984)

Common Equity: rcfd3210

Equity Capital Ratio: rcfd3210/rcfd2170

Net Income: riad4340

Gross Income: riad4340+riad4230

Return on Asset: riad4340/rcfd2170

Return on Equity: riad4340/rcfd3210

Gross Return on Asset: (riad4340+riad4230)/rcfd2170

Gross Return on Equity: (riad4340+riad4230)/rcfd3210

Non-performing Loan Ratio: (rcfd1403+ rcfd1407)/Total Loans and Leases

Net Charge-off Ratio: (riad4635- riad4605)/Total Loans and Leases

Loan Loss Provision Ratio: riad4230/Total Loans and Leases

Non-interest Expense: riad4093

Interest Income: riad4010

Lending Interest Rate: riad4010/Total Loans and Leases

Commercial and Industry Loan: rcfd1600

Real Estate Loan: rcfd1420

Table A.1: **Deregulation of Restrictions on Geographical Expansion**
This table lists states by the year they entered an interstate banking compact and the year they permitted intrastate branching.

	Interstate Banking	Intrastate Branching
Maine	1982	1975
Alaska	1982	*
New York	1982	1976
Connecticut	1983	1980
Massachusetts	1983	1984
Kentucky	1984	1990
Rhode Island	1984	*
Utah	1984	1981
Washington, DC	1985	*
Florida	1985	1988
Georgia	1985	1983
Idaho	1985	*
Maryland	1985	*
Nevada	1985	*
North Carolina	1985	*
Ohio	1985	1979
Tennessee	1985	1985
Virginia	1985	1978
Arizona	1986	*
Illinois	1986	1988
Indiana	1986	1989
Michigan	1986	1987
Minnesota	1986	1993
Missouri	1986	1990
New Jersey	1986	1977
Oregon	1986	1985
Pennsylvania	1986	1982
South Carolina	1986	*
Alabama	1987	1981
California	1987	*
Louisiana	1987	1988
New Hampshire	1987	1987
Oklahoma	1987	1988
Texas	1987	1988
Washington	1987	1985
Wisconsin	1987	1990
Wyoming	1987	1988
Colorado	1988	1991
Delaware	1988	*
Mississippi	1988	1986
South Dakota	1988	*
Vermont	1988	1970
West Virginia	1988	1987
Arkansas	1989	1994
New Mexico	1989	1991
Nebraska	1990	1985
Iowa	1991	*
North Dakota	1991	1987
Kansas	1992	1987
Montana	1993	1990
Hawaii	1997	1986

* pre-1970

Data is from *Jayaratne and Strahan* (1998) and *Morgan et al.* (2004).

APPENDIX B

The Strategic Under-Reporting of Bank Risk

Table B.1: **VaR Exceptions and the Regulatory Multiplier**
This table is reproduced from *BIS* (1996) and presents the Green, Yellow, and Red zones that supervisors use to assess VaR model backtesting results. This relationship between VaR exceptions and the regulatory multiplier k that is used for the market-risk capital charge. The number of exceptions is based on results from the last 250 trading days (one year).

Zone	**Number of Exceptions**	**Regulatory Multiplier**
Green Zone	0	3.00
	1	3.00
	2	3.00
	3	3.00
	4	3.00
Yellow Zone	5	3.40
	6	3.50
	7	3.65
	8	3.75
	9	3.85
Red Zone	10 or more	4.00

Table B.2: **Comparability Around the Green-Yellow Threshold**
This table is presents sample means for observations in the neighborhood of the Green-Yellow threshold in the regulatory multiplier function. This in includes bank-quarter observations where the trailing three quarters' exceptions is in the range [2-7], where observations with 2-3 exceptions (N=43) are in the Green group, and observations with 4-8 exceptions (N=21) are in the Yellow Group. The last two columns present the difference in the two means, and the *p*-value of that difference.

Variable	Green	Yellow	Difference	*p*-value
Total Assets (Bn)	1060.96	927.42	-133.54	(0.55)
Net Income (MM)	974.88	1116.34	141.46	(0.67)
NI-to-Assets (%,Q)	0.13	0.15	0.02	(0.51)
BookEq/Assets (%)	5.66	5.83	0.17	(0.83)
Exceptions next Quarter	0.51	2.47	1.96^{***}	(0.00)

APPENDIX C

Market Making Contracts, Firm Value, and the IPO Decision

C.1 Proofs of Propositions and Lemmas

Proof. Proof of Lemma 1: There are six possible outcomes for the investor's t=1 subjective valuation of the asset, as shown in Figure C.1.

As in Glosten and Milgrom (1985), the competitive bid price equals the expected asset value conditional on a sale, implying zero expected profit. In this model the competitive bid price must lie in the range $[(1-\epsilon)\mu, \mu)$. To see this, suppose first the bid price is weakly larger than $(1+\epsilon)\mu$. The investor will sell in all six cases displayed in Figure C.1, so the conditional expected asset value is μ. A bid price lower than $(1+\epsilon)\mu$ will lead to a conditional expectation of asset value less than μ, because the investor with positive private news does not sell. This implies that the maximum asset value conditional on a sale is μ, obtained only when the bid price is $(1+\epsilon)\mu$. Therefore, a bid price weakly larger than μ leads to negative expected profit to the market maker. Alternatively, suppose the bid price is less than $(1-\epsilon)\mu$. The investor only sells in Case (2), leading to a conditional expected asset value of $(1-\epsilon)\mu$. This gives the market makers a positive expected profit and implies that the competitive bid quote is weakly larger than $(1-\epsilon)\mu$. We therefore need only consider potential competitive bid prices, B, within $[(1-\epsilon)\mu, \mu)$.

To assess possible competitive bid prices, we consider in turn three ranges of ϵ: (1) $\epsilon \leq \epsilon^*(\epsilon^* \equiv \frac{2\lambda+(1-\lambda)p}{2(p+\lambda-p\lambda)}\rho)$, (2) $\epsilon^* < \epsilon \leq \epsilon^{**}(\epsilon^{**} \equiv \frac{p+2(1-p)\lambda}{p}\rho)$, and (3) $\epsilon^{**} < \epsilon$.

Range (1):

When $\epsilon \leq \epsilon^*$, let $B = (1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$. Note that $B = (1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu = (1 + \epsilon - \frac{2(p+\lambda-p\lambda)}{2\lambda+(1-\lambda)p}\epsilon)\mu \leq (1+\epsilon-\rho)\mu$ because $\epsilon \leq \frac{2\lambda+(1-\lambda)p}{2(p+\lambda-p\lambda)}\rho$. With this bid price, the investor sells in Cases (1), (2), (3), and (5). Given this trading behavior, the conditional expected asset value is $(1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$, implying that $B = (1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$ is a possible competitive bid price.

Next, we show that when $\epsilon \leq \epsilon^* < \rho$, $B = (1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$ is the unique competitive bid price. We do so by separating the range of $(0, \epsilon^*]$ into three subranges, $(0, \frac{\rho}{2}]$, $(\frac{\rho}{2}, \frac{2\lambda+p-2p\lambda}{2(p+\lambda-p\lambda}\rho]$, and $(\frac{2\lambda+p-2p\lambda}{2(p+\lambda-p\lambda}\rho, \epsilon^*]$. In the first subrange, any bid price within $[(1-\epsilon)\mu, \mu)$ is weakly larger than $(1+\epsilon-\rho)\mu$ because $\epsilon \leq \frac{\rho}{2}$. Therefore, the investor sells with any bid price within $[(1-\epsilon)\mu, \mu)$ in Cases (1), (2), (3), and (5), implying a conditional expected asset value of $(1 - \frac{1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$. If $B > (1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$, the expected profit to the market makers is negative. In contrast, if $B < (1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$, the expected profit to the market makers is positive. Therefore, $\frac{1-(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$ is the unique competitive bid price in the first subrange.

In the second subrange, because $\frac{\rho}{2} < \epsilon \leq \frac{2\lambda+p-2p\lambda}{2(p+\lambda-p\lambda)}\rho < \rho$, $(1-\epsilon)\mu < (1+\epsilon-\rho)\mu \leq \mu$ and $(1-\rho)\mu < (1-\epsilon)\mu$. So, $(1+\epsilon-\rho)\mu$ is the only possible subjective valuation of the asset within $[(1-\epsilon)\mu, \mu)$. If $B \geq (1+\epsilon-\rho)\mu$, the investor sells in Cases (1), (2), (3), and (5). This means the conditional expected asset value is $(1-\frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$, which is greater than $(1+\epsilon-\rho)\mu$, as noted earlier. Therefore, $(1-\frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$ is the only possible competitive bid price that is weakly larger than $(1+\epsilon-\rho)\mu$ and less than μ. Suppose $B < (1+\epsilon-\rho)\mu$. Since $\epsilon < \rho$ implies $(1-\rho)\mu < (1-\epsilon)\mu$, the investor sells in Cases (2), (3), and (5). In this case, the conditional expected asset value is $(1-\frac{p}{p+2(1-p)\lambda}\epsilon)\mu$, which is weakly larger than $(1+\epsilon-\rho)\mu$ because $(1-\frac{p}{p+2(1-p)\lambda}\epsilon)\mu = (1+\epsilon-\frac{p+2(1-p)\lambda}{p+2(1-p)\lambda}\epsilon-\frac{p}{p+2(1-p)\lambda}\epsilon)\mu = (1+\epsilon-\frac{2p+2\lambda-2p\lambda}{p+2(1-p)\lambda}\epsilon)\mu \geq (1+\epsilon-\frac{2p+2\lambda-2p\lambda}{p+2(1-p)\lambda}\frac{2\lambda+p-2p\lambda}{2(p+\lambda-p\lambda)}\rho)\mu = (1+\epsilon-\rho)\mu$. So, a bid price less than $(1+\epsilon-\rho)\mu$ will lead to a positive expected profit to the market makers. In summary, $(1-\frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$ is the only possible competitive bid price when $\epsilon \leq \frac{2\lambda+p-2p\lambda}{2(p+\lambda-p\lambda}\rho < \epsilon^*$.

In the third subrange, with $\frac{\rho}{2} < \frac{2\lambda+p-2p\lambda}{2(p+\lambda-p\lambda)}\rho < \epsilon < \epsilon^* < \rho$, $(1-\frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$ is the only possible competitive bid price that is weakly larger than $(1+\epsilon-\rho)\mu$ and less than μ. However, there is a bid price less than $(1+\epsilon-\rho)\mu$ that also meets the zero-expected-profit condition. When $B < (1+\epsilon-\rho)\mu$, since $\epsilon < \rho$ implies $(1-\rho)\mu < (1-\epsilon)\mu$, the investor sells in Cases (2), (3), and (5), which leads to conditional expected asset value $(1-\frac{p}{p+2(1-p)\lambda}\epsilon)\mu$. Because $(1-\frac{p}{p+2(1-p)\lambda}\epsilon)\mu = (1+\epsilon-\frac{p+2(1-p)\lambda}{p+2(1-p)\lambda}\epsilon-\frac{p}{p+2(1-p)\lambda}\epsilon)\mu = (1+\epsilon-\frac{2p+2\lambda-2p\lambda}{p+2(1-p)\lambda}\epsilon)\mu < (1+\epsilon-\frac{2p+2\lambda-2p\lambda}{p+2(1-p)\lambda}\frac{2\lambda+p-2p\lambda}{2(p+\lambda-p\lambda)}\rho)\mu = (1+\epsilon-\rho)\mu$, $B = (1-\frac{p}{p+2(1-p)\lambda}\epsilon)\mu$ also satisfies the necessary condition for a competitive bid price. We assume that competition between market makers leads to the higher of the two zero-expected-profit bid prices in equilibrium, that is, $B = (1-\frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$.

Range (2):

When $\epsilon^* < \epsilon \leq \epsilon^{**}$, let $B = (1-\frac{p}{p+2(1-p)\lambda}\epsilon)$. We have that $B = (1+\epsilon-\epsilon-\frac{p}{p+2(1-p)\lambda}\epsilon) = (1+\epsilon-\frac{2p+2\lambda-2p\lambda}{p+2(1-p)\lambda}\epsilon)\mu < (1+\epsilon-\rho)\mu$, because $\epsilon^* < \epsilon$. Further,

$B = (1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu \geq (1-\rho)\mu$, because $\epsilon \leq \epsilon^{**}$. With this bid price, the investor sells in Cases (2), (3), and (5), implying a conditional expected asset value of $(1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$. So $B = (1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$ is a possible competitive bid price.

Next, we show that, when $\epsilon^* < \epsilon \leq \epsilon^{**}$, $B = (1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$ is the unique competitive bid price. To do so we separate the range $(\epsilon^*, \epsilon^{**}]$ into two subranges, (ϵ^*, ρ) and $(\rho, \epsilon^{**}]$, and we also consider the special case $\epsilon = \rho$. In the first subrange, $(1+\epsilon-\rho)\mu$ is the only possible subjective valuation of the asset within $[(1-\epsilon)\mu, \mu)$, because $\frac{\rho}{2} < \epsilon^* < \epsilon < \rho$ and $(1-\rho)\mu < (1-\epsilon)\mu$. If $B \geq (1+\epsilon-\rho)\mu$, the investor sells in Cases (1), (2), (3), and (5), leading to a conditional expected asset value of $(1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$. Because $(1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu = (1 + \epsilon - \frac{2(p+\lambda-p\lambda)}{2\lambda+(1-\lambda)p}\epsilon)\mu$ and $\epsilon > \epsilon^* = \frac{2\lambda+(1-\lambda)p}{2(p+\lambda-p\lambda}\rho$, $(1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu < (1+\epsilon-\rho)\mu$. Therefore, any bid price weakly higher than $(1+\epsilon-\rho)\mu$ gives a negative expected profit. If $B < (1+\epsilon-\rho)\mu$, the investor sells in Cases (2), (3), and (5), implying a conditional expected asset value of $(1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$. A bid price different from this conditional expected value and less than $(1+\epsilon-\rho)\mu$ will lead to a nonzero expected profit to the market makers. Therefore, $(1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$ is the only competitive bid price when $\epsilon^* < \epsilon < \rho$.

In the second subrange, (ρ, ϵ^{**}), $(1-\rho)\mu$ is the only possible subjective valuation within $[(1-\epsilon)\mu, \mu)$, because $\epsilon > \rho$ and $(1+\epsilon-\rho)\mu > \mu$. If $B \geq (1-\rho)\mu$, the investor sells in Cases (2), (3), and (5) giving a conditional expected asset value of $(1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$, which is weakly larger than $(1-\rho)\mu$ because $\epsilon \leq \epsilon^{**} \equiv \frac{p+2(1-p)\lambda}{p}\rho$. So, a bid price different from this conditional expected value and larger than $(1-\rho)\mu$ will lead to a nonzero profit to the market makers. If $B < (1-\rho)\mu$, the investor sells in Cases (3) and (5), implying a conditional expected asset value of $(1-\epsilon)\mu$, which is less than $(1-\rho)\mu$ because $\epsilon > \rho$. So, a bid price different from $(1-\epsilon)\mu$ and less than $(1-\rho)\mu$ will lead to a nonzero expected profit to the market makers. In summary, when $\epsilon \in (\rho, \epsilon^{**})$, $(1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$ and $(1-\epsilon)\mu$ are the only two possible competitive bid prices. Since $\epsilon \leq \epsilon^{**} \equiv \frac{p+2(1-p)\lambda}{p}\rho$, $(1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu \geq (1-\epsilon)\mu$. We again assume that competition leads to the higher of the two potential bid prices, $B = (1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$.

When $\epsilon = \rho$, $(1-\epsilon)\mu = (1-\rho)\mu$ and $(1+\epsilon-\rho)\mu = \mu$. As discussed earlier, a competitive bid price must be within the range of $[(1-\epsilon)\mu, \mu)$, which is equivalent to $[(1-\rho)\mu, (1+\epsilon-\rho)\mu) with \epsilon = \rho$. So, with a competitive bid price in this special scenario, the investor sells in Cases (2), (3), and (5), which means the conditional expected asset value is $(1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$. A bid price different from this conditional expected value will lead to nonzero profit to the market makers. Therefore, $B = (1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$ is the unique competitive bid price when $\epsilon = \rho$. In summary, $B = (1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$ is the competitive bid price for Range (2), $\epsilon^* < \epsilon \leq \epsilon^{**}$.

Range (3):
When $\epsilon > \epsilon^{**} > \rho$, a bid price at $(1-\epsilon)\mu$ leads to an investor sale in Cases (3) and (5) because $(1-\rho)\mu > (1-\epsilon)\mu$. This implies a conditional expected asset value of $(1-\epsilon)\mu$, which equals the bid price. So $(1-\epsilon)\mu$ is a possible competitive bid price.

Next, we show that, when $\epsilon > \epsilon^{**}$, $B = (1-\epsilon)\mu$ is the unique competitive bid price. When $\epsilon > \epsilon^{**} > \rho$, $(1-\rho)\mu$ is the only subjective valuation of the asset within $[(1-\epsilon)\mu, \mu)$. If $B \geq (1-\rho)\mu$, the investor sells in Cases (2), (3), and (5), leading to a conditional expected asset value of $(1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu$. Since $\epsilon > \epsilon^{**} \equiv \frac{p+2(1-p)\lambda}{p}\rho, (1 - \frac{p}{p+2(1-p)\lambda}\epsilon)\mu < (1-\rho)\mu$. Therefore, a bid price weakly larger than $(1-\rho)\mu$ will lead to a negative expected profit to the market makers. If $B < (1-\rho)\mu$, the investor sells in Cases (3) and (5), implying a conditional expected asset value of $(1-\epsilon)\mu$. So, a bid price larger than $(1-\epsilon)\mu$ and smaller than $(1-\rho)\mu$

will lead to a negative expected profit to the market makers. Therefore, when $\epsilon > \epsilon^{**}$, $(1-\epsilon)\mu$ is the unique competitive bid price.

■

Proof. Proof of Proposition 1: When relative fundamental uncertainty is intermediate and given the competitive bid price, in equilibrium the investor does not sell if she is subject to a liquidity shock and is also informed that the asset value is high. The probability of no sale conditional on a liquidity shock is $q = \frac{p}{2}$, and the expected cost of illiquidity is $\frac{p}{2}\lambda\rho\mu$. As a consequence, the value of the asset to the investor is reduced to $V_I = (1 - \frac{p}{2}\lambda\rho)\mu$. The improvement in social welfare is reduced to $(\delta - \frac{p}{2}\lambda\rho)\mu$, and the firm will choose not to complete the IPO if $\delta < \frac{p}{2}\lambda\rho$.

When relative fundamental uncertainty is high, the competitive bid price is less than the investors private valuation should she be subject to a liquidity shock (probability λ) and informed that the asset value is high (probability $\frac{p}{2}$). In addition, the bid price is now lower than the investors private valuation of $(1-\rho)\mu$ should she be uninformed (probability $1-p$) and subject to a liquidity shock (probability λ). The probability that the investor does not sell, conditional on a liquidity shock, is $q = \frac{p}{2} + (1-p) = (1-\frac{p}{2})$. The expected illiquidity cost is $(1-\frac{p}{2})\lambda\rho\mu$. The value of the asset to the investor is reduced to $V_I = (1-(1-\frac{p}{2})\lambda\rho)\mu$. The improvement in social welfare is $(\delta - (1-\frac{p}{2})\lambda\rho)\mu$ and the firm will choose not to complete the IPO if $\delta < (1-\frac{p}{2})\lambda\rho$. Since $(1-\frac{p}{2}) > \frac{p}{2}$ for all $p < 1$, the range of the firms liquidity needs, δ, over which the market fails completely is larger, and the IPO price and the increase in welfare should the IPO occur is reduced, when relative fundamental uncertainty is high rather than intermediate.

■

Proof. Proof of Lemma 3: With the bid price set to $B^* = (1+\epsilon-\rho)\mu$, when $\epsilon^* < \epsilon < \rho$, the investor sells at t=1 if she is (i) informed that the asset value is high and incurs the liquidity shock (which occurs with probability $\frac{p}{2}\lambda$), (ii) uninformed and incurs the liquidity shock (which occurs with probability $(1-p)\lambda$), or (iii) informed that the asset value is low (which occurs with probability $\frac{p}{2}$). The probability of an investor sale is $\frac{p}{2}\lambda + (1-p)\lambda + \frac{p}{2}$, while the expected asset value conditional on a sale is $(1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu$. The market makers expected monetary loss is the product of the probability of a sale conditional on the contracted bid and the difference between the expectation of the asset value conditional on a sale and the contracted bid price. That is, $M(B^*) = -(\frac{p}{2}\lambda + (1-p)\lambda + \frac{p}{2})[(1 - \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon)\mu - (1+\epsilon-\rho)\mu] = (\frac{p}{2}\lambda + (1-p)\lambda + \frac{p}{2}) * (\epsilon + \frac{(1-\lambda)p}{2\lambda+(1-\lambda)p}\epsilon - \rho)\mu = (\frac{p}{2}(1-\lambda)+\lambda)(\frac{2(p+\lambda-p\lambda)}{2\lambda+(1-\lambda)p}\epsilon - \rho)\mu = (\frac{p}{2}(1-\lambda)+\lambda)\rho(\frac{\epsilon}{\epsilon^*} - 1)\mu$, where $\epsilon^* = \frac{2\lambda+(1-\lambda)p}{2(p+\lambda-p\lambda)}\rho$. Since $\epsilon > \epsilon^*$, $M(B^*) > 0$.

When $\epsilon > \rho$, the investor sells at t=1 if she is (i) informed that the asset value is high and incurs a liquidity shock (which occurs with probability $\frac{p}{2}\lambda$), (ii) uninformed (which occurs with probability $(1-p)$), or (iii) informed that the asset value is low (which occurs with probability $\frac{p}{2}$). The probability of a sale is $\frac{p}{2}\lambda + (1-p) + \frac{p}{2}$, and the market makers expectation of the value of the asset conditional on a sale at $(1+\epsilon-\rho)\mu$ is $(1 - \frac{(1-\lambda)p}{2-(1-\lambda)p}\epsilon)\mu$. Hence, the market makers expected monetary loss is $M(B^*) = -(\frac{p}{2}\lambda + (1-p) + \frac{p}{2})[(1 - \frac{(1-\lambda)p}{2-(1-\lambda)p}\epsilon)\mu - (1+\epsilon-\rho)\mu] = (\frac{p}{2}\lambda + (1-p) + \frac{p}{2})[\epsilon + \frac{(1-\lambda)p}{2-(1-\lambda)p}\epsilon - \rho]\mu = (\epsilon - \rho + (1-\lambda)\frac{p}{2}\rho)\mu$. Because $\rho < \epsilon$, $M(B^*) > 0$.

■

Proof. Proof of Proposition 2: When relative fundamental uncertainty is intermediate or high, if the firm completes the IPO and enters into a DMM contract calling for a bid price $B^* = (1+\epsilon-\rho)\mu$, the probability that the investor will not sell after a liquidity shock is reduced to $q(B^*) = 0$. With this bid price the market maker suffers an expected monetary loss as specified in Lemma 3, leading to requisite compensation to the market maker of $C = M(B^*)$. Since the market makers expected monetary loss is also the investors expected monetary gain from trading, the IPO price becomes

$\mu + M(B^*)$. Therefore, the firms net gain from completing the IPO with the DMM contract is $\mu + M(B^*) - C - (1-\delta)\mu = \delta\mu$. Without a DMM contract, the firms net gain from completing the IPO is $(1 - q(B)\lambda\rho)\mu - (1-\delta)\mu = (\delta - q(B)\lambda\rho)\mu$, which is less than $\delta\mu$ because $q(B)\lambda\rho > 0$. Since $\delta\mu > 0$, it is optimal for the firm to complete the IPO with a DMM contract that calls for a bid price $B^* = (1+\epsilon-\rho)\mu$, which also maximizes the social welfare gain to $\delta\mu$.

■

Proof. Proof of the threshold levels of δ and β summarized in Table 3.2: Let π_{com} denote the firms gain from completing the IPO and relying on competitive liquidity provision, which is $\pi_{com} = \beta(\delta - \lambda\frac{p}{2}\rho)\mu$ when $\epsilon^* < \epsilon \leq \epsilon^{**}$, and is $\pi_{com} = \beta(\delta - \lambda(1-\frac{p}{2})\rho)\mu$ when $\epsilon > \epsilon^{**}$. Therefore, the δ^* that yields π_{com} equal to zero is $\lambda\frac{p}{2}\rho$ when $\epsilon^* < \epsilon \leq \epsilon^{**}$, and is $\lambda(1-\frac{p}{2})\rho$ when $\epsilon > \epsilon^{**}$. When $\delta < \delta^*$, $\pi_{com} < 0$. Otherwise, $\pi_{com} \geq 0$.

Let π_{DMM} denote the firms gain from the IPO with a DMM contract. When $\epsilon^* < \epsilon \leq \rho$, $\pi_{DMM} = \beta\delta\mu - (1-\beta)(\epsilon(p+\lambda-p\lambda) - \rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda))\mu$. If $\delta < \delta^*(\pi_{com} < 0)$, the threshold level of β that makes the firm indifferent between completing the IPO with a DMM contract and forgoing the IPO should satisfy $\pi_{DMM} = 0$. Therefore, in this case, the threshold β^* is $\frac{\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}{\delta+\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}$. If $\delta \geq \delta^*(\pi_{com} \geq 0)$, the threshold level of β that makes the firm indifferent between completing the IPO with and without a DMM contract should satisfy $\pi_{DMM} = \pi_{com}$. Therefore, in this case, the threshold β^* is $\frac{\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}{\lambda\frac{p}{2}\rho+\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}$.

Similarly, when $\rho < \epsilon \leq \epsilon^{**}$ or $\epsilon > \epsilon^{**}$, $\pi_{DMM} = \beta\delta\mu - (1-\beta)(\epsilon - \rho + (1-\lambda)\frac{p}{2}\rho)\mu$. If $\delta < \delta^*$ $(\pi_{com} < 0)$, the threshold level of β that makes the firm indifferent between completing the IPO with a DMM contract and forgoing the IPO should satisfy $\pi_{DMM} = 0$. Therefore, in this case, the threshold β^* is $\frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\delta+\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}$. If $\delta \geq \delta^*(\pi_{com} \geq 0)$, the threshold level of β that makes the firm indifferent between completing the IPO with and without a DMM contract should satisfy $\pi_{DMM} = \pi_{com}$. When $\rho < \epsilon \leq \epsilon^{**}$, $\pi_{com} = \beta(\delta - \lambda\frac{p}{2}\rho)\mu$. Therefore, the threshold $\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\epsilon-\rho+\frac{p}{2}\rho}$. When $\epsilon > \epsilon^{**}$, $\pi_{com} = \beta(\delta - \lambda(1-\frac{p}{2})\rho)\mu$. Therefore, the threshold $\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho+\lambda\frac{p}{2}\rho+\lambda(1-p)\rho}$.

The derivatives of β^* with respect to the exogenous parameters λ, ρ, and p: When $\epsilon^* < \epsilon \leq \rho$ and $\delta < \lambda\frac{p}{2}\rho$, $\beta^* = \frac{\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}{\delta+\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}$. We have

$\frac{d\beta^*}{dp} = \frac{2\delta(2\epsilon-\rho)(1-\lambda)}{(2\delta+2\epsilon p+2\epsilon\lambda-2\epsilon\lambda p-\rho p-2\rho\lambda+\lambda p\rho)^2} \geq 0$ because $\frac{\rho}{2} < \epsilon^* < \epsilon$ and $0 < \lambda \leq 1$;[1]

$\frac{d\beta^*}{d\lambda} = \frac{2\delta(2(\epsilon-\rho)(1-p)-\rho p)}{(2\delta+2\epsilon p+2\epsilon\lambda-2\epsilon\lambda p-\rho p-2\rho\lambda+\lambda p\rho)^2} < 0$ because $\epsilon \leq \rho$ and $0 < p \leq 1$; and

$\frac{d\beta^*}{d\rho} = \frac{2\delta(\lambda p-2\lambda-p)}{(2\delta+2\epsilon p+2\epsilon\lambda-2\epsilon\lambda p-\rho p-2\rho\lambda+\lambda p\rho)^2} < 0$ because $0 < p \leq 1$ and $0 < \lambda \leq 1$.

When $\epsilon^* < \epsilon \leq \rho$ and $\delta \geq \lambda\frac{p}{2}\rho$, $\beta^* = \frac{\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}{\lambda\frac{p}{2}\rho+\epsilon(p+\lambda-p\lambda)-\rho(\frac{1}{2}p+\lambda-\frac{1}{2}p\lambda)}$. We have

$\frac{d\beta^*}{dp} = \frac{2\rho\lambda^2(\rho-\epsilon)}{(2\epsilon p+2\epsilon\lambda-2\epsilon\lambda p-\rho p-2\rho\lambda+2\lambda p\rho)^2} \geq 0$ because $\epsilon \leq \rho$;[2]

$\frac{d\beta^*}{d\lambda} = \frac{\rho p(\rho-2\epsilon)}{(2\epsilon p+2\epsilon\lambda-2\epsilon\lambda p-\rho p-2\rho\lambda+2\lambda p\rho)^2} < 0$ because $\frac{\rho}{2} < \epsilon^* < \epsilon$; and

$\frac{d\beta^*}{d\rho} = \frac{2\epsilon\lambda p(\lambda p-\lambda-p)}{(2\epsilon p+2\epsilon\lambda-2\epsilon\lambda p-\rho p-2\rho\lambda+2\lambda p\rho)^2} < 0$ because $0 < p \leq 1$, $0 < \epsilon \leq 1$, and $0 < \lambda \leq 1$.

When $\rho < \epsilon \leq \epsilon^{**}$ and $\delta < \lambda\frac{p}{2}\rho$, and when $\epsilon > \epsilon^{**}$ and $\delta < \lambda(1-\frac{p}{2})\rho$,

[1] The equality arises when $\lambda = 1$. Here, the investor always incurs a liquidity shock and always sells if the bid price is set to $B^* = (1+\epsilon-\rho)\mu$. In this case the probability of receiving private information no longer affects the equilibrium, and $\frac{d\beta^*}{dp} = 0$.

[2] The equality arises when $\rho = \epsilon$. The intuition is as follows. With $\delta \geq \lambda\frac{p}{2}\rho$, the net gain from completing the IPO with competitive market makers is positive, so the decision of whether to engage a market maker depends on the comparison between net gains from completing the IPO with and without a DMM contract. The net gain from completing the IPO with and without a DMM contract decreases with p at the same speed when $\rho = \epsilon$, so the difference between the net gains of these two options does not change with p. This leads to a derivative of β^* with respect to p equal to zero.

$\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\delta+\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}$. We have

$\frac{d\beta^*}{dp} = \frac{2\rho\delta(1-\lambda)}{(2\delta+2\epsilon-2\rho+\rho p-\lambda p\rho)^2} \geq 0$ because $0 < \lambda \leq 1$ and $0 < p \leq 1$;

$\frac{d\beta^*}{d\lambda} = \frac{-2p\rho\delta}{(2\delta+2\epsilon-2\rho+\rho p-\lambda p\rho)^2} < 0$; and

$\frac{d\beta^*}{d\rho} = \frac{-2(2-p+\lambda p)\delta}{(2\delta+2\epsilon-2\rho+\rho p-\lambda p\rho)^2} < 0$ because $0 < \lambda \leq 1$ and $0 < p \leq 1$.

When $\rho < \epsilon \leq \epsilon^{**}$ and $\delta \geq \lambda\frac{p}{2}\rho$, $\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\lambda\frac{p}{2}\rho+\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}$. We have

$\frac{d\beta^*}{dp} = \frac{2\rho\lambda(\rho-\epsilon)}{(2\epsilon-2\rho+\rho p)^2} < 0$ because $\rho < \epsilon$;

$\frac{d\beta^*}{d\lambda} = \frac{-\rho p}{2\epsilon-2\rho+\rho p} < 0$ because $\rho < \epsilon$; and

$\frac{d\beta^*}{d\rho} = \frac{-2\lambda\epsilon p}{(2\epsilon-2\rho+\rho p)^2} < 0$.

When $\epsilon > \epsilon^{**}$ and $\delta \geq \lambda(1-\frac{p}{2})\rho$, $\beta^* = \frac{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho}{\epsilon-\rho+(1-\lambda)\frac{p}{2}\rho+\lambda\frac{p}{2}\rho+\lambda(1-p)\rho}$. We have

$\frac{d\beta^*}{dp} = \frac{2\lambda\rho(\epsilon-\lambda\rho)}{(2\epsilon-2\rho+\rho p-2\lambda p\rho+2\lambda\rho)^2} > 0$ because $\epsilon > \rho$;

$\frac{d\beta^*}{d\lambda} = \frac{\rho(p-2)(\rho p-2\rho+2\epsilon)}{(2\epsilon-2\rho+\rho p-2\lambda p\rho+2\lambda\rho)^2} < 0$ because $\epsilon > \rho$; and

$\frac{d\beta^*}{d\rho} = \frac{2\lambda\epsilon(p-2)}{(2\epsilon-2\rho+\rho p-2\lambda p\rho+2\lambda\rho)^2} < 0$.

■

Proof. A possible DMM contract calling for a bid quote $\hat{B} = (1-\rho)\mu < B^*$: In this model, aggregate welfare gains shift at certain levels of B, but are constant within these breakpoints. Below we show that only two potentially relevant bid prices are associated with shifts in aggregate welfare. These are $B^* = (1+\epsilon-\rho)\mu$ and $\hat{B} = (1-\rho)$. For simplicity we focus on the smallest bid price that generates a given possible welfare gain. In general an increase in the bid price leads to a higher IPO price, greater market-maker losses, and a larger requisite payment from the firm to the market maker, but these increased cash flows are zero-sum except at the discrete points identified.

When relative fundamental uncertainty is intermediate, $B^* = (1+\epsilon-\rho)\mu$ is the only breakpoint relevant to the analysis, and the firm chooses between no IPO, IPO without a DMM contract, and IPO with a DMM contract calling for a bid quote equal to B^*. When relative fundamental uncertainty is high, the competitive bid quote is less than $\hat{B} = (1-\rho)\mu$, giving rise to a fourth possibility, that the firm completes the IPO but contracts for a bid quote of $\hat{B} < B^*$. When $\beta = 1$ the firm would not consider this alternative, but would maximize their gain from trade by contracting for $B = B^*$. However, when $\beta < 1$ the firm might prefer to contract for $B = \hat{B}$. In this case, $q(\hat{B}) > 0$ and $C = M(\hat{B}) > 0$, and the firm's net gain if it conducts the IPO and enters into the DMM agreement for this lower bid price $\hat{B}$ is $\pi = \beta\mu(\delta - q(\hat{B})\lambda\rho) - M(\hat{B})(1-\beta)$. Recall that the firm's net gain if it conducts the IPO without a DMM agreement is $\pi = \beta\mu(\delta - q(B)\lambda\rho)$ and the firm's net gain if it conducts the IPO with a DMM agreement for B^* is $\pi = \beta\mu(\delta - q(B^*)\lambda\rho) - M(B^*)(1-\beta)$.

Complete market failure occurs if the firm's net gain from completing the IPO is negative without or with a DMM agreement calling for a bid price at either B^* or $\hat{B}$. That is, the market fails completely if $\delta < q(B)\lambda\rho$ and $\beta < min\{\frac{M(B^*)}{M(B^*)+\mu\delta}, \frac{M(\hat{B})}{M(\hat{B})+\mu\delta-q(\hat{B})\lambda\rho\mu}\}$.

Partial market failure, in the sense that the firm completes the IPO but does not enter into any DMM agreement, occurs if the firm's net gain without a DMM agreement is positive and higher than the net gain with a DMM agreement calling for a bid price at either B^* or $\hat{B}$. That is, $\delta \geq q(B)\lambda\rho$ and

$$\beta < min\{\frac{M(B^*)}{M(B^*)+q(B)\lambda\rho\mu}, \frac{M(\hat{B})}{M(\hat{B})+(q(B)-q(\hat{B}))\lambda\rho\mu}\}.$$

Partial market failure, in the sense that the firm completes the IPO and enters into a DMM agreement calling for $\hat{B} = (1-\rho)\mu$ rather than B^*, occurs if the firm's net gain with a DMM agreement calling for $\hat{B}$ is positive and higher than the net gain without a DMM agreement or with a DMM agreement calling for B^*. This occurs if $max\{\frac{M(\hat{B})}{M(\hat{B})+(q(B)-q(\hat{B}))\lambda\rho\mu}, \frac{M(\hat{B})}{M(\hat{B})+\mu\delta-q(\hat{B})\lambda\rho\mu}\} < \beta < \frac{M(B^*)-M(B)}{M(B^*)-M(\hat{B})+q(\hat{B})\lambda\rho\mu}$.
Stated alternatively, the firm would choose to complete the IPO with a DMM agreement calling for a bid price at $B^* = (1+\epsilon-\rho)\mu$ if

$$\beta \geq max\{\frac{M(B^*)}{M(B^*)+\mu\delta}, \frac{M(B^*)}{M(B^*)+q(B)\lambda\rho\mu}, \frac{M(B^*)-M(\hat{B})}{M(B^*)-M(\hat{B})+q(\hat{B})\lambda\rho\mu}\}.$$

Thus, consistent with the simpler case addressed in the main text, the market fails partially or completely if the firm's bargaining power is less than a critical level that depends on the magnitude of the required payment to the market maker.

■

Proof. Proof that the only two bid prices associated with shifts in aggregate welfare are B^* and $\hat{B}$: In principle the firm could contract with the DMM to quote at any price greater than the competitive quote. We confine our attention to the economically relevant cases, which range from the competitive bid quote to the highest possible asset value $(1+\epsilon)\mu$.

When relative fundamental uncertainty is high ($\epsilon > \epsilon^{**} \equiv \frac{(p+2(1-p)\lambda}{p}\rho$), the competitive bid price is $(1-\epsilon)\mu$. Because $(1-\epsilon)\mu < (1-\rho)\mu < (1+\epsilon-\rho)\mu$, the investor sells in Cases (2) and (5) displayed in Figure C.1. The range of possible contract prices is $(1-\epsilon)\mu < B \leq (1+\epsilon)\mu$. When $B \in ((1-\epsilon)\mu, (1-\rho)\mu)$, the investor sells in Case (2) and (5). This trading behavior is the same as that with competitive bid price $(1-\epsilon)\mu$, implying that a contracted bid price in this range does not improve liquidity or welfare.

When $B \in [(1-\rho)\mu, \mu)$, the investor sells in Cases (2), (3), and (5). Because the investor changes from no sell to sell in Case (3) at a contracted price $B \in [(1-\rho)\mu, \mu)$, the illiquidity cost is reduced from $(1-\frac{p}{2})\lambda\rho\mu$ to $\frac{p}{2}\lambda\rho\mu$ at that point. Any contracted bid price within this range will lead to the same reduction, $(1-p)\lambda\rho\mu$, in expected illiquidity cost. When $\beta = 1$ the firm's net gain is $(1-p)\lambda\rho\mu$ and the firm is indifferent among contracted bid prices in the region $[(1-\rho)\mu, \mu)$. However, when $\beta < 1$, the compensation to the market maker is not fully recovered from the higher IPO price. The net gain from the IPO is $\beta(1-p)\lambda\rho\mu - (1-\beta)M(B)$, which decreases with B. Therefore, the firm prefers $B = (1-\rho)\mu$ to other contract prices in the region $[(1-\rho)\mu, \mu)$.

When $B \in [\mu, (1+\epsilon-\rho)\mu)$, the investor sells in Cases (2), (3), (4), and (5). Because the investor changes from no sell to sell in Case (3) with a contracted price $B \in [\mu, (1+\epsilon-\rho)\mu)$, the illiquidity cost is reduced from $(1-\frac{p}{2})\lambda\rho\mu$ to $\frac{p}{2}\lambda\rho\mu$. Note that the change from no trade to trade in Case (4) does not change the expected illiquidity cost because there is no liquidity shock in Case (4). With a bid price in the range of $[\mu, (1+\epsilon-\rho)\mu)$, the reduction in illiquidity cost is the same as that from a bid price $B = (1-\rho)\mu$, while the required compensation is higher. Therefore, the firm prefers $B = (1-\rho)\mu$ to any contract price in the region $[\mu, (1+\epsilon-\rho)\mu)$.

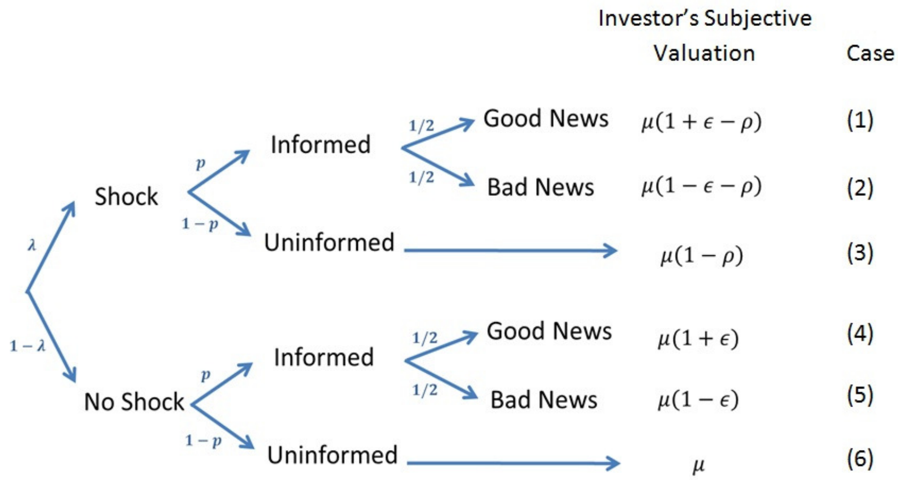
When $B \in [(1+\epsilon-\rho)\mu, (1+\epsilon)\mu)$, the investor sells in Cases (1), (2), (3), (5), and (6). Because the investor always sells after incurring a liquidity shock with a contracted price $B \in [(1+\epsilon-\rho)\mu, (1+\epsilon)\mu)$, the illiquidity cost is reduced from $(1-\frac{p}{2})\lambda\rho\mu$ to zero. Given $\beta = 1$, the firm is indifferent among prices in the region

$[(1+\epsilon-\rho)\mu,(1+\epsilon)\mu)$, while the firm prefers $B=(1+\epsilon-\rho)\mu$ when $\beta<1$. Therefore, when relative fundamental uncertainty is high there are only two relevant contract prices, $B^{*}=(1+\epsilon-\rho)\mu and \hat{B}=(1-\rho)$.

When relative fundamental uncertainty is intermediate, the competitive bid price is $(1-\frac{p}{p+2(1-p)\lambda}\epsilon)\mu$, which is weakly larger than $(1-\rho)\mu$. Therefore, $(1-\rho)\mu$ is not a liquidity-improving bid price. As discussed in the case with high relative fundamental uncertainty, $B=(1+\epsilon-\rho)\mu$ weakly dominates other possible contract prices. Therefore, we need only consider one possible contract price $B^{*}=(1+\epsilon-\rho)\mu$ when relative fundamental uncertainty is intermediate.

■

Figure C.1: **The subjective valuation of the asset to the investor at t=1.** The four lines represent the average equity ratios of four portfolios, where year zero is the interstate deregulation year and the year -1 is the portfolio formation year. Banks are sorted into quartiles based on their equity ratio in year -1. Holding the portfolios fixed for the next six years I compute the average equity for each portfolio.



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