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The Efficiency of FDIC-identified Community Banks

By Athina Petropoulou, Vasileios Pappas, Steven Ongena, Dimitrios Gounopoulos, and Richard Fairchild

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The efficiency of FDIC-identified community banks

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Abstract

The US Federal Deposit Insurance Corporation (FDIC) recently redrew its criteria to identify community banks by including location and business strategy. We analyze the resultant re-classification of community banks and show it affects a wide array of salient outcomes. The thus-defined community banks are one-fifth more cost-efficient than other banks. Most of this efficiency advantage finds its origin in market structure, regulatory, and business environment factors, with corresponding substantial state-level heterogeneity. Community banks fare especially better when competing with large non-community banks and where financial access is limited.

Keywords: Bank strategy, Community banks, Federal Deposit Insurance Corporation (FDIC), Persistent efficiency, Residual efficiency, Stochastic Frontier Analysis

JEL classification: G14; G21; G38

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1. INTRODUCTION

The structural changes that the US banking sector has undergone since the 1980s (i.e., failures, mergers and acquisitions, shift in banking activities, opening of interstate branching) have reduced the community banking sector by around 50 percent (DeYoung et al. (2004)). During the 2008 global financial crisis alone, more than 500 US banks failed or received financial support (Cornett et al. (2013); Berger, and Roman (2015)); most were community banks. Community banks remain an integral part of the US banking system: they account for the majority of financial institutions (Jacewitz, and Kupiec (2012)); are the only banking option in many areas of the country (McKee, and Kagan (2018)); and have been integral to the channeling of economic support to firms affected during the Covid-19 via the Paycheck Protection Program (PPP) (Granja et al. (2020); Li, and Strahan (2021)).

In recognizing the eminent role of US community banks, targeted measures have been introduced. Recently, the federal banking agencies (i.e., the Federal Reserve Board - FRB, the Federal Deposit Insurance Corporation - FDIC and the Office of the Comptroller of the Currency - OCC) proposed the community bank leverage ratio (CBLR) framework, which is intended to reduce the regulatory burden of the risk-based capital adequacy ratios (FRB (2021)).[1] The uptake was significant, with a 40 percent of the eligible banks adopting the framework at first instance (i.e., 2020Q1). The CBLR has been one of 157 federal rules and programs specifically targeted to community banks following the 2008 global financial crisis (FDIC (2020)). This reflects the commitment of policy makers to cater for the US community banking business model.[2] Eligible for this differential treatment are the Federal Deposit Insurance Corporation (FDIC)-identified community banks. But how does the FDIC identify these banks? Banking research has characterized community banks as small ones, based solely on a size

[1] Effectively, community banks filling call reports dated 2020 onwards would skip several items in Schedule RC-R Part I, and Part II in its entirety.
[2] Bank capitalization requirements are important and Rehbein and Ongena (2021) shows that poorly capitalized banks can induce important negative externalities to regional economic outcomes.

criterion (typically proxied via total assets). In recognizing the uniqueness of these financial institutions, the FDIC proposed a new community bank definition. This has been the first time spatial and business model characteristics are used in conjunction with redefined size criteria to identify community banks.

Due to vested regulatory interest in the new community bank definition, in this study we place the FDIC definition itself and the community banks under the microscope. Our strategy is as follows. From a definitional comparison perspective, we evaluate the financial profile of FDIC-identified community banks against a range of alternatives commonly used in banking research. We document that the new definition re-classifies a substantial number of banks that have been either previously considered as community banks or ignored. We show that the significantly different financial profile and the number of these re-classified community banks can affect a wide array of outcomes under examination. This is because the FDIC-identified community banks (but at the same time regarded as non-community using other definitions) exhibit higher financial stability (by 4.7% in z-score and capitalization (by 1.8% in equity/assets) when compared those adhering to both definitions. In contrast, FDIC-excluded community banks (but still classified as community using other definitions) are more profit oriented (by 12.3% in return on assets), feature lower core deposits ratios (by 13.1%) and higher shares of non-interest income (by 23.4%). Additionally, FDIC-identified community banks are significantly more efficient than community banks based on alternative definitions.

Next, we shift our attention to the community banks themselves. We evaluate the performance of the FDIC-identified community banks against their non-community counterparts. Efficiency is central to performance measurement (Mester (1996); Berger, and DeYoung (2006); Chen et al. (2015)) and our focus is on the more salient measure of cost efficiency. Our motivation is as follows. Even though the banking industry has continued to consolidate, community banks have been less likely to fail than non-community (FDIC (2020)). Chiorazzo *et al.* (2018) suggests that community banks, as users of traditional banking, are more likely to survive.[3] However, it does not employ the FDIC community bank definition. Besides, it does not focus on addressing the role of efficiency in the ongoing survival of these banks. Yet, efficiency in the resource allocation is critical for bank's survival and performance. So, how are these "die hard" community banks able to stay in the game? Are they super-efficient in their banking practices; thus, earning their spot? Or are they kept in the game due to exploiting market structure, regulatory and business environment facets?

To answer these questions, we use a cost efficiency model that separates persistent (long-run) and residual (short-run) efficiency[4] while accounting for unobserved bank-level heterogeneity. This decomposition is crucial for our setup. It allows us to delineate the community bank efficiency differential into a component reflective of market structure, regulatory/supervisory, and business environment characteristics, and another one related to managerial performance and business strategy.[5] The policy implications of the two components are different but equally important. The former is relevant for regulators and policy makers as it can be used to assess the efficiency of banking models within regions of interest. The latter is of primary concern at the bank-level as it can be affected by short-term adjustments or targeted strategic choices within the bank itself.

Our analysis finds that community banks are 19% more efficient, on average. We find that most of the efficiency premium afforded by community banks stems from long-run (persistent) market structure and business environment factors rather than short-run (residual) managerial skills. Interestingly, we

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[3] Chiorazzo *et al.* (2018) constructs a traditional index variable that has some similarities to the FDIC approach. However, they compare survival probabilities within a community bank sub-sample (i.e., all banks are below $10 billion).

[4] Within the efficiency literature persistent and residual efficiencies are also referred as long-run and short-run/transient efficiencies respectively.

[5] In terms of regulatory changes across our long observation period there are subperiods prior to the Basel Accord, and subperiods when the Basel I/II is in place. An alternative approach of splitting the sample is challenging in terms of identifying which regulation is applicable at each point in time to the community banks given their preferred treatment by the Fed, so as to come up with comparable samples of community and non-community banks. For instance, the capital requirements imposed by Basel II stopped being applied to community banks after the Federal Reserve's proclamation that only the largest US banks would be subject to Basel II and community banks would be subject to Basel I.

uncover substantial heterogeneity in the long-term efficiency differentials of the two bank types. These are significant in economic and statistical terms across all US states. Thus, not all states are equally suited for community banking.

We proceed to examine the drivers. Operating in states with large bank size differentials (relatively to their competitors) boosts community bank efficiency. Put simply, community banks fare better in a “David-vs-Goliath” setup. Additionally, community banks are highly efficient where financial access is limited. Our short-term efficiency results indicate that community banks are 2.3% more efficient compared to their counterparts. Short-term efficiency rises for community banks involved in residential mortgages and agricultural loans. A battery of robustness checks confirms our results. Specifically, the results are robust when we split our sample into four supervisory regimes and under different sample restrictions. The same holds when we split banks by size as well as when we investigate community banks that have changed their status at some point along their lifespan. We also use an instrumental variables regression set up to address efficiency-risk endogeneity concerns. We verify the higher efficiency of community banks when using alternative cost efficiency specifications as well as non-parametric nearest neighbor matching estimators.

Our study makes three contributions to the existing literature. This is the first study to compare the FDIC community bank definition against a range of alternatives commonly used in banking research. We examine the financial profile of the FDIC-identified community banks against previously misclassified ones. We provide novel insights on how community banks fare based on the regulatory mandated community bank definition. Second, we contribute to the comparative efficiency literature of US community and non-community banks in two ways: i) by comparing FDIC-identified community banks against their counterparts. Previous studies have relied on a range of alternative asset-based definitions that disregard spatial and business model characteristics, and which we show that can lead to a significantly different outcome; ii) by adopting a cost efficiency model that disentangles persistent and residual efficiency, while accounting for unobserved bank-level heterogeneity. The decomposition, novel in the US community banking, is crucial for disentangling efficiency from factors that are beyond bank's control (i.e., market structure, regulatory/supervisory and business environment) from directly controlled ones, typically related to managerial capabilities and strategy decisions at the bank level. Third, we examine the drivers of persistent and residual efficiency components to a comprehensive array of bank-specific, market-structure and macroeconomic factors.

The rest of the paper is organized as follows: Section 2 discusses the FDIC community bank definition and empirically investigates the financial profile of FDIC-identified community banks versus banks identified using other asset-size definitions. Section 3 introduces the methodology used to measure cost efficiency and discusses the efficiency performance of community banks. In section 4 we examine the determinants of efficiency, and we differentiate between the persistent and residual component. We test the robustness of our results in section 5. Finally, section 6 concludes the paper.

2. FDIC CLASSIFICATION VS ASSET-SIZE DEFINITIONS

2.1 Background information

Extant research has defined community banks using a single criterion: asset-size. Typically an upper limit of $1 billion in total assets has been used (Feng, and Zhang (2012); Smulowitz et al. (2020)), while more recently this has been raised to $10 billion to account for technological advances, inflation and the consolidation process (Bonilla et al. (2018); Chiorazzo et al. (2018)).[6] However, only defining community banks by a single asset size criterion has several drawbacks.

[6] It has been argued that economies of scale are of little importance to the community banking model specifics, with the optimal bank size in the region of only $100-$500 million (Jacewitz, and Kupiec (2012)).

First, community banks are traditional deposit-taking/loan-making financial institutions that abstain from complex financial derivative structures and other exotic investments and focus their operations to the real economy.[7] They are, perhaps, best known for being proponents of "relationship lending" practices. Community bankers have an intimate knowledge and feel of the local community that grants them detailed, soft information on aspects of their customers, such as managerial skill and reputation. The role of the loan officer is pivotal to the production and utilization of soft information within the bank. Loan officers are involved in the early negotiating stages, in loan restructuring[8] and monitoring that allows them significant access to private information (Uzzi, and Lancaster (2003)). The quality of soft information deteriorates when transmitted (Becker, and Murphy (1992); Radner (1993); Garicano (2000); Gartenberg (2014)). Because of this complexity large and multi-branch banks focus on hard information (e.g., financial statement lending, fixed asset lending, credit scoring), which can be processed within computer systems and outsourced.[9] Evidence suggests that community banks may prioritize soft information over hard information, leading to different lending decisions (Liberti, and Petersen (2019)). Hence, community banks have more flexibility in their decision making that may give them an advantage in particular lines of business such as agricultural and small-business loans. For example, relationship lending practices are more relevant in financing of start-up and/or small-businesses where proven track records and collateralizable assets may be hard to come by (Avery, and Samolyk (2004); Holod, and Torna (2018)).[10] Hence community banks are likely to provide credit on such occasions and because of their limited financial technology, they are more likely to maintain such

[7] For example, only 10% of the US banks with assets between $100 million and $1 billion (i.e., community) used interest rate derivatives (Carter, and Sinkey (1998)).

[8] A typical bank loan is renegotiated every nine months, with most parameters being calibrated subject to credit quality and the duration of the bank-lender relationship (Roberts (2015)).

[9] Besides the information quality argument, banks may be prohibited from sharing soft information on the grounds of being classified as privileged information (Frattaroli, and Herpfer (2021)).

[10] Community banks provide substantial financing in these categories. Agricultural lending requires knowledge of farming, often very specific to the region, to the farm or to the farmer, and a longer-term perspective as agricultural cycles are fairly long. Real estate lending, particularly for housing, is another business where knowledge of local conditions and borrowers is necessary.

products on their loan portfolio, rather than securitize them away.[11] Fintech lenders are also linked with credit to borrowers that do not satisfy bank requirements (Bao, and Huang (2021)), however these have significantly higher delinquency rates during crises; thus plausibly representing a sizeable threat to financial stability.

Second, on the funding side community banks are likely to instill loyalty to their depositors, who may be unwilling to switch banks as attractors of an "emotional dividend" from this banking relationship. The fact that investors appreciate attributes outside the risk/return dogma, such as social ones is not new – see for example Riedl and Smeets (2017) and references therein. Other alternative banking models are known to instil a particular behaviour in their clients, even if their remuneration is below the market rate, which has been linked with lower loan default rates (Baele et al. (2014)) and loyalty (Beck et al. (2019)). By contrast, non-community banks have ready access to capital markets, rely largely on fee-based income (e.g., securities brokerage, investment banking, consultancy, underwriting), and operate on the basis of a high volume-transactions based banking model.

Third, defining community banks by a single asset size criterion does not capture differences in the geographic scope of operations. Increased geographical distance between firm and bank decreases the likelihood of lending, which is particularly relevant within small business financing (Degryse, and Ongena (2004); Brevoort et al. (2006)). Besides, firms that are in close geographical proximity to their bank are more likely to develop strategic alliances (Frattaroli, and Herpfer (2021)). Yet research shows that specialized banks may command a certain degree of protection against geographical distance, with customers willing to go that extra mile (Beck et al. (2019)). A single size criterion also ignores stylized

[11] A sizeable literature argues that vertical integration in the loan making process improves lending quality, see for example Gartenberg and Pierce (2017) and references therein. It is argued that corporate governance factors (such as executive compensation, board structure, investor composition) are important mitigators to this relationship. However, we believe that for FDIC-identified community banks the effect of such factors would be relatively muted due to, primarily, the small size, geographical concentration, and private ownership of these banks.

facts of relationship banking, namely core deposits.[12] The positive effects traced to the stable source of funding provided via core deposits is relevant to the bank and the local economy. For example, banks with large core deposits shield firms from tight monetary policy effects (Berlin, and Mester (1999); Black et al. (2007); Li, and Strahan (2021))

Fourth, as community banks are often the only banking option outside metropolitan areas they may be better suited to earn high monopoly rents, which can reduce bank risk taking (Keeley (1990)). As far as community banks are not perceived as financially/systemically important they would be less likely to receive too-big-to-fail type of support that may potentially limit their risk taking. However, as they are regarded as economically important for the regions in which they operate, they enjoy preferential access to emergency lending facilities.[13]

Fifth, a single size asset criterion used across a long-time span may not properly account for factors such as inflation, economic growth, or the size of the banking industry. Bank-type rigidities, differences in adaptation rates to economic environment changes, different goals and priorities can have diverse effects on financial aspects of the two bank types (Kroszner, and Strahan (2014)). Consequently, community and non-community banks share very different business models making it important to comprehensively control for these differences. The FDIC definition of community banks aims to capture these differences.[14]

[12] Core deposits are defined as the sum of all transaction accounts, money market deposit accounts (MMDAs), non-transaction other savings deposits (excluding MMDAs), and time deposits of $250,000 and below, less fully insured brokered deposits of $250,000 and less.
[13] Ashcraft, Bech, and Scott Frame (2010) present evidence on the role of the Federal Housing Lending Bank (FHLB) in providing liquidity during the global financial crisis both for small and large banks. Banks can opt for FHLB membership and community banks receive certain exemptions on the membership requirements (e.g., a 10 percent rule on residential mortgage loans).
[14] Table B1 in the online appendix summarizes the criteria for the community bank designation under this definition.

2.2 An empirical assessment

We evaluate the insights we get from the FDIC (2020) community bank definition (henceforth FDIC) by comparing against alternative definitions that exist in the banking literature, and which define this bank group solely on a size criterion. First, we use the Feng and Zhang (2012) (henceforth FZ) definition that classifies as community banks those below 1$ billion in total assets. Second, the Chiorazzo *et al.* (2018) (henceforth CH) that classifies community banks as those between 500$ million and 2$ billion in total assets. Third, the Bonilla *et al.* (2018) (henceforth BN) which postulates a community bank is of less than 10$ billion in total assets. We refer to these three definitions as conventional asset-size definitions. The FDIC also incorporates an asset size threshold; however, this is continuously adjusted over time to account for financial consolidation and inflation. This is in addition to the financial and business orientation screening criteria. Table 1, panel A summarizes these definitions and presents information on the number of banks included in our sample and their average size.

We start our evaluation of the FDIC definition against the asset-size definitions by comparing the financial profile of community banks classified under each. To do so, we conduct a joint classification analysis whereby dual definitions used give rise to marginal cases under distinct groupings, namely *intersection*, *exclusion,* and *inclusion*. We elaborate on their construction next. The *intersection* group features FDIC-identified community banks that are jointly identified as community under each of the FZ/CH/BN definitions respectively. A community bank *by exclusion* is one that an asset-size definition (FZ/CH/BN) classifies as community, but the FDIC definition excludes it from the community bank universe; either because it is over the FDIC asset threshold and/or is in violation of the financial/business orientation screenings. A community bank by *inclusion* is the opposite. That is, an FDIC-identified community bank, which however is non-community under each of the FZ/CH/BN definitions. Table 1, panel B summarizes the construction of these classifications and contains a visual representation of how banks fall under the different groups.

Table 2 reports measures of financial risk (insolvency, credit and liquidity risk), key attributes of the community banking model (loan/assets, core deposits ratio, deposits per branch, non-interest income/total income) as well as earnings performance (cost/income, ROA, ROE) and capitalization (equity/assets).[15] For the case of the FZ definition, the intersection group is denoted as $(\mathrm{FZ} \cap \mathrm{FDIC})$. The exclusion and inclusion groups are denoted as $(\mathrm{FZ} \cap \mathrm{FDIC}')$ and $(\mathrm{FZ}' \cap \mathrm{FDIC})$ respectively. The groupings for the CH and BN definitions are similarly defined. For each indicator we report: i) the average value over the full sample period; ii) the percentage logarithmic difference for the following comparisons, namely that of the *intersection* group to each of the FZ/CH/BN individual classifications respectively, and that of the *exclusion* and *inclusion* groups to the *intersection* group; iii) the absolute value of the t-statistic. For example, the stability (as measured by the z-score) of the intersection group $(\mathrm{FZ} \cap \mathrm{FDIC})$ is 3.316 i.e., 0.44% higher compared to community banks solely under the FZ definition. Higher stability for the intersection group is also evident when we consider any of the other two definitions, CH and BN by 2.03% and 0.51% respectively. The exclusion group $(\mathrm{FZ} \cap \mathrm{FDIC}')$ has a z-score of 3.143 that indicates lower financial stability by 4.92% compared to the intersection group. A similar result holds for the exclusion groups based on the CH and the BN definitions (by 3.71% and 4.50% respectively). The inclusion group $(\mathrm{FZ}' \cap \mathrm{FDIC})$ has higher stability – by 3.65% – compared to the intersection group. Similarly, the inclusion groups based on the CH and the BN definitions show higher stability by 4.10% and 6.45% respectively. Based on the z-score, we observe that the FDIC definition excludes community banks with low financial stability, which would be included under the

[15] See section 4.2 for a detailed description and construction of the variables used here to portray the financial profile of banks. It is important to note that in identifying community banks the FDIC definition does not consider financial risk, profitability, or efficiency measures.

asset-size definitions. It also includes community banks of high financial stability; these are excluded from the community bank universe under any asset-size definition.

We further observe that the community banks within the intersection group exhibit lower credit and liquidity risk compared against those that are individually defined under the FZ/CH/BN definitions. Community banks identified based on the CH definition exhibit 12.01% and 44.98% lower credit risk and liquidity risk respectively against the community banks that also fulfil the FDIC definition. Key attributes of the community banking system are also affected by the definition choice. When FDIC criteria are also imposed, we document between 1.11-2.71% higher core deposit ratios, between 2.29-4.36% lower income from non-traditional activities, and markedly lower deposits per branch compared to the community banks identified solely upon asset-size. Furthermore, the earnings profile of FDIC-identified community banks is less oriented towards profitability as the intersection group exhibits around 5.59-48.73% lower ROE compared to the control groups. FDIC-identified community banks are also better capitalized.

We turn the focus of our analysis to the cost efficiency of community banks. We estimate a range of cost efficiency models, moving from one commonly used in banking efficiency studies model M1 to progressively more complex model M4. We provide full details of these models and their specifications in section 3.2. Table 3, panel A presents the individual classification results. Here each definition in considered in isolation. For community banks under each definition, we report key descriptive statistics of the cost efficiency estimates pertaining to models M1-M4. The logarithmic *Difference* compares the mean efficiency of FDIC-identified community banks to those under each of the asset-size definitions. Coverage (percent) is defined in a similar manner but compares the bank-quarter observations of community banks under each asset-size definition to the FDIC reference group.

An inspection of Table 3, panel A shows that the average efficiency of community banks under the FZ/CH/BN definitions is lower compared to the FDIC-identified ones. Referring to M1 we find that community banks under the asset-based definitions have lower efficiency by 0.44-3.37%. The same result holds from M2, M3 and M4 with model M4 having the largest difference, between CH definition and FDIC definition (21.67%). With respect to sample coverage, using the FZ/BN definitions against the FDIC leads to an over-classification of community banks by around 6.91-11.76 percentage points. Conversely, the CH uses less than 10% of the FDIC-identified community banks.

Table 3, panel B presents the joint classification analysis. We observe that the community banks of the intersection group have higher cost efficiency, on average, compared to the community banks identified solely based on each of the FZ/CH/BN definitions. The result is consistent across all models. For M1 this increase ranges between 0.39-0.44%, for M2 between 1.32-7.28%, for M3 between 1.28-5.36% and for M4 between 0.93-3.41%. This gives *prima facie* evidence that the financial/business orientation screenings of the FDIC definition lead to a significantly more efficient sample of community banks. Next, we focus on the community banks *by exclusion* and *by inclusion* groups. Banks that are excluded from the FDIC community banking definition exhibit significantly lower cost efficiency vis-à-vis the intersection group. This result is consistent across all models and ranges between 1.4-28.72%. For community banks by inclusion results are mixed and highlight the role of the efficiency model specifications. The simpler efficiency models (i.e., M1, M2) find these banks to be of higher efficiency compared to the intersection group. More advanced models (i.e., M1, M2) do not always agree. It is important though that the community banks solely identified by the FDIC criterion are significantly different to those conforming to the asset-based criteria.

The relative sizes of the groups are also important. The community bank observations within the intersection group have an imperfect overlap - ranging between 71.99-91.57% - to the individual

FZ/CH/BN definitions respectively. This attests further to the FDIC criteria giving rise to a substantially different sample. Furthermore, a pronounced difference exists in the respective sizes of the *by exclusion* and *by inclusion* groups. In particular, and benchmarking against the FZ definition, the FDIC excludes 105,420 community bank-quarter observations and includes 24,785 – around 9.21% and 2.2% of the total observations under the intersection group, respectively. The excluded observations are even larger (proportionally) under the CH definition. Thus, the high efficiency of FDIC-identified community banks is partially attributed to the exclusion of a substantial part of inefficient banks, which are included under the conventional asset-size definitions.[16]

Overall, the differences in the financial profile of FDIC-identified community banks to those under the asset-size definitions are significant by all counts and measures. The new screening criteria define two non-random groups; exclusion and inclusion. Our analysis here indicates that these groups include financial institutions with a significantly different financial profile, and in such quantities that can affect a wide array of outcomes under examination.

3. BANKING EFFICIENCY MEASUREMENT

3.1 Cost efficiency estimation: An overview

Efficiency can be measured either by using traditional financial ratio analysis (FRA) or by frontier estimation methods. A drawback of financial ratios is that they do not take into consideration the input prices and the output mix, and weights of the ratios are selected subjectively (Berger, and Humphrey (1992)). Within frontier estimation methods a bank's observed production point is compared with a

[16] The FDIC definition has two important differences against the FZ/CH/BN definitions of community banks. First, it uses an asset threshold that is adjusted over time to reflect inflation and consolidation in the banking industry, and second features business and financial screening criteria. Using only the asset size part (i.e., FDIC [Size only]) against the full FDIC definition (i.e., FDIC [Full]) we find a 0.72% and a 8.72% difference in the average efficiency and the sample size respectively. The marked difference in the sample size further corroborates that the additional information brough by the FDIC definition are largely due to the business and financial screening criteria.

production frontier that denotes best practice, with data envelopment analysis (DEA) and stochastic frontier analysis (SFA) being the two principal methods used to estimate the production frontier. Contrary to FRA, the frontier techniques produce an objectively determined efficiency score and accommodate multiple inputs/outputs; thus being better suited to capture the activities of a complex financial institution. Central to efficiency studies is the type of the production function, with the majority of studies opting for an intermediary role of the bank, which assumes they act like a wedge between fund surplus and deficit units (Sealey et al. (1977)). Technical efficiency is associated with the bank's ability to obtain maximum output with a given set of inputs; allocative efficiency is associated with the bank's ability to use the optimal inputs mix given their prices, whereas cost efficiency is the product of technical and allocative efficiency.[17]

Stochastic frontier analysis is well-suited to deal with panel data and allows for stochastic errors. A pertinent issue within SFA analysis has been on an appropriate formulation that would on the one hand control for unobserved bank-effects, but on the other hand would not confound them with the efficiency estimate. A typical cost frontier used extensively to estimate banking efficiency is specified as:

$$\ln c_{it} = h(y_{it}, w_{it}; \theta) + v_{it} + u_{it} \tag{1}$$

where bank i $(i = 1, \dots, N)$ observed over time period t $(t = 1, \dots T)$ is considered to produce a vector of outputs (y_{it}), given a vector of input prices (w_{it}) and specific technology, denoted as $h(\cdot)$, incurring a cost c_{it}. Of particular importance in this context are the two quantities v_{it} and $u_{it} \geq 0$ that represent

[17] We direct you to Miller and Parkhe (2002) for a brief overview of efficiency from a managerial perspective. Technical and cost efficiency measures are central to banking studies (Berger, and DeYoung (1997); Lozano-Vivas et al. (2002); Drake et al. (2006); Casu, and Girardone (2010); Casu et al. (2017)).

random noise and time-varying inefficiency respectively.[18] Even though panel data allow us to account for bank heterogeneity, this is left unexplored by these typical models.

To account for bank heterogeneity (i.e., to fully utilize the panel data) a series of studies, see (Kumbhakar (1991)) and references therein, introduce a third term, u_{0i}, which is time-invariant and captures a part of inefficiency that is not within the bank's capability to control directly (i.e., regulation, market structure, borrower/lender differences). This is referred to as persistent (long-run) inefficiency. However, the specification is similar to the true random (or fixed) effects model (Greene (2005)), albeit with two notable differences. First, as per Greene (2005) the interpretation of the term in question is that of bank-heterogeneity (i.e., bank random/fixed effects) that is, arguably, wider than persistent inefficiency. Second, persistent inefficiency must be non-negative (i.e., $u_{0i} \geq 0$), but no such restriction exists for the equivalent component in the true random (or fixed) effects model. As long as we regard persistent inefficiency to be different to bank heterogeneity, a case can be made for a model separating the two. This leads to the following four component model, introduced simultaneously (Colombi et al. (2014); Kumbhakar et al. (2014); Tsionas, and Kumbhakar (2014)), albeit with differences in the estimation procedure.

$$\ln c_{it} = h(y_{it}, w_{it}; \theta) + v_{0i} + u_{0i} + v_{it} + u_{it} \qquad (2)$$

where bank heterogeneity (in the spirit of Greene, 2005) is captured by v_{0i}, and u_{0i} captures persistent (or long-run) inefficiency in line with Kumbhakar (1991). The third and fourth components vary across banks and time and represent random noise and residual (or short-run) inefficiency respectively. The persistent inefficiency is associated with factors that are relatively constant over short time spans, such as structural inflexibilities or regulatory restrictions, and are not directly controlled by the bank. The

[18] We start our exposition from these models that assume efficiency to be time-varying, see for example Battese and Coelli (1992), Kumbhakar (1990). However, earlier models would have restricted efficiency to be time-invariant; a rather too restrictive assumption (Schmidt and Sickles (1984); Kumbhakar (1987)).

residual component reflects the usual managerial efficiency.[19] However, it allows a bank's efficiency to adjust over time as the bank may eradicate some of the short-term rigidities.

To estimate Equation 2, we use the multistep procedure outlined in Kumbhakar *et al.* (2014) and used also in Kumbhakar and Lien (2017) and Lien, Kumbhakar and Alem (2018). To facilitate exposition, we rewrite equation 2 as:

$$\ln c_{it} = \theta_0^* + h(y_{it}, w_{it}; \theta) + a_i + \varepsilon_{it} \tag{3}$$

where $a_i = v_{0i} + u_{0i} - E(u_{0i})$, $\varepsilon_{it} = v_{it} + u_{it} - E(u_{it})$ and $\theta_0^* = \theta_0 + E(u_{0i}) + E(u_{it})$. This ensures that α_i and ε_{it} have zero mean and constant variance. Using panel random effects in equation 3 we can get consistent estimates of θ and predicted values of a_i and ε_{it}. In the second step, we use the predicted value of a_i from step 1 (we ignore differences between the true and predicted values of a_i, see Lien et al., 2018), invoke different distribution assumptions for the two right-hand-side terms, namely $v_{0i} \sim N(0, \sigma_{v0}^2)$ and $u_{0i} \sim N^+(0, \sigma_{u0}^2)$, and use standard stochastic frontier estimation (see Jondrow et al. 1982) to get predicted values of u_{0i}. Persistent efficiency is then defined as $exp(-u_{0i})$.

In the third step, we use the predicted value of ε_{it} from step 1 (we ignore differences between the true and predicted values of ε_{it}, see Lien *et al.* (2018), invoke different distribution assumptions for the two right-hand-side terms, namely $v_{it} \sim N(0, \sigma_v^2)$ and $u_{it} \sim N^+(0, \sigma_u^2)$, and use standard stochastic frontier estimation, see Jondrow *et al.* (1982), to get predicted values of u_{it}. Residual efficiency is then defined as $exp(-u_{it})$. Finally, the overall cost efficiency (OCE) is calculated as the product of persistent (PCE) and residual (RCE) cost efficiency, namely: $OCE = PCE \times RCE = exp(-u_{0i}) \times exp(-u_{it})$.

[19] This is the component that is central in management studies, see for instance Chen *et al.* (2015).

3.2 Flexible technology and models specification

To estimate cost efficiency, we allow for flexible technology between community and non-community banks, by allowing individual cost frontiers for either bank type, which we estimate in a single model[20], namely:

$$\ln c_{it} = CB \times \ln c_{it}^{CB} + CB' \times \ln c_{it}^{CB'} \tag{4}$$

where CB is a dummy variable taking the value one for community banks; zero otherwise, and $CB' = 1 - CB$ and denotes non-community banks. The bank-type specific cost frontiers are given as:

$$\ln c_{it}^{CB} = h^{CB}\left(y_{it}^{CB}, w_{it}^{CB}; \theta^{CB}\right) + v_{0i}^{CB} + u_{0i}^{CB} + v_{it}^{CB} + u_{it}^{CB} \tag{5}$$

$$\ln c_{it}^{CB'} = h^{CB'}\left(y_{it}^{CB'}, w_{it}^{CB'}; \theta^{CB'}\right) + v_{0i}^{CB'} + u_{0i}^{CB'} + v_{it}^{CB'} + u_{it}^{CB'} \tag{6}$$

For the cost frontier we follow the intermediation approach that assumes the bank's role to be that of an intermediary between fund surplus and deficit units (Sealey et al. (1977)). The technology of the bank i $(i = 1, \dots, N)$ observed over time period t $(t = 1, \dots T)$ is specified by the following translog function with K outputs $(k = 1, \dots, K)$ and M $(m = 1, \dots, M)$ inputs. To allow for technology change over time and seasonality we include a quadratic time trend, quarterly binary variables and their respective interaction terms with outputs and input prices.

[20] Another option is to estimate separate frontiers for each bank type.

$$h(y_{it}, w_{it}; \theta) = \beta_0 + \sum_{k=1}^{K} \beta_k \ln y_{kit} + 0.5 \sum_{k=1}^{K} \sum_{n=1}^{N} \beta_{kn} \ln y_{kit} \ln y_{nit} + \sum_{m=1}^{M} a_m \ln w_{mit} \tag{7}$$

$$+ 0.5 \sum_{m=1}^{M} \sum_{l=1}^{L} a_{ml} \ln w_{mit} \ln p_{lit} + \sum_{m=1}^{M} \sum_{k=1}^{K} \gamma_{km} \ln y_{kit} \ln w_{mit}$$

$$+ \sum_{k=1}^{K} \delta_k t \ln y_{kit} + \sum_{m=1}^{M} \theta_m t \ln w_{mit} + \tau_1 t + \tau_2 t^2$$

$$+ \sum_{q=1}^{Q} \sum_{k=1}^{K} \psi_{qk} Q_q \ln y_{kit} + \sum_{q=1}^{Q} \sum_{m=1}^{M} \xi_{qm} Q_q \ln w_{mit} + \sum_{q=1}^{Q} \xi_q Q_q + v_{0i}$$

$$+ u_{0i} + v_{it} + u_{it}$$

To ensure regularity conditions of the cost function in equation 7 we impose symmetry restrictions ($\beta_{kn} = \beta_{nk}$ and $\alpha_{ml} = \alpha_{lm}$) and linear homogeneity in input prices by dividing total cost and input prices by w_1 $(\text{i.e.}, c/w_1, w_m/w_1, m = 2, \ldots, M)$.

We allow for a variety of models that are progressively less restrictive as they allow for fewer similarities between the two bank types and may be viewed as special cases of the four-component model. Model M1 is a widely used model used in banking efficiency studies, see for example Casu, Deng, and Ferrari (2017), Evanoff and Ors (2008), without any efficiency decomposition (i.e., $u_{0i} = 0$; $v_{0i} = 0$). On this occasion, the banks are assumed to produce total loans (y1) and securities (y2). The input variables are the price of labour (p1), defined as the salaries and employee benefits over the number of full-time equivalent employees; the price of capital (p2), defined as expenses on premises and fixed assets over premises and fixed assets; and the price of funds (p3), defined as total interest expenses over total deposits. We define total cost as the sum of total interest expense and total non-interest expense.[21] All monetary variables have been deflated using the GDP deflator. Model M2 further

[21] Our choice of input and output variables is in line with the literature in this field (Casu, and Molyneux (2003); Drake et al. (2006); Casu, and Girardone (2010); Johnes et al. (2014); Matousek et al. (2015); Fukuyama, and Matousek (2017)).

introduces flexible technology whereby community and non-community banks have separate production functions that can accommodate differences in their business models. Model M3 may be viewed as the four-component extension to M2 that allows for persistent (u_{0i}) and residual (u_{it}) efficiency decomposition.

Contrasted against M3, Model M4 uses a more extended output designation whereby banks are assumed to produce loans to individuals (y1), residential mortgages (y2), commercial and industrial loans (y3), agricultural loans (y4), construction and development loans (y5) and securities (y6). A finer decomposition of loan categories allows us to better control the heterogeneity in the bank loan-making strategy at the efficiency estimation stage. For example, if community banks do more mortgage lending than commercial lending (which is true in the sample) and mortgage lending can be done more efficiently than commercial lending, then community bank would appear to be more efficient if the portfolio composition is not controlled for when estimating efficiency.[22] Table 4 provides a compact view of M1-M4 model differences.

We use quarterly data ranging from 1984Q1 to 2019Q4, extracted from the Call Reports of US banks. Information about FDIC-identified banks, including the community bank binary variable is extracted from the FDIC website[23] and is matched to the Call Reports using the FDIC certificate number, which uniquely identifies every bank in our sample. We exclude banks where no data are available for the efficiency estimation. Our combined dataset is an unbalanced panel dataset consisting of 20,394 banks and over one million bank-quarter observations. Price variables in the efficiency estimation are

[22] In comparative analysis between alternative banking systems, it has been argued that focusing on profit analysis (whether in the form of profit efficiency or profit related financial ratios) may disadvantage the specialist banking group that could be following different objectives outside a strict profit maximisation dogma. In our case, community banks may be focusing on the welfare of the local community. Similar arguments have been put forward for comparative analysis between Islamic and conventional banks, where shying away from a profit efficiency study has been on the grounds that the former may have additional objectives encompassing social value and ethical behaviour (Johnes et al. (2014)). By contrast, profit efficiency assumes that profit maximisation is the sole goal of the bank (Berger, and Mester (1997)). This reasoning motivates our choice of cost efficiency.

[23] Available here: https://www.fdic.gov/resources/community-banking/cbi-study.html

winsorized at the 0.1/99.9 by bank type. Table 5 summarizes the main descriptive statistics for the input and output variables used in the analysis, for the full sample (panel A), community banks (panel B) and non-community banks (panel C). Differences in the choices of input mix is reported between the two bank types. The average price of labor takes the value of 26.264 for community banks and 25.973 for the non-community. The average price of capital takes the value of 0.254 for community banks and the value of 0.375 for non-community banks. Referring to the output quantities, the average values for both outputs are significantly higher for non-community banks.

3.3 Community bank efficiency performance

Estimates of cost efficiency and the two decompositions (where applicable) under models M1-M4 are presented for community and non-community banks in Table 6 alongside the usual statistical tests.[24] Community banks show superior cost efficiency compared to the non-community banks; the result being consistent and significant across all model specifications. Model M1 reports the lowest difference in overall cost efficiency between the two bank groups (3.6%) whereas when we consider the more refined model M4 the difference is 18.6%. Turning to efficiency components, both models (i.e., M3 and M4) suggest that community banks exhibit superior residual efficiency by 2.3% and 2.2% respectively. However, it is the difference in persistent efficiency between the two bank types that is more interesting. Both models find community banks to outperform their counterparts by a sizable 16%. The difference is economically and statistically significant and may be plausibly traced to market structure, regulatory/supervisory and business environment characteristics. For example, the consolidated capital requirement for community banks, the simplified capital standards and documentation for commercial

[24] The estimated coefficients for the translog cost functions are presented in Table B2(a) and Table B2(b) in the online appendix.

real estate (CRE) loans, and the delayed implementation of accounting rules changes (i.e., current expected credit losses).

Figure 1 plots the overall cost efficiency by bank type across time (left graph) and across states (right graph). Community banks show superior cost efficiency over the full sample period compared to the non-community banks. For non-community banks the time evolution of overall cost efficiency exhibits a volatile trend leading to the 2008 global financial crisis when we evidence a large drop for this bank type. The trend is muted for community banks, suggesting that these weathered the crisis better. The steep rise in overall cost efficiency for non-community banks before the crisis may be reflective of the rapid expansion of financial products and practices that, *a posteriori*, have been put under the microscope for aggravating the crisis (Martin-Oliver et al. (2013)). It is not uncommon for the more traditional banking sector to fail to keep up with such developments. Moreover, the rise may be *prima facie* evidence of the well-documented trade-off between risk and efficiency - referred to as “cost skimping” (Berger, and DeYoung (1997)) where short-term reductions in credit checks and loan monitoring may materialise in an artificial rise in residual cost efficiency. A cross state comparison of overall efficiency suggests that community banks outperform their counterparts in all states and especially in states located in the central and the northern parts of the country.

Figure 2 consists of a top and a bottom graph. The top graph plots the average residual cost efficiency for the two banking models at the state level, and its dispersion (95% confidence intervals) over the period of study. Bottom graph depicts the *relative percentage log difference* in the residual cost efficiency between the two banking models at the state level, and its dispersion over the period of study.[25] Community banks outperform their non-community counterparts in all states bar Vermont. On average we do not observe significant cross-state heterogeneity in the community bank residual cost efficiency differential. In most states community bank residual efficiency premium is below 5%.

Figure 3 repeats for the persistent cost efficiency. Compared to the previous graph, the differences in persistent efficiency are more pronounced across all states, with the community banks having a substantial lead. The important cross-state heterogeneity in the persistent efficiency differential ranges between -5% in Nevada to almost 40% in Delaware. The heterogeneity in the persistent efficiency differential between the two banks suggests that some states offer a more "fertile" environment for community banking. We proceed to examine the drivers behind the substantial persistent efficiency differential of community banks at the state level.

4. EFFICIENCY COMPONENTS: FURTHER INVESTIGATIONS

4.1 Econometric specification

Further analysis explores the determinants of cost efficiency in community and non-community banks. Given the different nature of the two types of efficiency estimates we conduct separate analysis for the residual and the persistent component.

Residual cost efficiency is time-varying; hence we use a set of bank-specific, market-structure and macroeconomic variables and estimate via robust panel estimation the following equation:

$$y_{ijt} = \alpha + \beta CB_{it} + \gamma X_{it} + \delta M_{it-1} + \zeta CB_{it} \times X_{it} \qquad (8)$$

$$+ \lambda CB_{it-1} \times M_{it-1} + \varepsilon_{ijt}$$

where i, j, t index banks, states and time respectively. The dependent variable y_{ijt} is the residual cost efficiency score derived from the first stage. CB_{it} is a dummy variable that takes the value of 1 if the bank is a community bank at time t; zero otherwise. X_{it} is a matrix of bank-specific independent variables; M_{it} is a matrix of variables capturing the market structure and macroeconomic environment;

$CB_{it} \times X_{it}$ is the interaction between bank-specific variables and the community bank dummy; $CB_{it-1} \times M_{it-1}$ is the interaction between market structure and macroeconomic variables and the community bank dummy; ε_{ijt} is an idiosyncratic error term. Estimated models I-VIII allow for an increasing number of control variables, with the former models controlling for bank-level characteristics, while the latter add market structure and macroeconomic variables as well as a full array of bank-type interaction terms.

Persistent cost efficiency is constant over time (at the bank level), thus we opt for a state-level analysis to explain the factors that drive differences among banking performance. To better understand the drivers of state-level persistent cost efficiency, we invoke the following relative difference robust panel estimation.

$$z_{jt} = \alpha + \beta X + \gamma M + \theta \mu_j + \varepsilon_{jt} \tag{9}$$

where j indexes the states; t indexes the time period; μ_j are state random effects and ε_{jt} is the stochastic error term. The explanatory variables include bank-specific information (denoted as X) and macroeconomic, market structure, business environment and financial development indicators (denoted as M). The dependent variable and bank-specific information enter the regression model as *relative percentage log differences* between the two banking models at the state level. The relative percentage log difference is defined as $z_{jt} \equiv \log\left(z_{jt}^{\{CB\}} / z_{jt}^{\{Non-CB\}}\right) \times 100$, where $z_{jt}^{\{CB\}}, z_{jt}^{\{Non-CB\}}$ indicate the persistent cost efficiency of community and non-community banks respectively in state j at time t. For a given state and time, positive values suggest that the community banking model is more efficient relative to the non-community counterpart. Relative percentage log differences for bank-specific variables are included in a similar manner.[26] Estimated models I-VIII allow for an increasing number

[26] For variables where negative differences were possible, we calculate the relative percentage difference instead (i.e., credit risk, liquidity risk, active states, active MSAs).

of control variables. In particular, models I-III allow for bank-specific information, while model IV caters for bank-specific and market structure characteristics. Model V further accounts for key macroeconomic and market sentiment characteristics, while models VI and VII account for state-level business environment factors. Finally, model VIII controls for size differences across federal reserve bank regions. We use a stepwise algorithm that maximizes the goodness of fit.

4.2 Bank-specific, market structure and macroeconomic explanatory variables

To investigate the determinants of community banks' efficiency we employ bank-specific, market structure and macroeconomic variables.[27] Specifically, we include the natural logarithm of bank assets to account for bank size differences as community and non-community banks are significantly different in terms of size. Deposits and loans are central components of the traditional banking model, so we include the ratio of core deposits to total assets and the ratio of loans to assets. To capture the extent to which banks generate non-interest income we include the income diversity measure. As common for banking studies we measure capitalization by equity to assets and profitability is proxied by the return on equity (ROE) ratio.

To proxy credit risk we use the respective measure of Imbierowicz and Rauch (2014).The credit risk proxy measures the unexpected loan default ratio of the bank and is calculated by dividing the average net loan losses (loan charge-offs minus loan recoveries) in the current period by the average loan loss allowance in the previous period. This measure captures the current riskiness of a bank's loan portfolio and the ability of the bank's risk management to anticipate near-term future loan losses.

To capture liquidity risk we use the respective measure of Imbierowicz and Rauch (2014). The intuition behind this ratio is that in case of sudden withdrawals from the bank, the full volume of liabilities may

[27] Our choice of variables here is motivated by the relevant banking literature (Mehra (1996); Degryse, and Ongena (2004); Beck et al. (2010); Anginer et al. (2014); Baele et al. (2014)). The full list of the variables with descriptions is provided in table B3 of the online appendix.

not be liquidated at short notice and/or without substantial cost. Hence the liquidity risk variable subtracts the volume of all assets that the bank can at short-time and low-cost turn into cash from the volume of liabilities that can be withdrawn from the bank on short notice. It considers the bank's exposure to the interbank lending market and derivatives market as well as off-balance sheet liquidity risk positions though, for example, unused loan commitments. The ratio is scaled by total assets with higher values of the liquidity risk ratio indicating a bank that is in worse situation to meet unexpected liquidity demand.

To proxy financial stability we employ the z-score that is commonly used in the banking literature, see for example (Laeven and Levine (2009); Demirgüç-Kunt and Huizinga (2010); Beck et al. (2021); Bostandzic et al. (2021)). In principle the z-score calculates the number of standard deviations that the bank's return on assets (ROA) must fall below its mean to deplete equity. The z-score increases with higher profitability and capitalization levels and decreases with volatile earnings. Therefore, high values of the z-score indicate more financially stable banks. In our study the z-score considers the past three years' values for the equity/assets, ROA and $\sigma(\mathrm{ROA_T})$. As the z-score exhibits high skewness we use the natural logarithm transformation, in line with Laeven and Levine (2009).[28]

Community banks are primarily loan makers; thus we investigate the impact of their loan making strategy upon cost efficiency by including the ratio of the five main loan categories to total assets; namely: i) residential mortgages; ii) agricultural loans; iii) commercial and industrial loans (C&I); iv) construction and development loans (C&D); and v) loans to individuals. Most community banks hold

[28] The z-score is considered a non-regulatory, accounting-based measure of risk. Bostandzic *et al.* (2021) argues that non-regulatory measures are better predictors of bank solvency compared to regulatory measures (i.e., core tier 1 capital ratio). Non-regulatory, market-based risk measures (i.e., value-at-risk, systemic risk) are only available for listed banks, which would exclude most of the community banks in our setup. Besides, market-based risk measures have been criticized for being inaccurate particularly during crises, see Zhang *et al.* (2015) and Löffler and Raupach (2018). In practice, there are several alternative definitions of the z-score, see Mare, Moreira and Rossi (2017) for a comprehensive review. As a robustness we compute alternative z-score measures, and the results remain qualitatively similar.

diversified loan portfolios with engagement in more than one of these loan sub-categories. By including these sub-categories, we gain useful insights as to how the different lending strategies employed by community banks affect efficiency performance.

Community banks provide financial services to a market segment with limited financial opportunities. Changes in the macroeconomic environment that impact the banking sector may have a more pronounced effect in geographical locations with high presence of community banks, which are known to be particularly affected by inflation dynamics (Bonilla et al. (2018)). This raises the question of how community banks respond to macroeconomic instability and regulatory changes compared to non-community banks. To account for the overall macroeconomic and market structure environment, we include the real GDP growth, the real output of non-financial sector, the interest rate spread between the 10-year constant maturity minus 3-month treasury constant maturity, the financial stress index, the financial institutions access index and the consumer sentiment index.[29] We take into account periods of crisis by including a crisis dummy that takes the value 1 during periods of banking crises as defined above; zero otherwise. Following Berger and Bouwman (2013) we consider the two banking crises that are relevant to our sample. These are: i) the credit crunch of the early 1990s (from 1990Q1 to 1992Q4) and ii) the subprime lending crisis (from 2007Q3 to 2009Q4). At state level we account for market concentration, the relative size of the community banking sector, productivity, the number of business applications as well as the degree of education of the state population.

Descriptive statistics of the bank financial characteristics are reported in Table 7. The average value of bank assets (in natural logs) is 11.202 for the community banks and 12.826 for the non-community; a significant size advantage for the non-community banks that is in line with our expectations. Deposits to assets are at 86% for the community banks and 81% for the non-community banks, corroborating the

[29] Bank-specific data are sourced from call reports and macroeconomic/market structure data are sourced from the FRED.

view that the former are more reliant on deposit funding, with the latter capable to attract more funding from capital markets. With respect to profitability, the mean value of ROE is significantly higher for the non-community banks compared to the community (8.7% against 4.1% respectively), which conforms to our expectations that the latter are not primarily focused on profit maximization. Community banks are significantly more capitalized compared to the non-community counterparts (10.2% against 9.5% in equity/assets respectively).

In terms of financial stability, community banks appear to perform better, with the average value of z-score around 3.32, significantly higher compared to the non-community banks, which stand at 3.15, on average. In addition, community banks have significantly lower credit risk compared to the non-community banks (0.212 against 0.408 respectively), plausibly due to their relationship lending approach that is known to reduce moral hazard and adverse incentives (Boot (2000)). Liquidity risk is lower in community banks compared to the non-community (0.228 against 0.820 respectively). This may be because the former have limited access to money markets to attract funding; hence are required to have enhanced liquidity management.

Substantial differences exist between the loan portfolios of the two bank types. Commercial and industrial loans constitute the highest proportion of the loan portfolio for non-community bank (23%). For community banks the highest proportion of loans is concentrated towards residential mortgages (17%). Agricultural loans account for around 6% of community banks' portfolio and 1.6% for that of non-community banks. For community banks, 7.4% of their loan mix is concentrated on loans to individuals whereas for non-community banks this percentage is higher (11%). Construction and development loans comprise around 3% of both community and non-community banks' loan mix.

4.3 Determinants of residual cost efficiency

In this section we present the results of the analysis on the determinants of residual cost efficiency. For our analysis we consider residual cost efficiency from Model M4. Table 8 presents estimated coefficients, robust standard errors, and standard goodness-of-fit statistics of equation 8. Models I to VIII present different specifications of the basic model where bank-specific, market structure and macroeconomic variables are included together with intercept and slope CB dummies.[30]

Of primary interest is the coefficient of the community bank binary variable. The results of all models suggest that community banks exhibit higher residual cost efficiency than non-community banks, as evident by the significant and positive coefficient of the community bank dummy. This result is in support of our earlier, unconditional findings that community banks outperform their non-community counterparts. The marginal effect, around 3.5% averaged across Models I-VIII is also comparable in magnitude to the earlier unconditional results corroborating further that community banks' operational environment and management practices translate into additional benefits in terms of residual cost efficiency. An investigation of the control variables explains in further detail the sources of this result.

The coefficient for bank size is significantly negative, suggesting that large banks exhibit lower residual cost efficiency possibly due to diseconomies of scale. The interaction with the community bank dummy further suggests that the negative effect of size on residual cost efficiency is around two times more pronounced for community banks. It appears that small bank size is a catalytic factor for community banks to maintain their efficiency advantages. The smaller the community bank the more efficient it can be in exploiting niche opportunities. In small business lending in particular it has a competitive

[30] For brevity we present a condensed version of the table showing only the CB binary variable, and direct the reader to the online appendix for the full version of the table (Table B4).

advantage over the information opacity of these firms.[31] Even though we do not find any evidence that larger banks derive benefits in terms of residual cost efficiency, our results show that non-community banks reap efficiency benefits by being part of a bank holding company. However, for community banks this effect is moderated as confirmed by the negative coefficient of the interaction term. As community banks may be pursuing goals other than profit maximization, being part of a bank holding company can change their focus and dilute their distinct character; thus balancing out the positive effect brought by economies of scale advantages.

A high core deposit to assets ratio is negatively associated with residual cost efficiency, suggesting that the banks that fund their assets primarily via deposits tend to be less efficient. The negative coefficient of the interaction term suggests that the effect is more pronounced for the community banks. Bank funding is typically done either via deposits and/or through capital market operations. Attracting funding via the latter is likely to be a competitive process on behalf of the bank, and inaccessible (or prohibitively costly) to the smallest of banks. By contrast, the small community banks are local in their operations, and often subject to little competition with regards to deposit taking from local clientele. Hence community banks may not have to work as hard to attract deposits as non-community banks do, simply because they may be the only bank in the vicinity.[32] In terms of profitability, a positive link is found between ROE and efficiency suggesting that more profitable banks tend to be more efficient.

With respect to the different loan categories, results on residential mortgages provide an interesting reading. The variable enters the regression with a positive coefficient, and the interaction terms suggest that the positive effect becomes more pronounced for community banks. Since residential mortgages are associated with higher residual efficiency this makes them an attractive product for banks, especially

[31] McKee and Kagan (2018) claim that as community banks increase their asset base, efficiency drops as a result of the bank's incapability to translate elevated assets into loans.
[32] The FDIC estimates that a significant part of the US population lives in underbanked environments, often only served by a few community banks.

given the fact that they are homogenous as a product and can easily be scaled up. This relationship can partially explain the attractiveness of this loan type and its popularity among online mortgage lenders. Fuster *et al.* (2019) document a quad-fold increase in Fintech offered mortgages in the US citing mainly faster processing times at no delinquency cost.[33] Agricultural loans are a key operation for community banks; and increased offering of agricultural loans increases residual cost efficiency. We also find that commercial and industrial loans are positively linked to residual efficiency. Extant research shows that these are among the first loans to be affected following capitalization adjustments (Cortés et al. (2020)).

When it comes to market structure, banks that operate in areas with higher community banking concentration are more efficient. More concentration creates less information dispersion, so banks are more effective in their screening process and reduce the likelihood of adverse selection which leads to inefficiencies.

4.4 Persistent cost efficiency: Cross-state variation and drivers

To better understand the drivers of the state-level difference in community bank persistent cost efficiency, we invoke relative difference robust panel estimation and results are presented in Table 9. The results show that controlling for bank's loan-making strategy better explains differences in efficiency. In fact, accounting for loan making differences at state level increases prediction power by 42%.

At the state level community banks achieve high persistent efficiency scores when their financial stability differential to non-community banks is pronounced. In other words, for a 1 percentage point increase in the relative financial stability, community banks gain around 3% in their persistent efficiency, *ceteris paribus*.[34] The relative magnitude of the core deposit ratio coefficient suggests that

[33] However, the Fuster *et al.* (2019) study does not cover a crisis, with Fintech lending evidence provided in Bao and Huang, (2021) suggesting that the Covid crisis has affected Fintech loans more severely than bank ones.
[34] This is calculated as exp(b)-1.

the key driver of the persistent efficiency difference between the two bank types is the strategic choice to focus on traditional activities, such as deposit taking. The negative coefficient on total assets shows that community banks' persistent efficiency differential decreases as they converge in size to non-community banks. Small community banks are most efficient when they are competing against large non-community banks at the state level. The higher persistent efficiency of community banks is also partly driven by their focused operations. The negative coefficient on income diversity indicates that community banks seeking to diversify their income stream are expected to be losing out in terms of persistent efficiency.[35] Indeed, the operational challenges of expanding to new markets and products (including online banking) are a key concern for community bankers (FDIC (2019)).

Coming now to discuss market structure variables, we find that community bank persistent efficiency differential is not affected by the non-community banks concentration. The finding may possibly echo the loyalty instilled to customers by community banks, who may be unwilling to look elsewhere for financial products.[36] Insofar as the traditional profile of their clientele that ranks proximity higher than technological innovations and/or remuneration prevails, community banks are more efficient. As depopulation and population aging change the profile of the bank users, financial product innovations are introduced by dominant and tech-savvy non-community banks. Hence community banks are either forced to use products and services that are beyond their technological capabilities; thus effectively diluting their business model, or be confined into a decreasing client base.

With regards to business related factors, productivity and higher education are positively related to a higher persistent efficiency differential of community banks. In particular, we find that higher proportion of educated population (Bachelor's degree) may lead to higher efficiency in community

[35] Expansion into new product lines has been associated with an initial decrease in performance for US software firms (Zahavi, and Lavie (2013)).
[36] Alternative banking models are shown to induce a loyalty factor upon clients (Beck et al. (2019)).

banks. This is plausibly related to the relationship banking model and the requirement for the extraction and management of soft information, which is known to require additional skills from the loan manager (Stein (2002)). Besides, education attainment is positively linked to establishment and success rates of new start-ups (Cooper et al. (1988)) and that are typically financed from community banks. Conversely, non-community banks rely more on transactional banking practices and have replaced expensive skilled labor to low skilled workers and computers (Feng, and Zhang (2012)).

The insights from macroeconomic variables suggest that the persistent efficiency differential of community banks is indifferent to the economic climate. The real GDP growth and financial stress index coefficient fail to reach significancy. Additionally, the community banking model is particularly efficient where individuals or firms have low access to financial institutions.[37]

6. ROBUSTNESS TESTS

We perform a series of robustness tests: (i) splitting the sample into four distinct supervisory periods, namely: 1984-1991 (pre Basel Accord and FDIC Improvement Act), 1991-1999 (prior to the Financial Modernization act), 2000-2010 (rise of financial holding companies, the housing bubble, and the subprime crisis), 2011-2019 (post Dodd-Frank act); (ii) including banks that have financial information across the full-time span of our study; (iii) splitting FDIC-identified community banks into size classes, namely: below \$100 million, \$100-250 million, \$250-500 million, \$0.5-1 billion, \$1-10 billion; (iv) utilizing dual definitions jointly, namely the FDIC, each of the asset-based definitions and their interaction that allow us to capture the exclusion, inclusion and intersection groups; (v) using an

[37] We have used several alternative indicators as robustness checks. Specifically, we substitute productivity of non-financial firms with manufacturing, business and non-farm businesses, with results remaining qualitatively similar. To proxy for business activity and sentiment we have also considered the Leading Index, the Coincident index and the OECD Consumer Opinion Index in alternative specifications. Financial institutions development (Depth) has also been considered and results were qualitatively similar to the Access category. We did not use the Efficiency category as it is conceptually similar to the bank-level characteristics we have included. Alternative measures to the Financial Stress Index that we considered include the Economic Policy Uncertainty (EPU) and the VIX index, giving similar results. Lastly the HHI index has also been calculated on the basis of Total Deposits and Total Loans, with results being qualitatively similar.

instrumental variable regression to account for the efficiency-risk endogeneity; (vi) controlling for banks that switch status (i.e., part-time community banks); (vii) using a non-parametric matching estimator approach to compare community and non-community banks with similar financial characteristics. Our results remain unchallenged across these tests.[38]

7. CONCLUDING REMARKS

This paper sheds light on the performance of community banks. First, we put under the microscope the FDIC definition for community banks, which uses geographical and business model characteristics in conjunction with redefined size criteria. A detailed analysis of FDIC-identified community banks shows important re-classifications against the traditional asset-size definitions commonly used in the banking literature. The financial and business criteria imposed exclude (include) banks that would otherwise be considered as community (non-community) respectively. We show that these groups include financial institutions with a significantly different financial profile, and in such quantities that can affect a wide array of outcomes under examination.

We turn our focus to the community banks themselves. Although consolidation trends and economic turmoil have slashed the community banking sector, this bank type continues to be resilient. This raises the question why these banks can stay afloat. We focus on the well reputed measure of bank performance, cost efficiency, and compare the performance of FDIC-identified community banks against their non-community counterparts. Our analysis finds that FDIC-identified banks are 19% more efficient, on average. The cost efficiency model we adopt allows us to decompose cost efficiency into a residual (short-run) and a persistent (long-run) component and explore whether the superior efficiency performance of community banks stems from managerial practices or market structure, regulatory and business environment facets. We find that community banks outperform their counterparts in terms of

[38] These results are presented and discussed extensively in the online appendix of the paper.

residual and persistent efficiency, however most of this efficiency premium stems from market structure and business environment factors. We uncover substantial heterogeneity in the persistent efficiency differentials of the two bank types across the US states suggesting that some are more suited for community banking. These are states with large bank size differential between community banks and their competitors, and limited financial access. Our results on residual efficiency suggest that community banks benefit from higher involvement in residential mortgages and agricultural loans.

Our results have implications for future research and policy makers. We have shown that FDIC-community banks are distinct from the community banks identified in the banking literature. Given that the FDIC definition is the basis for regulatory relief on these banks, we believe it is important that future research analyze other aspects, such as liquidity creation. From a policy perspective, our results confirm that the community banking performance is not uniform at the state level. Hence, the strategy of federal and state authorities may incorporate measures directly aimed towards those areas in greater need.

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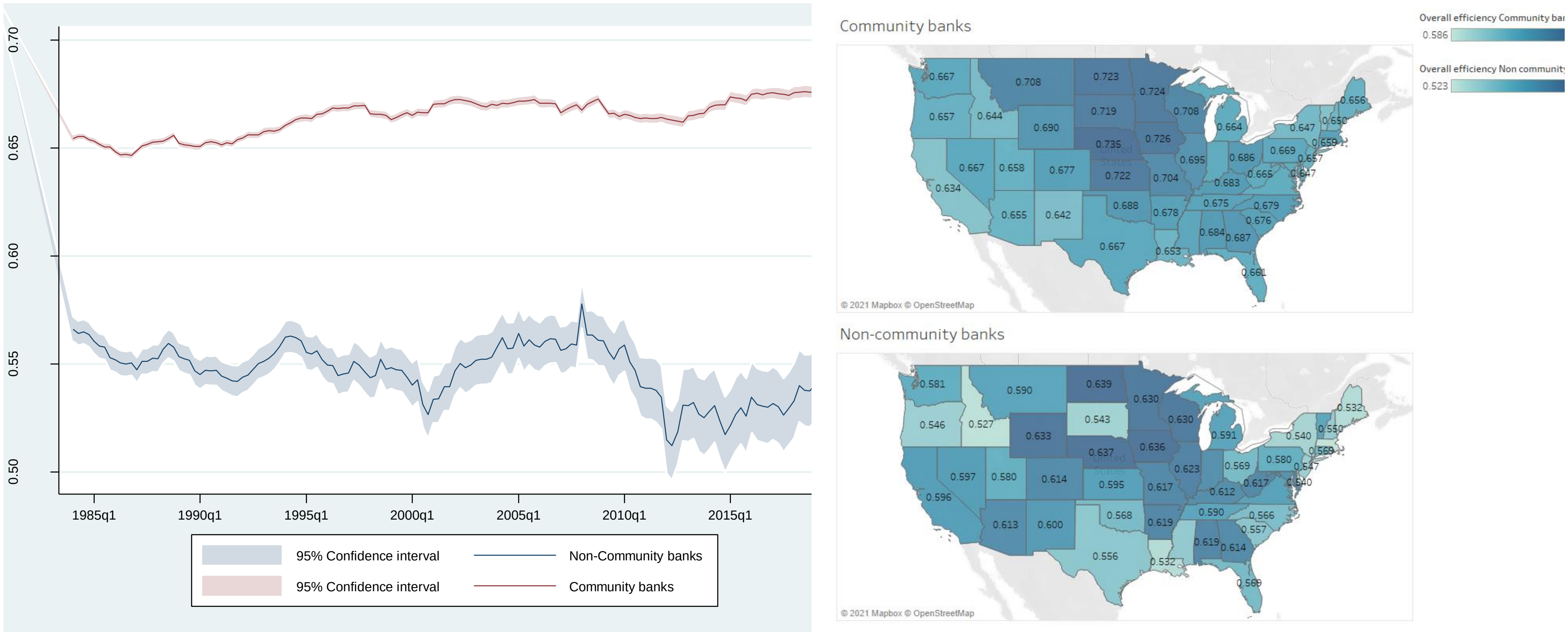


FIG 1. OVERALL COST EFFICIENCY BY BANK TYPE.

NOTES: The figure plots the overall cost efficiency by bank type across time (left graph) and across states (right graph). Efficiency is derived from model M3.

FIG 2. RESIDUAL COST EFFICIENCY BY BANK TYPE ACROSS STATES.

Notes: The top figure depicts the average residual cost efficiency for the two banking models at the state level, and its dispersion (95% confidence intervals) over the period of study. The bottom figure depicts the mean *relative percentage log difference* in the residual efficiency between the two banking models at the state level, and its dispersion (95% confidence intervals) over the period of study. The relative percentage log difference is defined as $y_{jt} \equiv \log\left(y_{jt}^{\{CB\}}/y_{jt}^{\{Non-CB\}}\right) \times 100$. Positive values suggest that the community banking model is more efficient relative to the non-community counterpart.

FIG 3. PERSISTENT COST EFFICIENCY BY BANK TYPE ACROSS STATES.

NOTES: The top figure depicts the average persistent cost efficiency for the two banking models at the state level, and its dispersion (95% confidence intervals) over the period of study. The bottom figure depicts the mean *relative percentage log difference* in the persistent efficiency between the two banking models at the state level, and its dispersion (95% confidence intervals) over the period of study. The relative percentage log difference is defined as $y_{jt} \equiv \log\left(y_{jt}^{\{CB\}}/y_{jt}^{\{Non-CB\}}\right) \times 100$. Positive values suggest that the community banking model is more efficient relative to the non-community counterpart.

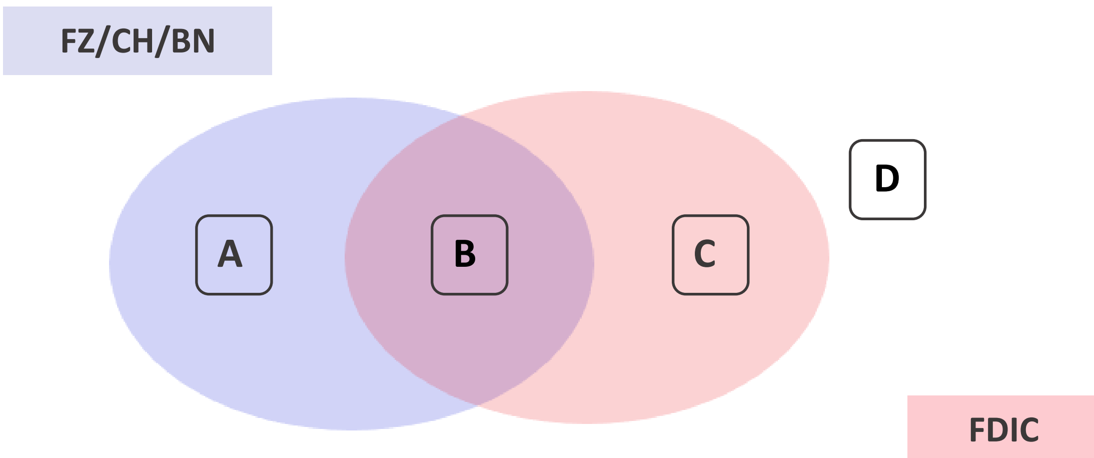
TABLE 1
COMPARISON OF THE DEFINITIONS FOR COMMUNITY BANKS

Panel A: Overview of community bank definitions

Definition	Total assets threshold	Threshold adjusted over time	Business & spatial criteria	Financial criteria	Bank-quarter observations	Unique banks	Mean total assets
FZ	1$ bn	No	No	No	1,252,998	20,124	132,470
CH	0.5-2$ bn	No	No	No	92,788	3,512	918,764
BN	10$ bn	No	No	No	1,310,415	20,537	253,079
FDIC	0.25~1$ bn	Yes	Yes	Yes	1,172,553	17,857	162,673

Panel B: Joint analysis classifications

	FDIC Definition	FZ/CH/BN
Intersection category	✓	✓
Community bank by exclusion	✗	✓
Community bank by inclusion	✓	✗



NOTES: Panel A reports differences between the community bank definitions for the period under study. FZ denotes the Feng and Zhang (2012) definition, CH the Chiorazzo *et al.* (2018), BN the Bonilla *et al.* (2018), FDIC the FDIC (2020) definition. Mean total assets is expressed in thousands USD. Panel B and the visual depiction present the categorization of community banks with respect to different definitions. Points A, B, C and D represent different banks. Bank A is classified as a community bank under the FZ/CH/BN definitions but not under the FDIC (i.e., Community bank by exclusion); Bank B is classified as community bank under the FZ/CH/BN definitions and the FDIC (i.e., Intersection category); Bank C is and FDIC-identified community bank but not community bank under the FZ/CH/BN definitions (i.e., Community bank by inclusion); Bank D is a non-community bank.

TABLE 2
THE FINANCIAL PROFILE OF COMMUNITY BANKS ACCORDING TO THE DIFFERENT DEFINITIONS

		Intersection			Exclusion			Inclusion	
Community bank definition	FZ ∩ FDIC	CH ∩ FDIC	BN ∩ FDIC	FZ ∩ FDIC′	CH ∩ FDIC′	BN ∩ FDIC′	FZ′ ∩ FDIC	CH′ ∩ FDIC	BN′ ∩ FDIC
z-score (ln)	3.316	3.428	3.319	3.143	3.182	3.156	3.442	3.458	3.540
Difference %	0.44	2.03	0.51	-4.92	-3.71	-4.50	3.65	4.10	6.45
Abs (T-statistic)	[39.85]	[95.46]	[22.06]	[83.43]	[56.66]	[89.52]	[35.05]	[4.24]	[4.38]
Credit risk	0.173	0.141	0.172	0.207	0.206	0.211	0.139	0.138	0.111
Difference %	-1.64	-12.01	-2.30	18.08	37.79	20.15	-21.74	-2.35	-44.48
Abs (T-statistic)	[28.57]	[46.31]	[17.03]	[28.85]	[31.95]	[36.87]	[14.55]	[1.04]	[1.41]
Liquidity risk	0.232	0.089	0.229	0.322	0.269	0.306	0.052	0.029	-0.074
Difference %	-3.19	-44.98	-3.51	32.55	110.78	29.22	-149.33	-112.84	-410.58
Abs (T-statistic)	[18.61]	[180.00]	[11.40]	[110.00]	[89.06]	[100.00]	[116.40]	[21.98]	[10.26]
Loans / Assets %	58.22	67.61	58.42	59.42	63.34	60.54	67.67	67.81	62.93
Difference %	-0.17	1.79	-0.38	2.04	-6.52	3.57	15.04	0.29	-7.16
Abs (T-statistic)	[67.12]	[95.96]	[15.59]	[23.25]	[40.33]	[46.42]	[94.65]	[1.24]	[2.38]
Core deposits ratio %	85.05	78.81	84.89	73.88	71.30	72.96	77.28	75.22	69.36
Difference %	1.11	2.71	1.49	-14.08	-10.01	-15.14	-9.58	-4.67	22.38
Abs (T-statistic)	[201.60]	[110.60]	[133.59]	[236.49]	[67.55]	[279.48]	[135.32]	[31.42]	[12.75]
Deposits per branch (in $ mil)	71.22	236.09	78.35	1,458.36	1,575.64	1,576.14	404.79	640.69	2,832.41
Difference %	-96.12	-94.68	-109.43	301.93	189.82	300.16	173.76	99.83	-97.23
Abs (T-statistic)	[56.48]	[81.09]	[41.21]	[130.00]	[40.21]	[140.00]	[130.00]	[53.25]	[15.88]
Non-Interest Income / T.Income %	9.37	14.14	9.49	12.29	15.30	13.50	15.13	15.39	15.50
Difference %	-2.61	-2.29	-4.36	27.18	7.90	35.24	47.94	8.43	-38.78
Abs (T-statistic)	[30.22]	[1.20]	[75.43]	[36.16]	[12.11]	[34.54]	[68.22]	[6.33]	[3.16]
Cost / Income %	81.94	75.42	81.76	84.93	76.58	82.74	73.41	70.81	66.12
Difference %	-0.31	-0.43	-0.13	3.58	1.52	1.19	-11.00	-6.31	23.66
Abs (T-statistic)	[29.40]	[12.83]	[50.75]	[4.34]	[10.02]	[1.83]	[62.62]	[12.98]	[10.01]
ROA %	0.512	0.553	0.513	0.573	0.631	0.580	0.562	0.577	0.588
Difference %	-1.01	-3.89	-1.37	11.35	13.25	12.30	9.31	4.28	-12.74
Abs (T-statistic)	[22.46]	[3.85]	[16.70]	[10.52]	[10.48]	[14.35]	[11.67]	[2.89]	[1.84]
ROE %	3.94	5.38	3.97	6.63	17.42	8.81	5.10	5.48	6.29
Difference %	-5.59	-48.73	-12.09	51.96	117.61	79.79	25.65	1.97	-36.91
Abs (T-statistic)	[1.35]	[0.79]	[10.67]	[1.41]	[1.02]	[1.82]	[2.43]	[0.13]	[4.09]
Equity / Assets %	10.24	9.87	10.24	9.59	9.24	9.50	9.97	10.41	9.97
Difference %	0.54	1.79	0.76	-6.61	-6.52	-7.43	-2.69	5.33	2.63
Abs (T-statistic)	[39.87]	[11.43]	[10.22]	[25.39]	[18.49]	[35.27]	[14.89]	[15.51]	[0.97]

NOTES: The table compares the financial profile of community versus non-community banks under different definitions over 1984Q1-2019Q4. See section 4.2 for a detailed description and construction of the variables. FZ denotes the Feng and Zhang (2012) definition, CH the Chiorazzo *et al.* (2018), BN the Bonilla *et al.* (2018), FDIC the FDIC (2020) definition. The intersection group features FDIC-designated community banks, jointly identified as community under each of the FZ/CH/BN definitions respectively, denoted as (FZ ∩ FDIC). The exclusion group contains community banks under the FZ/CH/BN definitions respectively, which are not designated as community by the FDIC, denoted as (FZ ∩ FDIC′). The inclusion group contains FDIC-designated community banks that are not classified as community under the FZ/CH/BN definitions respectively, denoted as (FZ′ ∩ FDIC). SD denotes the standard deviation; N denotes the number of bank-quarter observations. "Difference %" denotes the percentage logarithmic difference between the variable of interest of the *intersection* group compared against the FZ/CH/BN individual classifications respectively and the variable of interest of the *exclusion* and *inclusion* groups compared against the *intersection* group.

TABLE 3
THE EFFICIENCY PROFILE OF COMMUNITY BANKS ACCORDING TO THE DIFFERENT DEFINITIONS

Panel A: Individual classifications

	Community bank definition	FZ	CH	BN	FDIC
M1	Mean	0.7861	0.7637	0.7864	0.7899
	SD	0.1022	0.1158	0.1032	0.0959
	Difference %	-0.48	-3.37	-0.44	—
M2	Mean	0.7926	0.7537	0.7892	0.8039
	SD	0.1145	0.1544	0.1195	0.1012
	Difference %	-1.42	-6.63	-2.03	—
M3	Mean	0.7868	0.7287	0.7826	0.7965
	SD	0.0651	0.0947	0.0703	0.0486
	Difference %	-1.22	-8.89	-1.76	—
M4	Mean	0.6594	0.5335	0.6517	0.6626
	SD	0.1052	0.1119	0.1117	0.1017
	Difference %	-0.48	-21.67	-1.66	—
	N	1,247,819	91,673	1,304,435	1,167,184
	Coverage %	106.91	7.85	111.76	—

Panel B: Joint classifications

		Intersection			Exclusion			Inclusion		
	Community bank definition	FZ ∩ FDIC	CH ∩ FDIC	BN ∩ FDIC	FZ ∩ FDIC′	CH ∩ FDIC′	BN ∩ FDIC′	FZ′ ∩ FDIC	CH′ ∩ FDIC	BN′ ∩ FDIC
M1	Mean	0.7898	0.7667	0.7898	0.7450	0.7560	0.7567	0.7900	0.8177	0.8562
	SD	0.0959	0.0998	0.0959	0.1484	0.1488	0.1484	0.0971	0.0915	0.1247
	Difference %	0.48	0.39	0.44	-5.85	-1.40	-4.29	0.01	6.44	8.06
	Abs (T-statistic)	[21.02]	[6.56]	[30.01]	[96.34]	[10.60]	[80.92]	[0.18]	[44.12]	[4.38]
M2	Mean	0.8031	0.8106	0.8039	0.6788	0.6083	0.6635	0.8426	0.8745	0.9187
	SD	0.1012	0.1034	0.1012	0.1733	0.1673	0.1760	0.0970	0.0851	0.0938
	Difference %	1.32	7.28	1.86	-16.82	-28.72	-19.19	4.80	7.58	13.35
	Abs (T-statistic)	[190.41]	[205.87]	[55.78]	[229.32]	[181.13]	[289.96]	[63.33]	[58.60]	[10.10]
M3	Mean	0.7969	0.7689	0.7965	0.6767	0.6261	0.6646	0.7750	0.7864	0.8223
	SD	0.0485	0.0496	0.0486	0.1066	0.1047	0.1063	0.0487	0.0469	0.0553
	Difference %	1.283	5.365	1.758	-16.36	-20.55	-18.10	-2.79	2.25	3.20
	Abs (T-statistic)	[326.24]	[267.92]	[107.16]	[362.76]	[210.04]	[454.25]	[70.14]	[29.64]	[3.86]
M4	Mean	0.6655	0.5520	0.6626	0.5926	0.4862	0.5590	0.5264	0.5065	0.5311
	SD	0.0999	0.0950	0.1017	0.1338	0.1356	0.1449	0.0903	0.0864	0.1111
	Difference %	0.93	3.41	1.66	-11.60	-12.69	-17.00	-23.46	-8.61	-22.12
	Abs (T-statistic)	[345.83]	[21.69]	[156.60]	[172.55]	[71.36]	[257.61]	[239.31]	[41.73]	[9.76]
	N	1,142,399	65,889	1,167,116	105,420	25,784	137,319	24,785	7,067	68
	Coverage %	91.57	71.99	89.47	9.21	38.91	11.76	2.2	10.77	0.01

NOTES: The table compares the cost efficiency of community versus non-community banks under different definitions and models over 1984Q1-2019Q4. See section 3.2 for efficiency definitions and model specifications. In panel A each definition is used on an individual classification basis. In panels B and C dual definitions are used in a joint classification basis, with three groups defined as intersection, exclusion, and inclusion (see notes in table 2). SD (N) denote the standard deviation (bank-quarter observations). "Difference %" denotes the percentage logarithmic difference for: i) the efficiency of community banks under each of the FZ/CH/BN definitions compared against the FDIC definition (panel A); ii) the efficiency of the *intersection* group (panel B) compared against the FZ/CH/BN individual classifications respectively (panel A); iii) the efficiency of the *exclusion* and *inclusion* groups compared against the *intersection* group (panel B). "Coverage %" is defined similarly to "Difference %" but for the bank-year observations.

TABLE 4
COST EFFICIENCY MODEL SPECIFICATIONS

Model	Technology	Outputs X Inputs	Persistent / Residual efficiency decomposition
M1	Common	2x3	No
M2	Flexible	2x3	No
M3	Flexible	2x3	Yes
M4	Flexible	6x3	Yes

Notes: Table summarizes cost efficiency model differences. The input variables are the price of labor (p1), defined as the salaries and employee benefits over the number of full-time equivalent employees; the price of capital (p2), defined as expenses on premises and fixed assets over premises and fixed assets; and the price of funds (p3), defined as total interest expenses over total deposits. Output variables are total loans (y1) and securities (y2) in M1, M2 and M3 and loans to individuals (y1), residential mortgages (y2), commercial and industrial loans (y3), agricultural loans (y4), construction and development loans (y5) and securities (y6) in M4.

TABLE 5
SUMMARY STATISTICS FOR COST, OUTPUTS AND INPUT PRICES

Variable	Mean	Median	SD	Min	Max
Panel A: All banks					
Total Cost	24,337	3,377	404,984	2.525	75,400,000
Securities (y1)	129,537	23,224	2,093,164	0.009	372,000,000
Loans (y2)	385,875	56,752	5,262,633	0.009	740,000,000
Individual loans (y3)	61,551	5,104	1,287,261	0.010	221,000,000
Residential mortgages (y4)	117,030	14,168	2,548,800	0.010	459,000,000
Commercial and industrial loans (y5)	305,554	3,313	7,476,783	0.010	1,110,000,000
Agricultural loans (y6)	6,656	1,376	38,307	0.010	5,321,883
Construction and development loans (y7)	21,458	1,139	245,018	0.010	36,300,000
Price of labor (p1)	26.232	21.175	19.184	2.059	211.696
Price of capital (p2)	0.267	0.154	0.726	0.008	44.875
Price of funds (p3)	0.025	0.018	0.098	0.000	7.675
Panel B: Community banks					
Total Cost	6,483	3,001	13,735	3.951	1,133,133
Securities (y1)	46,171	21,220	106,364	0.009	9,727,484
Loans (y2)	121,439	50,703	264,362	0.010	12,400,000
Individual loans (y3)	10,951	4,556	29,659	0.010	2,029,261
Residential mortgages (y4)	38,323	12,627	116,435	0.010	8,205,054
Commercial and industrial loans (y5)	52,286	2,505	294,724	0.010	27,100,000
Agricultural loans (y6)	5,307	1,472	12,574	0.010	618,119
Construction and development loans (y7)	8,428	956	32,750	0.010	4,185,981
Price of labor (p1)	26.264	21.357	18.716	3.143	130.988
Price of capital (p2)	0.254	0.153	0.436	0.010	7.500
Price of funds (p3)	0.022	0.018	0.017	0.000	0.086
Panel C: Non-community banks					
Total Cost	167,803***	13,682***	1,207,192***	2.525	75,400,000
Securities (y1)	799,438***	68,453***	6,244,446***	0.009	372,000,000
Loans (y2)	2,510,804***	210,652***	15,600,000***	0.009	740,000,000
Individual loans (y3)	468,158***	24,559***	3,844,429***	0.010	221,000,000
Residential mortgages (y4)	749,494***	46,140***	7,625,018***	0.010	459,000,000
Commercial and industrial loans (y5)	2,340,735***	34,320***	22,400,000***	0.010	1,110,000,000
Agricultural loans (y6)	17,492***	554***	108,887***	0.010	5,321,883
Construction and development loans (y7)	126,159***	5,583***	722,152***	0.010	36,300,000
Price of labor (p1)	25.973***	19.856***	22.598***	2.059	211.696
Price of capital (p2)	0.375***	0.165***	1.794***	0.008	44.875
Price of funds (p3)	0.043***	0.024***	0.290***	0.000	7.675

NOTES: The table presents summary statistics for total cost, outputs and inputs used in the efficiency estimation for all banks (Panel A), community banks (Panel B) and non-community banks (Panel C). The price of labor is calculated as salaries and employee benefits over the number of full- time equivalent employees, the price of capital calculated as expenses on premises and fixed assets over premises and fixed assets and the price of funds calculated as total interest expenses over total deposits. Monetary amounts have been deflated using the GDP deflator and are expressed in thousands USD. ***, **, * denotes statistically significant difference between community and non-community banks at the 1, 5 and 10% level respectively. Prices of labor, capital and funds are winsorized at 0.1/99.9 by bank type.

TABLE 6
EFFICIENCY ESTIMATION RESULTS

Variable	Observations	Mean	Median	SD	Min	Max
Panel A: All Banks						
Cost efficiency (M1)	1,312,434	0.787	0.807	0.104	0.001	0.993
Cost efficiency (M2)	1,312,434	0.788	0.817	0.121	0.000	0.997
Overall cost efficiency (M3)	1,312,434	0.782	0.796	0.072	0.017	0.955
Overall cost efficiency (M4)	1,312,434	0.650	0.672	0.114	0.005	0.920
Residual cost efficiency (M3)	1,312,434	0.908	0.916	0.040	0.101	0.993
Residual cost efficiency (M4)	1,312,434	0.888	0.896	0.044	0.133	0.989
Persistent cost efficiency (M3)	1,312,434	0.860	0.874	0.066	0.026	0.976
Persistent cost efficiency (M4)	1,312,434	0.732	0.757	0.121	0.024	0.966
Panel B: Community Banks						
Cost efficiency (M1)	1,167,184	0.790	0.808	0.096	0.001	0.984
Cost efficiency (M2)	1,167,184	0.804	0.826	0.101	0.002	0.987
Overall cost efficiency (M3)	1,167,184	0.796	0.802	0.049	0.097	0.936
Overall cost efficiency (M4)	1,167,184	0.663	0.680	0.102	0.022	0.917
Residual cost efficiency (M3)	1,167,184	0.910	0.918	0.039	0.172	0.993
Residual cost efficiency (M4)	1,167,184	0.890	0.898	0.043	0.133	0.989
Persistent cost efficiency (M3)	1,167,184	0.875	0.879	0.038	0.156	0.969
Persistent cost efficiency (M4)	1,167,184	0.744	0.765	0.107	0.050	0.959
Panel C: Non-Community Banks						
Cost efficiency (M1)	145,250	0.762***	0.803***	0.151***	0.004	0.993
Cost efficiency (M2)	145,250	0.663***	0.688***	0.179***	0.000	0.997
Overall cost efficiency (M3)	145,250	0.663***	0.680***	0.108***	0.017	0.955
Overall cost efficiency (M4)	145,250	0.550***	0.572***	0.149***	0.005	0.920
Residual cost efficiency (M3)	145,250	0.889***	0.898***	0.047***	0.101	0.989
Residual cost efficiency (M4)	145,250	0.870***	0.879***	0.050***	0.134	0.986
Persistent cost efficiency (M3)	145,250	0.745***	0.762***	0.112***	0.026	0.976
Persistent cost efficiency (M4)	145,250	0.632***	0.660***	0.166***	0.024	0.966

NOTES: The table presents summary statistics for overall, residual and persistent cost efficiency for all banks (Panel A), community banks (Panel B) and non-community banks (Panel C). Details on models' specification are explained in section 3.2. ***, **, * denotes statistically significant difference between community and non-community banks at the 1, 5 and 10% level respectively.

TABLE 7

DESCRIPTIVE STATISTICS FOR VARIABLES IN FURTHER INVESTIGATIONS

	Observations	Mean	Median	SD
	Panel A: All banks			
Total Assets (ln)	1,326,950	11.383	11.234	1.398
Deposits/Assets	1,326,950	0.854	0.874	0.079
Credit Risk	1,322,292	0.234	0.045	13.450
Equity/Assets	1,326,950	0.102	0.093	0.048
Liquidity Risk	1,326,950	0.294	0.246	6.348
ROE	1,326,939	0.046	0.054	4.371
z-score (ln)	1,291,718	3.301	3.348	0.643
Loans to individuals	1,336,519	0.078	0.057	0.083
Residential mortgage loans	1,341,804	0.167	0.141	0.129
Commercial and industrial loans	1,336,415	0.124	0.057	0.244
Agricultural loans	1,336,453	0.052	0.012	0.082
Construction and development loans	1,341,893	0.034	0.011	0.057
	Panel B: Community banks			
Total Assets (ln)	1,178,773	11.202	11.124	1.192
Deposits/Assets	1,178,773	0.860	0.876	0.064
Credit Risk	1,176,037	0.212	0.040	4.343
Equity/Assets	1,178,773	0.102	0.094	0.043
Liquidity Risk	1,178,773	0.228	0.237	0.274
ROE	1,178,764	0.041	0.053	3.189
z-score (ln)	1,149,607	3.319	3.368	0.643
Loans to individuals	1,167,206	0.074	0.056	0.068
Residential mortgage loans	1,172,274	0.169	0.142	0.128
Commercial and industrial loans	1,167,184	0.110	0.052	0.208
Agricultural loans	1,167,209	0.058	0.017	0.086
Construction and development loans	1,172,288	0.034	0.011	0.058
	Panel C: Non-community banks			
Total Assets (ln)	148,177	12.826^{***}	12.466^{***}	1.968^{***}
Deposits/Assets	148,177	0.810^{***}	0.853^{***}	0.144^{***}
Credit Risk	146,255	0.408^{***}	0.088^{***}	38.522^{***}
Equity/Assets	148,177	0.095^{***}	0.080^{***}	0.074^{***}
Liquidity Risk	148,177	0.820^{***}	0.318^{***}	18.973^{***}
ROE	148,175	0.087^{***}	0.063^{***}	9.495^{***}
z-score (ln)	142,111	3.157^{***}	3.186^{***}	0.626^{***}
Loans to individuals	145,332	0.118^{***}	0.083^{***}	0.143^{***}
Residential mortgage loans	145,549	0.162^{***}	0.138^{***}	0.128^{***}
Commercial and industrial loans	145,250	0.231^{***}	0.120^{***}	0.385^{***}
Agricultural loans	145,263	0.016^{***}	0.001^{***}	0.038^{***}
Construction and development loans	145,624	0.035^{***}	0.016^{***}	0.053^{***}

NOTES: The table shows the summary statistics for the bank specific variables used in the second stage analysis. Data are retrieved from Call reports over 1984-2019. Sample consists of 20,394 banks. Panel A contains all banks in the sample, panel B contains only FDIC-identified community banks and panel C only non-community. Assets and z-score are expressed in logarithms. The credit and liquidity risk proxies are calculated following Imbierowicz and Rauch (2014), see section 4.2 for more details. Loan categories are expressed as percentage of total assets. ***, **, * denotes statistically significant difference between community and non-community banks at the 1, 5 and 10% level respectively.

TABLE 8
DETERMINANTS OF RESIDUAL COST EFFICIENCY

Model	I	II	III	IV	V	VI	VII	VIII
Community Bank (CB)	0.0138***	0.0140***	0.0157***	0.0142***	0.0109***	0.0070***	0.1138***	0.0864***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0027)	(0.0083)	(0.0067)
Bank/Loan-controls	Yes/No	Yes/Yes	Yes/No	Yes/No	Yes/No	Yes/No	Yes/Yes	Yes/No
Market structure and Macro-controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
CB interactions	No	No	No	No	No	Yes	Yes	Yes
State / Year Fixed Effects	No	Yes/No	No	No	No	Yes/Yes	No	Yes/Yes
Observations	1,291,716	1,291,716	1,286,188	1,282,514	1,193,497	356,865	1,220,578	1,282,514
Number of banks	20,173	20,173	20,168	20,090	19,495	8,990	19,713	20,090
R-squared	0.358	0.275	0.336	0.252	0.141	0.0637	0.158	0.307
Wald-test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

NOTES: The table presents coefficient estimate and robust standard errors for equation 8. The dependent variable is the residual cost efficiency. ***, **, * denote statistical significance at the 1, 5, 10% significance level. The full table with all controls is presented in the online appendix.

TABLE 9
DRIVERS OF PERSISTENT COST EFFICIENCY

Model	I	II	III	IV	V	VI	VII	VIII
Financial stability (Diff)	0.028	0.039*	0.033*	0.027*	0.032	-0.003	0.021	0.032
	(0.020)	(0.021)	(0.019)	(0.016)	(0.023)	(0.021)	(0.022)	(0.023)
Loans/Assets (Diff)	0.051	0.072	0.053		0.074	0.101		0.050
	(0.052)	(0.064)	(0.052)		(0.054)	(0.067)		(0.052)
Core ratio (Diff)	0.198***	0.212***	0.226***	0.173**	0.182***	0.207***	0.157*	0.189***
	(0.056)	(0.043)	(0.047)	(0.078)	(0.056)	(0.059)	(0.081)	(0.054)
Total Assets (Diff)	-0.797***	-0.843***	-0.808***	-0.902***	-0.759***	-0.729***	-1.119***	-0.884***
	(0.151)	(0.145)	(0.145)	(0.131)	(0.164)	(0.193)	(0.171)	(0.162)
Income diversity (Diff)	-0.090***	-0.073***	-0.081***	-0.071***	-0.090***	-0.053***	-0.070***	-0.089***
	(0.030)	(0.027)	(0.027)	(0.025)	(0.026)	(0.019)	(0.026)	(0.027)
Liquidity risk (Diff)		-0.004						
		(0.004)						
Credit risk (Diff)		-0.016***						
		(0.006)						
Active Offices (Diff)			0.010					
			(0.013)					
Active States (Diff)			0.038					
			(0.063)					
Active MSAs (Diff)			-0.281**					
			(0.122)					
Loans to Individuals (Diff)				-0.008			0.004	
				(0.010)			(0.010)	
Residential Mortgages (Diff)				0.076***			0.079***	
				(0.020)			(0.020)	
Commercial and Industrial loans (Diff)				0.015***			0.018***	
				(0.005)			(0.007)	
Agricultural Loans (Diff)				0.010			0.006	
				(0.010)			(0.010)	
Construction and Development Loans (Diff)				0.002			0.007	
				(0.010)			(0.010)	
HHI (CB) (-1)					21.746*	13.007	9.830	20.069*
					(11.335)	(9.989)	(9.779)	(10.992)
HHI (Non-CB) (-1)					2.156	-0.997	-2.281	-2.574
					(3.305)	(2.884)	(2.787)	(2.871)
CB Total Assets % Share						0.040	0.085	0.075
						(0.074)	(0.055)	(0.054)

High School Degree %						-0.859*		
						(0.483)		
Bachelor's degree %						0.997**		
						(0.415)		
Business Applications (log) (-1)						0.106		
						(1.302)		
Δ(Industrial Production)						1.169***		
						(0.279)		
Real GDP growth (-4)					-0.038			
					(0.211)			
Financial Stress Index (-1)					-0.797			
					(0.558)			
Financial Institutions Access (-1)					-0.732***			
					(0.170)			
Consumer Sentiment (-1)					-0.043			
					(0.038)			
Spread 10Y-3M (-1)					-0.225			
					(0.184)			
FRD Total Assets % Share								0.123
								(0.132)
Constant	-5.905**	-6.972***	-25.130***	-7.006***	59.899***	28.722	-14.144***	-17.779***
	(2.525)	(2.532)	(8.006)	(2.492)	(15.791)	(36.764)	(4.365)	(5.649)
FRD Fixed Effects	No	No	No	No	No	Yes	No	Yes
Observations	4,864	3,957	4,850	4,689	4,336	2,510	4,630	4,801
R-squared	0.354	0.404	0.339	0.538	0.344	0.412	0.495	0.445
Wald-test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

NOTES: The table presents coefficient estimates and robust standard errors for Eq.9. The dependent variable is the *relative percentage log difference* in persistent efficiency between community banks (CBs) and non-community banks (Non-CBs) at the state level defined as $z_{jt} \equiv \log\left(z_{jt}^{\{CB\}}/z_{jt}^{\{Non-CB\}}\right) \times 100$, with positive values indicating that community banking exhibits higher persistent efficiency relatively to the non-community banking counterpart. "Diff" denotes the relative percentage log difference transformation; "HHI (CB)" and "HHI (Non-CB)" denote the Hirschman-Herfindahl index for concentration at the state level based on total assets for each banking model; "FRD" denotes the Federal Reserve District; "Δ" denotes the logarithmic difference. Loan categories are expressed as percentage of total assets . ***, **, * denote statistical significance at the 1, 5, 10% significance level.