Laboratoire
de Recherche
en Gestion
& Economie

Working Paper
2017-08

Technical Efficiency in Bank Liquidity Creation

Iftekhar HASAN & Jean-Loup SOULA

April 2017

Université de Strasbourg
Pôle Européen de Gestion et d'Economie
61 avenue de la Forêt Noire
67085 Strasbourg Cedex
http://large.em-strasbourg.eu/

Institut de Finance de Strasbourg

Technical Efficiency in Bank Liquidity Creation

Iftekhar Hasan

Gabelli School of Business, Fordham University

Jean-Loup Soula[1]

Strasbourg University, LaRGE Research Center

April, 2017

Abstract

This paper generates an optimum bank liquidity creation benchmark by tracing an efficient frontier in liquidity creation (bank intermediation) and questions why some banks are more efficient than others in such activities. Evidence reveals that medium size banks are most correlated to efficient frontier. Small (large) banks - focused on traditional banking activities - are found to be the most (least) efficient in creating liquidity in on-balance sheet items whereas large banks – involved in non-traditional activities – are found to be most efficient in off-balance sheet liquidity creation. Additionally, the liquidity efficiency of small banks is more resilient during the 2007-2008 financial crisis relative to other banks.

JEL classification: G21, G28, G32

Keywords: banks, technical efficiency, liquidity creation, diversification

[1] Corresponding author at : Institut d'Etudes Politiques, Université de Strasbourg, 47 Avenue de la Forêt Noire, 67082 Strasbourg Cedex, France.
E-mail address: jlsoula@unistra.fr

Introduction

Liquidity creation is an essential role of banks, along with risk transformation. Banks create liquidity by financing illiquid assets such as loans with liquid liabilities such as demand deposits. Doing so, banks offer a service to the economy as liquidity production by banks enhances the total funding an economy could benefit from. Using information on all assets, liabilities, equity, and off-balance sheet activities, Berger and Bouwman (2009) developed a comprehensive measure of liquidity transformation (extent of bank intermediation) revealing that large banks, multibank holding company members, and merged banks create the most liquidity. While others related the extent of liquidity creation be affected by bank value (Cowan and Salotti, 2015), competition (Horvath et al. 2015), and regulatory policies and interventions (Berger et al. 2015). While these studies provide insights about the factors associated with higher levels of liquidity production, they do not necessarily reflect the extent of efficiency by banks in creating such liquidity.

In other words, banks identified as producing most funding liquidity are not necessarily the most efficient liquidity provider. This paper attempts to fill this void in the literature. This paper investigates factors associated with most efficient bank liquidity production. It reports that size does matter but in a non-linear shape where smaller banks – experienced in processing soft information and relationship lending – are closer to the efficient frontier of the on-balance sheet liquidity creation as opposed to large banks – depended on hard information and transaction lending – being more correlated to efficient off-balance sheet frontier of liquidity creation.

In the Berger and Bouwman's framework, a bank produces most liquidity when originating the most illiquid loans (for instance to young, small businesses) and collecting the most liquid liabilities, i.e. demand deposits. However, the ability to both originate opaque loans and collect deposits is determined by the technological, organizational, and business mix choices in terms of specialization or diversification made by banks. In other words, the level of liquidity produced by a bank is the result of a production process. Thus, the level of liquidity produced is determined by the ability of each bank to make the best use of its productive resources, i.e. financial and physical capital, and labor. This calls for measuring the productive performance of banks in their ability to provide liquidity to the economy. Efficiency measures used in production economics provide a consistent framework to address this issue. This article uses Berger & Bouwman's (2009) measure of liquidity creation as a measure of bank output. This measure is a more comprehensive measure of a bank's output than traditional measures (such as loans or total assets). Indeed, it accounts for all bank activities contributing to bank liquidity creation. To the best of our knowledge, this is the first paper to study efficiency in bank liquidity production. Building an efficiency measure of the liquidity production of banks, this paper identifies three main factors that may determine the efficiency of bank liquidity production.

A first factor identified by the research as affecting the quantity of liquidity produced is the size of the bank. Research evidences scale economies as a major factor governing productivity in the banking sector. Scale economies arise from an improved division of labor and specialization in larger banks. The risk diversification of large loan portfolios can also explain increasing return to scale. The literature evidences that economies of scale increase with bank size (Berger & Mester, 1997; Hughes & Mester, 1998). Scale economies may foster the production of illiquid loans and/or facilitate the collection of deposits. Thus, we expect larger banks to be more efficient in terms of liquidity production.

Drawing on the potential effect of the size on efficiency to produce liquidity, we also investigate the effect of bank activity mix. Indeed, diversification is associated with larger scale economies while increased risk taking and inefficiency are related to smaller scale economies (Hughes et al., 2001). Bank diversification stems from a mix of traditional and non-traditional activities (Apergis, 2014). Traditional banking includes deposit taking, lending, and payment services. Non-traditional activities include asset management, brokerage, insurance, non-financial-business, and securities underwriting services (Berger et al., 2010). Moreover, banks of different size differ in portfolio composition and performance. Large banks are more diversified in terms of product mix and tend to be more engaged in non-traditional banking (e.g. Stiroh, 2004; Stiroh & Rumble, 2006).

Moreover, performing their intermediation activity (creating liquidity), banks rely on lending technology. Berger & Udell (2006) distinguish between relationship lending from transaction lending. These types of lending rely respectively on two technologies, using either soft or hard information (Stein, 2002). Research also evidences the relationship between lending technology and bank size. Smaller banks tend to process soft information, performing relationship lending. On the contrary, large banks tend to specialize in the use of hard information and perform transaction lending (e.g. Berger & Udell, 2002) . The relationship between size and the kind of information used by banks is particularly observed in the US banking industry. It has been identified as a consequence of deregulation and technological change. Indeed, DeYoung et al. (2004) underline that both factors have divided the US banking industry into two kinds of business models: large banks tend to use hard information and small banks tend to use soft information.

However, to the best of our knowledge, the literature does not relate bank business models to productive efficiency. The purpose of this article is to analyze to what extent bank business models could explain efficiency in bank liquidity production. We hypothesize that the relationship oriented model would be more efficient in producing liquidity. This could be due to the fact that this model is more intense in information regarding customers. Indeed the relationship oriented model consists in associating the highest value-added liabilities (core deposits) to the highest value-added loans (relationship loans) (Song & Thakor, 2007).

Finally, liquidity creation goes hand in hand with exposure to liquidity risk, as the gap between illiquid assets and liquid liabilities increases as more liquidity is produced. Relying on liquid liabilities, banks are potentially unable to settle obligations with immediacy over a specific horizon by using available liquid assets and cash, or incurring new debt at reasonable price (Drehmann & Nikolaou, 2013). Furthermore, Acharya & Naqvi (2012) underline that banks creating substantial liquidity might pursue lending policies generating asset price bubbles, thus increasing the fragility of the banking sector. Berger and Bouwman (2016) indeed observe that liquidity creation tends to be abnormally high before financial crises. We might expect that banks less efficient in producing liquidity could be less profitable and, all things being equal, be more exposed to liquidity shocks. Moreover, liquidity regulations may have heterogeneous effects on banks that not only differ in their liquidity production levels, but also differ in their efficiency to produce liquidity. While the present article cannot address directly these issues, considering liquidity in a productive perspective might highlight a management channel of liquidity regulation. Indeed, if the cost of liquidity increases through tighter liquidity regulations, banks less efficient might be more affected, i.e.

reduce their liquidity production by e.g. originating relatively less illiquid loans, thus altering their activity mix.

The contribution to the literature is threefold. First, we reconsider the question of bank technical efficiency considering an alternative measure of bank production. We thus investigate what determines banks' ability to produce liquidity while saving resources. More particularly, a second contribution of this article is to investigate the factors associated with most efficient bank liquidity production. We find that size matters in a non-linear shape. Small banks – experienced in processing soft information and relationship lending – are closer to the efficient frontier of the on-balance sheet liquidity creation as opposed to large banks – relying on hard information and transaction lending – being more correlated to efficient off-balance sheet frontier of liquidity creation. Medium banks are the most efficient in producing overall liquidity. Bank technical inefficiency tends to increase with diversification in nontraditional banking activities. At a macro point of view, we also provide information about how global financial conditions seem to affect efficiency in producing liquidity, particularly since the beginning of the 2007-2008 financial crisis until 2010. Whatever the size, efficiency decreases with the crisis. However, the larger the bank the more pronounced this decline, and the smaller banks become the most efficient in producing liquidity. In other words, efficiency is more sensitive to liquidity shocks when the bank is more engaged in nontraditional banking. Thirdly, at the regulatory level, the literature evidences the influence of deregulation on the choice of activity mix by banks (DeYoung et al., 2004). Because of the relationship we observe between activity mix and efficiency in producing liquidity, we argue that regulation might not be neutral in terms of efficiency in creating liquidity. Identifying bank characteristics affecting efficiency in producing liquidity could help understand the consequences of regulation in terms of welfare of the economy.

Literature review

How to assess bank productive efficiency

The literature usually uses three measures of bank aggregated output: total assets, gross total asset, and lending (see Berger & Bouwman, 2016 for a survey of the literature). Here we use the measure of liquidity creation developed by Berger & Bouwman (2009) to account for the production of banks. This measure of liquidity creation is a more comprehensive measure of a bank's output than traditional measures. Indeed, the "catfat" version of the measure takes into account the contribution to bank liquidity creation of all bank activities. Indeed, it uses information on all assets, liabilities, equity, and off-balance sheet activities. This measure is constructed in three steps. Firstly, all bank assets, liabilities, and off-balance sheet activities are classified as liquid, semi-liquid, or illiquid. Secondly, weights are assigned to the elements classified. The final step sums the activities classified and weighted. Table 1 in Berger & Bouwman (2009) provides a synthetic view of this methodology. A second "catnonfat" version of the measure assesses liquidity creation on-balance sheet only. The authors also measure liquidity creation off-balance sheet. To the best of our knowledge, this study is the first to use Berger & Bouwman's (2009) measure of liquidity production as a global indicator of banks' production in order to analyze productive efficiency.

Several studies address the issue of the efficiency in banks' production with intermediation and production approaches or value-added approaches. The intermediation approach considers banks' liabilities as inputs to produce loans and other banking assets (Rogers, 1998; Sealey & Lindley, 1977). The production or value-added approach considers in addition to loans, deposits as a service offered to banks' customers. Therefore, in the value-added approach, inputs comprise only labor and capital. As the measure of bank output is here the liquidity creation measure, the choice of the value-added approach is appropriate. Indeed, bank's liabilities are included in this measure. Under the intermediation approach inputs and output would overlap. Moreover, under this approach all the liquidity created is viewed as output as it accounts for the value added by banks. Using a production function, we study the technical efficiency of banks, that is if managers organize production so that the firm maximizes the amount of output produced with a given amount of inputs.

Relationship between bank size, activity mix and liquidity creation

This article explores the relationship between efficiency in producing liquidity and bank mix of activity. Closest to the issue of this article, Hughes et al. (1997) analyze the effect of a set of variables characterizing bank production on market value inefficiency.

Bank mix between traditional and nontraditional activities determine banks' level of diversification (Apergis, 2014). Traditionally, banks take deposits, lend, and provide payment services. Banks developed nontraditional activates such as asset management, brokerage, insurance, non-financial-business, and securities underwriting services (Berger et al., 2010). Large banks tend to engage more in nontraditional activities, while small banks favor traditional activities (Stiroh & Rumble, 2006).

Moreover, the literature on bank lending business identifies two kind of business models and relates these business models to the size of banks. The relationship oriented model relies on soft information and is associated with small banks. The transaction oriented model uses hard information and is related to large banks. Berger & Black (2011) define soft information as qualitative information that is difficult to quantify and communicate. This is a personal and subjective knowledge about the borrower and the activity a bank finance. Hard information is defined as quantitative information that can be credibly communicated to others. This encompasses financial ratios, collateral values and credit scores. Cole et al. (2004) evidence that small banks tend to use more subjective measures such as the character of the borrower (i.e. soft information) while large banks use quantitative financial data (i.e. hard information). The literature underlines the comparative advantage of large (small) banks in using lending technologies based on hard (soft) information. Berger and Udell (2002) relate the advantage of small and large banks in using soft and hard information to their organizational structure. Berger et al. (2005) explain the choice of the type of information banks rely on by different sets of incentives within organization structure according to the size of banks. Smaller organization structures are best at resolving agency problems and managing soft information. Namely, large banks rely on hard information that they can communicate to others in the bank, while small banks use soft information to be more flexible. The literature provides empirical evidence of the relative advantages associated with the different lending technologies given asset size (e.g. Berger & Black, 2011; de la Torre et al., 2010).

A whole strand of the literature analyses the relationship between bank business models and lending business technologies. A first strand of the literature addresses the issue of the relationship between business model and bank's performance in the lending business as a whole. The literature underlines the advantage of large banks in lending to large firms and the advantage of small banks in lending to small firms. Berger et al (2005) observe that large banks tend to lend to larger, older SMEs and small banks to SMEs with which they have stronger relationship. Firstly, the respective advantage of large (small) banks in lending to large (small) firm might be explained by the business model used by the banks. Berger et al. (2005) observe that firms interacting with large banks tend to communicate in impersonal ways, with less excusive bank relationship than firms interacting with small banks. Secondly, this respective advantage could be due to borrower characteristics. Smaller banks may benefit relatively more from the credit information steaming from deposit accounts. Carter & McNulty (2005) find that small banks perform better than large banks in the small business lending market. The authors argue that a small bank dealing with a small firm observe all the information on account deposit flows, as the firm usually have one deposit relationship. Also, Song & Thakor (2007) argue that banks associate the highest value-added liabilities (core deposits) to the highest value-added loans (relationship loans). Doing so, banks minimize the fragility imposed by withdrawal risk and maximize the value added in relationship lending. Thus, the business model of relationship lending would create more value and also more liquidity.

Another strand of the literature looks at the performance of lending technologies on the more specific business of small lending. Berger & Black (2011) investigate the comparative advantage of large (small) banks lending to small businesses using hard (soft) information lending technologies. More particularly, the authors propose an identification of hard information based on fixed-asset lending technologies. Finally, some studies investigate the effect of characteristics of lending products on business lending. DeYoung et al. (2004) relate the use of soft information by smaller banks to the evaluation of customized loans such as small business loans. Larger banks tend to use hard information to evaluate more standardized loans, such as credit card loans. Carter & McNulty (2005) provide empirical evidence of the better performance of smaller (larger) banks in providing non-standardized (standardized) loans.

Thus, the intensity of the intermediation function of banks is affected by the activity mix between traditional and nontraditional banking, and by the choice of business model in lending. Consequently, we expect the activity mix to affect bank efficiency in producing liquidity.

Methodology

Model

Levels of technical efficiency are estimated using the standard Stochastic Frontier Approach (SFA) along the lines suggested by Aigner et al. (1977) and Meeusen & van den Broeck (1977). We use the Battese and Coelli (1995) model of a stochastic frontier function for panel data. Firm effects are assumed to be distributed as truncated normal random variable and are permitted to vary systematically over time. The standard translog functional form as well as the two-component error structure is estimated using a maximum likelihood procedure. The stochastic frontier production function to be estimated is specified as follows:

$$\ln(Y_{it}) = \beta_0 + \sum_{j=1}^{4} \beta_j x_{jit} + \sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} x_{jit} x_{kit} + V_{it} + U_{it} \qquad (1)$$

where ln denotes the natural logarithm, the subscripts, *i* and *t*, represent the *i*-th bank (i = 1, 2, … 2562) and the *t*-th quarter of observation (t = 1, 2, …, 48), respectively;

Y represents the liquidity creation both in and off-balance sheet defined as the “catfat” measure of Berger & Bouwman (2009);

x_1 is the logarithm of financial capital defined as the total equity of the bank;

x_2 is the logarithm of labour capital defined as total expenses in salaries and employee benefits;

x_3 is the logarithm of physical capital defined as expenses of premises and fixed assets;

x_4 is the logarithm of non-performing loans of the bank;

the $V_{it}s$ are random variables associated with measurement errors in input variables or the effects of unspecified explanatory variables in the model. There are assumed to be independent and identically distributed with $N(0,\sigma_v^2)$ – distribution, independent of the $U_{it}s$;

the $U_{it}s$ are non-negative random variables, associated with the inefficiency of the use of the inputs in the banks, given the levels of the inputs, and U_{it} is obtained by the truncation (at zero) of the $N(\mu_{it},\sigma^2)$-distribution.

In equation 1, the technical inefficiency effects are assumed to be defined by:

$$U_{it} = \delta_0 + \sum_{j=1}^{14} \delta_j z_{jit} + W_{it} \qquad (2)$$

where:

z_1 is the size of the bank defined as the logarithm of total assets;

z_2 is a dummy variable equal to one if the bank is part of a bank holding company, zero otherwise;

z_3 to z_5 are proxies of diversification between traditional and non-traditional banking activities, respectively the diversification of activities, assets, and loans;

z_6 to z_{14} are variables assessing the interaction between dummies of bank size class and diversification of banking activities, denoted by bank size dummy * diversification index; for instance, small bank dummy * activity diversification indice.

The model for inefficiency effects in equation (2) specifies that the inefficiency effects are different for different size of banks, bank holding company status, diversification of banking activities between traditional and non-traditional, and the interaction between bank size class and diversification of activity mix.

The model for technical inefficiency effects in a stochastic frontier production function for panel data is estimated. We use a value-added approach to specify inputs in the model (e.g. Chaffai & Dietsch, 2015). Therefore, we do not use stocks of assets or liabilities as inputs but rely on flow of services. Moreover, financial capital is included as an input in the production process as it provides a cushion against losses and depends on the risk profile of the bank (Mester, 1996). Finally, comparing efficiency between banks, one should take into account output quality (Berger & Mester, 1997). Thus we include nonperforming loans as a input to control for the quality of bank output (e.g. Mester, 1996).

The parameters of the stochastic frontier model, defined by equations (1) and (2), are simultaneously estimated by the method of maximum likelihood. The variance parameters in the frontier model are estimated in terms of the variance parameters:

$$\sigma_s^2 = \sigma_v^2 + \sigma^2 \text{ and } \gamma = \sigma^2/\sigma_v^2 \tag{3}$$

where γ is a parameter with possible values between zero and one.

The technical efficiency of liquidity production for the i-th bank in the t-th quarter of observation, given the values of the inputs, is defined by the ratio of the stochastic frontier liquidity production to the observed liquidity production. The stochastic frontier liquidity production is defined by the value of liquidity production if the technical inefficiency effect, U_{it}, was zero, i.e. the bank was fully efficient in liquidity production. Technical efficiency of liquidity production is defined by:

$$TE_{it} = \exp(-U_{it}) \tag{4}$$

By definition technical efficiency is no greater than one. The reciprocal of technical efficiency, $\exp(U_{it})$ can be interpreted as a measure of technical inefficiency of liquidity production.

Hypotheses

We investigate two main hypotheses. First, the literature evidences scale economies as affecting productivity in the banking sector. More particularly, economies of scale increase with bank size (Berger & Mester, 1997; Hughes & Mester, 1998), as well as risk diversification (Hughes et al., 2001). Thus, a first hypothesis is that larger banks would need to input less resources for a given level of liquidity production. Indeed, scale economies may foster the production of illiquid loans and/or facilitate the collection of deposits. Thus, we expect larger banks to be more efficient in terms of liquidity production (hypothesis 1). This hypothesis is reinforced by the link between bank size and bank business model. Indeed, the relationship business model would require more labor and physical capital to collect deposits and grant loans, compared to the transactional business model. Furthermore, because of risk diversification inherent in larger loan portfolio, larger banks would need a lower amount of equity capital for a given level of liquidity production. Following Berger & Bouwman (2009), we create three size dummies: a large dummy equal to one if banks' gross total asset (GTA) exceeds \$3 billion, a medium dummy equal to one if banks' GTA is comprised between \$1 billion and \$3 billion, and a small dummy for banks' GTA up to \$1 billion. This threshold is usually used by the literature studying the US banking industry (e.g. DeYoung, 2004).

Then, we analyze the link between bank business models and efficiency in producing liquidity. Our second hypothesis is that banks engaged in traditional banking would be more efficient than banks involved in nontraditional activities (hypothesis 2). Indeed, traditional banking is grounded in the relationship oriented model of associating the highest value-added liabilities (core deposits) to the highest value-added loans (relationship loans) (Song & Thakor, 2007). Doing so, we expect banks to be more efficient. On the contrary, nontraditional activities such as brokerage and securities underwriting, do not participate to the core intermediation function of banks. These banking activities reduce the level of liquidity creation in Berger and Bouwman's methodology. As a result, technical efficiency of banks engaged in nontraditional activities would be lower.

However, bank business model and activity mix are related to bank size. Large banks tend to engage more in nontraditional banking such as financial market activities (Stiroh & Rumble, 2006) and rely more on the use of hard information to perform transactional lending (Berger & Udell, 2002). On the contrary, smaller banks have an advantage in terms of lending as mentioned previously. Consequently, we wonder which effect prevails between hypothesis 1 and 2. Nevertheless, we expect that the effect of traditional banking activities on technical efficiency is stronger that the size effect of economies of scale, as it directly increases the quantity of liquidity produced. Thus, our third hypothesis is that the largest banks would be less efficient because of their involvement in nontraditional banking activities (hypothesis 3).

To investigate these last hypotheses, we estimate the effect of activity, asset, and loan diversification on technical efficiency. The literature underlines the potential benefits of diversification in terms of economies of scope (e.g. Laeven & Levine, 2007). Namely, making loans, banks acquire information about clients that facilitate the provision of other financial services, such as the underwriting of securities. Conversely, other activities than traditional intermediation, such as securities and insurance underwriting, brokerage and mutual fund services, produce information that can improve loan making. Econometric difficulties prevent from measuring economies of scope in the provision of financial services (Berger & Humphrey, 1997). Consequently, the literature hardly finds evidence of significant economies of scope. For instance, Laeven and Levine (2007) find evidence of a diversification discount applied to financial conglomerates. Rather than measuring economies of scope, we investigate whether diversification in nontraditional banking activities influences bank efficiency in producing liquidity.

First, we construct an income-based measure of diversification. Indeed, DeYoung & Rice (2004) observe that smaller banks have a much lower level of non-interest income compared to larger banks. Furthermore, the sources of non-interest income for smaller banks are more likely to come from traditional banking activities such as fees on deposit account or cash management. On the contrary, non-interest income for larger banks stems from mortgage securisation, credit cards, investment banking, and fiduciary accounts. As a consequence, activity diversification, measured by the source of non-interest income, indicates the extent of non-traditional banking activities. These sources of non-interest income might increase the level of liquidity production by large banks as found in Berger & Bouwman (2009), consistently with potential economies of scope. Namely, being larger, these banks have a higher level of non-interest income stemming from traditional banking activities. However, financial market activity might reduce efficiency in liquidity production, as derivatives for instance, does not account for liquidity creation but for liquidity destruction. Consequently, activity diversification would tend to be associated with less technical efficiency, as it consists of using resources to pursue activities that do strictly produce liquidity. Nontraditional activities would tend to reduce efficiency in creating liquidity.

Drawing on Deng et al. (2007), Estes (2014), Schmidt and Walter (2009), and Stiroh (2004b), we compute a Herfindahl-Hirschman Index (HHI) of non-interest income (NONII) categories. This HHI captures the level of activity diversification. The HHI of NONII is the sum of squares for each segment as a proportion of total NONII. A high value indicates a concentration of fee sources, i.e. more activity specialization, while banks engaging in a mix of activities have a relatively low HHI. Thus, higher values of HHI of NONII indicate traditional banking activities and would be associated to higher level of technical efficiency (hypothesis 3). The non-interest income categories come from the call reports. They are presented in the table 6 below. The HHI of activity diversification is computed as follows:

$$HHI_{Activity_{i,t}} = \left(\frac{FID}{NON}\right)_{i,t}^2 + \left(\frac{SRV}{NON}\right)_{i,t}^2 + \left(\frac{TRAD}{NON}\right)_{i,t}^2 + \left(\frac{S\&I}{NON}\right)_{i,t}^2 + \left(\frac{VENT}{NON}\right)_{i,t}^2 \left(\frac{SERV}{NON}\right)_{i,t}^2 + \left(\frac{SEC}{NON}\right)_{i,t}^2 + \left(\frac{GAINS}{NON}\right)_{i,t}^2 + \left(\frac{OTH}{NON}\right)_{i,t}^2$$

where i represents the i^{th} bank for the time period t, NON is the sum of non-interest income, FID is fiduciary income, SRV is service charges on deposit accounts, TRAD is the trading revenue, S&I is the sum of all securities brokerage, investment banking, annuity, and insurance fees and commissions, VENT is venture capital revenue, SERV is net servicing fees, SEC is net securization income, GAINS is the sum of gains/losses on sales of loans, other real estate, and other assets, and OTH is other non-interest income. Banks can report negative income for these NONII categories. For each category of NONII, this results in a positive number. However, the summation of NONII categories would underestimate the portfolio of non-interest activities. Thus, we take the absolute value for each NONII category to obtain the denominator (NON).

Then, to account for the reliance of banks on traditional banking activities, we also look at asset diversification. We compute a Herfindahl-Hirschman Index (HHI) of asset diversification. Banks oriented towards traditional activities focus on lending and tend to have a higher share of loans in total asset. Clearly there is a link between the measure of diversification of assets and the degree to which banks engage in lending or non-lending activities. If a bank only make loans, it will have a low asset diversification and a high HHI of asset diversification. Thus, the HHI of asset diversification determines where the bank lies along the spectrum from pure commercial banking to a mix of commercial and investment banking. We except high asset concentration (i.e. high values of HHI) to be associated with more efficiency in producing liquidity. Indeed, the more a bank engages in traditional lending activity, the more it allocates its resources to the assets producing the most liquidity. Using asset categories of the call reports, we construct the Herfindahl-Hirschman Index of asset diversification as follows:

$$HHI_{Asset_{i,t}} = \left(\frac{CASH}{ASSETS}\right)_{i,t}^2 + \left(\frac{SECU}{ASSETS}\right)_{i,t}^2 + \left(\frac{LOANS}{ASSETS}\right)_{i,t}^2 + \left(\frac{FIX}{ASSETS}\right)_{i,t}^2 + \left(\frac{OTH}{ASSETS}\right)_{i,t}^2$$

where i represents the i^th^ bank for the time period t, ASSETS is the sum of all assets, CASH is the cash held by the bank, SECU is the sum of all securities including repo securities, LOANS is the total net loans, FIX is the sum of fixed assets and real estate assets, OTHER is all other assets (see table 6).

Finally, we construct a Herfindahl-Hirschman Index of loan diversification based on loan categories, following Deng et al. (2007) and Estes (2014). This index reflects how much a bank rely on traditional banking in its lending operations. Indeed, traditional banking includes making loans to different sectors such as commercial and industrial, real estate agriculture, financial institutions, individual, and others (Deng et al., 2007). Thus, a more diverse loan portfolio tends to indicate traditional banking. Moreover, diversification of the loan portfolio can benefit to a bank in terms of economies of scope. Namely, making loans to a given sector, banks acquire information about clients that facilitate the provision of loans to the same clients of another sector. Similarly, making loans to a given clientele, banks acquire information about sectors, facilitating the provision of loans to other clients of the same sectors. Thus, we expect banks with a diversified loan portfolio to be more efficient in terms of liquidity production. The HHI of loan diversification determines where the bank lies along the spectrum from traditional diversified lending to non-traditional specialized lending. Higher level of HHI of loan diversification indicates a higher concentration of lending activity which denotes nontraditional banking activities, as traditional lending include making loans to different economic sectors (Deng et al., 2007). We expect high loan concentration (i.e. high value of HHI) to be associated with less efficiency in producing liquidity. We construct the index using loans categories of the call reports, as follows:

$$HHI_{Loans_{i,t}} = \left(\frac{1-4RE}{LOANS}\right)_{i,t}^2 + \left(\frac{CONST}{LOANS}\right)_{i,t}^2 + \left(\frac{FARM}{LOANS}\right)_{i,t}^2 + \left(\frac{MULTI}{LOANS}\right)_{i,t}^2 + \left(\frac{CRE}{LOANS}\right)_{i,t}^2 + \left(\frac{AG}{LOANS}\right)_{i,t}^2 + \left(\frac{CI}{LOANS}\right)_{i,t}^2 + \left(\frac{CONS}{LOANS}\right)_{i,t}^2 + \left(\frac{OTH}{LOANS}\right)_{i,t}^2$$

Where i represents the i^th^ bank for the time period t, LOANS is the sum of all loans, 1-4RE is loans secured by 1-4 family residential properties, CONST is loans secured by real estate and used for construction or other land development, FARM is loans secured by farmland, MULTI is loans secured by multifamily residential properties, CRE is loans secured by nonfarm non-residential properties, AG is agricultural loans, CI is all commercial and industrial loans, CONS is consumer loans, including credit card loans, and OTH is the sum of loans to depository institutions, foreign or state and local government, lease financing, and other loans (see table 6).

Data sources

This paper uses data from the reports of income and condition ("call reports") published by the Federal Deposit Insurance Corporation (FDIC) for all domestic commercial banks in the United States. The dataset contains quarterly balance sheet and income statement data on FDIC-insured banks from 1999 to 2014 on a quarterly basis. This paper also uses the measure of liquidity creation by banks computed by Berger & Bouwman (2009). For consistency, we apply the same GDP deflator as Berger & Bouwman (2009) to the data extracted from the call reports.

We apply to the dataset several treatments. First, following Kashyap et al. (2002) we conduct the analysis on the bank-level and use unconsolidated data. We consider banks as decision making units regarding lending and deposit taking activities resulting in the production of liquidity. Secondly, to handle the distorting effect of bank mergers and acquisitions for the continuity of time series, we follow Campello (2002). We eliminate observations with asset growth in excess of 50 percent, those with total loan growth exceeding 100 percent and those with loans-to-asset ratios below 10 percent. Following Beltratti & Stulz (2012), we keep observations with a ratio of deposit equal to 20 percent or larger. Finally, the measure of liquidity creation contains large positive and negative outliers. To make sure that these outliers do not drive our results, we winsorize this variable at the 0.5% level (Cebenoyan & Strahan, 2004).

The resulting unbalanced sample consists of 103 583 observations and 7 113 banks, for a forty-eight-quarters period going from 1999 to 2014. In table 1, we report the mean, standard deviation, and median for several variables of our sample banks. The average size of a sample bank is $1 403 million with a median size of $144 million. Around 2% of banks are labelled as large with total assets higher than $1 billion and around 92% are affiliated with a bank holding company. On average, the activity diversification HHI is around 50% and asset and loans HHI are respectively around 49% and 32%, on average.

We break out the sample into small, medium, and large banks in order to contrast bank efficiency. We use the same thresholds for the size dummies than Berger and Bouwman (2009). Table 2 reports means and standard deviation along with t-tests for comparisons of the three measures of liquidity creation: overall “catfat” liquidity creation, on-balance sheet “catnonfat” liquidity creation, and off-balance sheet liquidity creation. Consistently with Berger & Bouwman (2009), small banks (gross total asset (GTA) up to $1 billion) create on average less liquidity for the three measures of liquidity creation. Large banks (GTA exceeding $3 billion) create more overall liquidity and off-balance sheet than the other banks. Medium banks create on average more liquidity on-balance sheet. Banks member of a bank holding company and listed banks create more overall liquidity on average. Federal chartered banks produce more liquidity off-balance sheet. Banks with foreign income produce more liquidity off-balance sheet, but less on-balance sheet, as opposed to banks with activities in the US exclusively. We define activity, asset, and loans diversification dummies as equal to 1 if the bank is part of the 50% of the banks with the lowest HHI index, zero otherwise. Activity diversification improves on average the production of liquidity, while asset and loan diversification reduces liquidity creation.

Results

Our primary goal is to investigate the link between the size of a bank and technical efficiency in creating liquidity. We do this in two ways.

We first estimate technical efficiency scores for the three types of liquidity creation measures (see tables 3 and 4, the three first models). Then we compare the average technical efficiency scores for small, medium, and large banks throughout the 1999-2014 period of study (table 5). A graphical analysis of the technical efficiency scores throughout the period illustrates the relationship between the technical efficiency in creating liquidity and the size of the banks (graph 1). One main result is that large banks are not the most efficient in terms of liquidity creation, although they produce the most liquidity (Berger & Bouwman, 2009). Throughout the period, large banks have most of the time on average lower technical efficiency scores regarding overall liquidity creation (“catfat”), and on-balance sheet liquidity creation ("catnonfat"). Large banks are on average as efficient as medium banks regarding off-balance sheet liquidity creation. Medium banks are throughout the period most of the time the most efficient in overall liquidity creation. Regarding on-balance sheet liquidity creation, small banks were the most efficient until 2005. From 2005 to 2009, medium banks are the most efficient in on-balance sheet liquidity creation on average, except in 2007 where the largest banks are the most efficient. In terms of overall liquidity creation, small banks are on average more efficient than large banks, but less efficient than medium banks. However, small banks are on average by far least efficient in creating liquidity off-balance sheet.

Regarding the evolution of technical efficiency over time, the figures show a decrease in both on-balance sheet and off-balance sheet liquidity creation from the beginning of the financial crisis in 2007 for large banks, and in 2008 for medium banks. Technical efficiency of small banks seems unaffected by the financial crisis. This observation could be explained by the decrease in the level of liquidity production, particularly for larger banks, as shown by Berger and Bouwman (2016), while the productive resources remained quasi constant or were adjusted gradually. Off-balance sheet, the drop in liquidity creation during the crisis was likely due to borrowers drawing down their loan commitments, as documented by Campello et al. (2011). The drop in technical efficiency off-balance sheet was larger for large banks but the slope is similar between medium and large banks. However, due to the advantage of large banks in creating liquidity off-balance sheet, overall liquidity creation efficiency decreased more for large banks. Furthermore, the drop of technical efficiency in on-balance sheet liquidity creation is more pronounced for large banks both regarding the loss and the speed of the decrease. A possible explanation is a negative synergy between off-balance sheet and on-balance sheet liquidity creation during the 2007-2008 crisis. Indeed, the literature underlines the synergies between off-balance sheet commitments and deposits (Gatev & Strahan, 2006; Kashyap et al., 2002). Namely, during a non-banking financial crisis, banks are viewed as a safe haven by investors. Deposits tend to increase while borrowers want to draw funds from their loan commitments. However, in 2007-2008 a liquidity crisis affected banks. More particularly, large banks experienced a decline in funding participating to liquidity creation on the liability side. The literature indeed documents runs that occurred from 2007-2008 in asset-backed securities markets (Brunnermeier, 2009) such as the asset-backed commercial papers market (Covitz et al., 2013), the repurchase agreement market (Gorton & Metrick, 2012), federal funds markets, (Afonso et al., 2011), and other interbank markets (Acharya & Merrouche, 2012). Ivashina and Scharfstein (2010) documented the simultaneous run by short-term bank creditors and borrowers who drew down their credit lines. Consequently, because of the negative synergy between loan commitment and funding, the drop in technical efficiency in creating liquidity on-balance sheet was more pronounced for large banks. Here we stress that the efficiency of the small banks in on-balance sheet liquidity creation seems unaffected by the financial crisis compared to the medium and large banks. As a result, from 2009, small banks became the most efficient in producing liquidity.

A second way to investigate the link between bank size and technical efficiency in creating liquidity is to include a size variable in the estimation of the determinants of inefficiency effects of the production function. The effect of size is included through the natural logarithm of total asset in the estimation of inefficiency effect for the three types of liquidity creation measure (table 4). Results confirm the link observed above. Size increases inefficiency in on-balance sheet liquidity creation and reduces inefficiency in off-balance sheet liquidity creation. Ultimately, efficiency in creating overall liquidity decreases with size. Consequently, the first hypothesis that the larger a bank, the more efficient, is not validated, except regarding liquidity creation off-balance sheet.
We also look at the link between technical efficiency in producing liquidity and bank characteristics other than size. While the research underlines that multibank holding company members create the most liquidity, we find that this membership increases inefficiency in both on and off-balance sheet liquidity production (table 4). This result is consistent with the comparison of mean technical efficiency scores across these two groups (table 5). Furthermore, comparing group means, we find that being either a state chartered or a federal chartered bank has a marked link with technical efficiency. Federal chartered banks tend to be on average more efficient than state chartered in both on and off-balance sheet liquidity creation. Banks involved in activities in other countries than the US tend to be less efficient in on-balance sheet liquidity creation. Finally, listed banks tend to be less efficient in on-balance sheet liquidity production but more efficient in off-balance sheet liquidity production.

A second stage of the analysis of bank characteristics related to technical efficiency in creating liquidity is to consider the effect of bank activity mix. We do this by including diversification indices in the estimation of the determinants of inefficiency effects of the production function. Results of the second specification of the model indicate that activity concentration and asset concentration reduce inefficiency while loan concentration increases inefficiency (table 5, model 2). Indeed, the higher the Herfindahl-Hirschman index, the lower the diversification. However, we expect these overall effects of diversification on technical efficiency to differ along with bank size. Indeed, as exposed above, there is a link between bank size and bank business model. The third specification of the model associates the three diversification indices to the size class of the banks, either small, medium, or large.

Firstly, the Herfindahl-Hirschman Index (HHI) of activity diversification measures the extent of diversification in the sources of non-interest income. A high value of the HHI indicates a concentration of fee sources and traditional banking, while a low value indicates diversification and non-traditional banking. A negative coefficient means that a higher level of the activity concentration reduces inefficiency (table 5). Activity diversification is associated to more inefficiency in liquidity production for small banks only. Small banks focused on traditional banking activities, are the most efficient in on-balance sheet liquidity creation. Diversifying their activities, small banks use resources to pursue activities that do strictly produce liquidity. On the contrary, diversifying their sources of non-interest income, medium and large banks decrease inefficiency in liquidity production. Medium and large banks are specialized in non-traditional activities. Diversifying their activities medium and large banks get relatively more involved in nontraditional banking activities and improve efficiency in creating liquidity. We explain this result by economies of scope and scale stemming from diversification. Activity diversification of medium and large banks benefit to efficiency in on-balance sheet and also off-balance sheet liquidity creation because of synergies between on and off-balance sheet liquidity creation (Gatev & Strahan, 2006; Kashyap, Rajan, et al., 2002).

Drawing from this result, diversification of bank activities benefits in terms of economies of scope and scale conditionally on the bank being specialized in non-traditional banking.

Then, the development of nontraditional banking activities leads to greater diversification of bank asset. Indeed, traditional banking focus on lending. As banks develop nontraditional activities, the share of loans in total asset tends to decrease. We expect a bank concentrating its asset to produce

more liquidity all things being equal. Indeed, concentrating its asset, a bank holds a higher proportion of loans which produce the most liquidity among other assets. On the contrary, diversifying their asset with other assets than loans, such as securities, banks allocate resources to assets destroying liquidity.
Results indicate that a higher asset diversification is associated with more inefficiency regardless the size of the bank. Indeed, a negative coefficient indicates that the higher the asset concentration (i.e. the higher the HHI of asset diversification), the lower the inefficiency (table 5). This effect of asset diversification confirms the second hypothesis that nontraditional banking activities reduce efficiency in creating liquidity.

Furthermore, the larger the size class of the bank, the lower the coefficient of interaction between the size class dummy and the asset diversification index. Thus, the larger the banks the higher the cost of diversification in terms of inefficiency. Because of their traditional banking activities, smaller banks have a lower degree of diversification of asset which mainly comprises loans. Nevertheless, small banks still benefit from asset concentration. As opposed to small banks, medium and large banks tend to lose significantly more from asset diversification, despite the fact that they are already more engaged in nontraditional banking such as financial market activities (Stiroh & Rumble, 2006). Therefore, medium and large banks tend to be even more efficient while specializing in lending. In other words, banks could produce liquidity more efficiently with specialization conditionally on benefiting from scale economies. Larger banks tend to have other activities than lending but because of economies of scale, they might be more efficient in terms of liquidity production. This seems particularly the case of the medium banks, whose efficiency in on-balance sheet liquidity creation is close to the small banks' and even larger regarding overall liquidity creation (see graph 1). This result is in line with the observation of Berger and Bouwman (2009) that larger banks produce the most liquidity. Our contribution is to view liquidity creation in terms of productive efficiency and scale economies i.e. identifying the ability of banks to produce liquidity while saving resources. Thus, we show that the capacity of larger banks to produce liquidity efficiently is related to their benefits in terms of economies of scale and synergies in asset composition and between balance sheet and off-balance sheet liquidity creation. Larger banks could produce liquidity more efficiently despite an asset structure destroying liquidity a priori.

Finally, loan diversification increases efficiency in producing liquidity, regardless the size of the bank. Indeed, the positive coefficients indicate that the higher the loan concentration (i.e. the higher the HHI of loan diversification), the higher the inefficiency. Traditional lending includes making loans to different sectors and is thus associated to loan diversification (Deng et al., 2007). Results indicate that nontraditional lending, i.e. concentration of the loan portfolio on one type of product such as commercial loans, increases inefficiency. Making loans to various sectors or clientele, banks benefit from economies of scope which improves efficiency in producing liquidity. Indeed, banks acquire information facilitating the provision of loans to other sectors or clients. This result also validates our second hypothesis that nontraditional banking activities reduce efficiency.

Conclusion

Computing technical efficiency scores, we analyze the productive performance of U.S. banks in producing liquidity throughout the 1999-2014 period. We look essentially at two characteristics across banks. We consider bank size, as the literature underlines that large banks create the most liquidity, and activity mix which is likely to affect the intensity of the intermediation function of banks. Results show that the medium banks are the most efficient in producing overall liquidity, i.e. on-balance sheet and off-balance sheet. Small banks – experienced in processing soft information and relationship lending – are the most efficient in producing liquidity on-balance sheet. In other words, small banks are the most able to have the best use of productive resources to conduct the intermediation activity. This is consistent with the relationship oriented model of small banks allowing an intermediation process maximizing both value and liquidity creation (Song & Thakor, 2007). The largest banks – relying on hard information and transaction lending – which produce the most liquidity, are found to be the least efficient in on-balance sheet liquidity creation. This confirms the third hypothesis that the largest banks would be less efficient because of their involvement in nontraditional banking. Creating liquidity off-balance sheet, large banks are as efficient as medium banks. Medium banks also rely on hard information and transaction lending. They are the most efficient in overall liquidity creation. Indeed, their efficiency is close to the small banks' on-balance sheet and to the large banks' off-balance sheet.

The mix of activity affects bank efficiency. Results summarized above show that banks relying on traditional activity and relationship oriented model tend to be the most efficient in producing liquidity. This confirms the second hypothesis that traditional banking leads to higher efficiency in creation liquidity. Furthermore, concentrating their asset on loans and diversifying their loan portfolio, therefore shifting from non-traditional to traditional banking, banks tend to improve efficiency, regardless of their size. More particularly, loan diversification is likely to bring economies of scope, benefiting to efficiency in liquidity creation. However, we underline the capability of medium and large banks to improve efficiency through activity diversification evidencing nontraditional banking. This result comes from benefits in terms of economies of scale in creating liquidity and from synergies of liquidity creation on and off-balance sheet. This is consistent with the observation that large banks create the most liquidity (Berger & Bouwman, 2009).

Finally, the efficiency of small banks is more resilient during the 2007-2008 financial crisis, particularly regarding on-balance sheet liquidity creation. On the contrary, liquidity production of large banks drops substantially. Consequently, the economy benefits from liquidity creation of small banks both in terms of efficiency levels and the resiliency of this efficiency throughout of liquidity shocks. This calls for a particular vigilance of the effect of regulation in terms of welfare of the economy. Especially, liquidity regulation might take into account banks characteristics linked to efficiency in producing liquidity in order to anticipate, or modulate its consequences.

References

Acharya, V., & Naqvi, H. (2012). The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle. *Journal of Financial Economics*, *106*(2), 349–366. http://doi.org/10.1016/j.jfineco.2012.05.014

Acharya, V. V., & Merrouche, O. (2012). Precautionary Hoarding of Liquidity and Interbank Markets: Evidence from the Subprime Crisis. *Review of Finance*, *17*, 107–160.

Afonso, G., Kovner, A., & Schoar, A. (2011). Stressed, not frozen: the federal funds market in the financial crisis. *Journal of Finance*, *66*, 1109–1139.

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models, *6*(1), 21–37.

Apergis, N. (2014). The long-term role of non-traditional banking in profitability and risk profiles: Evidence from a panel of U.S. banking institutions. *Journal of International Money and Finance*, *45*, 61–73. http://doi.org/10.1016/j.jimonfin.2014.03.003

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency in a stochastic frontier production function for panel data. *Empirical Economics*, *20*(235–332), 325–332.

Beltratti, A., & Stulz, R. M. (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics*, *105*(1), 1–17. http://doi.org/10.1016/j.jfineco.2011.12.005

Berger, A. N., & Black, L. K. (2011). Bank size, lending technologies, and small business finance. *Journal of Banking and Finance*, *35*(3), 724–735. http://doi.org/10.1016/j.jbankfin.2010.09.004

Berger, A. N., & Bouwman, C. H. S. (2009). Bank Liquidity Creation. *Review of Financial Studies*, *22*, 3779–3837.

Berger, A. N., & Bouwman, C. H. S. (2016). Bank Liquidity Creation and Financial Crises. *Academic Press, Elsevier*.

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175–212.

Berger, A. N., & Mester, L. J. (1997). Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions? *Journal of Banking & Finance*, *21*(7), 895–947.

http://doi.org/10.1016/S0378-4266(97)00010-1

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, *76*(2), 237–269. http://doi.org/10.1016/j.jfineco.2004.06.003

Berger, A. N., Molyneux, P., & Wilson, J. O. S. (2010). Banking An overview. *Oxford Handbook of Banking*.

Berger, A. N., & Udell, G. F. (2002). Small Business Credit Availability and Relationship Lending : The Importance of Bank Organisational Structure. *The Economic Journal*, *112*(477), 32–53.

Berger, A. N., & Udell, G. F. (2006). A more complete conceptual framework for SME finance. *Journal of Banking and Finance*, *30*(11), 2945–2966. http://doi.org/10.1016/j.jbankfin.2006.05.008

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007-2008. *Journal of Economic Perspectives*, *23*(1), 77–100.

Campello, M. (2002). Internal Capital Markets in Financial Conglomerates : Evidence from Small Bank Responses to Monetary Policy. *Journal of Finance*, *57*(6), 2773–2805.

Campello, M., Giambona, Er., Graham, J. R., & Harvey, C. R. (2011). Liquidity Management and Corporate Investment During a Financial Crisis. *The Review of Financial Studies*, *24*(6), 1944–1979. http://doi.org/10.1093/rfs/hhql31

Carter, D. A., & McNulty, J. E. (2005). Deregulation, technological change, and the business-lending performance of large and small banks. *Journal of Banking and Finance*, *29*(5), 1113–1130. http://doi.org/10.1016/j.jbankfin.2004.05.033

Cebenoyan, A. S., & Strahan, P. E. (2004). Risk management, capital structure and lending at banks. *Journal of Banking and Finance*, *28*(1), 19–43. http://doi.org/10.1016/S0378-4266(02)00391-6

Chaffai, M., & Dietsch, M. (2015). Modelling and measuring business risk and the resiliency of retail banks. *Journal of Financial Stability*, *16*, 173–182. http://doi.org/10.1016/j.jfs.2014.08.004

Cole, R. A., Goldberg, L. G., White, L. J., Cole, R. A., Goldberg, L. G., & White, L. J. (2004). Cookie Cutter vs . Character : The Micro Structure of Small Business Lending by Large and

Small Banks, *39*(2), 227–251.

Covitz, D., Liang, N., & Suarez, G. (2013). The Evolution of a Financial Crisis: Collapse of the Asset-Backed Commercial Paper Market. *Journal of Finance*, *68*(3), 815–848.

Cowan, A. R., & Salotti, V. (2015). The resolution of failed banks during the crisis: Acquirer performance and FDIC guarantees, 2008-2013. *Journal of Banking and Finance*, *54*, 222–238. http://doi.org/10.1016/j.jbankfin.2014.12.016

de la Torre, A., Martinnez Peria, M. S., & Schmukler, S. L. (2010). Bank involvement with SMEs: Beyond relationship lending. *Journal of Banking and Finance*, *34*(9), 2280–2293. http://doi.org/10.1016/j.jbankfin.2010.02.014

Deng, S. (Esther), Elyasiani, E., & Mao, C. X. (2007). Diversification and the cost of debt of bank holding companies. *Journal of Banking and Finance*, *31*(8), 2453–2473. http://doi.org/10.1016/j.jbankfin.2006.10.024

DeYoung, R., Hunter, W. C., & Udell, G. F. (2004). The Past, Present, and Probable Future for Community Banks. *Journal of Financial Services Research*, *25*(2/3), 85–133. http://doi.org/10.1023/B:FINA.0000020656.65653.79

DeYoung, R., & Rice, T. (2004). How do banks make money? A variety of business strategies. *Economic Perspectives, Federal Reserve Bank of Chicago*, *28*(4), 52–67.

Drehmann, M., & Nikolaou, K. (2013). Funding liquidity risk: Definition and measurement. *Journal of Banking & Finance*, *37*(7), 2173–2182.

Estes, K. (2014). Diversification and Community Bank Performance. *International Journal of Finance and Banking Studies*, *3*(4), 1–40.

Gatev, E., & Strahan, P. E. (2006). Bank's Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market. *Journal of Finance*, *61*(2), 867–892.

Gorton, G. (2009). Information, liquidity and the (ongoing) panic of 2007. *American Economic Review*, *99*, 567–572.

Gorton, G., & Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial Economics*, *104*, 425–451.

Hughes, J. P., & Mester, L. J. (1998). Bank Capitalization and Cost : Evidence of Scale Economies in Risk Management and Signaling Author (s): Joseph P . Hughes and Loretta J . Mester Source : The Review of Economics and Statistics , Vol . 80 , No . 2 (May , 1998), pp . 314-325 Published b, *80*(2), 314–325.

Hughes, J. P., Mester, L. J., & Moon, C. G. (2001). *Are scale economies in banking elusive or illusive?: Evidence obtained by incorporating capital structure and risk-taking into models of bank production*. *Journal of Banking and Finance* (Vol. 25). http://doi.org/10.1016/S0378-4266(01)00190-X

Ivashina, V., & Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics*, *97*(3), 319–338. http://doi.org/10.1016/j.jfineco.2009.12.001

Kashyap, A. K., Rajan, R. G., & Stein, J. C. (2002). Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-Taking. *Journal of Finance*, *57*(1), 33–73.

Kashyap, A. K., Stein, J. C., & Rajan, R. G. (2002). Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-Taking. *Journal of Finance*, *57*(1), 33–73.

Laeven, L., & Levine, R. (2007). Is there a diversification discount in financial conglomerates? *Journal of Financial Economics*, *85*(2), 331–367. http://doi.org/10.1016/j.jfineco.2005.06.001

Meeusen, W., & van den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, *18*(2), 435–444.

Mester, L. J. (1996). A study of bank efficiency taking into account risk- preferences A study of bank efficiency taking into account. *Journal of Banking & Finance*, *20*, 1025–1045. http://doi.org/10.1016/0378-4266(95)00047-X

Rogers, K. E. (1998). Nontraditional activities and the e • ciency of US commercial banks. *Journal of Banking & Finance*, *22*.

Schmidt, M. M., & Walter, I. (2009). Do financial conglomerates create or destroy economic value? *Journal of Financial Intermediation*, *18*, 193–216. http://doi.org/10.1016/j.jbankfin.2009.06.007

Sealey, C. W., & Lindley, J. T. (1977). Inputs , Outputs , and a Theory of Production and Cost at Depository Financial Institutions. *Journal of Fina*, *32*(4), 1251–1266.

Song, F., & Thakor, A. V. (2007). The Society for Financial Studies Relationship Banking , Fragility , and the Asset-Liability Matching Problem. *Review of Financial Studies*, *20*(6), 2129–2177.

Stein, J. C. (2002). Information Production and Capital Allocation : Decentralized versus Hierarchical Firms. *Journal of Finance*, *57*(5), 1891–1921.

Stiroh, K. J. (2004a). Diversification in Banking : Is Noninterest Income the Answer ? *Journal of*

Money, Credit and Banking, *36*(5), 853–882.

Stiroh, K. J. (2004b). Do Community Banks Benefit from Diversification? *Journal of Financial Services Research*, *25*(2/3), 135–160. http://doi.org/10.1023/B:FINA.0000020657.59334.76

Stiroh, K. J., & Rumble, A. (2006). The dark side of diversification: The case of US financial holding companies. *Journal of Banking and Finance*, *30*(8), 2131–2161. http://doi.org/10.1016/j.jbankfin.2005.04.030

Table 1 Descriptive statistics for sample banks (1999 – 2014)

This table reports means, standard deviations, minimum, maximum, and medians for several variables for sample banks over the period of 1999 through 2014. The number of observations is 103 583. The sample comprises 7 113 banks. The small variable is equal to 1 if the bank's gross total assets (GTA, i.e. total assets plus the allowance for loans and lease losses and transfer risk reserve) is lower than $1 billion, zero otherwise. The medium variable is equal to 1 if the bank's GTA is between $1 and $3 billion, zero otherwise. The large variable is equal to 1 if the bank's GTA exceeds $3 billion, zero otherwise. The BHC variable is equal to 1 if the bank is part of a bank holding company, 0 otherwise. The federal chartered variable is equal to 1 of the bank is a federal-chartered-bank, zero if it I a state-chartered bank. The multinational variable is equal to 1 if the bank has foreign income, zero otherwise. The listed variable is equal to 1 if the bank is listed or if it belongs to a listed bank holding company, zero otherwise. The activity, asset and loan diversification HHI indices are computed as explained by the methodology. For each of these three indices a dummy variable is computed. It is equal to 1 if the bank is part of the 50% of the banks with the lowest HHI index, zero otherwise. The liquidity creation variables consist of the "catfat", "catnonfat", and "off-balance sheet liquidity creation" measures of Berger & Bouwman (2009) divided by total assets. Computation of the labor, physical, and financial capital are detailed in the column description of the table. Financial capital is equal to total equity divided by total assets. Non-performing loans is equal to allowance for loan and lease losses divided by total assets.

Variables	Description	Mean	Standard Deviation	Minimum	Maximum	Median
Size	Total assets (in millions)	1403,403	27228,421	23,912	1501661,889	144,311
Size	Ln(total assets)	18,95	1,173	16,99	28,04	18,79
Small	Dummy variable	93,44%	160%	0	1	1
Medium	Dummy variable	4,14%	19,93%	0	1	0
Large	Dummy variable	2,42%	15,36%	0	1	0
BHC	Dummy variable	91,77%	27,49%	0	1	1
Federal chartered	Dummy variable	10,05%	30,06%	0	1	0
Multinational	Dummy variable	1,36%	11,59%	0	1	0
Listed banks	Dummy variable	9,35%	29,11%	0	1	0
Activity diversification	Herfindhal-Hirschman Index of activity diversification	50,43%	19,18%	0,60%	1	49,12%
Asset diversification	Herfindhal-Hirschman Index of asset diversification	48,83%	10,24%	21,24%	91,90%	46,67%
Loan diversification	Herfindhal-Hirschman Index of loan diversification	31,53%	10,83%	13,03%	1	29,25%
Activity diversification dummy	Dummy variable	50,00%	50,00%	0	1	1
Asset diversification dummy	Dummy variable	50,00%	50,00%	0	1	1
Loan diversification dummy	Dummy variable	50,00%	50,00%	0	1	1
Liquidity creation	(Catfat measure of Berger & Bouwman (2009)) / total assets	31,89%	19,15%	-42,66%	424,14%	32,43%
Liquidity creation	(Cat non fat measure) / total assets	26,29%	15,85%	-44,30%	79,23%	27,42%
Liquidity creation	(Cat off-balance sheet measure) / total assets	5,60%	7,90%	-1,78%	402,75%	4,45%
Labour capital	(Total expenses in salaries and employee benefits) / income before income taxes and extraordinary items	2,02	28,54	-3357	2869	1,24

Physical capital	(Expenses of premises and fixed assets) / income before income taxes and extraordinary items	0,520	8,608	-625,000	1485,000	0,289
Financial capital	Total equity / total assets	10,72%	3,32%	0,03%	56,48%	10,13%
Non-performing loans	Allowance for loan and lease losses / total assets	1,03%	0,63%	0	9,92%	0,89%

Table 2 Comparisons of liquidity creation across bank group characteristics (1999-2014).

This table reports means and standard deviations in parentheses for several groups of sample banks over the period of 1999 through 2014. Groups of banks are defined along the size (small, medium, and large dummies) BHC, federal-chartered, multinational, non-traditional, listed dummies, and activity, asset, and loan diversification dummies. See table 1 for variable definitions. Liquidity creation is measure as a percentage of total asset. Statistical significance for tests of differences in means and variances at the 5% or 1% level are indicated by **, ***, respectively.

Variable	Liquidity Creation Catfat		Liquidity Creation Catnonfat		Liquidity Creation Off-balance sheet	
Small banks	31,07%***	(0,19)***	25,85%***	(0,16)***	5,21%***	(0,06)***
Other banks	43,67%	(0,21)	32,54%	(0,14)	11,12%	(0,18)
Medium banks	41,56%***	(0,15)***	33,66%***	(0,13)***	7,90%***	(0,04)***
Other banks	31,48%	(0,19)	25,97%	(0,16)	5,50%	(0,08)
Large banks	47,27%***	(0,29)***	30,63%***	(0,16)***	16,64%***	(0,28)***
Other banks	31,51%	(0,19)	26,19%	(0,16)	5,33%	(0,06)
BHC	31,98%***	(0,19)***	26,40%***	(0,16)***	5,57%***	(0,08)***
Non BHC	30,95%	(0,20)	25,04%	(0,17)	5,91%	(0,05)
State Chartered	31,76%***	(0,19)***	26,28%	(0,16)***	5,47%***	(0,07)***
Federal Chartered	33,13%	(0,23)	26,38%	(0,17)	6,75%	(0,14)
No multinational activities	31,77%***	(0,19)***	26,31%***	(0,16)***	5,46%***	(0,07)***
Multinational activities	40,65%	(0,3)	24,69%	(0,19)	15,96%	(0,27)
Non listed bank	30,77%***	(0,19)***	25,57%***	(0,16)***	5,21%***	(0,07)***
Listed bank	42,75%	(0,20)	33,31%	(0,14)	9,44%	(0,14)
No activity diversification	29,61%***	(0,21)***	24,03%***	(0,17)***	5,58%	(0,10)***
Activity diversification	34,18%	(0,17)	28,56%	(0,14)	5,62%	(0,05)
No asset diversification	39,41%***	(0,19)***	32,95%***	(0,16)***	6,47%***	(0,08)***
Asset diversification	24,38%	(0,16)	19,64%	(0,13)	4,74%	(0,08)
No loan diversification	32,51%***	(0,20)***	26,88%***	(0,16)***	5,63%	(0,10)***
Loan diversification	31,28%	(0,18)	25,71%	(0,15)	5,57%	(0,06)

Table 3 Estimation of the stochastic frontier model

Maximum-likelihood estimates for parameters of the translog stochastic frontier model for liquidity production of US banks over the 1999-2014 period. Three specifications of the model are considered. The first specification is estimated for the three measures of liquidity creation (overall "catfat", on-balance sheet "catnonfat", and off-balance sheet). It includes a size variable defined as the natural logarithm of total assets, and a bank holding company dummy, as determinants of technical inefficiency effects. The second specification includes the two previous variables, and activity, asset, and loans diversification Herfindahl-Hirschman Indices (HHI). The last specification includes the size variable, the BHC dummy, and interaction terms between the three dummies of size class and the three HHI, taken separately. Standard errors are shown in brackets with *, and ** indicating significance at 5% and 1% respectively.

Variable	1 Catfat	1 Catnonfat	1 Off-balance sheet	2 Catfat	3 Catfat
Intercept	-24.491	-19.694	-34.878	-23.388	-16.063
	(19.28)**	(13.90)**	(25.37)**	(19.20)**	(13.68)**
Financial capital	2.566	1.448	3.110	2.407	2.053
	(9.39)**	(4.64)**	(13.08)**	(9.24)**	(9.27)**
Labour capital	-0.331	0.553	-1.167	-0.422	0.336
	(1.32)	(1.94)	(5.47)**	(1.74)	(1.67)
Physical capital	-0.710	-2.260	2.328	-0.691	-2.506
	(2.38)*	(7.43)**	(20.24)**	(2.25)*	(8.36)**
Non-performing loans	2.632	3.939	0.898	2.774	3.333
	(12.53)**	(15.41)**	(5.53)**	(13.79)**	(19.25)**
(Financial capital)^2	0.059	0.063	0.004	0.059	0.055
	(24.88)**	(28.01)**	(1.21)	(24.38)**	(23.64)**
(Labour capital)^2	-0.018	-0.018	-0.017	-0.021	-0.019
	(7.69)**	(8.64)**	(4.10)**	(9.13)**	(8.28)**
(Physical capital)^2	0.251	0.356	-0.022	0.244	0.318
	(14.61)**	(20.89)**	(4.30)**	(13.71)**	(18.84)**
(Non-performing loans)^2	0.022	0.023	0.011	0.023	0.025
	(50.01)**	(62.94)**	(16.28)**	(48.81)**	(46.49)**
Labour capital * Physical capital	-0.006	-0.062	0.047	-0.001	-0.052
	(0.34)	(3.24)**	(3.17)**	(0.06)	(3.69)**
Labour capital * Financial capital	0.047	0.042	0.028	0.052	0.054
	(11.34)**	(11.80)**	(4.43)**	(12.49)**	(13.25)**
Labour capital * Non-performing loans	0.022	0.025	0.045	0.024	0.020
	(9.76)**	(12.48)**	(11.88)**	(9.81)**	(7.87)**
Physical capital * Financial capital	-0.262	-0.215	-0.123	-0.251	-0.214
	(13.56)**	(9.86)**	(6.89)**	(13.58)**	(13.31)**
Physical capital * Non-performing loans	-0.156	-0.265	-0.018	-0.163	-0.186
	(10.54)**	(15.06)**	(1.40)	(11.43)**	(14.90)**
Financial capital * Non-performing loans	-0.049	-0.029	-0.076	-0.053	-0.063
	(21.41)**	(13.37)**	(22.55)**	(22.73)**	(27.69)**

Table 4: Estimation of the technical inefficiency effects

Maximum-likelihood estimates for parameters of the inefficiency effects of the translog stochastic frontier model for liquidity production of US banks over the 1999-2014 period. See table 3 for comments on the specification. Standard errors are shown in brackets with *, and ** indicating significance at 5% and 1% respectively.

Variable	1	1	1	2	3
	Catfat	Catnonfat	Off-balance sheet	Catfat	Catfat
Intercept	8.870	5.490	13.463	10.880	9.308
	(43.36)**	(25.68)**	(24.40)**	(21.97)**	(57.26)**
Ln (total assets)	0.175	0.324	-0.160	0.095	0.164
	(51.01)**	(92.52)**	(32.80)**	(27.21)**	(35.65)**
BHC dummy	0.424	0.469	0.744	0.098	0.066
	(40.97)**	(44.96)**	(52.42)**	(8.91)**	(5.92)**
HHI_activity (indice)				-1.280	
				(68.86)**	
HHI_asset (indice)				-0.986	
				(32.71)**	
HHI_loan (indice)				1.972	
				(63.95)**	
Small dummy * HHI_activity					-1.465
					(75.18)**
Medium dummy * HHI_activity					1.116
					(11.29)**
Large dummy * HHI_activity					0.601
					(3.87)**
Small dummy * HHI_asset					-0.779
					(25.21)**
Medium dummy * HHI_asset					-4.591
					(38.55)**
Large dummy * HHI_asset					-5.620
					(38.40)**
Small dummy * HHI_loan					1.858
					(58.33)**
Medium dummy * HHI_loan					1.953
					(10.94)**
large dummy * HHI_loan					3.576
					(21.29)**
Vsigma	-3.031	-3.365	-1.195	-3.052	-3.038
	(270.11)**	(271.45)**	(122.85)**	(267.26)**	(267.44)**
N	103,583	103,583	103,583	103,583	103,583

Table 5 Comparisons of technical efficiency scores across bank group characteristics (1999-2014).

This table reports means and standard deviations in parentheses of the technical efficiency scores for several groups of sample banks over the period of 1999 through 2014. Groups of banks are defined along the size (small, medium, and large dummies), BHC, federal-chartered, multinational, non-traditional, and listed dummies. See table 1 for variable definitions. Technical efficiency scores are estimated respectively with "1 catfat", "1 catnonfat", and "1 off-balance sheet" models (cf. table 3). Statistical significance for tests of differences in means and variances at the 10%, 5%, and 1% level are indicated respectively by *, **, and ***.

Variable	Technical Efficiency 1 Catfat		Technical Efficiency 1 Catnonfat		Technical Efficiency 1 Off-balance sheet	
Small banks	63,14%***	(0,21)**	65,93%***	(0,21)***	59,25%***	(0,20)***
Other banks	59,44%	(0,20)	55,06%	(0,22)	71,93%	(0,13)
Medium banks	60,88%***	(0,19)***	58,36%***	(0,21)	69,47%***	(0,13)***
Other banks	62,98%	(0,21)	65,51%	(0,21)	59,68%	(0,20)
Large banks	56,96%***	(0,22)***	49,40%***	(0,24)***	76,14%***	(0,09)***
Other banks	63,04%	(0,21)	65,61%	(0,21)	59,68%	(0,20)
BHC	62,45%***	(0,21)	64,69%***	(0,21)***	59,43%***	(0,19)***
Non BHC	67,85%	(0,21)	71,06%	(0,2)	67,37%	(0,21)
State Chartered	62,34%***	(0,21)***	64,62%***	(0,21)***	59,72%***	(0,19)***
Federal Chartered	67,88%	(0,20)	70,53%	(0,19)	63,35%	(0,20)
No multinational activities	63,11%***	(0,21)***	65,55%***	(0,21)***	59,95%***	(0,20)***
Multinational activities	47,41%	(0,23)	40,99%	(0,24)	69,35%	(0,18)
Non listed bank	62,58%***	(0,21)***	65,33%***	(0,21)**	59,03%***	(0,20)***
Listed bank	65,88%	(0,19)	64,16%	(0,21)	70,30%	(0,14)
No activity diversification	63,61%***	(0,22)***	66,75%***	(0,21)***	58,97%***	(0,21)***
Activity diversification	62,17%	(0,20)	63,69%	(0,20)	61,20%	(0,18)
No asset diversification	68,66%***	(0,19)***	70,79%***	(0,19)***	63,11%***	(0,19)***
Asset diversification	57,13%	(0,20)	59,64%	(0,21)	57,05%	(0,20)
No loan diversification	61,33%***	(0,21)***	63,64%***	(0,22)***	57,78%***	(0,21)***
Loan diversification	64,46%	(0,20)	66,80%	(0,20)	62,38%	(0,18)

Table 6: Construction of the Herfindhal-Hirschman Indices

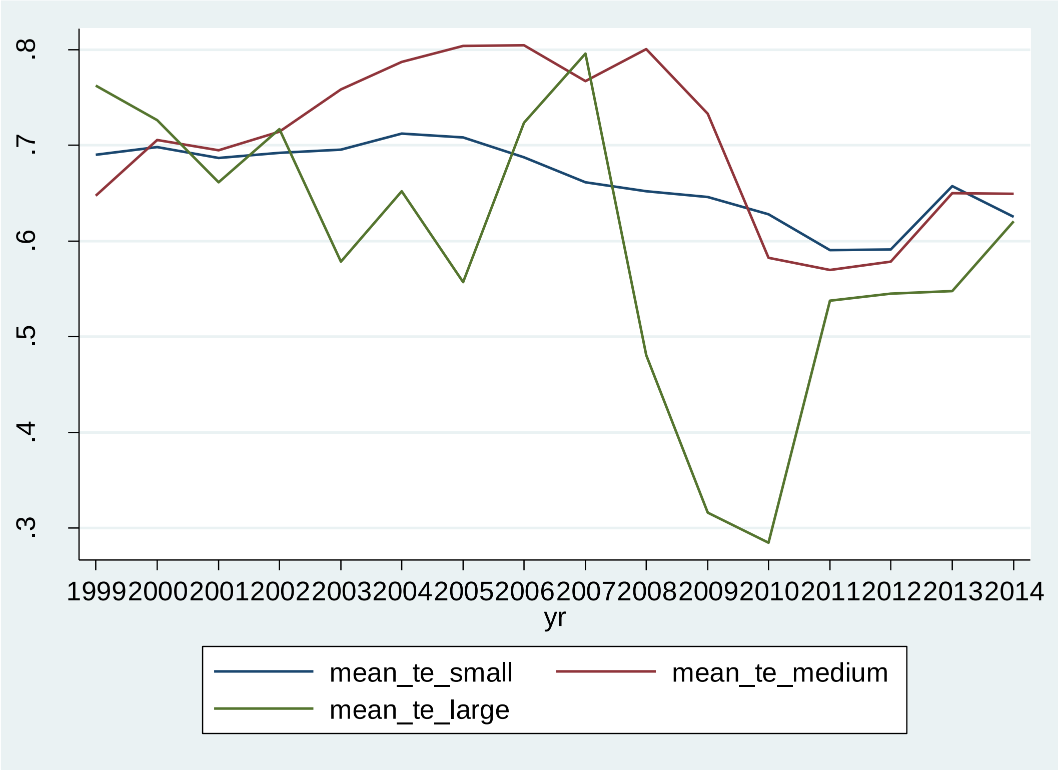
Descriptions of the Call Report categories used to construct the activity, asset, and loan Herfindahl-Hirschman indices.

Variable description	Variable
Income for fiduciary activities	FID
Service charges on deposit accounts	SRV
Trading revenue	TRAD
Fees and commissions from securities brokerage, investment banking, annuity sales, and insurance	S&I
Venture capital revenue	VENT
Net servicing fees	SERV
Net securisation income	SEC
Gains on sales of loans, other real estate, and other assets	GAINS
Other non-interest income	OTH
Total non-interest income	NON
Activity diversification: HHI of a bank's non-interest income sources	$HHI_{Activity}$
Cash and balances due from depository institutions	CASH
Securities	SECU
Net loans	LOANS
Fixed and real estate assets	FIX
Other assets	OTH
Total assets	ASSETS
Asset diversification: HHI of a bank's asset categories	HHI_{Asset}

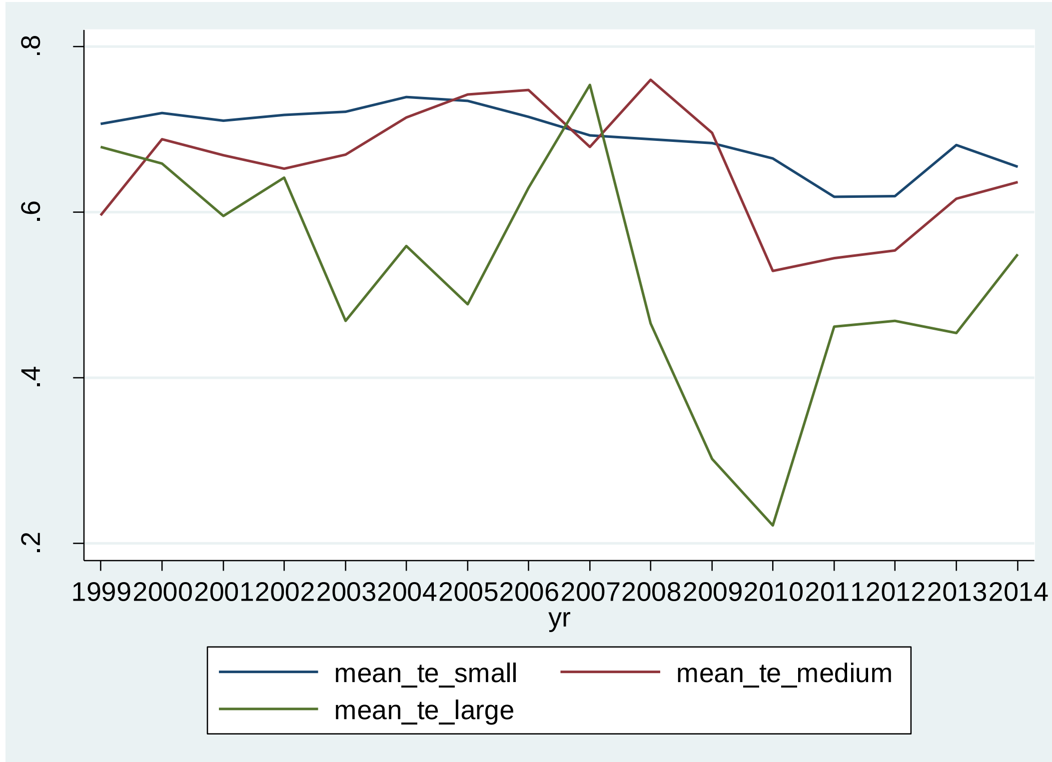
1-4 family residential loans	1-4RE
Construction, land development, and other land loans	CONST
Loans secured by farmland	FARM
Loans secured by multifamily properties	MULTI
Secured by nonfarm, non-residential properties	CRE
Agricultural loans	AG
Commercial and industrial loans	CI
Consumer and credit card loans	CONS
Other loans	OTH
Total loans	LOANS
Asset diversification: HHI of a bank's loans categories	HHI_{Loans}

Graph 1 – Evolution of average technical efficiency scores by bank size

These graphs plot the evolution across time of mean technical efficiency scores by bank size. Technical efficiency scores are estimated for the overall "catfat", on balance seet "catnonfat", and off-balance sheet liquidity creation measures with the first three models (cf. table 3). Following Berger & Bouwman (2009), banks with a gross total asset (GTA, i.e. total assets plus the allowance for loans and lease losses and transfer risk reserve) lower than $1 billion are labelled as small. Medium banks have a GTA between $1 and $3 billion. Large banks have a GTA exceeding $3 billion.



Liquidity Creation Overall "Catfat"



Liquidity Creation on-balance sheet “Catnonfat”

Liquidity Creation Off-balance sheet

Working Papers

Laboratoire de Recherche en Gestion & Economie

http://ideas.repec.org/s/lar/wpaper.html

Université de Strasbourg
Pôle Européen de Gestion et d'Economie
61 avenue de la Forêt Noire
67085 Strasbourg Cedex

http://large.em-strasbourg.eu/