Bank Liquidity Creation and Risk-Taking: Does Managerial Ability Matter?

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Abstract

This study investigates the impact of managerial ability on banks' liquidity creation and risk-taking behavior. We find that higher ability managers create more liquidity and take more risk. During financial crisis times, however, higher ability bank managers reduce liquidity creation as a way to de-leverage their balance sheets. Our findings inform recent theoretical and empirical studies that investigate determinants of liquidity creation and risk by introducing managerial ability as a prominent antecedent of the banks' intermediation and risk-transforming service. Moreover, this study has policy-related implications, since managerial ability can be quantified as a key performance indicator for prudential supervision of banks and could help regulators to target intervention efforts more purposefully during crisis times.

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1. Introduction

Bank intermediation, as facilitated by liquidity creation, is one of the central services banks provide for the economy. Surprisingly, this core function of banks has only recently received attention in the empirical literature (see, for example, Berger and Bouwman, 2009). Similarly, the impact of managerial ability on a firm's outcome has long been ignored, under the assumption that managers are largely homogeneous entities that follow identical goals. Only recently has this view been challenged by a growing body of literature that recognizes the impact that managers have on firm performance (see, for example, Bamber, Jiang, and Wang, 2010; Bertrand and Schoar, 2003; Demerjian, Lev, and McVay, 2012). Understanding the link between managerial ability and bank intermediation is important, especially for policy-makers and regulators. This study is the first to contribute to this discussion by investigating the impact of managerial ability on bank liquidity creation. Since risk transformation may coincide with liquidity creation, this paper also makes assertions regarding the impact of managerial ability on bank risk-taking behavior.

The main goals of this study are twofold. Firstly, we investigate whether managerial ability has a positive impact on bank liquidity creation. More ably managed banks have, for example, been found to report higher quality earnings (see, for example, Cantrell, 2013). Higher ability managers are also found to decisively influence corporate outcomes (Bertrand and Schoar, 2003; Choi, Han, Jung, and Kang, 2015; Dejong and Ling, 2013) and to positively affect firm performance (see, for example, Demerjian, Lev, and McVay, 2012) in industrial firms. Liquidity creation is a key feature of a bank's outcome and has been shown to be positively related to bank performance (Berger and Bouwman, 2009). Hence it is reasonable to assume that more able managers will leverage their bank's assets to create greater liquidity, aiming for higher performance. Therefore, we hypothesize that more able managers create more liquidity. In addition, we postulate that, because of their superior ability, more able bank managers can better manage, and in fact do take, more risk. This is a natural corollary to the above argumentation since, as shown in Berger and Bouwman (2009), banks' risk-taking is linked to liquidity creation, as for example when banks issue risk-less liquidity deposits to finance risky illiquid loans.

Secondly, we investigate the link between managerial ability and liquidity expansion or contraction caused by adverse economic shocks, such as the ones evidenced during the recent financial crisis. On the managerial ability ambit, Andreou, Ehrlich, Karasamani, and Louca (2015) find that higher ability managers invest more during the recent financial crisis period compared to their less able peers, because they reduce the information asymmetry gap with the markets and have greater capacity to access financing resources; this evidence lends support to the notion that managerial ability effectiveness is heightened during such periods. On the bank intermediation ambit, Bebchuk and Goldstein (2011) develop a theory to support the hypothesis that it may be individually optimal for banks to curtail their intermediation activity in the face of negative shocks to the economy. In this respect, Ivashina and Scharfstein (2010) report that loans extended by banks to large borrowers were significantly reduced during the recent financial crisis. However, Berger and Bouwman (2014) (see also discussions in Berger and Bouwman, 2009, 2013) present empirical evidence to the contrary. Their collective findings indicate that some banks may even increase liquidity creation during crises and that such an increase improves these banks' value creation and competitiveness. This suggests that during crises managers under certain conditions may have incentives to expand the intermediation activity. Banks led by more able managers should therefore be in a much better position to either contract or expand liquidity in crises, if it is indeed optimal for them to do so. In this paper, we develop arguments that lead to testable hypotheses that take into account the divergent views in the literature. As previously, it is again reasonable to consider a corollary risk-taking hypothesis that emerges from the banks' liquidity creation behavior; hence we hypothesize as to whether higher ability bank managers take more or less risk during the financial crisis.

Our empirical tests utilize data from virtually every US bank from 1994 to 2010, comprising 100,976 bank-year observations. Berger and Bouwman (2009) show that liquidity creation differs considerably among large banks (those with gross total assets (GTA) exceeding \$3 billion), medium banks (those with GTA of \$1 billion to \$3 billion), and small banks (those with GTA up to \$1 billion). Therefore, since size differences among banks are substantial in terms of liquidity creation, our empirical mediation also takes into account these three size groups separately. With respect to bank liquidity creation, we rely on the main measure as operationalized in the seminal work of Berger and Bouwman (2009), which accounts for a bank's liquidity creation due to on- and off-balance-sheet activities. To quantify managerial ability, we elaborate on the methodological ideas in Demerjian, Lev, and McVay (2012), adjusted however to the banking environment confronted in our study. In particular, we employ stochastic frontier analysis to compare bank managers' efficiency relative to their industry peers regarding the transformation of corporate resources to profits, a process that is in line with the important tenet of a profit-maximizing firm. Managerial ability is then estimated out of the efficiency scores after taking into account a large array of bank-specific characteristics that cannot be attributed to the management team.

For our empirical analysis, we regress bank liquidity creation and risk measures on the lagged managerial ability while controlling for other bank-related characteristics that may affect those dependent variables. We use the dollar amount of bank liquidity divided by GTA as our measure of bank liquidity creation, since, as explained in Berger and Bouwman (2009), it is necessary to make the liquidity measure meaningful and comparable across banks, while avoiding to give undue weight to the largest institutions. Regarding risk measures, we rely on the widely applied risk proxies that capture a bank's fragility such as the: (i) tier 1 ratio calculated as tier 1 capital divided by risk weighted assets using Basel II rules, (ii) risk-weighted assets divided by GTA, and (iii) Z-Score, which captures distance from default. To avoid omitted variables, we include (depending on the regression specification) a large array of control variables, such as risk, size, bank holding company membership, merger and acquisition history, local market competition, economic environment, and bank cost efficiency score. In the empirical investigations of our hypotheses, for all of the variables relating to managerial ability and other bank characteristics, we use lagged values rather than contemporaneous values to mitigate endogeneity concerns that may arise from reverse causality.

Consistent with our hypotheses, the results show that managerial ability is significantly positively related to liquidity creation for small and medium-sized banks as well as for the overall sample. We also find that, for the case of medium and large banks, higher managerial ability contributes significantly to the riskiness of the bank. For small banks, this relation is reversed; yet, this can be rationalized since small banks are confronted with very different incentives, funding constraints and regulatory scrutiny, which may force higher managerial ability bank managers to handle risk differently from their peers who lead larger-sized banks. Regarding the effects of managerial ability on liquidity creation and risk-taking during the financial crisis, findings reveal that more able managers significantly reduce both their banks' liquidity and risk during this period. A large set of robustness checks regarding the definition of the liquidity creation measure, alternative construction methods for the managerial ability measure, and various treatments for endogeneity concerns reveal that our results remain unchanged and provide qualitatively similar conclusions.

The results in this paper contribute to the understanding of the banking industry in several important ways. This is the first study to investigate the impact of managerial ability on the liquidity creation of banks. It is also the first study that links bank risk-taking to the ability of managers. These findings offer a nexus of vital information to assess banks following the CAMELS rating criteria.[1] Moreover, our findings provide valuable evidence regarding the impact of financial crises on

[1]CAMELS is an acronym for Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity

bank liquidity creation and risk-taking through the channel of managerial ability. Our study adds to the body of evidence provided by recent papers such as, for example, those of Berger and Bouwman (2009) and Berger and Bouwman (2014), which aim to understand what drives bank liquidity creation and risk-taking, among other things.

This paper is also of particular interest to policy-makers, since it can inform decisions on the allocation of supervision resources and support funding, especially in times of crises. In this respect, since managerial ability is found to exert a significant impact on bank liquidity creation, it has the potential to act as an important performance indicator for regulators. Distinguishing between more or less ably managed banks would enable the regulator to target intervention efforts more purposefully. Additionally, since managerial ability has a clear link to risk-taking behavior, it can further inform the prudential supervision of banks. Information about factors that facilitate intermediation activity and risk-taking becomes even more valuable in times of crisis. In such times, regulator- and supervision-monitoring need to trade-off moral hazard concerns against the risk of premature liquidation of positive NPV projects by banks, which may lead to financial contagion between banks. Thus, if managerial ability can predict liquidity creation and risk of banks during crises, the policy-maker may wish to consider this when deciding which banks to support and which to allow to fail.

The rest of this paper is organized as follows. Section 2 reviews the various strands of the literature and develops the hypotheses. Section 3 discusses the construction of the managerial ability measure for banks. The empirical analyses are reported in Section 4, while Section 5 discusses various robustness checks. Section 6 concludes.

2. Review of the Literature and Development of Hypotheses

This section discusses the literature underpinning the subsequent analysis. Firstly, we summarize the growing literature related to managerial ability and its importance for firm organizational outcomes. Secondly, we discuss liquidity creation and risk-taking behavior of banks. Finally, this discussion motivates predictions about the impact of managerial ability on liquidity creation and risk-taking.

2.1. The Importance of Managerial Ability for Firm Outcomes

Where the impact of firm management is concerned, mainstream finance and accounting research has largely followed the neoclassical paradigm, which leaves only limited space for manager idiosyncrasies

to market risk. As discussed for example in Federal Reserve Bank of San Francisco (1999), the "Management" component specifically targets the quality of bank management.

(Berk and Stanton, 2007). The agency theoretical paradigm, frequently encountered in banking, relaxes the stringency of the neoclassical view, but still posits that individuals are more or less homogeneous and merely react rationally to the regulations and incentives that surround them (see Bamber, Jiang, and Wang, 2010, for further discussion).

The management literature, on the other hand, has long emphasized the importance of managers for the outcomes achieved by the enterprise. One theoretical approach that has formalized reasons for the pervasiveness of management factors in driving success is summarized by Hambrick and Mason's (1984) and Hambrick's (2007) upper echelons theory. This theory predicts that the complexity of actual decision-making situations necessitates an idiosyncratic importance of the top management team. Hence a growing literature attempts to investigate the importance of managers for firm outcomes. For instance, Bertrand and Schoar (2003) find that managers influence their organization's behavior over and above time- and firm-specific characteristics. Management ability has been shown to have a distinct effect on a firm's disclosure policies, accounting behavior and reporting quality incrementally to the effects driven from the firm and environment characteristics (see, for example, Bamber, Jiang, and Wang, 2010, Ge, Matsumoto, and Zhang, 2011, Dejong and Ling, 2013, Choi, Han, Jung, and Kang, 2015, among others). Similarly, Rajgopal, Shevlin, and Zamora (2006) find that CEO compensation is systematically linked to talent, which indicates that the ability of managers is recognized by the firm. Moreover, Leverty and Grace (2012) suggest that managerial ability is important and economically significant in terms of influencing firm performance. Finally, Beatty and Liao (2011) find that more ably managed banks forecast loan losses better and thus recognize these earlier. Thus, the recent literature shows the importance of manager idiosyncrasies for firm policies and performance.

2.2. Liquidity Creation and Risk-taking

Bank liquidity creation is widely considered as one of the main raisons d'être for intermediaries. Liquidity creation is the ability of banks to transform more liquid liabilities into less liquid assets and many small units of deposits into fewer larger units of loans. The extent to which banks are able to do this is reflected in the overall amount of liquidity created. In the simplest sense, banks create liquidity when they use short-term liabilities to fund long-term assets as is, for example, the case when demand deposits are used to fund commercial and industrial loans. In this case, depositors maintain easy and immediate access to their funds, while firms receive liquidity for a longer contractually defined time period. This liquidity transformation process involves banks taking more risk, although the amount of liquidity created does not always move in tandem with the amount of risk piled up in the process. The loan portfolios maintained by the banks reflect the bank manager's trade-off between risk and performance in a unique way. In other words, bank managers balance profit and wealth maximization objectives against their appetite for risk. They do so by choosing optimal sources of funding and the corresponding allocations for those funds, according to the risk-performance characteristics of the available assets and liabilities. This process ultimately determines the quantity of liquidity created. In this respect, Berger and Bouwman (2009) go on to show that it is primarily large banks that create liquidity, and that liquidity creation is inextricably linked to bank riskiness, it is value-relevant and sensitive to crises. Berger and Bouwman (2013) also find that banks that were better capitalized and thus more resilient prior to and during financial crises benefited with respect to their market share in terms of liquidity creation as well as value creation, post crisis.

Recent work by Berger and Bouwman (2009) provides an operational measure of liquidity creation, hereinafter $CATFAT$, which is used in this study. To obtain this measure, all assets and liabilities are categorized (hence the CAT acronym) by the effort, duration and cost required to liquidate a given asset or liability in the market. The measure is constructed on the premise that if a liability (an asset) is easy (difficult) to liquidate quickly at low (high) cost, the position contributes to liquidity creation. Following Berger and Bouwman (2009), we define three classes for the assets and liabilities, and then assign heuristic weights of $\frac{1}{2}$, 0 or $-\frac{1}{2}$ to each class, according to whether it is deemed to create liquidity, be neutral, or destroy liquidity. This heuristic choice of weights reflects the postulate that maximum liquidity of unity should be created or destroyed if a liquid liability is used to create an illiquid asset or vice versa. Semiliquid assets and liabilities are assigned zero weights, so as to err on the side of caution in terms of the classification procedure outlined above. The $CATFAT$ measure also includes off-balance-sheet items in the analysis (hence the FAT acronym). Thus, this procedure is logically consistent, while being more refined than the simple description of bank liquidity creation provided initially by Deep and Schaefer (2004) since it allows for the destruction of liquidity, takes into account medium term assets and liabilities, and explicitly recognizes the importance of off-balance-sheet items.[2]

[2]Berger and Bouwman (2009) also carry out tests where off-balance-sheet items are omitted ($CATNONFAT$) or where assets and liabilities are categorized purely based on their maturity ($MATFAT$, $MATNONFAT$). However, their investigation shows that the $CATFAT$ measure is best able to capture bank liquidity creation.

2.3. Development of Hypotheses

The discussion in Section 2.1 has shown that more able managers tend to run more successful firms (see, for example, Bertrand and Schoar, 2003; Bamber, Jiang, and Wang, 2010 and Ge, Matsumoto, and Zhang, 2011). By the same token, banks managed by more able top management teams can also be expected to display a superior performance. As discussed in Section 2.2, one key feature of bank performance is the creation of liquidity. Hence it seems reasonable to suppose that more ably managed banks will also create more liquidity. Notice that this hypothesis does not require the assumption that managers explicitly target liquidity creation. It simply relies on the superior funding and allocation choices made by more able managers. This claim has so far not been investigated in the empirical or theoretical literature and motivates the first hypothesis:

H1: Ability-Liquidity hypothesis*: More (less) ably managed banks create more (less) liquidity per dollar of assets.*

A second important question concerns the impact that more able managers have on bank risk-taking. Intuitively, more able managers should be confident in their ability to take desirable, controlled risk in the process of creating more liquidity. Hence, one might expect that more able managers will also be found to take more risk overall and this motivates the second hypothesis:

H2: Ability-Risk hypothesis*: More (less) ably managed banks take greater (lesser) risk.*

Notice that this hypothesis is a corollary to the first. Broadly speaking, if creating more liquidity involves borrowing short and lending long, banks that create more liquidity should be more risky. Thus, if hypothesis $H1$ finds support in the data we should expect hypothesis $H2$ to be supported as well.

Another interesting question relates to the interplay between managerial ability and liquidity creation as well as that between managerial ability and risk during times of crisis. Forming a reasonable prior about the impact that managerial ability is likely to have on liquidity creation in crisis times is not straightforward. On the one hand, the collective findings of Berger and Bouwman (2009, 2013) document that banks that were well capitalized and expanded their liquidity creation market share during and post crises were able to benefit in terms of value creation. This suggests that there is an incentive for managers to increase liquidity creation during crises in order to take advantage of subsequent value gains. Ceteris paribus, more able managers should be better able to exploit these opportunities. It follows that one ought to expect more ably managed banks to expand liquidity creation during crises. On the other hand, the theory of Bebchuk and Goldstein (2011) suggests the opposite. More specifically, in an economy where the success of loans to industrial firms depends on the overall volume of loans extended by banks, it may be individually rational for banks to reduce intermediation activity following a negative shock to the economy. This follows from each bank's expectation that other banks will also curtail their intermediation activity and hence failure rates among industrial firms will be high. The financial crisis would certainly qualify as such a negative shock. Therefore one can argue that it is individually optimal for banks to reduce intermediation activity in this case. Again, more able managers should be expected to react more effectively in order to protect their banks from risk. Hence, to capture the opposing views in the literature, the third hypothesis has two propositions:

H3a: Ability-Liquidity Expansion hypothesis*: More ably managed banks increase liquidity creation per dollar of assets during crisis times.*

H3b: Ability-Liquidity Contraction hypothesis*: More ably managed banks decrease liquidity creation per dollar of assets during crisis times.*

Finally, crisis events are frequently marked by a flight to quality and de-leveraging, respectively (see, for example, Brunnermeier, 2009). Angelopoulos and Georgopoulos (2015) also report that the crisis reverses the generally positive value effect of income diversification and intensifies the value premium of efficient cost management. This is the natural reaction of a bank to adverse economic shocks because it serves to protect its valuable charter from the impact of the shock. Ceteris paribus, more able managers should be in a better position to actively respond to such a shock by de-leveraging. On the contrary, Beatty and Liao (2011) show that better managers, those who write down nonperforming loans in a more timely fashion, experience considerably fewer reductions in lending during recessionary, relative to expansionary, periods. This suggests that the risk that has been taken by managers of greater ability has been reliably estimated beforehand and need not be hidden from outsiders by, for example, rolling over bad loans (see, for example, Aghion, Bolton, and Fries, 1999; Mitchell, 2001). At the same time, while there can be instances where banks do not create liquidity, they may still provide a valuable risk-transformation service for the economy (Berger and Bouwman, 2009). Due to the divergent views in the literature on the relation between liquidity creation and the banks' risk behavior during crisis times, the fourth hypothesis again has two components:

H4a: Ability-Risk Expansion hypothesis*: More ably managed banks increase risk during crisis times.*

H4b: Ability-Risk Contraction hypothesis*: More ably managed banks decrease risk during crisis times.*

3. Estimating Managerial Ability for Banks

For a long time, managerial ability, being latent, has been a very challenging concept to operationalize empirically. Thus the focus of prior literature has been first on CEO fixed effects (Bertrand and Schoar, 2003), second on CEO press visibility (Francis, Huang, Rajgopal, and Zang, 2008) and third on firm performance (Barr, Seiford, and Siems, 1993; Barr and Siems, 1997; Leverty and Grace, 2012). Constructing CEO fixed effects requires firm and manager observations over time. However, the availability of the required data is limited and favors large firms. The same holds for press visibility, where a substantial bias towards large and listed firms is likely. Furthermore, managerial turnover may coincide with circumstances that are otherwise problematic for the firm and may thus be a fuzzy measure of managerial ability (Bennedsen, Pérez-González, and Wolfenzon, 2006). In addition, focusing on only the CEO ability ignores the fact that it is most probably the top management team as a whole that drives firm outcomes, as argued, for example by Hambrick (2007). Studies that use firm performance measures as proxies for managerial ability use either firm efficiency, parameterized using data envelopment analysis, or firm profitability as proxies for the ability of management. However, it is clear that these proxies are not likely to be very precise, since firm efficiency and profitability subsume influences that are not due to management but rather to the firm itself, such as, for instance, the ability to operate at optimal scale, functional organizational structures, the goodwill of clients that has accrued to the institution over its lifespan, bargain power due to size, etc. Therefore mainstream research on managerial ability has heretofore been hampered in breadth and accuracy by the lack of a measure of managerial ability that reliably disentangles it from other factors and is readily available for large numbers of firms.

An important contribution that can be used to parameterize managerial ability more effectively is made by Demerjian, Lev, and McVay (2012), who construct a broad and valid measure of managerial ability that can be obtained with relatively frugal data requirements. Specifically, they realize that only the portion of firm success not due to firm-specific characteristics ought to be attributed to managers. In order to capture a broad measure of firm success, the authors turn to a relative measure of firm performance, efficiency. This concept, also known as X-efficiency, has been widely applied to measure the performance of banks (Hughes and Mester, 2015). Thus, for instance, Berger and Humphrey (1997) document 130 studies that have applied the efficiency concept so as to capture bank performance. X-efficiency quantifies a bank's performance relative to a frontier that is spanned by the institutions active in the market. Together these institutions define the technology of the banking industry, i.e. the efficient frontier. Banks that operate in a fully efficient manner will find themselves on the frontier while inefficient banks will fall short. This concept and the attendant parameterization methods, most notably data envelopment analysis (DEA) and stochastic frontier analysis (SFA), have attracted substantial attention in the literature, as they allow insights into the determinants of efficiency (see, for example, Berger, 2003; Berger and Bonaccorsi di Patti, 2006; Feng and Serletis, 2010; Mester, 1997; Wheelock and Wilson, 2001). Thus Demerjian, Lev, and McVay (2012) use revenue efficiency as their raw measure of firm success and then purge this measure of all firm-specific effects. Revenue efficiency indicates the ability to generate revenues with a given bundle of inputs and outputs relative to other similar firms and they use this as their basis of managerial ability. Managerial ability is then obtained by running Tobit regressions of the raw efficiency scores on characteristics that are assumed to be specific to the firm and outside the manager's influence. Given its wide coverage, the resulting measure of managerial ability particularly lends itself to the study of the US banking industry, where a majority of banks are small, not covered by the financial press and not publicly traded. Therefore we rely on the methodological ideas as in Demerjian, Lev, and McVay (2012) to operationalize managerial ability in the banking industry.

Our estimation methodology for the managerial ability measure proceeds in two steps. The first step is to compute bank profit efficiency using SFA. While Demerjian, Lev, and McVay (2012) use DEA to obtain firm-level efficiency, we favor SFA because DEA has the disadvantage of being deterministic, i.e. unable to accommodate noise in the measurement of input, output and price variables. SFA does not require the data to be observed without errors. However, it does postulate a functional form that underlies the production process. A number of studies in banking have shown that the common parameterizations, such as the Translog, can capture profit, cost and revenue efficiency, hence we focus on this method (Altunbas and Chakravarty, 2001; Berger, 2003; Mester, 1997). We do, however, examine results obtained by way of DEA in the robustness checks and find our conclusions qualitatively unaffected. Since profitability is likely to be the main motivation of bank owners and by extension bank managers, we focus on computing profit efficiency as our basis for bank performance, instead of the revenue efficiency as in Demerjian, Lev, and McVay (2012). The second step of the estimation methodology is to purge the efficiency scores of any bank-specific influences that cannot be attributed to the management team. This is accomplished by running a Tobit regression of the efficiency scores on a set of bank characteristics.

This section proceeds as follows: Section 3.1 discusses the calculation of efficiency scores for banks as the main ingredient to managerial ability, while Section 3.2 provides evidence on the plausibility of the managerial ability proxy used in this analysis.

3.1. Quantifying Managerial Ability

The first step in obtaining the managerial ability measure relies on the use of stochastic frontiers in the analysis of firm efficiency that traces its lineage to Aigner, Lovell, and Schmidt (1977). Since then, numerous studies have applied this method in various industries to compute the X-efficiency of firms (see Hughes and Mester (2015) for a review). In general the aim is to parameterize an efficient frontier by utilizing information about how firms use the resources (inputs and outputs) available to them.

Profit efficiency measures how well a bank is generating profits by using its inputs and outputs relative to best practice banks on the efficient frontier. However, especially among small banks, which comprise the vast majority of the US banking landscape, but also among banks more generally, some standard assumptions of conventional efficiency measurement methods are unlikely to hold. Specifically, we expect there to be limits to disposability for certain inputs and outputs, noise in the measurement of output prices, some degree of at least local market power and substantial differences in the quality of banking services. Therefore we follow Berger and Mester (1997) in applying the alternative profit efficiency approach as the main tool for our analysis. This approach accounts for the issues mentioned above and parameterizes the efficient frontier in terms of input prices and output levels, instead of input and output prices. Below we explain the specifics of the approach.

The estimation is based on the model that assumes that the total level of profit can be described as follows:

$$\pi_i = s(\mathbf{y_i}, \mathbf{w_i}, \boldsymbol{\beta}) \exp(\epsilon_i). \tag{1}$$

In the above equation, $s(.)$ is the deterministic kernel of the profit creation function, $\mathbf{y_i}$ is the $M \times 1$ output bundle of bank i, $\mathbf{w_i}$ represents the N input prices faced by the i^{th} bank and π_i is the total profit generated by this bank, which can be computed by way of $\mathbf{w_i' x_i}$, where $\mathbf{x_i}$ represents the $N \times 1$ input vector of the i^{th} bank. $\epsilon_i = v_i - u_i$ is the composed error term, where v_i is assumed $\sim iidN(0, \sigma_v^2)$ and represents the random influences of the environment the bank operates in. The nonnegative inefficiencies of banks are represented by u_i, which is assumed to be $\sim iidN^+(0, \sigma_u^2)$. Both error components are assumed to be independent of each other and the regression parameters.

To estimate firm-level profit efficiency using SFA one must specify a deterministic kernel that represents the production technology. We employ the widely used Translog functional form with linear homogeneity in prices imposed (See Coelli, Rao, O'Donnell, and Battese, 2005, for the derivation):

$$\ln(\pi_i + \phi) - \ln w_{1i} = \beta_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \sum_{n=2}^{N} \beta_n (\ln w_{ni} - \ln w_{1i}) + \sum_{q=1}^{Q} \gamma_q \ln z_{qi}$$
$$+ \frac{1}{2} \sum_{m=1}^{M} \sum_{j=1}^{M} \alpha_{mj} \ln y_{mi} \ln y_{ji} + \sum_{n=1}^{N} \sum_{\substack{k=1 \\ n<k}}^{N} \beta_{nk} (\ln w_{ni} \ln w_{ki} - \frac{1}{2}(\ln w_{ni})^2 - \frac{1}{2}(\ln w_{ki})^2)$$
$$+ \frac{1}{2} \sum_{q=1}^{Q} \sum_{r=1}^{Q} \gamma_{qr} \ln z_{qi} \ln z_{ri} + \sum_{m=1}^{M} \sum_{n=1}^{N} \delta_{mn} \ln y_{mi} (\ln w_{ni} - \xi \ln w_{mi} - (1-\xi) \ln w_{1i})$$
$$+ \sum_{m=1}^{M} \sum_{q=1}^{Q} \eta_{mq} \ln y_{mi} \ln z_{qi} + \sum_{q=1}^{Q} \sum_{n=1}^{N} \kappa_{qn} \ln z_{qi} (\ln w_{ni} - \lambda \ln w_{qi} - (1-\lambda) \ln w_{1i}) + u_i + v_i, \quad (2)$$

where

$$\xi = \begin{cases} 1 & \text{if } m \leq N \\ 0 & \text{else} \end{cases}$$

and

$$\lambda = \begin{cases} 1 & \text{if } q \leq N \\ 0 & \text{else.} \end{cases}$$

Here y_{mi} represents the quantity of output m produced by bank i, w_{ni} represents the price of the n^{th} input used by bank i, and z_{qi} is the quantity of the q^{th} fixed input/output used by bank i. $\alpha, \beta, \gamma, \delta, \eta$ and κ are coefficients to be estimated. Bank profit is proxied by the economic value added (EVA), while ϕ is a coefficient added to each profit realization to ensure nonnegative values before taking logs. This parameterization corresponds to the alternative profit efficiency approach of Berger and Mester (1997). To extract the firm-level inefficiencies from the data, we use the Battese and Coelli (1988) estimator. We generate estimates of all parameters using maximum likelihood, obtained through gradient-descent-based maximization of the log likelihood function.

Our sample data to compute bank efficiency via SFA are obtained from the Call Reports provided by the Chicago Federal Reserve bank, starting with the year 1994 and ending in 2010. Variable definitions follow Berger, Bonime, Goldberg, and White (2004) and Fiordelisi (2007) and are by and large standard in the computation of bank efficiency. Specifically, EVA is defined as net operating profits after tax minus cost of capital, multiplied by capital invested. For inputs, we consider labor (x_1), financial capital (x_2) and core deposits (x_3). Accordingly, w_1 signifies the price of labour, w_2 denotes the price of financial capital, and w_3 stands for the price of core deposits. Equity (z_1) and fixed assets (z_2) are fixed inputs. For outputs, y_1 implies consumer loans, y_2 denotes business loans,

y_3 stands for real estate loans, and y_4 stands for securities. Off-balance-sheet items are denoted by y_5. Table 1 reports the summary statistics of bank inputs and outputs used to compute the efficiency scores.

[Table 1 about here.]

In Table 2 we report the coefficients for the stochastic frontier over the full sample of banks. The quotient of the inefficiency to noise component, $\lambda = \frac{\sigma_u}{\sigma_v} = 2.03$, shows that banks in our sample vary greatly in terms of profit efficiency. Additionally, the inefficiency effect is greater than the noise in the data, which is in line with our expectations, given that banks have previously been shown to be relatively less profit-efficient (see, for example, Berger and Bonaccorsi di Patti, 2006). The profit efficiency variation in the sample enables us to effectively identify the impact of managerial ability from the firm efficiency scores.

[Table 2 about here.]

Having obtained the profit efficiency scores of the banks, the second step is to disentangle managerial ability from bank-specific effects. To this end, we follow Demerjian, Lev, and McVay (2012) and derive a measure of managerial ability as the residual from a Tobit regression of bank profit efficiency scores on a set of bank-specific explanatory variables and year fixed effects. Concretely, the regression takes the following form:

$$\begin{aligned}\pi - \text{eff}_{SFA,i,t} =& \alpha + \beta_1 BKSIZE_{i,t} + \beta_2 NUMEMP_{i,t} + \beta_3 AGE_{i,t} + \beta_4 LEVRAG_{i,t} \\ &+ \beta_5 FCF_{i,t} + \sum_{t=1}^{T} \theta_t d_t + \epsilon_{i,t}.\end{aligned} \tag{3}$$

Here $\pi - \text{eff}_{SFA,i,t}$ represents profit efficiency as computed by SFA. $BKSIZE$ is the log of gross total assets, $NUMEMP$ is the log of the number of full time equivalent employees (in thousands), AGE is the log of the age of the bank (in years), $LEVRAG$ represents leverage, FCF is an indicator variable that takes the value one when cash flow for the year is positive and zero otherwise, and d_t represents the year dummies. Table 3 reports the results.

[Table 3 about here.]

We find that banks that are more profit-efficient are larger in terms of assets ($BKSIZE$), more highly leveraged ($LEVRAG$), and generate greater free cash flow (FCF). They also tend to have fewer employees ($NUMEMP$) and be younger banks (AGE). The magnitude and the signs of these coefficients are as expected. Thus, for example, one would expect larger and more highly leveraged institutions with fewer employees to be more profitable. From the above regression, we compute the residual between actual and predicted profit efficiency and, similarly to Demerjian, Lev, and McVay (2012), use this variable as our measure of managerial ability (MA). MA captures all effects that can be attributed to the managers and not the bank. In the following section, we carry out a number of tests in order to ensure that our MA measure indeed captures the ability of bank management.

3.2. Validating the Managerial Ability Measure

Once the managerial ability measure has been obtained, we investigate its plausibility and test whether it is value- and performance-relevant. We first investigate the correlations between this measure and generic performance indicators. We use the return on assets (ROA) and return on equity (ROE) and the shareholder value ratio ($SHVR$), which, in the spirit of Cipollini and Fiordelisi (2012), is defined as the quotient between economic value added and gross total assets. These provide first evidence on the value relevance of the managerial ability measure. This analysis also considers how managerial ability is related to the Z-Score ($ZIND$)[3], the three-year moving standard deviation of return on assets ($SDROA$), the ratio of risk-weighted assets over total assets ($CREDRSK$), the quantity of liquid assets divided by gross total assets ($LAGTA$) and tier 1 ratio ($T1R$). These variables capture the association between managerial ability and risk. Results are reported in Table 4.

[Table 4 about here.]

Table 4 shows that managerial ability (MA) displays significantly positive correlations with the performance (ROA, ROE) and value creation characteristics ($SHVR$). In terms of risk, it is found that more ably managed banks bear higher levels of risk-weighted assets ($CREDRSK$) and lower levels of tier 1 ratio ($T1R$) and liquid assets ($LAGTA$), while there is no statistical relation to bank fragility ($ZIND$). Thus the bulk of this evidence points towards more ably managed banks taking more risk. This may indicate that these banks bear higher levels of riskiness since their managers have the necessary skills and talent to better understand the business environment and be effective in managing more risky business portfolios with lower levels of capital cushions without affecting the fragility of their banks. Thus the main conclusion of this analysis points towards more ably managed banks being both more profitable and value creating, but also more risky.

[3] $ZIND$ is computed as return on assets plus capital to asset ratio, divided by the (previous three years') standard deviation of return on assets.

As an additional analysis of MA for banks, we test its predictive power for bank performance. The current literature on managerial ability has so far been mainly concentrated on showing the importance of MA for industrial firm performance. Initial evidence that Demerjian, Lev, and McVay's (2012) managerial ability measure is also appropriate for banks is provided by Cantrell (2013), who documents that the MA measure is indicative of superior reporting quality. However, evidence that the MA measure is important for explaining bank performance is as yet incomplete. Therefore, as additional analysis, we regress ROA and ROE on the first order lag of MA. If MA is a useful predictor of bank performance, one would expect a positive relation with return on assets and return on equity. The specification can be formalized as follows:

$$PM_{j,i,t} = \alpha + \beta MA_{i,t-1} + \boldsymbol{\xi}' \mathbf{z}_{i,t} + \sum_{t=1}^{T} \theta_t d_t + \upsilon_i + \epsilon_{i,t}, \tag{4}$$

where PM_j signifies performance measure jth for $j \in \{ROA, ROE\}$. MA denotes the managerial ability measure, d_t are year dummies, and $\mathbf{z}$ is a vector containing control variables. The control variables include the log of gross total assets ($BKSIZE$) to capture differences in profitability due to bank size such as economies of scale, and cost efficiency parameterized by SFA (CE) to capture differences in technology and allocation which may drive profitability. Furthermore, we control for organizational characteristics such as holding company status, and recent mergers and acquisitions. This is accomplished by way of dummy variables that take the value one if a bank is part of a multi-bank holding company ($MBHC$) or one-bank holding company ($OBHC$). Additional indicator variables control for the influence of mergers and acquisitions activity on bank efficiency (for a discussion of mergers and efficiency see, for example, Ahmad, Ariff, and Skully, 2007). Specifically, MRG is set to one in the case of a merger and zero otherwise, and ACQ to one in the case that the bank was acquired during the last three years and zero otherwise. It is further advantageous to control for local market characteristics by including the bank-level Herfindahl-Hirschmann index ($BKHHI$), the market share of medium and large banks in the area ($BKMSML$), the log bank-level population ($BKPOP$), and population density ($BKPDNS$), as well as the percent income growth rates ($BKICHG$).[4] Using these variables, we capture the differences between banks that arise from their organizational form or location. Raw demographic data are obtained from the Bureau of Economic

[4] We define local markets according to Metropolitan Statistical areas (MSAs) or counties that are not MSAs. We then use data on the deposits held by each bank in each of these markets to calculate the relative significance of the market for the bank. Using these quotients as weights, we compute the weighted bank-level local market characteristic variables for each bank.

Analysis (www.bea.gov), while data on bank deposits are obtained from the Federal Deposit Insurance Corporation (www.fdic.gov). Because the regression specifications are in keeping with Berger and Bouwman (2009), the basic setup uses three-year moving averages of the regressors. Hence the final dataset spans the years 1994-2010 and contains 100,976 bank-year observations. In addition, in all regression specifications models we use one period lagged of the managerial ability measure, namely MA_{t-1}.

[Table 5 about here.]

The results of these regressions are reported in Table 5. The coefficients show that for both ROA and ROE, one year lagged managerial ability has a strongly significant and positive impact. Thus we document that the MA measure can capture bank profitability. The controls show that size is negatively associated with profitability as is cost efficiency. Banks that operate in more affluent ($BKICHG$), less densely populated ($BKPOP$, $BKPDNS$) markets, with a greater presence of medium and large banks ($BKMSML$) tend to be more profitable. Bank holding companies are more profitable than non-bank holding companies ($MBHC$, $OBHC$). Further, recent mergers and acquisitions impair profitability (MRG, ACQ). This may be due to integration costs incurred before the benefits of economies of scale and scope due to mergers or acquisitions can be fully realized. Overall, the control variables provide plausible information; but more importantly, the regressions confirm the expected positive relation between managerial ability and profitability and thus qualify the MA measure as a valid measure that should capture the impact of managerial ability on banks' outcomes.

4. Empirical results

4.1. Managerial Ability, Bank Liquidity Creation and Risk-Taking

In this section, we analyze the influence that managerial ability exerts on liquidity creation and bank risk characteristics. Liquidity creation is addressed first. Subsequently, this section also investigates bank risk-taking along a number of dimensions.

We study liquidity creation using bank-level data that is stratified by bank size. It is well known (see, for example, Feng and Serletis, 2009) that the US banking industry is composed of a large number of small banks, and substantially smaller numbers of medium and very large banks. Accordingly, in line with Berger and Bouwman (2009) we use cutoffs at GTA \$1 billion and GTA \$3 billion USD to separate small, medium and large banks respectively, and we run the analysis for each subsample of the population separately as well as for the full sample of banks. Table 6 reports summary statistics for the key bank characteristic variables used in the analysis. We observe that the MA measure decreases with bank size within the sample, with small banks showing the greatest average managerial ability among the three subsamples. Since MA is constructed as a residual, it is natural to observe that for the full sample managerial ability is close to zero on average. Consistent with findings in Berger and Bouwman (2009), liquidity creation per dollar of assets ($CATFAT$) is much greater in large banks. Large banks also exhibit lower levels of tier 1 capital ($T1R$) and also have greater quantities of risk-weighted assets ($CREDRSK$) on their books. They usually are more risky in terms of distance to default ($ZIND$) as well, while the variation of return on assets ($SDROA$) also tends to be greater. Medium and large banks tend to be more cost-efficient (CE) than small banks and they operate in more populous ($BKPOP$), affluent ($BKMSML$) and less concentrated markets ($BKHHI$). Medium banks also exhibit the highest merger and acquisition activity (MRG) in the sample as well as the lowest level of liquid assets ($LAGTA$). Overall, the characteristics of the sample are in line with those reported in previous studies such as Berger and Bouwman (2009).

[Table 6 about here.]

Next, this section investigates bank liquidity creation in more detail in order to test the Ability-Liquidity hypothesis ($H1$). The model specification uses bank and year fixed effects and we report standard errors clustered by bank. Specifically,

$$\frac{CATFAT_{i,t}}{GTA_{i,t}} = \alpha + \beta_1 MA_{i,t-1} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{T} \theta_t d_t + \upsilon_i + \epsilon_{i,t}, \tag{5}$$

where $CATFAT$ is the liquidity creation measure as defined by Berger and Bouwman (2009) and GTA represents gross total assets. The main variable of interest, MA, is lagged by one period so as to avoid possible endogeneity issues and $\mathbf{z}$ is a vector of contemporaneous bank characteristic variables that are used as regressors. Following Berger and Bouwman (2009), as proxies for risk, we use the three-year moving averages of the sum of risk-weighted assets scaled by gross total assets ($CREDRSK$), the moving standard deviation of the ROA ($SDROA$) and the Z-Score ($ZIND$).[5]

[5]Since these variables all measure risk, the last two are orthogonalized by regressing $ZIND$ and $SDROA$ on each other, $CREDRSK$ and all other explanatory variables, and using the resulting errors as the eventual independent variable. Orthogonalizing these measures against one another and the remaining covariates ensures that the impact of collinearity is minimized and that the orthogonalized variables capture only the dimension not covered by the other variables. Moreover, this procedure ensures comparability of the present results with those provided in Berger and Bouwman (2009), who introduce this regression specification.

We further include the log of gross total assets to control for bank size ($BKSIZE$) and equity over asset ratio (EA) to account for bank capitalization.[6] Additionally, the regression specification controls for organizational characteristics and local market characteristics as defined previously. If the Ability-Liquidity hypothesis holds, one would expect a positive association between the lagged managerial ability and liquidity creation. Table 7 reports the results of the regression analysis, where each subsample of the bank population is treated in a separate column.

[Table 7 about here.]

The main result relates to the significance of MA_{t-1}. Importantly, we find that managerial ability is significantly positively associated with liquidity creation for small and medium banks as well as the overall population. This is as initially theorized and lends credence to the Ability-Liquidity hypothesis. In addition, the findings on the control variables are very similar to those reported in the literature. Thus, in keeping with Berger and Bouwman (2009), results show that $ZIND$ and $SDROA$ have a negative effect on liquidity creation, while banks with higher $CREDRSK$ create more liquidity. We observe that the effect of these risk proxies on liquidity creation is more significant in the case of smaller banks. Similarly, EA is significant and negatively related to liquidity creation mainly for small banks, reflecting the key role of capital for liquidity creation. Further, we observe that being a bank holding company ($MBHC, OBHC$) is beneficial for liquidity creation among small banks. This is likely due to better access to resources channeled through the holding company. Additionally, bank merger activity (MRG) has a significant and positive association for liquidity creation and the result holds across all bank sizes. In term of bank market demographics, the results show that small banks that are active in more concentrated ($BKHHI$), more populous ($BKPOP$) and affluent markets ($BKICHG$) create more liquidity. The latter finding is highly significant also for medium and large banks in our sample.

Next, we investigate whether ability of managers has an influence on bank risk-taking behavior. If so, this would be an important feature of banks which has heretofore not been examined. Specifically, the Ability-Risk hypothesis ($H2$) posits that more able managers will take more risk due to their greater confidence in their ability to manage such risk. Hence the following analysis proceeds by regressing proxies for bank risk-taking on the lagged managerial ability measure, while controlling for other bank characteristics. As measures of bank risk, we use the tier 1 ratio ($T1R$), the ratio of liquid

[6]While bank capitalization is likely to be an important determinant of liquidity creation, endogeneity concerns may arise (Berger and Bouwman, 2009). Hence we rerun our regressions without EA and find the results to be qualitatively unchanged. We orthogonalize EA against $SDROA$, $CREDRSK$ and $ZIND$ and the other controls, and use only the residual as a regressor, since EA may be capturing risk. Again our results hold.

assets to total assets ($LAGTA$) and Z-Score ($ZIND$)[7]. Our choice of bank risk proxies is motivated by their ability to capture three important dimensions of bank operations. First, the tier 1 ratio is a key regulatory measure of capitalization, which banks are likely to target in their decision-making more strongly than, for example, the equity over asset ratio. Second, the quantity of liquid assets captures the liquidity of a bank, which is a key dimension of its resilience to shocks. This quantity is defined by using the CAT classification of Berger and Bouwman (2009) and considering only liquid assets. Finally, Z-Score is a well known measure of a bank's distance to default that captures bank fragility.

If the Ability-Risk hypothesis holds, we expect a negative association between managerial ability and the three risk measures, $T1R$, $LAGTA$ and $ZIND$. The regressions take the form in Equation (6):

$$KRI_{k,i,t} = \alpha + \beta_1 MA_{i,t-1} + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \sum_{t=1}^{T} \theta_t d_t + \upsilon_i + \epsilon_{i,t}, \tag{6}$$

where KRI_k represents the key risk indicator, where k indexes into $\{T1R, LAGTA, ZIND\}$. All other regressors are as previously defined. Table 9 reports the results.

The key variable of interest is the one year lagged managerial ability measure (MA_{t-1}). The results in Panel A indicate that more able managers prefer to hold greater levels of tier 1 capital in small banks but lower for medium banks. Panel B shows that managers of small and medium banks prefer to hold lower quantities of liquid assets. Finally, Panel C shows that medium to large banks with more able managers tend to face greater fragility as they exhibit smaller distance to default. Overall, we find that for the case of medium and large banks, managerial ability contributes significantly to the riskiness of the bank. Thus, these findings support the Ability-Risk hypothesis that more able managers take greater risk and this effect can be clearly observed among larger banks. For small banks, however, this relation is reversed. This is consistent with the results found for the tier 1 ratio above. This finding is suggestive of differences in incentives and constraints that managers from small and other banks face. Thus it is conceivable that managers of larger institutions that tend to be rewarded with a significant compensation (for example, in the form of stock options) will be more prepared to take greater risk than managers of smaller institutions, who are more likely to focus on the bank's survival. Additionally, due to limited access to finance, small banks will opt for larger capital buffers and take on less risk than large banks that have more easy access to funding from capital

[7]Since we utilize three observations of ROA to compute the standard deviation of ROA, we use the third lag of all other regressors in the regressions that have $ZIND$ as the dependent variable and omit $ZIND$ from the right-hand-side.

markets (Berger and Bouwman, 2009). In terms of the other covariates, we find that greater holdings of risk-weighted assets per unit assets ($CREDRSK$) tend to be negatively associated with the tier 1 capital levels, liquid assets, and distance to default. Additionally, equity capital ratio is consistently positive and significant across the various risk measures. This indicates that bank capitalization, an important determinant of liquidity creation, is positively related to risk-taking.

[Table 8 about here.]

Overall, this section provides strong support for the hypotheses that more able bank managers generally contribute positively to liquidity creation in the economy. Furthermore, as the split sample analysis shows, this finding is not driven merely by larger banks that may pay more and thus attract greater managerial talent. Managerial ability matters for small banks' liquidity creation as well. In addition, results suggest that more able bank managers tend to pursue more risky strategies in terms of liquidity, loan portfolio risk and distance to default. This holds particularly for the case of medium and large banks. The next section addresses the question how managerial ability influences liquidity creation during crisis times.

4.2. Effects of Managerial Ability on Liquidity Creation and Risk-Taking During the Financial Crisis

This section investigates the Ability-Liquidity Expansion ($H3a$) or Contraction hypotheses ($H3b$), and the Ability-Risk Expansion ($H4a$) or Contraction hypotheses ($H4b$), where we test whether bank managerial ability influences the liquidity creation and risk-taking behavior after the onset of the financial crisis in 2007. In order to isolate the ability of bank managers from the effect of the financial crisis, we measure managerial ability one year prior to the start of the financial crisis, specifically at the end of fiscal year 2006 (MA_{06}). Our model specification is as follows:

$$\frac{CATFAT_{i,t}}{GTA_{i,t}} = \alpha + \beta_1\delta_c + \beta_2 MA_{i,06} \times \delta_c + \boldsymbol{\xi}'\mathbf{z}_{i,t} + \upsilon_i + \epsilon_{i,t}, \tag{7}$$

where we regress the liquidity creation measure for the period 2007-2010 on an indicator variable, δ_c, set to one for years belonging to the financial crisis period, and the interaction of δ_c with the bank's pre-crisis managerial ability measure, MA_{06}, while controlling for bank and time fixed effects and bank characteristics as previously. For the analysis, we consider the period of financial crisis as encompassing the years 2007-2009.[8] The model specification takes managerial ability to be predetermined with respect to the financial crisis period, since it is estimated in 2006, which is a period that resides outside the period spanned by the data used in the above regression model; in this respect, the analysis also mitigates any endogeneity concerns that could arise from expectations regarding the anticipation of the crisis.[9] Therefore, the model specification is suitable to reveal the true impact of managerial ability on liquidity creation, which can also be conceived as an acid test of whether or not managerial ability affects bank liquidity creation.

We expect the coefficients on the crisis indicator variable (δ_c) to be negative and significant due to the disruptive effects of the financial crisis on bank intermediation. The coefficient estimates for the interaction of MA_{06} with δ_c will allow us to disentangle hypothesis $H3a$ from $H3b$. Specifically, the regression specification asks the question whether more able managers expand intermediation during the crisis, consistent with Berger and Bouwman (2013) and the Ability-Liquidity Expansion hypothesis, or whether anticipation of risk led more able managers to reduce it, consistent with Bebchuk and Goldstein (2011) and the Ability-Liquidity Contraction hypothesis. The results of this analysis are reported in Table 9.

[Table 9 about here.]

As expected, the results show that the crisis has a strongly significant negative impact on liquidity creation (δ_c), indicating that banks reduced liquidity creation during the crisis. Furthermore, the main variable of interest, the interaction of pre-crisis managerial ability with the crisis indicator variable, $MA_{06} \times \delta_c$, shows that more able managers reduced the liquidity creation of their banks during the crisis period more significantly, which is consistent with the Ability-Liquidity Contraction hypothesis. This result holds in the overall pooled sample and its statistical significance is mostly driven by small banks.

Next, we investigate the risk-taking behavior during the financial crisis period as postulated by the Ability-Risk Expansion hypothesis or Ability-Risk Contraction hypothesis. The preceding analyses

[8] Our main results continue to hold for alternative definitions of the crisis period, where we let the crisis periods range from 2007-2008 or 2008-2009 (results available on request).

[9] One could argue that owners, anticipating a crisis, may have tried to hire more able managers at the last minute. However, the market for managerial talent is limited and therefore, even if such behavior were to have obtained, it could only have affected a very small fraction of the sample of banks. This is especially the case because the majority of the sample consists of small banks where the mobility of managers in terms of their workplace as well as their visibility to competitors is much smaller than, for example, in listed banks, where news coverage and disclosure make for much more visible managers. More importantly, given the time needed to decide to replace, to find and to actually recruit a top management team, it seems extremely unlikely that owners will have been able to replace their banks' management in anticipation of an impending crisis event.

have shown that, during normal times, more able managers tend to prefer running more risky banks in terms of capitalization ($T1R$), liquidity ($LAGTA$) and distance to default ($ZIND$). If more able managers have indeed taken more controlled risks in normal times, then they should be more successful in de-leveraging during the fincancial crisis period if it is optimal to do so. Therefore, if the Ability-Risk Contraction hypothesis holds, we would therefore expect positive signs on $T1R$, $LAGTA$ and $ZIND$. Alternatively, if the Ability-Risk Expansion hypothesis holds, then we would expect negative signs on $T1R$, $LAGTA$ and $ZIND$, implying that more able managers increased their banks' riskiness; however, due to the fact that data have supported the Ability-Liquidity Contraction hypothesis during the financial crisis, we would expect to observe a predominance of the Ability-Risk Contraction hypothesis. The following analysis considers the results during crisis times by running the regression specification:

$$KRI_{k,i,t} = \alpha + \beta_1 \delta_c + \beta_2 MA_{i,06} \times \delta_c + \boldsymbol{\xi}' \mathbf{z}_{i,t} + \upsilon_i + \epsilon_{i,t}, \tag{8}$$

where again KRI_k represents the key risk indicator, with $k \in \{T1R, LAGTA, ZIND\}$. All other regressors are as previously defined. Table 10 reports the results.

[Table 10 about here.]

It is very interesting to observe that the coefficients on the crisis indicator variable, δ_c, exhibit in general plausible signs. For instance, one would expect that, in an environment where asset values drop precipitously, losses accumulate and equity is hard to raise, therefore tier 1 capital ($T1R$) will decline (Panel A). One would also expect that banks will attempt to increase their holdings of liquid assets ($LAGTA$) as a reaction to the onset of the financial crisis (Panel B). Finally, it is natural that the crisis shock will induce banks to come closer to default ($ZIND$)(Panel C).

Regarding the hypotheses under scrutiny, the results indicate that more able managers reduce risk as a reaction to the crisis. Thus Panels A and B show that pre-crisis managerial ability increases both the tier 1 ratio ($T1R$) and liquid assets ($LAGTA$). This holds significantly for small banks and in the overall sample and, for $LAGTA$, also for large banks. In Panel C we repeat the regression above with the risk measure based on $ZIND$ as the dependent variable and with regressors lagged by three years to avoid overlapping sample periods, as previously. Again the result confirms our main findings. Specifically, we observe that, while the crisis plausibly increases banks' fragility since δ_c is large and significantly negative, higher pre-crisis managerial ability dampens a bank's fragility significantly.

Hence this result again confirms that more able managers are better at de-leveraging during the crisis. To test the robustness of our findings, we repeat this analysis without taking the lag of the independent variables and find results qualitatively unchanged. Overall, there is overwhelming evidence to support the interpretation that managerial ability facilitated banks' reactions to the financial crisis in terms of risk reduction, and therefore provides support for the Ability-Risk Contraction hypothesis.

In sum, the analyses show, first, that banks that were more ably managed before the crisis reduce their liquidity creation activity more strongly than other banks, which supports the Ability-Liquidity Contraction hypothesis. Second, more ably managed banks find it easier to react to the crisis by increasing their capitalization and liquidity holdings. This supports the view expressed in the Ability-Risk Contraction hypothesis that more able managers are better able to react to exogenous shocks by de-leveraging. Together these findings strongly suggest that the resilience of banks to exogenous shocks depends, at least in part, on the ability of their managers.

5. Robustness Checks

In this section, we discuss a number of robustness tests carried out. First, we investigate the sensitivity of the results to the choice of liquidity creation measure. Therefore we replicate the main analysis using both Berger and Bouwman's (2009) $CATNONFAT$ measure as well as the liquidity transformation gap of Deep and Schaefer (2004). While it has been noted that this latter variable is somewhat more crude than that of Berger and Bouwman (2009), it does provide a useful check on the robustness of the main results. Using these measures of liquidity creation we find that the results for the whole sample period as well as the results for the financial crisis hold in qualitative terms.

Second, a source of endogeneity may arise in the regression analysis due to the presence of bank size, risk-weighted assets, volatility of ROA and the Z-Score as regressors, as these components can influence liquidity creation, and also managerial decision-making. Therefore we rerun all the analyses omitting EA, $BKSIZE$, $CREDRSK$, $SDROA$ and $ZIND$. Additionally, to purge the concerns of endogeneity, Berger and Bouwman (2009) propose the identification strategy of using three-year *lagged* moving average values of the independent variables, instead of using the three-year moving averages. Hence we also replicate our results with this identification strategy.

Third, we test for the validity of our findings using alternative constructions of the managerial ability measure. While Demerjian, Lev, and McVay (2012) demonstrate the validity of the managerial ability measure, there are other parameterizations possible, with each having their own specific strengths and weaknesses. Thus efficiency scores can be obtained from various methodologies such as DEA or SFA. While DEA makes the assumption that the data is observed without noise, SFA requires the assumption of a known functional form for the profit function as well as the distributions of error terms. In addition, instead of profit maximization, revenue generation given fixed resources, as postulated by Demerjian, Lev, and McVay (2012), might be the primary goal of management. Hence we consider the different outcomes from the analysis when the managerial ability measure (MA) is quantified using: (i) revenue efficiency obtained from SFA, (ii) revenue efficiency obtained from DEA, and (iii) profit efficiency obtained from DEA. Furthermore, for each of these efficiency scores, the first stage Tobit regressions that eventually yield MA as the residual can plausibly be conducted with various sets of regressors. We investigate whether this choice has any effect on the results. Specifically, we analyze whether including the bank holding company type as a regressor along with the original control variables alters the results. This approach is chosen since this characteristic is both likely to influence bank performance (bank holding company members typically have access to the BHC's resources in crisis times) and be beyond the individual manager's immediate control. In addition, one could argue that out of the original regressors inspired by Demerjian, Lev, and McVay (2012) and Cantrell (2013), $BKSIZE$, $NUMEMP$ and $LEVRAG$ have the potential to be endogenous to bank revenue or profit efficiency. Therefore we introduce a third set of regressors that excludes these potentially endogenous variables, while instead including the bank demographic controls as defined in the main analysis. Finally, the Tobit regressions can be conducted over a pooled sample of banks, as in the main analysis, or for each year of bank data separately. The latter approach has the advantage that any potential confounding look-ahead effects that emanate from including future data in the regression can be avoided. We also check for this influence. In sum, we replicate the analysis for 18 different specifications of managerial ability and find very robust results.

Fourth, one potential concern with our analysis could be that our measure of managerial ability is contaminated by risk and hence is trivially related to bank risk-taking and liquidity creation. One way of addressing this concern is to include additional risk variables in the Tobit regressions which yield MA as the residual. This should purge the MA measure of the impact of risk. Clearly, bank risk-taking will be heavily influenced by management and hence it is not clear that purging risk characteristics from efficiency scores is consistent with the paradigm of Demerjian, Lev, and McVay (2012). On the other hand, the concern that our MA results might be driven by risk is valid and hence we investigate the robustness of our results by including $CREDRSK$, $SDROA$ and $ZIND$ in our initial MA regressions. This risk-adjusted measure of managerial ability yields very similar results to the main analysis. During crisis times, more able managers reduce their liquidity creation more and also significantly reduce risk. Thus, overall results are very similar to those found in the main analysis, which confirms that our findings are not merely driven by risk.

Fifth and finally, the base case analysis uses the entire period (1996-2010) to identify the influence that managerial ability has on liquidity creation and the other bank characteristics in normal times. As this period includes the financial crisis itself, results could be driven by these effects. Therefore, (i) we rerun the base case regressions for the 1996-2006 subsample, (ii) we investigate whether restricting the crisis period to 2008-2009 or 2007-2008 instead of 2007-2009 influences the results, and (iii) we analyze the results that we obtain for a placebo crisis between 2003 and 2004. Our findings are not sensitive to particular sample periods and the observed effects remain qualitatively very similar.

6. Conclusion

We investigate the impact of managerial ability on liquidity creation and risk-taking. While liquidity creation is a primary and crucial function of banking organizations, their risk-taking behavior is also important to regulators. We find that more able managers create more liquidity per dollar of assets and more ably managed banks also take on more risk. Next, we examine whether managerial ability has a role to play during financial crisis periods in this context of liquidity creation and risk-taking behavior. The impact of the crisis, as mediated by managerial ability, on liquidity creation is an empirical question, since the theoretical literature suggests that banks should decrease their liquidity creation, while some empirical findings contest this assertion. Our test results indicate that the former case holds true: more ably managed banks reduce liquidity creation during the financial crisis. Finally, the paper analyzes the significance of managerial ability for bank risk-taking during the financial crisis. We find that more able managers are better at de-leveraging their bank during the crisis. Our findings are found to be robust to a large number of checks and imply that regulators may do well in favoring better-managed banks in normal times in order to maximize the creation of liquidity in the economy. In crisis times, on the other hand, more ably managed banks may require additional incentives to lend.

A. Appendix A

In this appendix, we report the definitions of the main variables used in the analysis throughout this paper.

[Table 11 about here.]

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Table 1: Summary Statistics of Bank Inputs and Outputs

This table reports summary statistics for the main variables used to compute our efficiency scores. Specifically, x_1 = labor, x_2 = financial capital, x_3 = core deposits y_1 = consumer loans, y_2 = business loans, y_3 = real estate loans, y_4 = securities, y_5 = off-balance-sheet items, w_1 = price of labor, w_2 = price of financial capital, w_3 = price of core deposits, z_1 is equity and z_2 stands for fixed assets; both z_1 and z_2 are treated as fixed. Values for input and output quantities are in millions of 2005 US dollars, where adjustment to this basis period was achieved using the GDP implied deflator.

Variable	Mean	Standard deviation	Minimum	Maximum	Definition
x_1	197.55	2,732.24	2	213,967.00	Number of employed full-time equivalent by the bank
x_2	354.78	9,387.34	0.07	969,472.10	Financial capital is defined as the sum of purchased funds
x_3	492.22	6,567.28	0.61	636,319.30	Savings deposits, transactions accounts, time deposits (< USD 100,000)
y_1	60.55	1,005.37	0	84,001.8	Credit card and similar as well as installment loans to individuals originated in domestic offices
y_2	184.92	4,040.78	0	401,295.80	Agricultural, commercial and industrial loans and loans to depository institutions
y_3	266.61	3,641.24	0	370,750.80	Loans secured by real estate
y_4	337.55	7,926.45	0.48	998,783.20	Financial assets that are not loans
y_5	101.59	2,797.38	0	379,477.90	Off-balance-sheet items such as derivatives, letters of credit, and commitments
w_1	53.16	11.99	5.22	286.31	Price of labor, including salary and benefits per FTE
w_2	0.07	0.02	0.007	0.49	Expense of purchased funds divided by price of purchased funds
w_3	0.04	0.01	0.003	0.26	Expense of core deposits divided by price of core deposits
z_1	76.67	1,319.38	0.53	117,810.60	Total equity capital
z_2	10.23	120.53	0	7,997.87	Premises and other fixed assets

Table 2: Estimates of SFA-based profit efficiency.

This table reports estimates of alternative profit efficiency. Estimates follow the specification in Equation (2). T-statistics are reported in parentheses. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels respectively.

α_1	0.243***	β_1	-2.859***	δ_{53}	0.502**
	(11.07)		(-51.78)		(2.51)
α_2	0.0322	β_2	2.875***	η_{11}	0.0264
	(0.92)		(37.90)		(1.08)
α_3	0.620***	β_3	1.029***	η_{12}	-0.0393
	(19.21)		(22.20)		(-0.91)
α_4	0.215***	β_{12}	15.62***	η_{21}	0.313***
	(4.77)		(34.69)		(7.31)
α_5	-0.0332	β_{13}	-12.75***	η_{22}	0.284***
	(-0.99)		(-34.74)		(4.20)
α_{11}	0.124***	β_{23}	8.096***	η_{31}	0.323***
	(4.62)		(16.97)		(9.07)
α_{12}	-0.161***	γ_1	-0.257***	η_{32}	-0.0944
	(-6.40)		(-10.02)		(-1.59)
α_{13}	-0.0807***	γ_2	0.331***	η_{41}	0.166***
	(-3.53)		(5.38)		(3.27)
α_{14}	0.0539	γ_{11}	-0.583***	η_{42}	-0.340***
	(1.59)		(-11.20)		(-3.04)
α_{15}	0.0737***	γ_{12}	-0.158**	η_{51}	-0.165***
	(3.23)		(-2.37)		(-4.64)
α_{22}	-0.138**	γ_{22}	0.427***	η_{52}	-0.0745
	(-2.12)		(2.69)		(-1.20)
α_{23}	-0.231***	δ_{12}	-0.359**	κ_{12}	3.040***
	(-6.16)		(-2.35)		(15.14)
α_{24}	-0.185***	δ_{13}	0.531***	κ_{13}	-1.495***
	(-3.12)		(4.01)		(-8.73)
α_{25}	0.202***	δ_{23}	0.0403	κ_{23}	1.375***
	(5.38)		(0.18)		(3.87)
α_{33}	0.00622	δ_{32}	-0.0702	Constant	8.519***
	(0.14)		(-0.38)		(197.93)
α_{34}	-0.0138	δ_{42}	-0.378	σ_u	1.195
	(-0.29)		(-1.34)	σ_v	0.588
α_{35}	0.118***	δ_{43}	-1.545***		
	(3.96)		(-6.03)		
α_{44}	0.164	δ_{52}	-0.548**		
	(1.57)		(-2.28)		
α_{45}	0.0646				
	(1.22)				
α_{55}	-0.212***				
	(-5.02)				

Table 3:
Validation of Managerial Ability Measure.
Coefficients from pooled Tobit regressions with time fixed effects. The dependent variable is the alternative profit efficiency score obtained from stochastic frontier analysis. $BKSIZE$ stands for the natural log of gross total assets, $NUMEMP$ is the natural log of the number of thousand full-time equivalent employees, AGE is the log of bank age, $LEVRAG$ is the leverage of the bank, while FCF is a dummy variable set to one if the bank has free cash flow. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels respectively. Monetary values are in 2005 US Dollars.

$BKSIZE$	0.0907***
	(29.58)
$NUMEMP$	-0.129***
	(-39.97)
AGE	-0.00261***
	(-4.49)
$LEVRAG$	0.0153***
	(55.06)
FCF	0.0182***
	(12.98)
Constant	0.00567
	(0.22)
Time FE	Yes
N	100976

Table 4:
Correlations of Managerial Ability with Bank Performance Measures.
This table reports Pearson correlation coefficients of managerial ability and bank performance characteristics. ROA (ROE) stands for return on assets (equity). Shareholder value ratio, $SHVR$, is the quotient between economic value added and gross total assets. $ZIND$ stands for the Z-Score measure of distance to default where the variance of the return on assets has been computed for each bank individually using the last three observations. $CREDRSK$ is the quantity of risk weighted assets over total assets. $T1R$ stands for the tier 1 ratio. $LAGTA$ stands for liquid assets scaled by total assets. MA represents one-year lagged managerial ability measure as obtained following the methodology of Demerjian, Lev, and McVay (2012) using SFA-based alternative profit efficiency. Stars (***) report significance at the 0.01 level.

	MA
ROA	0.0442***
ROE	0.0725***
$SHVR$	0.0811***
$ZIND$	0.00211
$CREDRSK$	0.2180***
$T1R$	-0.1260***
$LAGTA$	-0.3120***

Table 5:
Bank Performance and Managerial Ability.
This table reports results from fixed effects regressions of return on assets (ROA) and return on equity (ROE) on lagged managerial ability (MA_{t-1}) and and lagged (3-year moving averages of) bank characteristic control variables, with bank and time fixed effects and standard errors clustered by bank. The definitions of all the variables are detailed in Appendix A. All variables are winsorized at the 1st and 99th percentile to reduce the influence of outliers. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels respectively. T-statistics are reported in parentheses.

	ROA	ROE
MA_{t-1}	0.000249***	0.00401***
	(4.53)	(5.86)
$BKSIZE$	-0.000834***	-0.0196***
	(-3.38)	(-6.91)
CE	-0.000250***	-0.00571***
	(-3.41)	(-6.79)
$BKHHI$	0.000142	0.00161
	(1.13)	(1.09)
$BKMSML$	0.000949***	0.0117***
	(7.05)	(7.25)
$BKPOP$	-0.00194***	-0.0214***
	(-5.76)	(-5.44)
$BKPDNS$	-0.000963***	-0.0124***
	(-3.61)	(-3.79)
$BKICHG$	0.000897***	0.0116***
	(17.97)	(19.33)
MBHC	0.000131	0.00495***
	(1.05)	(3.48)
$OBHC$	0.000283**	0.00665***
	(2.48)	(4.98)
MRG	-0.0000318**	-0.000419
	(-2.02)	(-1.59)
ACQ	-0.0000485	-0.000834**
	(-1.46)	(-2.13)
$Constant$	0.00672***	0.0645***
	(44.87)	(35.98)
Adj. R^2	0.153	0.154
N	84356	84356

Table 6: Summary Statistics.

This table reports the summary statistics (mean and standard deviation(sd)) for the variables used in the empirical analysis. The definitions of all the variables are detailed in Appendix A.

	Panel A: Small Banks		*Panel B: Medium Banks*		*Panel C: Large Banks*		*Panel D: All Banks*	
	(mean)	(sd)	(mean)	(sd)	(mean)	(sd)	(mean)	(sd)
MA	0.0034	0.0828	-0.0247	0.1472	-0.0728	0.1788	0.0006	0.0901
$CATFAT$	0.2610	0.1704	0.3772	0.1627	0.4006	0.1750	0.2684	0.1728
$T1R$	0.1549	0.0655	0.1175	0.0363	0.1088	0.0368	0.1524	0.0648
$LAGTA$	0.3573	0.1435	0.3199	0.1260	0.3558	0.1347	0.3559	0.1429
$CREDRSK$	0.6652	0.1219	0.7196	0.1190	0.7300	0.1342	0.6687	0.1229
$ZIND$	1.0764	1.3403	1.1145	1.3919	0.9385	1.2045	1.0748	1.3395
$SDROA$	0.2644	0.3360	0.3031	0.4730	0.3035	0.4274	0.2667	0.3445
EA	0.1014	0.0295	0.0927	0.0261	0.0922	0.0305	0.1009	0.0294
$BKSIZE$	11.5948	0.9468	14.2699	0.3093	15.6499	0.3871	11.7854	1.2033
CE	0.9248	0.0393	0.9502	0.0385	0.9455	0.0556	0.9262	0.0401
$BKHHI$	0.2335	0.1479	0.1870	0.0921	0.1895	0.0883	0.2308	0.1456
$BKMSML$	0.4105	0.3085	0.7409	0.1633	0.7746	0.1821	0.4310	0.3128
$BKPOP$	12.1488	2.3154	14.2467	1.6006	14.7718	1.3207	12.2858	2.3399
$BKPDNS$	2.9128	0.9235	3.2122	0.7739	3.3376	0.6794	2.9334	0.9174
$BKICHG$	0.0475	0.0429	0.0452	0.0345	0.0504	0.0305	0.0475	0.0424
$MBHC$	0.2242	0.4170	0.4078	0.4915	0.6473	0.4779	0.2405	0.4274
$OBHC$	0.5771	0.4940	0.4972	0.5001	0.3008	0.4587	0.5679	0.4954
MRG	0.0001	0.0097	0.0016	0.0398	0.0013	0.0365	0.0002	0.0134
ACQ	0.0722	0.2589	0.0762	0.2653	0.0675	0.2510	0.0723	0.2589
N	94944		3781		2251		100976	

Table 7: Bank Liquidity Creation and Managerial Ability.

This table reports regression results of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on lagged managerial ability (MA_{t-1}) and lagged (3-year moving averages of) bank characteristic control variables, with bank and time fixed effects and standard errors clustered by bank. The definitions of all the variables are detailed in Appendix A. All variables are winsorized at the 1st and 99th percentile to reduce the influence of outliers. Monetary values are in 2005 US Dollars. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels respectively. T-statistics are reported in parentheses.

	Small	Medium	Large	All
MA_{t-1}	0.0387***	0.0366***	-0.0131	0.0340***
	(7.87)	(3.00)	(-0.75)	(7.44)
$CREDRSK$	0.616***	0.667***	0.826***	0.624***
	(55.92)	(14.11)	(10.84)	(58.21)
$ZIND$	-0.000854**	-0.00191	0.00160	-0.000729**
	(-2.54)	(-1.42)	(0.64)	(-2.26)
$SDROA$	-0.00814***	-0.0328***	-0.0311**	-0.00994***
	(-3.62)	(-4.30)	(-2.02)	(-4.64)
EA	-0.419***	-0.0715	0.156	-0.374***
	(-13.15)	(-0.51)	(0.68)	(-12.21)
$BKSIZE$	-0.0137***	-0.0164	0.00259	-0.0128***
	(-5.45)	(-1.50)	(0.19)	(-5.68)
$BKHHI$	0.0160**	-0.0360	0.00884	0.0134*
	(2.05)	(-0.64)	(0.05)	(1.66)
$BKMSML$	0.0200***	-0.00491	-0.0847	0.0186***
	(4.51)	(-0.19)	(-1.48)	(4.31)
$BKPOP$	0.00797***	0.0229***	0.0230	0.00850***
	(4.84)	(2.72)	(1.32)	(5.35)
$BKPDNS$	0.000596	-0.0142	-0.0102	-0.00120
	(0.17)	(-1.05)	(-0.26)	(-0.35)
$BKICHG$	0.201***	0.561***	0.619*	0.220***
	(10.76)	(4.62)	(1.92)	(11.86)
$MBHC$	0.0185***	0.0131	0.0290	0.0182***
	(5.11)	(0.80)	(0.66)	(5.29)
$OBHC$	0.0135***	0.0196	0.0379	0.0141***
	(4.74)	(1.26)	(0.88)	(5.07)
MRG	0.0376***	0.0740***	0.0254*	0.0652***
	(4.71)	(4.58)	(1.86)	(8.07)
ACQ	0.000608	0.00410	-0.00800	0.000361
	(0.39)	(0.55)	(-0.63)	(0.24)
Constant	-0.0875***	-0.145	-0.355	-0.0976***
	(-2.66)	(-0.74)	(-1.28)	(-3.19)
Bank FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Adj. R^2	0.478	0.461	0.376	0.475
N	79152	3341	1863	84356

Table 8: Bank Risk-Taking and Managerial Ability.

This table reports regression results for three measures of bank risk: tier 1 ratio ($T1R$), liquid assets over total assets ($LAGTA$) and Z-Score ($ZIND$) on lagged managerial ability (MA_{t-1}) and lagged (3-year moving averages of) bank characteristic control variables, with bank and time fixed effects and standard errors clustered by bank. The definitions of all the variables are detailed in Appendix A. All variables are winsorized at the 1st and 99th percentile to reduce the influence of outliers. In the case when $ZIND$ is the dependent variable (Panel C), regressors are lagged by three timesteps to avoid overlap between $ZIND$ and the regressors. MRG is omitted from certain regressions where the subsamples do not record any merger activity. Monetary values are in 2005 US Dollars. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels respectively. T-statistics are reported in parentheses.

	Panel A: T1R				*Panel B: LAGTA*				*Panel C: ZIND*			
	Small	Medium	Large	All	Small	Medium	Large	All	Small	Medium	Large	All
MA_{t-1}	0.00805***	-0.00618**	0.00369	0.0112***	-0.0725***	-0.0510***	-0.00234	-0.0695***	1.312***	-2.746***	-1.823***	0.315
	(4.96)	(-1.99)	(1.24)	(7.42)	(-13.73)	(-4.55)	(-0.19)	(-14.90)	(5.87)	(-4.07)	(-2.72)	(1.47)
$CREDRSK$	-0.212***	-0.104***	-0.0943***	-0.206***	-0.643***	-0.601***	-0.632***	-0.644***	-1.061***	-1.817	-4.276**	-1.014***
	(-68.95)	(-8.67)	(-7.56)	(-67.89)	(-57.60)	(-12.69)	(-11.43)	(-60.30)	(-3.94)	(-1.48)	(-2.13)	(-3.91)
$ZIND$	0.000297***	0.000589	0.000368	0.000354***	0.000344	0.00197	0.00139	0.000251				
	(2.62)	(1.47)	(0.63)	(3.14)	(1.03)	(1.61)	(0.84)	(0.79)				
$SDROA$	-0.00356***	0.00674**	0.00447	-0.00314***	0.00792***	0.0193***	-0.00102	0.00878***	0.381***	-0.160	0.0209	0.324**
	(-5.75)	(2.26)	(1.50)	(-5.23)	(3.76)	(3.05)	(-0.06)	(4.46)	(3.01)	(-0.22)	(0.02)	(2.55)
EA	1.310***	0.823***	0.601***	1.252***	0.0907***	-0.0310	-0.0608	0.0910***	22.68***	-5.244	3.793	22.05***
	(84.18)	(9.64)	(8.87)	(80.22)	(3.01)	(-0.28)	(-0.35)	(3.21)	(15.05)	(-0.73)	(0.40)	(15.08)
$BKSIZE$	-0.000725	-0.00983***	-0.00800***	-0.00283***	0.00715***	-0.00329	0.0176	0.00851***	1.897***	0.451	-0.0123	1.744***
	(-0.83)	(-2.60)	(-3.02)	(-3.60)	(3.19)	(-0.38)	(1.63)	(4.35)	(17.54)	(1.26)	(-0.03)	(17.55)
$BKHHI$	-0.000550	-0.0223	0.00975	-0.000734	0.00626	-0.0390	-0.0679	0.00973	-0.278	1.293	5.606	-0.0613
	(-0.22)	(-1.07)	(0.44)	(-0.30)	(0.79)	(-0.79)	(-0.51)	(1.25)	(-0.68)	(0.42)	(1.32)	(-0.15)
$BKMSML$	0.00118	0.0203**	0.0346***	0.000987	-0.0150***	0.0233	0.0361	-0.0117***	0.292	0.909	-4.911*	0.138
	(0.86)	(2.32)	(2.86)	(0.73)	(-3.43)	(1.07)	(0.81)	(-2.80)	(1.38)	(1.03)	(-1.71)	(0.67)
$BKPOP$	-0.000238	-0.00565*	-0.00793***	-0.000446	-0.00469***	-0.00371	0.00799	-0.00438***	0.0698	-1.111**	1.237*	0.0325
	(-0.51)	(-1.96)	(-2.62)	(-0.96)	(-3.10)	(-0.48)	(0.59)	(-3.03)	(1.22)	(-2.07)	(1.82)	(0.53)
$BKPDNS$	0.000702	0.0113*	0.00701	0.00120	-0.000232	-0.00177	0.0154	0.00159	0.223	-0.110	0.351	0.317**
	(0.59)	(1.90)	(1.36)	(1.02)	(-0.07)	(-0.15)	(0.50)	(0.49)	(1.35)	(-0.19)	(0.55)	(2.00)
$BKICHG$	-0.0627***	-0.112***	-0.145***	-0.0680***	0.0190	-0.159	-0.193	0.0132	-2.618***	-6.192	1.965	-2.417***
	(-11.93)	(-2.64)	(-2.84)	(-12.85)	(1.10)	(-1.44)	(-0.76)	(0.78)	(-3.48)	(-0.81)	(0.14)	(-3.21)
$MBHC$	-0.0151***	-0.00228	-0.0357***	-0.0146***	-0.00921***	-0.00549	-0.0380	-0.0107***	-0.284**	0.773	-1.431	-0.220
	(-11.52)	(-0.44)	(-2.78)	(-11.60)	(-2.74)	(-0.33)	(-1.22)	(-3.35)	(-2.06)	(1.30)	(-1.22)	(-1.60)
$OBHC$	-0.00518***	0.000439	-0.0331**	-0.00555***	-0.0135***	-0.0100	-0.0419	-0.0148***	-0.452***	0.297	-1.403	-0.409***
	(-5.28)	(0.10)	(-2.55)	(-5.64)	(-4.94)	(-0.63)	(-1.41)	(-5.56)	(-4.04)	(0.64)	(-1.38)	(-3.74)
MRG	-0.0253	-0.00494	-0.00474**	-0.0203**	0.0277	-0.0224	-0.0204*	-0.0230			2.368***	0.807***
	(-0.69)	(-1.02)	(-2.31)	(-2.04)	(0.75)	(-1.61)	(-1.77)	(-1.07)			(4.07)	(14.92)
ACQ	-0.00282***	-0.00602***	-0.00357	-0.00305***	0.000579	-0.0157**	0.00458	0.000536	-0.0529	0.0928	0.676	-0.0222
	(-5.38)	(-2.66)	(-1.41)	(-5.89)	(0.40)	(-2.28)	(0.52)	(0.39)	(-0.90)	(0.34)	(1.03)	(-0.38)
Constant	0.314***	0.378***	0.387***	0.335***	0.789***	0.890***	0.236	0.765***	-13.75***	18.14*	-0.665	-12.22***
	(33.04)	(6.35)	(7.43)	(35.92)	(27.14)	(4.80)	(1.09)	(28.58)	(-10.46)	(1.96)	(-0.06)	(-9.20)
Bank FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.636	0.478	0.413	0.616	0.366	0.363	0.280	0.365	0.751	0.727	0.612	0.743
N	79152	3341	1863	84356	79152	3341	1863	84356	57007	2705	1392	61104

Table 9: Impact of Managerial Ability on Bank Liquidity Creation During the Financial Crisis.

This table reports regression results of Berger and Bouwman's (2009) $CATFAT$ measure of liquidity creation scaled by total assets on an indicator variable, δ_c, set to one for years belonging to the financial crisis period, the interaction of δ_c with the bank's pre-crisis managerial ability measure, MA_{06}, parameterized by SFA profit efficiency as measured at the end of 2006, and lagged (3-year moving averages of) bank characteristic control variables, with bank and time fixed effects and standard errors clustered by bank. The definitions of all the variables are detailed in Appendix A. All variables are winsorized at the 1st and 99th percentile to reduce the influence of outliers. Monetary values are in 2005 US Dollars. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels respectively. T-statistics are reported in parentheses.

	Small	Medium	Large	All
$MA_{06} \times \delta_c$	-0.103***	-0.0432	-0.00889	-0.0551***
	(-6.12)	(-1.43)	(-0.24)	(-4.04)
δ_c	-0.00430***	-0.0108**	-0.0160***	-0.00649***
	(-4.99)	(-2.51)	(-2.63)	(-7.82)
$CREDRSK$	0.769***	0.719***	0.779***	0.777***
	(29.60)	(6.97)	(4.12)	(30.86)
$ZIND$	0.00170***	0.00235	0.00602	0.00161***
	(2.81)	(0.86)	(1.15)	(2.76)
$SDROA$	-0.0234***	-0.0372***	-0.0288*	-0.0242***
	(-6.08)	(-3.89)	(-1.71)	(-6.88)
EA	0.0197	-0.135	0.128	0.0430
	(0.30)	(-0.53)	(0.29)	(0.70)
$BKSIZE$	-0.0641***	-0.0250	-0.0149	-0.0532***
	(-9.09)	(-1.04)	(-0.93)	(-8.66)
$BKHHI$	-0.000732	-0.132**	-0.412***	-0.0183
	(-0.06)	(-2.34)	(-3.88)	(-1.48)
$BKMSML$	0.0359***	0.103***	0.0844	0.0361***
	(5.36)	(2.60)	(0.72)	(5.56)
$BKPOP$	0.00395	0.00685	-0.0231	0.00282
	(1.34)	(0.62)	(-0.64)	(1.00)
$BKPDNS$	-0.0213***	-0.0490*	-0.00395	-0.0249***
	(-3.36)	(-1.93)	(-0.07)	(-4.03)
$BKICHG$	0.216***	0.549***	0.358	0.253***
	(10.35)	(4.33)	(1.28)	(12.27)
$MBHC$	0.000837	0.0235	0.0648	0.00279
	(0.12)	(1.01)	(1.49)	(0.41)
$OBHC$	0.00323	0.0333	0.0452	0.00448
	(0.55)	(1.47)	(1.20)	(0.79)
MRG		0.0806***		0.0847***
		(4.81)		(15.68)
ACQ	0.00572*	-0.0231	-0.0317	0.00408
	(1.71)	(-1.09)	(-0.87)	(1.22)
Constant	0.511***	0.204	0.394	0.421***
	(5.97)	(0.65)	(0.84)	(5.48)
Bank FE	yes	yes	yes	yes
Adj. R^2	0.228	0.310	0.311	0.232
N	19793	1059	529	21381

Table 10: Impact of Managerial Ability on Bank Risk-Taking During the Financial Crisis.

This table reports regression results for three measures of bank risk: tier 1 ratio (T1R), liquid assets over total assets ($LAGTA$) and Z-Score ($ZIND$) on an indicator variable, δ_c, set to one for years belonging to the financial crisis period, the interaction of δ_c with the bank's pre-crisis managerial ability measure, MA_{06}, parameterized by SFA profit efficiency as measured at the end of 2006, and lagged bank characteristic (3-year moving averages of) bank characteristic control variables, with bank and time fixed effects and standard errors clustered by bank. The definitions of all the variables are detailed in Appendix A. All variables are winsorized at the 1st and 99th percentile to reduce the influence of outliers. In the case when $ZIND$ is the dependent variable (Panel C), regressors are lagged by three timesteps to avoid overlap between $ZIND$ and the regressors. MRG is omitted from certain regressions where the subsamples do not record any merger activity. Monetary values are in 2005 US Dollars. Stars report significance at the 0.1 (*), 0.05 (**) and 0.01 (***) levels respectively. T-statistics are reported in parentheses.

	Panel A: T1R				*Panel B: LAGTA*				*Panel C: ZIND*			
	Small	Medium	Large	All	Small	Medium	Large	All	Small	Medium	Large	All
$MA_{06} \times \delta_c$	0.0279***	-0.0147*	0.00262	0.00949**	0.107***	0.0260	0.0531*	0.0750***	5.111***	5.152**	1.727	4.192***
	(4.53)	(-1.71)	(0.29)	(2.02)	(5.93)	(1.12)	(1.86)	(5.73)	(4.29)	(2.48)	(0.77)	(4.49)
δ_c	-0.00176***	0.000114	-0.00101	-0.00153***	0.00553***	0.00470	0.00246	0.00616***	-4.611***	-1.226***	-1.628***	-4.444***
	(-6.96)	(0.11)	(-0.71)	(-6.55)	(6.94)	(1.65)	(0.51)	(8.23)	(-75.64)	(-6.36)	(-4.65)	(-74.76)
$CREDRSK$	-0.202***	-0.109***	-0.107***	-0.198***	-0.843***	-0.816***	-0.627***	-0.849***	-22.53***	-25.27***	-29.85***	-23.00***
	(-27.18)	(-4.12)	(-3.40)	(-27.56)	(-34.71)	(-9.75)	(-4.28)	(-36.47)	(-14.50)	(-4.27)	(-3.12)	(-15.32)
$ZIND$	-0.000395**	0.000494	-0.000527	-0.000306*	-0.000285	0.00380*	0.00136	0.0000428				
	(-2.29)	(0.60)	(-0.54)	(-1.84)	(-0.52)	(1.80)	(0.45)	(0.08)				
$SDROA$	-0.00374***	0.00873**	0.00410	-0.00167	0.0153***	0.00877	-0.00409	0.0135***	-0.499	-2.826	-3.341	-0.561
	(-3.30)	(2.55)	(0.95)	(-1.55)	(4.47)	(1.06)	(-0.31)	(4.40)	(-1.33)	(-1.59)	(-1.30)	(-1.55)
EA	1.010***	0.826***	0.601***	0.983***	-0.385***	0.235	-0.560**	-0.366***	-34.87***	-27.19	-79.55***	-37.30***
	(41.03)	(10.00)	(6.12)	(41.30)	(-6.50)	(1.58)	(-2.04)	(-6.65)	(-7.39)	(-1.29)	(-3.90)	(-8.26)
$BKSIZE$	-0.00803***	-0.00848	0.000417	-0.00695***	0.0214***	-0.0154	0.0160	0.0203***	-3.863***	-6.163***	-7.697***	-4.169***
	(-3.75)	(-1.52)	(0.12)	(-3.96)	(3.24)	(-1.23)	(1.20)	(3.81)	(-12.57)	(-6.95)	(-4.01)	(-14.85)
$BKHHI$	-0.00881**	0.00564	0.0445**	-0.00595*	0.0327***	0.0507	0.156*	0.0405***	0.432	13.62*	10.72	0.790
	(-2.52)	(0.40)	(2.21)	(-1.72)	(2.75)	(1.04)	(1.73)	(3.51)	(0.30)	(1.78)	(0.78)	(0.55)
$BKMSML$	0.00879***	0.00898	0.0265	0.0101***	-0.0582***	0.0293	-0.0373	-0.0548***	-9.443***	-10.54***	-29.59**	-9.667***
	(5.15)	(1.06)	(1.14)	(6.21)	(-9.23)	(0.96)	(-0.39)	(-9.15)	(-11.47)	(-4.35)	(-2.35)	(-12.28)
$BKPOP$	-0.00131	0.00187	-0.0101	-0.00133	0.00349	-0.00113	0.0445*	0.00402*	-0.476*	-0.590	0.522	-0.462*
	(-1.40)	(0.78)	(-1.28)	(-1.47)	(1.38)	(-0.14)	(1.83)	(1.69)	(-1.96)	(-0.42)	(0.31)	(-1.95)
$BKPDNS$	0.00193	0.00677	0.0292**	0.00249	0.00429	0.0157	-0.0572	0.00603	-2.993***	-6.123**	8.812*	-2.781***
	(1.16)	(1.01)	(2.13)	(1.54)	(0.71)	(0.90)	(-1.29)	(1.06)	(-5.45)	(-2.48)	(1.82)	(-5.24)
$BKICHG$	-0.0544***	-0.121***	-0.248***	-0.0632***	-0.0970***	-0.712***	-0.645***	-0.134***	-38.36***	-105.9***	-96.31***	-41.07***
	(-9.72)	(-4.64)	(-5.36)	(-11.64)	(-5.14)	(-8.22)	(-3.26)	(-7.24)	(-15.73)	(-10.08)	(-4.72)	(-16.97)
$MBHC$	-0.00918***	0.00776	-0.0636***	-0.00881***	-0.00247	-0.0299*	-0.0435	-0.00575	-2.077***	-1.418	-1.348	-2.016***
	(-2.82)	(1.14)	(-3.28)	(-2.89)	(-0.32)	(-1.67)	(-1.34)	(-0.80)	(-4.39)	(-1.09)	(-0.58)	(-4.63)
$OBHC$	-0.00227	0.0100	-0.0627***	-0.00325	-0.0111*	-0.0352**	-0.0474	-0.0127**	-1.520***	-1.680	-0.349	-1.569***
	(-0.85)	(1.51)	(-3.30)	(-1.23)	(-1.73)	(-2.05)	(-1.64)	(-2.07)	(-4.23)	(-1.32)	(-0.14)	(-4.51)
MRG		-0.00464		0.000998		-0.0298**		-0.0246***				
		(-1.26)		(0.57)		(-2.33)		(-5.14)				
ACQ	-0.00529***	-0.00767	0.00446	-0.00532***	0.00123	0.000732	0.0235	0.00192	0.676***	1.206	1.065	0.693***
	(-4.39)	(-1.17)	(0.71)	(-4.48)	(0.38)	(0.05)	(1.23)	(0.62)	(3.49)	(1.50)	(0.63)	(3.66)
Constant	0.399***	0.255***	0.273***	0.381***	0.633***	1.121***	0.169	0.636***	96.23***	154.3***	141.3***	100.7***
	(14.80)	(3.63)	(2.87)	(16.22)	(8.15)	(5.89)	(0.45)	(9.66)	(22.12)	(6.52)	(4.31)	(23.51)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.529	0.467	0.561	0.516	0.272	0.400	0.327	0.277	0.496	0.673	0.657	0.505
N	19793	1059	529	21381	19793	1059	529	21381	18022	1013	463	19498

Table 11: Definition of Variables.

Variable Name	Variable Definition
	Managerial Ability
MA	Managerial Ability is computed according to the method of Demerjian, Lev, and McVay (2012). Specifically, we compute profit efficiency for each bank using Stochastic Frontier Analysis (SFA) and regress the resulting efficiency score on a set of bank-specific variables. The residual from this regression is that component of efficiency that cannot be explained by bank-specific factors and hence should be attributed to management.
	Liquidity Creation
$CATFAT$	Liquidity creation is measured following Berger and Bouwman's (2009) approach. Assets and liabilities are classified as to the ease, cost and time with which they can be liquidated and assigned weights of 0, $-\frac{1}{2}$ and $\frac{1}{2}$ so that maximum liquidity is created (destroyed) when illiquid assets are financed by liquid liabilities and vice versa.
	Risk-taking
$T1R$	The tier 1 ratio calculated as tier 1 capital divided by risk weighted assets using Basel II rules.
$LAGTA$	Liquid assets over gross total assets
$ZIND$	Z-Score calculated as return on assets plus capital to asset ratio, divided by the (previous three years') standard deviation of return on assets
	Bank-specifics
$CREDRSK$	Ratio of risk weighted assets to gross total assets
$SDROA$	Standard deviation of return on assets calculated using three bank-year observations
EA	Equity over asset ratio
$BKSIZE$	Log of gross total assets
CE	Cost efficiency score derived from SFA
$MBHC$	Dummy variable, set to one if a bank is part of a multibank holding company and zero otherwise
$OBHC$	Dummy variable, set to one if a bank is part of a onebank holding company and zero otherwise
MRG	Dummy variable, set to one if a bank has been involved in at least one merger in the last three years and zero otherwise
ACQ	Dummy variable, set to one if a bank has been acquired in the last three years and zero otherwise
	Bank Market Characteristics
$BKHHI$	Weighted Herfindahl-Hirschmann index calculated using a bank's deposits in a given market as weights
$BKMSML$	Market share of medium and large banks faced by a bank in its markets, calculated using a bank's deposits in a given market as weights
$BKPDNS$	Population density of a bank's markets calculated using a bank's deposits in a given market as weights
$BKPOP$	Population of a bank's markets calculated using a bank's deposits in a given market as weights
$BKICHG$	Income change of a bank's markets calculated using a bank's deposits in a given market as weights