The Cross Section of Bank Value*

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Abstract

We study the determinants of value creation in the cross section of U.S. commercial banks. We develop novel measures of individual bank's productivities at collecting deposits and making loans. We relate these measures to bank market values and find that variation in deposit productivity explains the majority of cross-sectional variation in bank value. We show that variation in productivity is driven by differences across banks in technology, customer demographics, and market power. We also find evidence of synergies between deposit-taking and lending. Our findings suggest that there is significant heterogeneity in banks' abilities to capture value by manufacturing safe assets.

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1 Introduction

Raising deposits and making loans are the central activities of banks. But how important is each to the business of banking, and what drives variation in the answer across banks? How much of a bank's value comes from its ability to issue information-insensitive deposits to consumers who value such debt? And how much comes from its ability to screen and monitor borrowers?

In this paper, we systematically examine the cross section of banks to understand the quantitative contributions of deposit-taking and lending to bank value. We begin by developing an economic framework in which banks have two divisions: (i) a deposit-producing division that raises funds by offering consumers services and interest payments, and (ii) a revenue-producing division that takes funding as an input and converts it into risk-adjusted revenue by making loans and holding securities.[1] We then use tools from industrial organization to construct novel estimates of a bank's productivity in each division in a manner analogous to the literature on the productivity of non-financial firms. Our framework therefore allows us to estimate "primitive" measures of deposit productivity and asset productivity for each bank at each point in time.

Intuitively, a bank with high deposit productivity is able to collect more deposits than a less productive bank, holding fixed the "inputs" it uses to collect those deposits, such as its deposit rate and number of branches. For example, BB&T and SunTrust each had about $150 billion of deposits in 2015Q4, and they paid similar deposit rates. However, SunTrust generated its deposits with 23% fewer branches. Thus, our measures label SunTrust the more deposit-productive bank, since it generated the same amount of deposits with fewer inputs. Analogously, a bank with higher asset productivity is able to generate more risk-adjusted revenue with the same asset base. For example, given similar asset bases of approximately $200 billion, BB&T generated more revenue than SunTrust in 2015Q4 despite having lower levels of observable risk. Thus, our measures label BB&T as the more asset-productive bank.

We use tools from industrial organization to estimate our productivity measures. To estimate how productive a bank is at raising deposits, we construct a consumer demand system for deposits that builds upon existing work by Dick (2008), Egan, Hortaçsu, and Matvos (2016), and Xiao (2017). In our framework, banks compete for deposits by setting interest rates in a standard Bertrand-Nash differentiated products setting, which we estimate using a common model of demand

[1] Consistent with the theoretical literature, we focus on the traditional banking activities of deposit taking and lending, rather than on non-traditional banking activities like private wealth management. Most banks in our sample are largely traditional banks. For the median bank in our sample, deposits comprise 86% of the bank's liabilities and interest and deposit fee income comprise 90% of total income.

from the industrial organization literature (Berry, 1994; Berry, Levinsohn, and Pakes, 1995). A bank with higher deposit productivity faces a consumer deposit demand curve that is shifted up, meaning it can raise more deposits, holding fixed the deposit services and interest rates it offers. To estimate a bank's asset productivity, we flexibly estimate the ability to produce interest and fee income as a function of the size of loan and securities portfolios. Higher asset productivity allows a bank to produce more risk-adjusted income, holding fixed the size of its portfolio. Thus, our estimation procedure allows us to construct at the bank-by-quarter level two complementary measures of bank productivity, which capture a bank's skill at raising deposits and its skill at using these funds to generate revenue.

Uncovering these primitive measures of productivity is important because metrics like interest income and interest expense are endogenous functions of productivity. For example, all else equal, a bank that is better at raising deposits will rationally choose to become larger. In the presence of diminishing returns, this will drive the rate the bank pays on deposits closer to the rates paid by less deposit-productive banks. Thus, variation in observables is likely to understate the true variation in primitives across banks. We believe that our ability to estimate primitive productivity differences across banks represents an important step forward in our ability to identify differences in banks' business models.

We combine our asset and deposit productivity estimates with banks' market-to-book ratios (M/B) from 1994 to 2015 to identify the primary determinants of cross-sectional variation in bank value. The benefit of looking at M/B is that it provides us with a natural economic benchmark: under the frictionless null hypothesis that banks create no value, all banks should have an M/B of one. Hence, the use of M/B allows us to better understand the relative quantitative contributions of deposit taking and lending to bank value.

Our main finding is that the liability side of the balance sheet drives the majority of cross-sectional variation in bank value. We find that a one-standard deviation increase in deposit productivity is associated with an increase in M/B of 0.2 to 0.5 points, consistent with there being significant heterogeneity in banks' abilities to capture value by manufacturing safe assets. In contrast, a one-standard deviation increase in asset productivity is associated with an increase in M/B of 0.1 to 0.2 points. Hence, variation in deposit productivity accounts for about twice as much variation in bank value as variation in asset productivity. This finding suggests that liability-driven theories of bank value creation explain more variation in the cross section of banks than asset-driven theories. Under plausible additional assumptions, we reach similar conclusions about the level of bank value: it is primarily driven by the liability side. Our estimates indicate that the share of value attributable to deposits for the average bank in our sample is 71%.

We then disaggregate these results, asking which products and business lines are most closely associated with variation in bank valuations. We find that a bank's ability to collect savings deposits is the main driver of value, explaining over three times as much variation in M/B as any other factor. Relative to other types of deposits, demand for savings deposits is inelastic or "sticky," which helps explain its role in value creation for banks. We also find that a bank's ability to collect deposits is only weakly correlated with overall leverage in the cross section. Banks that are good at raising deposits are not significantly more levered than those that are not. Instead, they substitute non-deposit debt for deposits.

On the asset side, we find that banks with high asset productivity hold more real estate and commercial and industrial (C&I) loans, which are likely to be information intensive. Consistent with "information production" theories of banking, this suggests that the screening and monitoring of loans is an important source of bank value, though it accounts for less variation in bank value than deposit productivity.

Our estimation approach closely follows the literature on total factor productivity in non-financial firms (see, e.g., Syverson, 2011). As in this literature, we define productivity based on the residuals from regressions of production outputs (i.e., deposits and interest income) on production inputs. By design, our measures capture more than just technological differences; they also capture the effects of managerial and employee skill, market power, and geographic and demographic factors. To better understand the economic content of our productivity measures, we group these various effects into two categories: (i) differences in consumer demographics and market power, which capture banks' exposures to different types of customers, and (ii) differences in banks' production technologies, which capture variation in productivity holding customer exposures fixed.

We show that both categories of potential drivers are important for explaining our productivity measures and bank value. To explore variation in productivity driven by customer demographics and market power, we analyze the relationships between banks' geographical footprints and our productivity measures. We find that the demographic characteristics of the areas banks operate in explain twice as much variation in deposit productivity as asset productivity. Banks with less sophisticated clients that operate in areas with less competition tend to be more productive at both gathering deposits and investing. Our results suggest bank location matters and is correlated with a bank's ability to collect deposits and invest. However, even after flexibly controlling for banks' geographic footprints, we still find that both of our productivity measures are strongly related to bank value, with deposit productivity again explaining significantly more variation than asset productivity. This suggests that differences in market power and customer demographics alone do not fully explain variation in our productivity measures or the explanatory power of our measures for value. Technological differences in productivity also play an important role.

To examine technological differences across banks, we use additional data on the quality and pricing of bank services. Banks that are deposit-productive receive fewer customer complaints. These banks also appear to use more sophisticated, decentralized pricing strategies in setting deposit and mortgage rates. These findings help to validate our productivity measures and illustrate how firm structure, technology, and the quality of inputs drive productivity.

Finally, we utilize our measures to assess the degree of synergies between banks' deposit-taking and lending activities in a manner distinct from the existing literature. We find that a bank's ability to collect deposits is correlated with its skill in investing: about 25% of the cross-sectional variation in asset productivity can be explained by deposit productivity, consistent with the theoretical literature on synergies, which suggests that deposit-taking facilitates lending. The ability to collect all types of deposits, except for transactions deposits, is positively correlated with asset productivity. This finding suggests that the ability to raise "sticky" short-term funding is a key source of bank synergies. We also find that deposit-productive banks offer more loan commitments and lines of credit, consistent with Kashyap, Rajan, and Stein (2002) and Gatev and Strahan (2006).

Our results are robust to a variety of potential concerns. We consider alternative constructions of productivity, measures of asset-side output beyond revenue, and other measures of shareholder value such as profitability and total market capitalization, and find that our main results do not change. We also verify that our results are not driven by measurement error using both instruments and empirical Bayes estimation. Finally, we show that our results are not driven by the largest banks, the financial crisis, or banks that do not primarily engage in traditional banking activities.

In summary, this paper empirically quantifies the primary determinants of bank value. We find that the asset and liability sides both play an important role, and cross-sectional variation in deposit productivity accounts for the majority of cross-sectional variation in bank value. Under plausible additional assumptions, we obtain similar results for the level of bank value.

Our paper is related to several strands of the literature on what makes banks "special," which highlights frictions that break the Modigliani-Miller irrelevance result and allow banks to create value. An important caveat in interpreting our results is that while the theoretical literature is largely concerned with the total social value created by banks, we examine private value accruing to bank shareholders, the component of total value that is empirically observable. As such, we believe our analysis is an important step in empirically understanding the total social value created by banks. One strand of the literature argues that banks produce "safe," liquid, and adverse-selection free liabilities, such as bank deposits.[2] Our paper adds to this literature by quantifying the effects of liability creation on bank value. We find strong links between a bank's value and its ability to produce deposits. In addition, our results shed light on the characteristics of bank debt that create value. Our strongest results are for savings deposits, which, while safe, are not fully liquid. In addition, we find no evidence that non-deposit debt creates value for banks.

A second strand of the literature argues that banks produce valuable information about borrowers through the screening and monitoring of loans.[3] Consistent with this literature, we find evidence that a bank's skill at investing in information sensitive assets is linked to its value. However, differences in asset productivity across banks appear to be less important in the cross-section than differences in their abilities to produce deposits. A related literature focuses on estimating bank production functions.[4] These papers have largely focused on total cost and profit efficiency, with the aim of assessing economies of scale in banking, rather than separately examining the asset and deposit production functions of a bank. We extend this literature by estimating a bank's *liability* productivity in addition to introducing a new methodology to estimate bank asset productivity and studying the value implications of both measures.

Our findings are also consistent with the literature on synergies between deposit-taking and lending.[5] We find that deposit-productive banks also tend to be asset-productive. Our results

[2]For the theoretical literature, see, e.g., Gorton and Pennacchi (1990), Pennacchi (2012), Stein (2012), Gennaoili, Shleifer, and Vishny (2013), DeAngelo and Stulz (2015), Dang, Gorton, and Holmström (2015), Dang, Gorton, Holmström, and Ordoñez (2016), and Moreira and Savov (2016). The empirical literature in this area, e.g., Calomiris and Nissim (2007, 2014), Krishnamurthy and Vissing-Jorgensen (2012, 2015), Gorton, Lewellen, and Metrick (2012), Greenwood, Hanson, and Stein (2015), Sunderam (2015), and Nagel (2016) has largely focused on understanding whether bank liabilities are special by examining the behavior of aggregate prices and quantities. Recent empirical and theoretical work by Chen, Goldstein, Huang, and Vashishtha (2018), Dreschler, Savov, and Schnabl (2017), Dreschler, Savov, and Schnabl (2018) and Gomes, Grotteria, and Wachter (2018) highlight the importance of the deposit franchise in banking activities.

[3]Asset-driven theories of bank value creation include Leland and Pyle (1977), Diamond (1984), Diamond (1991), Rajan (1992), Winton (1995), and Allen, Carletti, and Marquez (2011). Empirical literature includes Hoshi, Kashyap, and Scharfstein (1990, 1991), Petersen and Rajan (1994), Berger and Udell (1995), Demsetz and Strahan (1997), Acharya, Hassan, and Saunders (2006), Sufi (2007), Calomiris and Nissim (2007), and Keys et. al. (2010). A separate literature studies the "charter value" that accrues to banks due to entry restrictions that allowed incumbents to extract rents (e.g., Keeley, 1990; Jayaratne and Strahan, 1996). In addition, Atkeson et al. (2018) argue that most variation in the time series of bank value is driven by the changing value of government guarantees. In contrast, we show that most variation in the cross section stems from differences in banks' deposit productivities.

[4]See, e.g., Berger and Humphrey (1997), Berger and Mester (1997), Hughes and Mester (1998), Stiroh (2000), Berger and Mester (2003), Rime and Stiroh (2003), and Wang (2003).

[5]See, e.g., Diamond and Dybvig (1983), Calomiris and Kahn (1991), Berlin and Mester (1999), Diamond and

shed light on the nature of synergies, highlighting the importance of savings and time deposits for supporting C&I lending and credit lines. Finally, our paper joins the growing literature at the intersection of industrial organization and finance.[6]

The remainder of this paper is organized as follows. Section 2 presents a simple framework that highlights the economic linkages between deposit productivity, asset productivity, and bank value. Section 3 describes our estimation procedure and provides more details on our measures of productivity. Our main results are discussed in Section 4. Section 5 presents robustness exercises, and Section 6 concludes.

2 Economic Framework

In this section, we present a simple economic framework linking a bank's value with its productivity at raising deposits and its skill at investing its assets. Let A_{jt} be the total assets of bank $j = 1, ..., J$ at time t. Banks fund their assets by raising deposits D_{jt} and with equity E_{jt}. Per-period bank profits are then given by

$$\pi_{jt} = f(A_{jt}; \phi_{jt}) - c(D_{jt}; \delta_{jt}). \tag{1}$$

Here $f(\cdot;\cdot)$ gives the bank's revenue as a function of its assets, $c(\cdot;\cdot)$ gives the bank's funding costs as a function of the quantity of deposits it raises, and $A_{jt} = D_{jt} + E_{jt}$.

The primitives in this framework are asset productivity ϕ_{jt} and deposit productivity δ_{jt}, which the bank takes as given. Asset productivity ϕ_{jt} reflects bank j's skill in making loans and holding securities. Higher values of ϕ_{jt} mean that the bank is better at lending – it generates more revenue from a fixed asset base. Deposit productivity δ_{jt} captures differences in efficiency across banks in raising deposits. Higher values of δ_{jt} mean that the bank is better at raising deposits – it can raise

Rajan (2000, 2001), Kashyap, Rajan, and Stein (2002), Gatev and Strahan (2006), Ben-David, Palvia, and Spatt (2016), and Hanson, Shleifer, Stein, and Vishny (2016). Mehran and Thakor (2011) argue that there are synergies between equity capital and lending and provide evidence from the cross section of bank valuations. Berger and Bouwman (2009) focus on one economic activity banks pursue, liquidity creation, constructing a comprehensive measure of bank liquidity creation on both sides of the balance sheet and showing that it is positively correlated with banks' M/B. In contrast, we start with M/B and attempt to attribute it to different bank activities. Bai, Krishnamurthy, and Weymuller (2016) link bank "liquidity mismatch" to bank stock returns. Billett and Garfinkel (2004) link banks' quantities of insured and uninsured deposits directly to their M/B. However, none of these papers perform a quantitative decomposition of the determinants of bank value. To our knowledge, our paper is the first in the literature to do so.

[6]Our deposit demand estimates relate most closely to Dick (2008), Egan, Hortaçsu, and Matvos (2017), and Xiao (2017). Similar tools have been used by Hortaçsu and Syverson (2004) for index mutual funds, Koijen and Yogo (2015) for investment assets, Koijen and Yogo (2016) for life insurance, Egan (2016) for retail bonds, and Hastings, Hortaçsu, and Syverson (2016) for privatized social security. Our estimation of bank asset production functions uses techniques similar to those used by Maksimovic and Phillips (2001) and Schoar (2002) to study non-financial firms.

a fixed amount of deposits at a lower cost. In our empirical analysis below, we explore the drivers of differences in productivity primitives across banks. Conceptually these differences can arise for a variety of reasons, including differences in technologies for making loans or serving depositors, differences in human capital of loan officers or bank tellers, differences in management quality, differences in market power or customers served, and other factors.

Bank j takes ϕ_{jt} and δ_{jt} as given and chooses its assets and deposits to maximize Eq. (1). The first order condition from this optimization implicitly defines the bank's equilibrium assets, deposits, and profits in terms of ϕ_{jt} and δ_{jt}. In other words, differences across banks are driven by differences in the primitives ϕ_{jt} and δ_{jt}.

We assume that fraction λ of profits are paid out to shareholders and that profits grow at rate g. In addition, we assume the market for equity is competitive and profits are discounted at required rate of return k. The market value of bank j's equity is then

$$M_{jt}(\phi_{jt}, \delta_{jt}) = \frac{\lambda \pi^*_{jt}(\phi_{jt}, \delta_{jt})}{k - g}$$

where $\pi^*_{jt}(\phi_{jt}, \delta_{jt})$ is the bank's equilibrium profits. The market-to-book (M/B) ratio is obtained by dividing by book equity E_{jt}. Like equilibrium profits, market values and M/B ratios are determined by the primitives ϕ_{jt} and δ_{jt}.

This simple framework demonstrates why we need to recover productivity primitives in order to decompose bank value between lending and deposit taking. The bank's equilibrium assets and deposits depend on both primitives. Similarly, the return on assets the bank earns and the cost of deposits the bank pays depend on both primitives. If a bank is good at gathering deposits, it will optimally scale up. If it faces diminishing returns, as the bank scales up, it will earn less on its assets and pay more on its deposits. Similarly, if a bank is good at lending, it will optimally scale up, and as it scales up, it will earn less on its assets and pay more on its deposits. Thus, the bank's equilibrium balance sheet, as well as its equilibrium interest income and interest expense, mix how good the bank is at raising deposits with how good it is at lending. In order to attribute bank value to deposit taking or lending, we must therefore first recover the primitives ϕ_{jt} and δ_{jt}.

2.1 Bank Assets

We now describe how we use a standard, flexible framework from the industrial organization literature to recover the primitives ϕ_{jt} and δ_{jt} in the data. On the asset side, we model bank j

as generating revenue of $Y_{j,t} = f(A_{j,t}; \phi_{j,t})$ from making loans and holding securities, where total assets A_{jt} equal the sum of the deposits and other capital.

We approximate the bank's asset production function using a first-order Taylor series as

$$Y_{jt} = \phi_{jt} A_{jt}^{\theta}. \tag{2}$$

The parameter θ reflects returns to scale in production, and ϕ_{jt} is bank j's asset productivity, reflecting the excess risk-adjusted revenue the bank can earn on its loans and securities. Variation in ϕ_{jt} may arise from skill in underwriting loan or trading securities, selection of markets to operate in, and other factors.

Asset productivity translates directly to bank profits and value in our framework. To illustrate, suppose a bank's asset productivity increases from ϕ_j^0 to ϕ_j^1. All else equal, this increase in asset productivity results in an increase in profits of $(\phi_j^1 - \phi_j^0)A_{jt}^{\theta}$. In other words, the partial derivative of profits with respect to asset productivity is simply $\frac{\partial \pi}{\partial \phi_{jt}} = A_{jt}^{\theta}$.

2.2 Bank Deposits

On deposit side, we model banks as producing deposit products that are valued by consumers. The value consumers place on deposits is a function of the deposit rate and quality of services provided. A consumer depositing funds at bank j at time t earns the deposit rate i_{jt}, which yields utility αi_{jt}. The parameter $\alpha > 0$ measures the consumer's sensitivity to deposit rates. Depositors also derive utility from deposit services produced by banks, given by $F_{jt}(X_{jt}) + \varepsilon_{jkt}$. The function $F_{jt}(X_{jt})$ is a bank-specific production function for turning costly inputs X_{jt}, such as capital, labor, and non-interest expenditures, into services valued by consumers like ATMs and checking services. We parameterize the production function as $F_{jt}(X_{jt}) = \beta X_{jt} + \delta_{jt}$. The parameter β reflects a technology that is common across banks for turning costly inputs into services valued by consumers. We assume that these non-interest inputs X_{jt} are relatively fixed on short-term (quarter-to-quarter) basis, while deposit rates are flexibly adjusted. The bank-specific effect, δ_{jt}, denotes the bank's productivity at raising deposits. Conditional on the other inputs, banks with higher deposit productivity offer superior services and hence higher utility to consumers. Thus, deposit productivity captures differences in efficiency across banks in producing deposits from costly inputs X_{jt}. Variation in productivity could be driven by differences in production technologies (i.e., physical productivity), brand/franchise value, selection of markets to operate in, and other factors.

Finally, the term ε_{jkt} is a consumer-bank-specific utility shock capturing preference heterogeneity across consumers: some consumers may inherently prefer Bank of America to Citibank (or vice versa). Thus, the total indirect utility derived by a depositor k from bank j at time t is:

$$u_{jkt} = \alpha i_{jt} + \beta X_{jt} + \delta_{jt} + \varepsilon_{jkt}. \tag{3}$$

Our analysis focuses on deposit productivity, δ_{jt}. Conditional on the offered deposit rate i_{jt} and other bank characteristics (X_{jt}), more banks productive attract more depositors.[7] From the bank's perspective, a more productive bank faces a demand curve for deposits that is shifted up.

Each consumer selects the bank that maximizes their utility. We follow the standard assumption in the industrial organization literature (Berry, 1994; Berry, Levinsohn, and Pakes, 1995) and assume that the utility shock ε_{jkt} is independently and identically distributed across banks and consumers and follows a Type 1 Extreme Value distribution. Given this distributional assumption, the probability that a consumer selects bank j follows a multinomial logit distribution. We also assume that consumers have access to an outside good, which represents placing funds outside the traditional banking sector. Without loss of generality, we normalize the utility of the outside good to zero ($u_0 = 0$). The market share for bank j, denoted s_j, is then

$$s_{jt}\left(i_{jt}, \mathbf{i_{-jt}}; \boldsymbol{\delta_t}\right) = \frac{exp(\alpha i_{jt} + \beta X_{jt} + \delta_{jt})}{\sum_{l=1}^{J} exp(\alpha i_{lt} + \beta X_{lt} + \delta_{lt}) + 1}. \tag{4}$$

The total market size for deposits at time t is denoted N_t, so bank j raises $s_{jt}N_t$ deposits.

Deposit productivity has a direct effect on the cost of raising deposits. Let $c(D_{jt}, \mathbf{i_{-jt}}; \boldsymbol{\delta_t})$ denote the interest cost of collecting D_{jt} deposits. One can show that a one unit increase in deposit productivity decreases the cost of collecting D_{jt} deposits by $\frac{1}{\alpha}D_{jt}$, i.e., $\frac{\partial c(D_{jt}\mathbf{i_{-jt}};\boldsymbol{\delta_t})}{\partial \delta_{jt}} = -\frac{1}{\alpha}D_{jt}$. Thus, a one unit increase in deposit productivity leads to a $\frac{1}{\alpha}D_{jt}$ increase in profits.[8]

2.3 Summary

Putting together the asset side and deposit side, the specific version of the profit function Eq. (1) we work with empirically is:

[7] Our formulation closely follows that of Egan, Hortaçsu, and Matvos (2017), with one exception. Previous research such as Egan, Hortaçsu, and Matvos (2017) and, more recently, Martin, Puri, and Ufier (2017) finds that depositors (particularly uninsured depositors) may be sensitive to the financial stability of a bank. In this paper, we treat consumers' perceptions about bank solvency as part of the bank's deposit productivity.

[8] The formal argument is the following. In our framework, the cost in terms of interest expense of collecting D_{jt} deposits is given by $D_{jt} \times i(D_{jt}, \mathbf{i_{-jt}}; \boldsymbol{\delta_t})$ where $i(D_{jt}, \mathbf{i_{-jt}}; \boldsymbol{\delta_t})$ is the deposit rate required to collect D_{jt} deposits, which can be obtained by inverting Eq. (4). From Eq. (4), one can show that $\partial i(D_{jt})/\partial \delta_{jt} = -1/\alpha$.

$$\pi_{jt} = \phi_{jt} A_{jt}^{\theta} - i_{jt} \times \underbrace{N s_{jt}\left(i_{jt}, \mathbf{i_{-jt}}; \boldsymbol{\delta_j}\right)}_{D_{jt}} - X_{jt}.$$

Note that bank profits are linear in both deposit and asset productivity, $\frac{\partial \pi_{jt}}{\partial \phi_{jt}} = A_{jt}^{\theta} > 0$ and $\frac{\partial \pi_{jt}}{\partial \delta_{jt}} = \frac{1}{\alpha} D_{jt} > 0$. In the empirics, we use these specifications to recover each bank's deposit and asset productivity in the data and then examine how variation in bank deposit and asset productivity contribute to bank value.

3 Data and Estimation

3.1 Data

Our primary data source is the Federal Reserve FR Y-9C reports, which provide quarterly balance sheet and income statement data for all U.S. bank holding companies. We supplement the Y-9C data with stock market data from CRSP and weekly branch-level data on advertised deposit rates from RateWatch. We also obtain branch-level deposit quantities from the annual FDIC Summary of Deposits files and data on consumer complaints from the Consumer Financial Protection Bureau. Finally, we obtain county- and MSA-level demographic characteristics from the U.S. Census Bureau, and mortgage originations from Home Mortgage Disclosure Act (HMDA) data.

Our sample is the universe of publicly-listed U.S. bank holding companies. Our primary data set consists of an unbalanced panel of 847 bank holding companies over the period 1994 through 2015. Observations are at the bank holding company-by-quarter level. Table 1 provides summary statistics for our main data set. Our two primary measures of bank risk are equity beta and the standard deviation of return on assets. Following Baker and Wurgler (2015), we calculate the equity beta for each bank using monthly returns over the past two years. Similarly, we measure the standard deviation of return on assets using quarterly data over the past two years.

3.2 Estimation: Bank Deposits

We estimate the demand system described in Section 2.2 using our bank data set over the period 1994 through 2015. We can write the logit demand system in Eq. (4) as:

$$\ln N_t s_{jt} - \ln(N_t s_{0t}) = \alpha i_{jt} + \beta X_{jt} + \delta_{jt}. \tag{5}$$

Because we do not observe the characteristics of the outside good, s_0, we include a time fixed effect. This allows us to estimate the key demand parameters without actually specifying the outside good. Thus, we estimate the following specification:

$$\ln N_t s_{jt} = \alpha i_{jt} + \beta X_{jt} + \mu_j + \mu_t + \xi_{jt}. \tag{6}$$

We estimate demand in two ways. First, in our baseline specifications, we define the market for deposits and compute the associated bank market shares at the aggregate US-by-quarter level. We also estimate a second demand system, defining the market at the county-by-year level.

A standard issue in demand estimation is the endogeneity of price, i.e., deposit rates.[9] The term ξ_{jt} in Eq. (6) represents an unobserved bank-time specific shock. If banks observe ξ_{jt} prior to setting deposit rates, the offered deposit rate will be correlated with the unobservable term ξ_{jt}. For example, suppose bank j experiences a demand shock so that ξ_{jt} is positive. It will then optimally offer a lower deposit rate. This will cause our estimate of α to be biased downwards.

We use two sets of instruments to account for the endogeneity of deposit rates. First, following Villas-Boas (2007) and Egan, Hortaçsu, and Matvos (2017), we construct instruments from the bank-specific pass-through of 3-month LIBOR into deposit rates. As documented by Hannan and Berger (1991), Neumark and Sharpe (1992), Driscoll and Judson (2013), Gomez, Landier, Sraer, and Thesmar (2016), and Drechsler, Savov, and Schnabl (2017), deposit rates at different banks respond differently to changes in short-term interest rates. Investment opportunities are a key supply-side reason for this variation. When short rates rise, banks with good investment opportunities will not wish to lose deposit funding to competitors and thus will raise their deposit rates more. Hence, variation in investment opportunities induces variation in deposit rates that is unrelated to the deposit demand conditions.[10] Thus, we can instrument for i_{jt}, the deposit rate offered by bank j at time t, with the fitted value of a bank-specific regression of i_{jt} on 3-month LIBOR. The exclusion restriction here is that bank j's average degree of pass-through in the time series interacted with 3-month LIBOR is orthogonal to the deposit demand it faces at time t.

Our second set of instruments are traditional Berry, Levinsohn, and Pakes (1995)-type instruments: the average product characteristics of a bank's competitors. We use lags of slow-moving

[9]The X_{jt} terms reflect slow-moving inputs such as the number of branches a bank operates. It is unlikely that banks can change these slow-moving inputs in response to an unobservable, unanticipated bank-quarter specific demand shock; hence, we do not instrument for the X_{jt} terms.

[10]As Drechsler, Savov, and Schnabl (2017) show, variation in pass-through is also driven by market power, a supply-side characteristic, not by consumer demand.

competitor product characteristics. Specifically, we use the number of bank branches, number of employees, non-interest expenditures, and banking fees of a bank's competitors, but we do not use the deposit rates they offer. We calculate the average product characteristics offered by each bank's competitor at the county-by-quarter level. We then form our instrument by taking the weighted average of a bank's competitors' product characteristics across all counties the bank operates in. Intuitively, a bank must offer higher deposit rates if its competitors offer better products. The exclusion restriction in this setting is that lagged average competitor product characteristics are orthogonal to current bank-quarter specific demand shocks.

Table 2 displays the corresponding demand estimates using aggregate bank-quarter data from the Y-9C reports. We measure deposit rates i_{jt} as total interest expense on deposits, net of fees on deposit accounts, divided by total deposits. We account for all other expenses reported in the Y-9C reports in X_{jt}, which includes banks' non-interest expenditures, number of employees, and number of branches. Non-interest expenditures should capture investments made by the bank in providing higher-quality services to consumers, such as better ATMs or longer branch hours. In addition, the number of branches and number of employees may also factor into a consumer's selection of a depository institution. The coefficient β on X_{jt} captures how well banks are able to transform these inputs into utility/services valued by consumers.[11] Column (1) of Table 2 displays the simple OLS estimates corresponding to Eq. (6), while column (2) uses both sets of instruments (which yield first-stage F-statistics in excess of 25). We estimate a positive and significant relationship between demand for deposits and the offered deposit rate. Moreover, as we would expect, the IV estimates tend to be higher than the OLS estimates. For a bank with an initial market share of 10%, the coefficient 20.9 in column (2) implies that a one percentage point increase in the offered deposit rate is associated with a 1.9 percentage point increase in market share. These demand elasticities are in line with the existing literature (Dick, 2008; Egan, Hortaçsu, and Matvos, 2016; Xiao, 2017). In Section 5.1.1 below, we show robustness to a variety of alternate demand specifications.

We use our estimated demand system to calculate each bank's deposit productivity at each point in time. Specifically, we measure bank j's deposit productivity at time t as

$$\hat{\delta}_{jt} = \ln N_t s_{jt} - \hat{\alpha} i_{jt} - \hat{\beta} X_{jt} - \hat{\mu}_t. \tag{7}$$

Our estimates of deposit productivity have an intuitive reduced-form interpretation. More pro-

[11] Note that since we do not allow β to vary across banks, any differences in β (i.e., differences in how good banks are at converting inputs like branches into deposits) will be captured by our productivity measure.

ductive banks are raising more deposits with the same inputs than less productive banks. Bank deposit productivity is highly persistent in the data, with a quarterly auto-correlation of 0.99.

3.3 Estimation: Bank Assets

We next estimate our asset production function to recover each bank's asset productivity at a given point in time. In particular, we can write the bank's log production function as:

$$\ln Y_{jt} = \theta \ln A_{jt} + \phi_{jt}. \tag{8}$$

We treat the asset and liability sides of the bank differently because in contrast to the liability side, where banks have one main product (deposits), on the asset side banks produce many different products. We measure asset-side output using income because it aggregates across all products.

We parameterize and estimate the production function as:

$$\ln Y_{jt} = \theta \ln A_{jt} + \Gamma X_{jt} + \gamma_j + \gamma_t + \epsilon_{jt}. \tag{9}$$

The dependent variable Y_{jt} measures the interest and fee income generated by bank j at time t.[12] As an additional robustness check, in Section 5.1.4 we re-estimate our bank asset production function including realized losses on loans and securities in Y_{jt}. We measure a bank's assets lagged by one year to capture the potential lag between the time an investment decision is made and initial returns are realized. Additional control variables X_{jt} include the bank's equity beta and standard deviation of its return on assets, to capture the riskiness of bank assets. As in our deposit demand estimation, we also control for the other production inputs in X_{jt}, including banks' non-interest expenditures, number of employees, and number of branches. The regression includes time fixed effects to absorb common variation in bank asset productivity over time. Although Eq. (9) is motivated by the specific asset production function outlined in Section 2.1, it is a first-order approximation of any arbitrary production function (see, e.g., Syverson, 2011).

A challenge in estimating Eq. (9) is the potential endogeneity of bank size ($\ln A_{jt}$). If a bank observes its productivity ϕ_{jt} prior to determining its investments, then size is endogenous in Eq. (9). This is a well-known problem dating back to Marschak and Andrews (1944), which much of

[12] We omit noninterest income to focus our analysis on traditional banking activities, i.e., lending and investing in interest-bearing securities. In Section 5.4, we show that our results are robust to excluding banks for which noninterest income is a significant fraction of total income.

the industrial organization literature on production has been devoted to addressing.[13]

Conceptually, we need an instrument that is correlated with bank size but is otherwise uncorrelated with the bank's asset productivity. We construct cost-shifter instruments in the style of Berry, Levinsohn, and Pakes (1995). Specifically, we instrument for bank size ($\ln A_{jt}$) using the weighted average deposit productivity of bank j's competitors.[14] The idea is that if a bank faces competitors that are better at raising deposits, it will naturally be smaller, so competitor deposit productivity induces variation in bank size that is orthogonal to the bank's own asset productivity.

Table 3 displays the corresponding estimates. In columns (1)-(3), we report OLS estimates, and in columns (4)-(6), we report the IV estimates. Our instruments are empirically relevant and yield first stage F-statistics in excess of 20 for each specification. In each specification, we also estimate a coefficient on $\ln A_{jt}$ (θ) that is less than one, implying that banks face decreasing returns to scale.[15] In columns (2)-(3) and (5)-(6), we measure risk using equity beta and the standard deviation of returns. We include both backward-looking measures over the previous two years, as well as forward-looking measures of risk calculated from year t to year $t+2$.[16] The estimates in our IV specifications in columns (4)-(6) of Table 3 are quite similar to the OLS estimates. This suggests that within a quarter, banks either do not observe ϵ_{jt} prior to determining their asset size or that banks are unable to easily adjust asset size within a quarter.[17]

We use the estimated production function to compute bank j's asset productivity at time t as

$$\hat{\phi}_{jt} = \ln Y_{jt} - \hat{\theta} \ln A_{jt} - \hat{\Gamma} X_{jt} - \hat{\gamma}_t.$$

[13]For example, Olley and Pakes (1996), Levinsohn and Petrin (2003), and many others. For an overview of the literature, see Griliches and Mairesse (1998), Ackerberg et al. (2007), and van Biesebroeck (2008).

[14]Specifically, we construct instruments based on the quality of services offered by a bank's competitors, where we define a bank's competitors based at the county by year level. We denote the set of counties bank j operates in as K, and the set of banks in each county k is denoted as L_k. Our instrument $\overline{\delta_{-j}}$ is then constructed as follows (note time subscripts t are omitted for ease of notation):

$$\overline{\delta_{-j}} = \overline{\sum_{k \in K} \frac{N_k}{N} \sum_{l \in L_{-jk}} \hat{\delta}_l}.$$

The term $\hat{\delta}_l$ corresponds to Eq.(7). The estimates of $\hat{\delta}_j$ are from the demand estimates reported in Appendix Table A7, which uses an expanded data set comprised of bank holding companies, rather than just the public companies we focus on in our main results. Put differently, our instruments are based on all competitors a bank faces, not just its competitors that are public firms. In our IV specifications, we winsorize $\overline{\delta_{-j}}$ at 1%, and we use the variables $\overline{\delta_{-j}}$ and $\overline{\delta_{-j}}^2$ to instrument for $\ln A_{kt}$.

[15]Our finding of decreasing returns to scale depends on including bank fixed effects in our estimation. In untabulated results, when we estimate the production function without bank fixed effects, we find roughly constant returns to scale. This suggests that there are constant returns to scale in the cross section of banks, but banks face decreasing returns to scale when adjusting scale on the margin.

[16]We obtain similar results if we only use the backward-looking measures.

[17]Our control variables explain 99% of the variation in the dependent variable. This is common in the production function literature, as inputs are highly correlated with outputs. Size explains 95% of the variation in interest income.

Note that this construction implies that if there are differences in economies of scale (θ) across banks, our asset productivity measures will include them. In our main results, we calculate bank asset productivity using this equation based on the estimates in column (4) of Table 3. The reduced-form interpretation of our results is simply that more asset-productive banks generate more income with the same inputs than less productive banks. Asset productivity is highly persistent in the data, with a quarterly auto-correlation of 0.95.

4 Results

4.1 Productivity and Bank Value

We begin by examining how our productivity measures relate to a stock-market based measure of value: the market-to-book (M/B) ratio.[18] It is worth noting up front that because we are using a market-based measure of value, our results only directly speak to private value created for shareholders, not total social value created.

We regress M/B on our estimates of deposit and asset productivity as well as time fixed effects and additional bank-level controls:

$$\left(\frac{M}{B}\right)_{jt} = \gamma_0 + \gamma_1 \hat{\delta}_{jt} + \gamma_2 \hat{\phi}_{jt} + \Gamma X_{jt} + \mu_t + \varepsilon_{jt}. \tag{10}$$

We use M/B as a proxy for average Q, the average market value created per dollar of book assets, not marginal Q, as it is sometimes used in the investment literature. M/B is a particularly useful measure because it provides a natural economic benchmark: under the null hypothesis that the Modigliani-Miller theorem holds, banks create no social or private value. Thus, all banks should have an M/B of one. In Section 5.2, we also verify that our results hold using alternative measures of bank value such as profitability and total market capitalization.

Table 4 displays the results. All specifications include time fixed effects, so our analysis is solely based on cross-sectional variation. We standardize our productivity measures so that the coefficients correspond to a one-standard deviation increase in productivity. Standard errors are computed by bootstrap to account for the fact that our productivity measures are estimated.

Column (1) documents the baseline relationship between deposit productivity and M/B. In

[18] In our static framework in Section 2, there is an unambiguous positive relationship between market-to-book and both deposit and asset productivity. The relationship in a dynamic model can be ambiguous, depending upon the persistence of productivity and the functional form of the production function.

column (2), we add controls X_{jt}: lagged (log) assets, as well as leverage, the bank's estimated equity beta, and the standard deviation of its return on assets (ROA) to account for risk.[19] We control for size as a proxy for growth expectations. Larger banks will tend to grow more slowly and thus have lower M/B ratios. The remaining controls are meant to account for any correlation between our productivity measures and risk.

The results show that a one-standard deviation increase in deposit productivity is associated with an increase in M/B of 0.2 to 0.5 points, an economically significant effect. The cross-sectional standard deviation of M/B is 0.69 in our sample.[20] Columns (3) and (4) show that a one-standard deviation increase in asset productivity is associated with an increase in M/B of 0.1 to 0.2 points, an effect that is also economically significant.

4.2 Deposit-driven Value versus Asset-driven Value

We next compare the relative importance of deposit and asset productivity in determining bank value. We use two distinct approaches to examine the relative importance of the liability and asset side of a bank. First, we use regressions to compare how M/B loads on our deposit and asset productivity measures. Second, we use our framework from Section 2 to calculate the model-implied relative contribution of asset and deposit productivity to bank value and show that these estimates line up with of our regression results.

We start by re-estimating our M/B regressions (Eq. 10), simultaneously including both deposit and asset productivity. Columns (5) and (6) of Table 4 display the corresponding estimates. Bank value loads positively on both asset and deposit productivity in both specifications. However, deposit productivity has a larger impact on M/B than asset productivity. The results in column (5) indicate that a one-standard deviation increase deposit productivity is associated with an increase of 0.2 points in M/B, whereas a one-standard deviation increase in asset productivity is associated with an increase of 0.1 points in M/B. Relative to asset productivity, the impact of deposit productivity is about twice as large in column (5), where we only include time fixed effects, and nearly five times as large in column (6), where we include the full suite of controls. This suggests that liability-driven theories of bank value creation, which focus on the special services provided by bank deposits,

[19]Note that risk acts like measurement error here. It may affect the independent variables, but it should not affect M/B because it increases both cash flows and discount rates. To see this, imagine a bank with no deposits that just held a newly-issued investment grade bond with a 3% coupon trading at par. This bank would have M/B=1. If the bank instead held a newly-issued high-yield with a 10% coupon trading at par, it would also have M/B=1. Similar intuition applies for differences in loan maturity across banks. Consistent with this intuition, we find that our risk controls do not affect our point estimates very much. We discuss measurement error further in Section 5.3 below.

[20]This number is within-time and thus lower than the overall standard deviation of M/B in Table 1.

explain more variation in the cross section of banks than asset-driven theories.

Why does deposit productivity play a larger role in explaining dispersion in bank value than asset productivity? As discussed in Section 2, our two productivity measures directly affect bank cash flows.[21] For example, if a bank's deposit productivity increases from δ^0 to δ^1, the bank can offer a lower deposit rate and still collect the same amount of deposits. The cost savings of increasing deposit productivity, all else equal, are given by

$$Cost\,Savings = Deposits \times \frac{\Delta\delta}{\alpha} \tag{11}$$

where α is the elasticity of demand for deposits. Similarly, if a bank's asset productivity increases from ϕ^0 to ϕ^1, all else equal its income increases by

$$\Delta Y = \left[exp(\phi^1) - exp(\phi^0)\right] exp(\Gamma X_j) A_j^\theta.$$

Figure 1 uses these equations to decompose the dispersion in net income across banks. The red shaded histogram shows how the average bank's net income changes as we vary bank deposit productivity (δ_{jt}) across its observed distribution in the data. Similarly, the blue histogram shows the analogous exercise varying asset productivity across its distribution in the data. Consistent with the evidence presented in Table 4, Figure 1 shows that heterogeneity in deposit productivity explains more variation in bank net income than heterogeneity in asset productivity.

Figure 2 ignores the structure imposed by our framework, and simply plots variation in interest income and interest expense, each normalized by assets. In this accounting-based decomposition of bank value, the contributions of the asset-side (interest income) and liability-side (interest expense) measures look comparable. The stark differences between Figure 1 and Figure 2 therefore highlight the value of a more rigorous economic analysis. In particular, the accounting-based decomposition obscures the "primitives" that enter the bank's optimization problem and are responsible for determining a bank's value. For example, if banks that are good at raising deposits and investing optimally increase their scale and there are diminishing returns, then variation in observed (scaled) interest income and interest expense will be smaller than the underlying variation in productivity. This is exactly what we find in Figures 1 and 2.

Finally, we show that our simple framework yields good quantitative predictions of the ob-

[21] In untabulated results, we find little evidence that our productivity measures are associated with other components of M/B like future growth rates or equity returns.

served distribution of bank M/Bs. We capitalize our estimates of bank productivity and calculate the model implied M/B for each bank. Figure 3 plots model-implied estimates of M/B for each bank against observed M/Bs (the details of our procedure for constructing model-implied M/B are outlined in the Appendix). The figure shows that our simple framework is capable of explaining a significant fraction of the observed variation in banks' market values.

4.2.1 From the Cross Section to Levels

So far, we have focused on the cross section of bank value. With additional normalizing assumptions, we can make statements about the level of bank value. Specifically, we normalize the level of asset productivity by assuming that for a bank earning an asset yield equal to the 5-year Treasury yield, asset productivity's contribution to value is zero. For banks earning more than the 5-year Treasury yield, asset productivity's contribution is positive. Similarly, we normalize the deposit productivity distribution assuming that if a bank pays depositors a rate equal to 3-month LIBOR, deposit productivity's contribution to value is zero. For banks paying less than 3-month LIBOR, deposit productivity contributes positively to value.[22] These normalizing assumptions pin down which points in the distributions of asset and deposit productivity line up with zero on the x-axis in Figure 1. As Figure 1 shows, with these normalizing assumptions, deposit productivity contributes more to the level of bank value, as the average of the deposit productivity distribution is to the right of the average of the asset productivity distribution.

Our normalizing assumptions also allow us to determine the share of value coming from deposits for each bank. Figure 4 shows the distribution of deposit's share of net income across banks. On average, deposit productivity accounts for about twice as much of bank value as asset productivity. The mean deposit value share is 71%. However, there is heterogeneity across banks: for some banks, the majority of value comes from asset productivity.

Overall, a variety of approaches suggest that deposit productivity is more important than asset productivity for explaining both the level of bank value and variation in value across banks.

[22]We use the 5-year Treasury yield because Begenau and Stafford (2018) and Drechsler, Savov and Schnabl (2018) suggest that the average maturity of bank assets is roughly five years. This normalization means that 17% of banks do not generate any asset side value. Our normalization of the deposit productivity distribution means that the bottom 13% of banks in terms of deposit productivity quarter do not generate any value on the deposit side of the bank.

4.3 Bank Productivity and Business Lines

In this section, we disaggregate our results in order to understand which products and business lines are most closely associated with variation in bank value.

4.3.1 Decomposing Bank Productivity

We start in Table 5 by asking whether certain types of assets and deposits contribute particularly strongly to our overall productivity measures. Specifically, we compute productivity measures for different subcategories of assets and deposits the same way we construct our overall productivity measures. These more granular measures tell us whether, for instance, a bank is particularly good at raising savings deposits given the rate it pays on savings deposits and other inputs.

Columns (1) and (2) of Table 5 examine the relationship between overall deposit productivity and our subcategory estimates for savings deposits, small time deposits, large time deposits, and transaction deposits. As before, the productivity measures are standardized. All of the subcategory measures are positively correlated with our overall deposit productivity measure. The correlation is strongest for savings deposit productivity. This is not simply driven by the composition of bank deposits. A one-standard deviation increase in savings deposit productivity is associated with a 0.73 standard deviation increase in total deposit productivity, though savings deposits make up only 41% of a bank's total deposits on average. Our estimates for small and large time deposits are similar, suggesting that our productivity estimates are not driven by differences in the quantity and pricing of insured versus uninsured deposits across banks.

Columns (3) and (4) of Table 5 display the relationship between asset productivity and our subcategory measures: lending productivity and securities productivity.[23] Our asset productivity measure is more highly correlated with loan productivity than with securities productivity. This accords with intuition: there is more scope for banks to use their screening and monitoring technologies to generate excess returns in loan markets than in securities markets.

Finally, columns (5) and (6) link our subcategory productivity measures to banks' M/B. The results suggest that not all deposits are created equal: columns (5) and (6) suggest that the main driver of bank value is savings deposits, with transaction deposits a distant second. In column (6), savings deposit productivity explains over three times as much variation in M/B as any other subcategory productivity measure.[24]

[23]Interest income is only disaggregated in the Y-9C reports into interest income from loans and interest income from securities, so this is the most granular decomposition we can do on the asset side.

[24]The negative coefficient on small time deposits is a product of running a multiple regression. The univariate

Why are saving deposits so strongly correlated with value? A key part of the answer, as Eq. (11) shows, is that the price elasticity of demand is negatively correlated with value. The demand for savings deposits is almost completely inelastic.[25] This means that a bank that is good at gathering savings deposits can gather them at very low rates. In contrast, demand for time deposits is quite elastic, so they contribute little to value; a less productive bank can always offer a time deposit rate slightly higher than the most productive bank and collect more time deposits.

These decompositions have interesting implications for mapping our results back to theory. Our results in Section 4.2 suggest that liabilities are an important source of bank value. However, the liabilities that are most strongly associated with deposit productivity are not transaction deposits, which provide the most liquidity services. Instead, the source of most liability-side bank value comes from savings deposits, which provide limited services relative to transaction deposits. Again, an important caveat is that our regression results explain cross-sectional dispersion in private bank value, not social value.

4.3.2 Our Productivity Measures and Balance Sheet Composition

Another way to understand what products and business lines drive our productivity measures is to examine how they correlate with banks' balance sheet composition. This is a revealed preference argument: banks with high productivity in certain business lines should tilt towards those products.

In Table 6a, we examine the correlations between our deposit productivity measure and the composition of the liability side of banks' balance sheets. Both the dependent and independent variables are standardized. Column (1) shows that while banks with higher deposit productivity do have higher leverage, the effect is tiny: a one-standard deviation increase in deposit productivity is associated with a 0.02 standard deviation increase in bank leverage.[26] Hence, banks that are particularly good at raising deposits do not appear to lever up much more than other banks. Columns (2)-(7) show that banks with higher deposit productivity tend to have significantly more deposits as a fraction of their total liabilities, as expected. Given that leverage does not change significantly with deposit productivity, this implies that more productive banks substitute non-deposit debt for deposits.

Table 6b displays correlations between our asset productivity measure and banks' asset compo-

correlation between M/B and small time deposit productivity is positive. However, this result is consistent with the claim that banks lose money on smaller accounts (Bord 2017).

[25]Demand estimates for each type of deposit are in Appendix Table A1a.

[26]Note that our standard suite of controls includes lagged leverage. If we omit this control from the regression, we obtain a small and statistically insignificant correlation.

sition. Columns (1)-(3) show that more productive banks tend to hold more real estate loans, more C&I loans, and more loan commitments (credit lines). This is consistent with the idea that more productive banks have better screening and monitoring technologies that allow them to make loans with high risk-adjusted returns. Columns (4)-(6) show that productive banks also tend to have lower quantities of securities and liquid assets. Overall, we find strong evidence that our productivity measures are capturing meaningful information about bank-specific business line specialization.

4.4 What Drives Differences in Productivity?

What are the underlying sources of variation in our productivity measures? The industrial organization literature finds that a number of variables including technology, quality of inputs, market power, and firm structure are primary drivers of non-financial firms' productivity (Syverson, 2011). In the context of banks, explanations for differences in productivity can be categorized broadly as either being "technological" or "customer-based." Customer-based explanations for variation in bank productivity are ones in which two banks would have the same productivity if they had the same customers. This category includes differences in productivity due to market power, customer sophistication, or customer price elasticities. Technological explanations for variation in productivity are ones in which two banks would have different productivities even if they had the same customers. This category includes differences in quality of inputs, variety of products, or sophistication in price-setting or marketing strategies.

In this section, we use additional data sources to show that our deposit and asset productivity measures appear to be driven by both technological and customer-based explanations. While fully decomposing our productivity measures into either customer-based or technological sources is difficult, given that we only have rough proxies for each and that the two broad sources may be intimately related (Syverson, 2004; Holmes et al., 2012), these results provide additional insights into the factors driving our asset and deposit productivity measures, and hence bank value.

4.4.1 Customers

To examine customer-based explanations for variation in our productivity measures, we analyze the demographic and geographic correlates of our productivity measures in Table 7a. We combine county-level Census data with the FDIC's Summary of Deposits to compute average demographic characteristics of the counties where a bank operates, weighted by the fraction of the bank's deposits in each county. Column (1) shows the correlation between asset productivity and these demographic characteristics. There is a concave, increasing relationship between asset productivity and population. Banks in higher-population areas have higher asset productivity, but the relationship fades as population increases since the coefficients on the squared terms are negative. Banks in high house price areas also have higher asset productivity. We do not find any evidence of non-linearity in this relationship, and therefore only report the linear relation. Market power also appears to matter. Banks with high asset productivity tend to operate in less competitive areas, as measured by the Herfindahl-Hirschman index (HHI) of mortgage originations from Home Mortgage Disclosure Act (HMDA) data.

In column (2), we add geographic fixed effects to control flexibly and nonparametrically for other unobservables. Specifically, we regress asset productivity on 387 dummy variables, each of which indicates whether the bank operates in a particular MSA. We use MSA dummies rather than county dummies to keep the number of independent variables manageable. The within-time R^2 of the regression in column 2 is 39%, suggesting that demographic and geographic variation explain a significant fraction of asset productivity. Columns (3) and (4) repeat these exercises for deposit productivity with similar results. Demographic and geographic variables explain more of the variation in deposit productivity than asset productivity. The within-time R^2 of the regression in column 4 is 70%. Interestingly, the age of bank branches is strongly correlated with deposit productivity, possibly reflecting that older branches have over time isolated the stickiest deposits.

These results suggest that customer-based explanations play a large role in explaining variation in our deposit productivity and asset productivity measures. However, Table 7b shows that even controlling for MSA fixed effects and after directly including demographic characteristics and market concentration variables in our regressions our main findings hold: our productivity measures are still strongly related to bank value, and deposit productivity continues to have a larger impact than asset productivity. In total, demographic and geographic variables explain only about 40% of the variation in M/B, suggesting there is significant remaining variation for technological differences in productivity to explain.

4.4.2 Technology: Consumer Complaints

We next turn to technological sources of variation in productivity by examining the quality of services offered by the bank. We supplement our baseline data with consumer complaint data from the Consumer Financial Protection Bureau's (CFPB) Consumer Complaint Database. The CFPB collects data on consumer complaints filed over the period 2011-2015 on various financial products.

We manually match firm names in the CFPB database to 79 bank holding companies in our baseline data set. We measure the quality of services a bank offers as the number of complaints it receives in a given year per dollar of deposits it collects ($CFPB\,Complaints_{jt}$), winsorized at the 5% level.

Columns (1)-(2) of Table 8 display the correlations between deposit productivity and our external measure of bank quality, CFPB complaints. The results suggest that banks that are more deposit productive offer higher quality products. In other words, banks that are good at producing deposits have better quality inputs. This result is consistent with Egan, Hortaçsu, and Matvos (2017), who find that banks with larger brand effects receive fewer complaints per depositor. Columns (3)-(4) of Table 8 examine the relationship between asset productivity and CFPB complaints. There is little relationship between asset productivity and the number of CFPB complaints a firm receives. To the extent that asset productivity measures the investment and risk management skill of a bank, it is not surprising that we do not find a relationship between asset productivity and CFPB complaints. Conversely, the results suggest that customer service appears to be a key driver of deposit productivity.

4.4.3 Technology: Rate Setting

Finally, we examine another technological source of variation in productivity: firm structure decisions and pricing technology. Specifically, we look at the relationship between a bank's rate setting technology and productivity.

We examine the variation in deposit and mortgage rates offered by a bank. The idea is that banks with more sophisticated rate setting technologies will offer location-specific rates that depend on local demand conditions. Specifically, we first calculate the median 3-month certificate of deposit rate and 30-year fixed mortgage rate offered at the bank-by-county-by year level.[27] We then calculate the standard deviation of certificate of deposit and mortgage rates across the counties a bank operates in for each year, σ_{CDjt} and σ_{MTGjt}. Table 9 shows the correlations between asset and deposit productivity and our measures of rate setting sophistication. Banks that set more heterogeneous deposit and mortgage rates are more deposit- and asset-productive, respectively.

Overall, the results in this section suggest that both customer-based and technological sources of variation are important in driving our productivity measures.

[27] We examine mortgage rates for a $175,000 loan with no origination fees or mortgage points.

4.5 Synergies

In previous sections, we have examined deposit productivity and asset productivity separately. However, because of synergies between collecting deposits and lending, a bank's asset productivity may be linked to its deposit productivity. Here, we examine synergies between the two sides of the balance sheet in two ways. First, we augment our M/B regressions with the interaction of our productivity measures, finding that deposit productivity is more valuable for a bank that is relatively asset productive. Second, we directly examine the relationship between deposit productivity and asset productivity, finding that banks that are more deposit productive are also more asset productive, consistent with higher deposit productivity increasing a bank's asset productivity.

4.5.1 Existence of Synergies

Building on our baseline M/B regressions (Eq. 10), we first examine how a bank's deposit productivity, asset productivity, and the interaction of the two contribute to bank value:

$$\left(\frac{M}{B}\right)_{jt} = \gamma_0 + \gamma_1 \hat{\delta}_{jt} + \gamma_2 \hat{\phi}_{jt} + \gamma_3 \hat{\delta}_{jt} \times \hat{\phi}_{jt} + \Gamma X_{jt} + \mu_t + \varepsilon_{jt}. \quad (12)$$

Table 10a displays the corresponding results. We estimate a positive and significant coefficient γ_3 on the interaction term, indicating that deposit productivity is more valuable for a bank with higher asset productivity. The results in column (2) indicate that a one standard deviation increase in a bank's asset productivity is associated with a roughly 0.05/0.5=10% increase in the value generated by its deposit productivity. Being a skilled investor is more valuable when a bank is also skilled at collecting deposits.

We next directly examine the relationship between our productivity measures in Table 10b. Specifically we run regressions of the form

$$\hat{\phi}_{jt} = \gamma_0 + \gamma_1 \hat{\delta}_{jt} + \Gamma X_{jt} + \mu_t + \varepsilon_{jt}. \quad (13)$$

The table shows that our two productivity measures are correlated. Column (1) shows that a one-standard deviation increase in deposit productivity is associated with a 0.37 standard deviation increase in asset productivity. This is economically significant: 25% of the variation in our asset productivity measure can be explained by variation in deposit productivity. This correlation is consistent with the idea that synergies allow a high deposit productivity bank to become more asset productive. However, it can be thought of as an upper bound on the strength of synergies, as it may be explained by factors like good management, in addition to the banking-specific synergies focused by the theoretical literature. Once we include controls in column (2), the association between asset productivity and deposit productivity strengthens somewhat. Columns (3)-(6) break asset productivity into its constituent pieces: loan productivity and securities productivity. Overall, Table 10b is suggestive of synergies between deposit productivity and asset productivity. Taken together, our results suggest that not only is a bank's ability to collect deposits is highly correlated with its ability to invest, but there are synergies between the two.

4.5.2 Sources of Synergies

To better understand the drivers of these observed synergies, we examine the correlations between our subcategory measures of asset and deposit productivity in Table 10c. We separately examine the relationship between overall asset (columns 1-2), loan (columns 3-4), and securities (columns 5-6) productivity and our subcategory deposit productivity measures. We find positive relationships between savings and time deposit productivity and our various measures of asset productivity. However, we find less evidence of a relationship between transaction deposits productivity and our measures of asset productivity. Thus, synergies appear to be related to the term structure of deposits: banks that are more productive in collecting long-term deposits appear to have more productive lending and securities portfolios.

In Table 11, we use variation in bank balance sheet composition to explore the sources of these synergies in more detail. Table 11a relates bank asset composition to deposit productivity. Column (1) shows that there is no correlation between deposit productivity and real estate lending. In contrast, column (2) shows there is a strong correlation between deposit productivity and C&I lending. Since C&I loans are more illiquid than mortgages, this suggests that the ability to raise deposits in a cost-effective manner is important for banks that wish to make profitable, illiquid loans, as argued by Hanson, Shleifer, Stein, and Vishny (2016). Column (3) shows that banks with higher deposit productivity also tend to write more loan commitments. This is consistent with Kashyap, Rajan, and Stein (2002) and Gatev and Strahan (2006), who argue that there are synergies between taking deposits and writing loan commitments because in bad times deposits tend to flow into banks while loan commitments are simultaneously drawn down. Our results suggest that this effect is particularly strong for banks that are good at gathering deposits.

In Table 11b, we examine the relationship between bank liability composition and asset productivity. The strongest correlation that arises here is in column (4), which shows that banks that are better at investing tend to gather more large time deposits. This is consistent with our previous result that suggests that synergies may be related to the term structure of deposits.

5 Robustness

We find that banks that are more productive in raising deposits and generating asset income have higher M/B ratios, with deposit productivity accounting for twice as much variation in bank value as asset productivity.

In this section, we provide a variety of robustness tests. First, we show robustness to alternative constructions of our productivity measures. For instance, we use more granular data to construct deposit productivity measures that are fully purged of geography and that allow different banks to face consumers with different deposit rate elasticities. In addition, we construct asset productivity measures that control for additional measures of risk, including the bank's asset composition, and that take into account losses on loans and securities. Second, we show robustness to alternative measures of value, including total market capitalization and profitability. Third, we show that our results are not driven by measurement error. Finally, we perform a variety of subsample analysis.

5.1 Alternative Production Function and Demand Estimates

5.1.1 Alternative Demand Estimates

In this section, we examine the robustness of our main findings to alternative demand specifications. We begin by re-estimating our demand system using more granular county-by-year data from RateWatch in Table A2a where we define the market for deposits at the county level. The data runs from 2002 to 2012, covering 447 of the 847 banks in our main sample. We now include county by time fixed effects in estimating the county-year analog of Eq. (6). The county-by-time fixed effects, absorbing market level characteristics such consumer demographics and competition. In addition, we allow consumers' sensitivity with respect to deposit rates to vary with county demographics such as wages, age, and education. The estimates are very similar to those we find at the aggregate level in Table 2.

We use these estimates in two ways. First, we use the estimates in Table A2a to compute an alternative measure of deposit productivity that is purged of geography.[28] Table A2b displays

[28]We first construct county-by-firm-by-year measures of deposit productivity using our county level demand esti-

our baseline set of tests using this alternative measure of deposit productivity. The results are comparable to our main results. M/B is positively correlated with our alternative measure of deposit productivity, and deposit productivity has a greater impact on M/B than asset productivity. Columns (3) and (4) of Tables A2b indicate that there are also still strong synergies between asset productivity and this alternative measure of deposit productivity.

Second, we examine how the average demand elasticity a bank faces impacts the contribution of deposit productivity to value. Recall from Eq. (11) that, all else equal, deposit productivity is more valuable if a bank faces an inelastic demand curve. We augment Eq. (10) to include the interaction of deposit productivity with the average demand sensitivity faced by a bank ($\bar{\alpha}_{jt}$) across the counties it operates in. Table A2c displays the corresponding estimates. The coefficient on the interaction of deposit productivity and the average deposit rate elasticity is negative and significant, indicating that deposit productivity creates more value when banks face relatively inelastic demand for deposits. The results in column (1) indicate that a one-standard deviation increase in demand elasticity decreases the value of deposit productivity by 25%.

5.1.2 Alternative Production Function Estimates - Spline Estimation

One potential concern with our asset production function estimates is that our empirical specification may not be flexible enough to capture a bank's true production function. Here, we re-estimate the bank's production function, allowing more flexibly for economies of scale. Specifically, we estimate the production function where we use a spline with $K = 5$ knot points

$$\ln Y_{jt} = \theta \ln A_{jt} + \sum_{k=1}^{K-1} (\theta_k \max(\ln A_{jt} - q_k, 0)) + \Gamma X_{jt} + \phi_j + \phi_t + \epsilon_{jt}. \quad (14)$$

The term q_k represents the kth quantile of the distribution of bank asset holdings in the data. We report the alternative production function estimates in the Appendix (Column 1 of Table A8). The results suggest that our baseline specification captures the curvature of a bank's production

mates. Let $\hat{\delta}_{jlt}$ denote the estimated deposit productivity of firm j in county l at time t where

$$\hat{\delta}_{jlt} = \ln N_{lt} s_{jlt} - \hat{\alpha} i_{jt} - \hat{\mu}_{lt}.$$

Since we are subtracting off the county-time effect $\hat{\mu}_{lt}$, $\hat{\delta}_{jlt}$ is purged of geographic effects. We then aggregate the firm's deposit productivity across counties as

$$\delta_{jt} = \ln \left(\sum_{k \in K} N_{kt} exp(\delta_{kjt}) \right)$$

where we denote the set of counties bank j operates as K.

function quite well.

We next replicate our main findings measuring asset productivity using these alternative production function estimates. These findings are reported in Table A3a. Columns (1) and (2) display the relationship between M/B and our alternative measure of asset productivity. Our results remain the same. Both asset and deposit productivity are both positively correlated with M/B, and deposit productivity has a larger impact than asset productivity. Similarly, columns (3) and (4) indicate that there are strong synergies between deposit productivity and our alternative measure of asset productivity.

5.1.3 Alternative Production Function Estimates - Additional Risk Controls

We next re-estimate our bank asset income production function where we control for a bank's asset composition, as well as the Fama and French (1993) factors. We report the alternative production function estimates in the Appendix (Column 2 of Table A8). The production function estimates are comparable to our baseline estimates.

Using our alternative asset productivity estimates, we next replicate our main results. The results of this exercise are documented in Table A3b. The alternative set of results are both qualitatively and quantitatively similar to those in our baseline analysis. Columns (1) and (2) show that our alternative measure of asset productivity is positively associated with M/B, but deposit productivity still has a larger impact. We also find evidence of strong synergies between deposit productivity and our alternative measure of asset productivity as reported in Columns (3) and (4).

5.1.4 Alternative Production Function Estimates - Alternative Output Measures

We measure bank productivity and output on the asset side as a bank's ability to generate risk-adjusted interest income. As a robustness check, we re-estimate our bank asset production function, adjusting interest income for realized losses on loans and securities. Specifically, we re-estimate Eq. (9) where we measure a bank's interest income Y net of loan and lease loss provisions, gains/losses on the sales of loans, leases, and real-estate, and realized gains/losses on securities. We report the alternative production function estimates in the Appendix (Column 3 of Table A8). To some extent, our measures of risk should already help account for these ex-post measures of bank gains/losses in our baseline analysis.

We replicate our main results using our alternative measure of bank output and report the corresponding results in Table A3c. The results indicate that our main findings are robust to this alternative measure of bank output and asset productivity. Consistent with our baseline results, we find that both deposit and asset productivity impact bank value, but deposit productivity has a larger impact. Similarly, we find strong synergies between our measure of deposit productivity and our alternative measure of asset productivity.

5.2 Alternative Measures of Value

In our baseline analysis, we document the relationship between M/B and productivity. In this section, we also verify that our main findings are robust to other measures of bank value, including Tobin's q, profitability, which we measure as return on equity (ROE), and total market capitalization. Tables A4a , A4b, and A4c display the results corresponding to our main specification (Eq. 10) with these alternative value measures.

The estimates displayed in Table A4 show that, consistent with our main results in Section 4, both deposit and asset productivity are positively correlated with these alternative measures of value. In addition, these measures tend to load about twice as much on deposit productivity as on asset productivity. The ROE results in Table A4b are of particular interest. Since M/B can be mechanically decomposed into the product of ROE and the price-earnings ratio, these results imply that our M/B results cannot be explained by correlations between our productivity measures and the components of the price-earnings ratio: expectations of future growth, risk, and returns.

5.3 Measurement Error

Because our productivity measures are estimated, they inherently contain measurement error. This may lead us to overstate the amount of variation in productivity and bias down the relationship between productivity and value. We employ two well-known methods to address measurement error. First, we instrument for our deposit and asset productivity measures using alternative measures of productivity. Second, we construct empirical Bayes estimates of productivity. Our main findings are robust to these alternatives.

5.3.1 Instrumental Variables

We instrument for our measures of deposit and asset productivity using our subcategory measures of productivity. Specifically, we instrument for total deposit productivity using our productivity estimates for savings deposits, small time deposits, and other types of deposits. Similarly, we instrument for total asset productivity using our separate estimates of loan and securities productivity.

As shown in Table 5, our instruments are clearly relevant. Provided that the measurement error in our productivity estimates (assets and deposits) is orthogonal to the subcategory productivity measures, our instrumental variable strategy will correct for any bias caused by measurement error.

Table A5 displays the IV estimates corresponding to our baseline set of results. Consistent with our previous results, we find a positive relationship between deposit productivity and M/B and between asset productivity and M/B (columns 1 and 2). The IV estimates reaffirm our earlier finding that M/B loads more heavily on deposit productivity relative to asset productivity. The IV estimates reported in columns (3) and (4) of Table A5 again indicate there are strong synergies between asset and deposit productivity.

5.3.2 Empirical Bayes Estimation

We construct empirical Bayes estimates of deposit and asset productivity as an additional robustness check. Much of our analysis is focused on the distributions of deposit and asset productivity in the population of banks. If our estimates of productivity suffer from classical measurement error, then the estimated distributions of productivity will overstate the true variance of productivity.[29] As is common in the education and labor literature (e.g., Jacob and Lefgren, 2008; Kane and Staiger, 2008; and Chettty, Friedman, and Rockhoff, 2014), we shrink the estimated distributions of asset and deposit productivity to match the true distribution of asset and deposit productivity.

We examine a bank's average deposit and asset productivity in our sample using the estimated bank fixed effect in Eqs. (6) and (9). We shrink the estimated distribution of fixed effects by the factor λ. Under the assumption that the variance of the estimation error is homoskedastic, the appropriate scaling factor is $\lambda = \frac{F-1-\frac{2}{k-1}}{F}$, where F is the F-test statistic from a joint test of the statistical significance of the fixed effects and k is the number of fixed effects (Cassella, 1992). The estimated shrinkage factors are close to one for both deposit and asset productivity (0.998 and 0.971), which suggests that most of the variation in our productivity estimates is driven by true variation in productivity rather than measurement error.

We replicate Figure 1 using our empirical Bayes estimates of deposit and asset productivity and display the corresponding results in Figure A1. Figure A1 allows us to determine how much of the

[29] For example, suppose our estimates of deposit productivity are unbiased estimates of true deposit productivity $\hat{\delta}_j = \delta_j + \epsilon_j$ and assume that the measurement error is uncorrelated with deposit productivity. The variance of the estimated distribution of productivity is then equal to the true variance of deposit productivity plus the variance of the measurement error, $\sigma^2_{\hat{\delta}} = \sigma^2_{\delta} + \sigma^2_{\epsilon}$. We address this concern by "shrinking" the estimated distribution of productivity by the factor $\frac{\sigma^2_{\delta}}{\sigma^2_{\delta}+\sigma^2_{\epsilon}}$ to account for measurement error. Conceptually, the greater σ^2_{ϵ} is relative to σ^2_{δ}, the more we want to shrink the estimated distribution of productivity.

dispersion in net income across banks can be explained by heterogeneity in terms of deposit and asset productivity. The estimated effects on net income of deposit productivity (red shaded area) and asset productivity (blue shared area) are nearly identical in Figures 1 and A1.

5.4 Sub-sample Analysis

We next run several robustness checks regarding the set of banks in our sample, excluding the largest banks, observations from the financial crisis, and nontraditional banks with business models not centered around deposit taking and lending.

5.4.1 Excluding Large Banks

We start by replicating our main findings after excluding the largest 5% of banks. Specifically, we drop all observations of banks that appear in the top 5% of the sample in terms of assets at any point in time. In total, we drop 41 of the largest banks from the sample. We then replicate our baseline tests using this alternative set of banks in Table A6a. The results are both qualitatively and quantitatively similar to those in our baseline analysis. Columns (1) and (2) show that our alternative measure of asset productivity is positively associated with M/B, but M/B loads more on deposit productivity relative to asset productivity. The results in column (4) suggest that the synergies between asset and deposit productivity may actually be larger for the smaller banks in our sample. Collectively, these results demonstrate that our productivity measures are not simply capturing differences between large banks and small banks such as greater funding subsidies or implicit too-big-to-fail guarantees. In untabulated results, we also drop all observations for the acquiring bank in the year following bank mergers, verifying that our findings are not driven by sharp productivity gains or losses around mergers.

5.4.2 Excluding the Financial Crisis

Although we include time fixed effects in all of our analysis, one may still be concerned that abnormal variation in bank productivity and valuations during the financial crisis could be driving our main results. We replicate our baseline tests excluding 2008 and 2009 in Table A6b. Again, we find that both asset and deposit productivity are both positively correlated with M/B and that deposit productivity has a relatively larger impact on M/B. We also find comparable evidence suggesting that there are strong synergies between asset and deposit productivity.

5.4.3 Excluding Non-traditional Banks

The scope of business activities that bank holding companies engage in has broadened over time. However, the median firm in our sample still generates 90% of its income from interest and deposit fees. Regardless, we separately examine those banks that follow a traditional deposit taking and lending business model. Specifically, in Table A6c, we restrict our sample to bank-quarter observations in which the bank operated at least two branches and generated at least two-thirds of its income from interest. 90% of observations in our data satisfy these restrictions. The results indicate that our main findings hold for the set of traditional banks and are not driven by the growth of the non-traditional banking sector. Among traditional banks we find that while both deposit and asset productivity contribute to value, value loads more heavily on deposit productivity, and that there are strong synergies between deposit and asset productivity (columns 2-4).

6 Conclusion

What are the key determinants of bank value? In this paper, we draw upon the industrial organization literature to develop a simple empirical framework to answer this question. Banks can create value through three primary mechanisms: through excelling at the gathering of deposits, through excelling at the production of loans and other assets, and through synergies between loan and deposit production.

We find evidence that all three channels affect banks' market values and that their contributions vary by bank. Of the three channels, we find that a bank's ability to produce deposits is the most important factor in explaining cross-sectional variation in bank market value. In particular, we find that variation in deposit productivity accounts for about twice as much variation in bank value as variation in asset productivity. Moreover, we find that savings deposit productivity is particularly important for explaining bank value: the liabilities that are most strongly associated with value are not those that provide the most transaction and liquidity services. Under plausible additional assumptions, we reach similar conclusions about the level of bank value: it is primarily driven by deposit productivity. Overall, our paper represents the first attempt to provide evidence on all three sources of potential bank value creation within a unified framework, and to assess which theoretical levers are most important in explaining the cross section of value.

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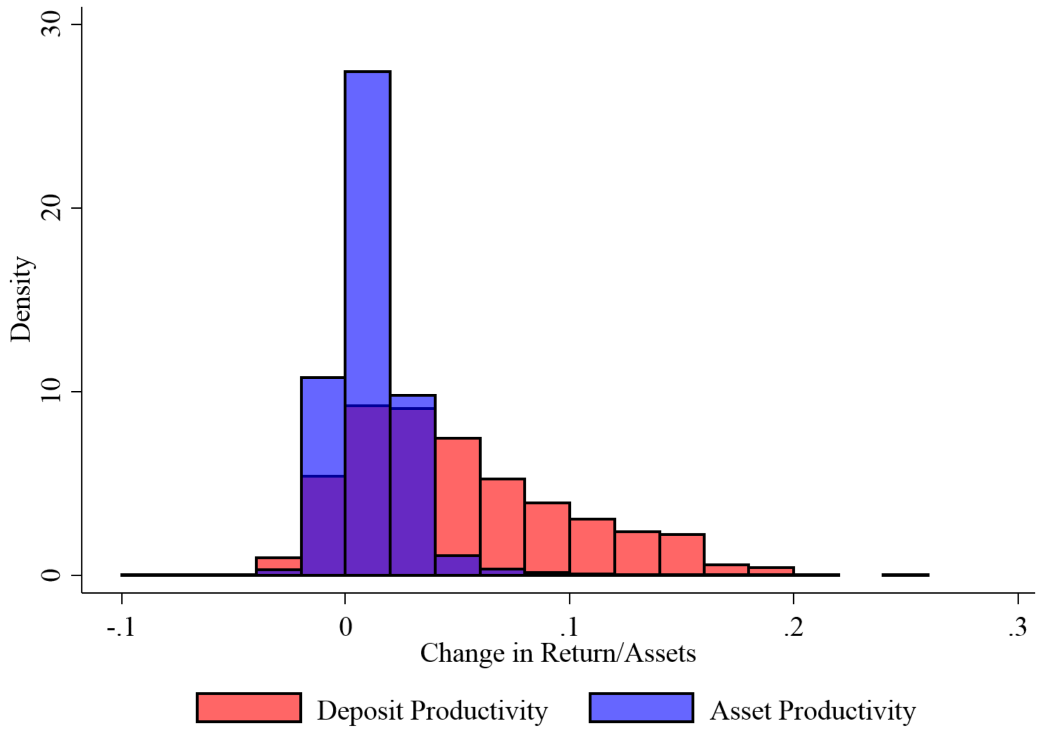
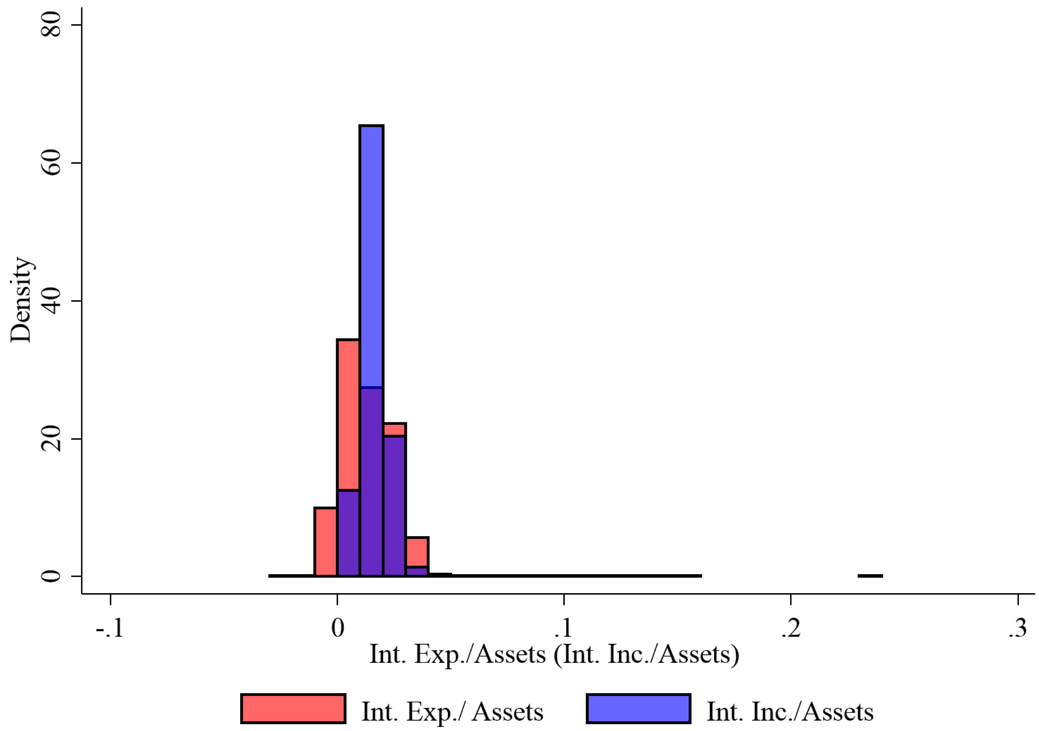
Figures

Figure 1: Value Creation: Asset Productivity vs. Deposit Productivity



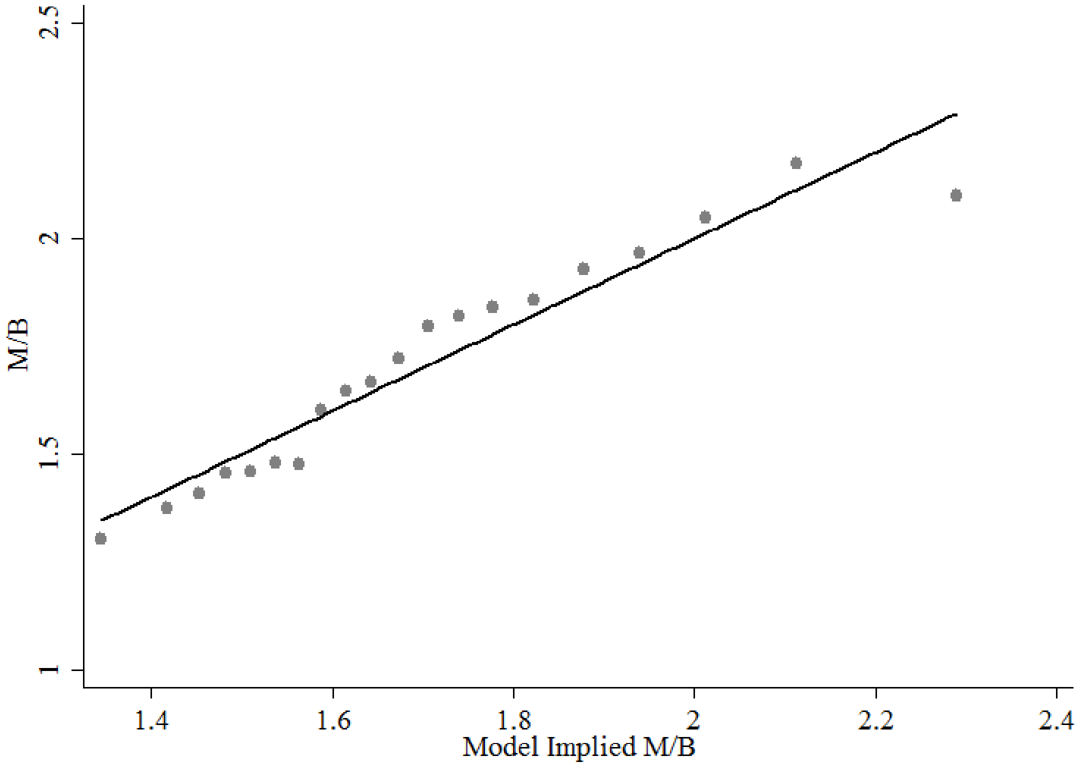
Note: Figure 1 displays the estimated distributions of asset and deposit productivity. The red shaded histogram plots the distribution of bank deposit productivity weighted by $\overline{\frac{Deposits}{Assets}\frac{1}{\alpha}}$. The blue histogram displays the scaled distribution of asset productivity $\frac{\overline{Assets}^{\theta}}{Assets} exp(\phi_{jt} + \overline{\Gamma X_{jt}})$. We normalize the level of asset productivity relative to five year constant maturity treasury rates such that the small set of banks earning risk adjusted returns below the five year treasury rate have negative asset productivity. Similarly, we also normalize the deposit productivity distribution relative to 3-month LIBOR such that the small set of banks that offer deposit rates above 3-month LIBOR have negative deposit productivity. The deposit productivity estimates correspond to the specification reported in column (2) of Table 2. The asset productivity estimates correspond to the specification reported in column (5) of Table 3.

Figure 2: Interest Expense vs Interest Income



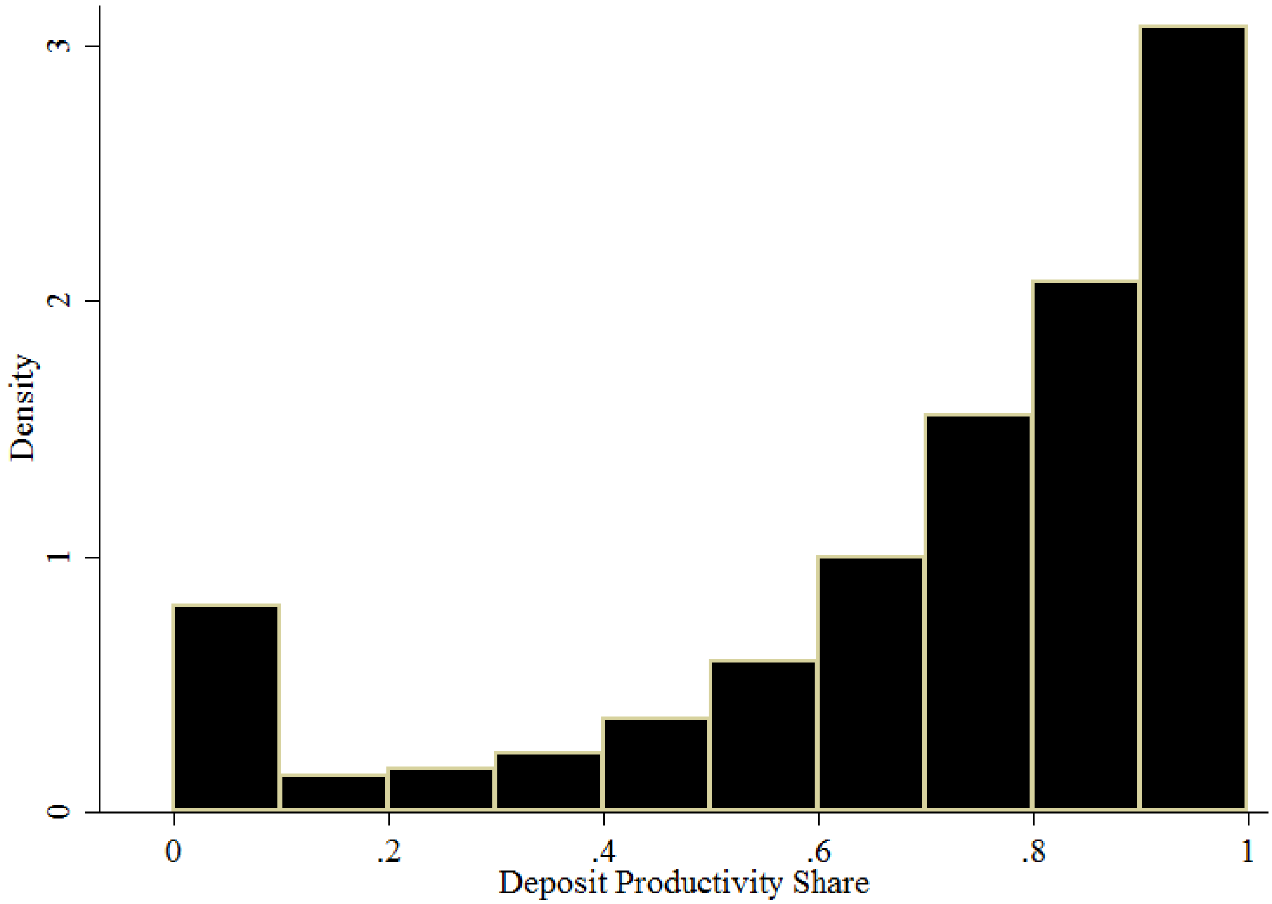
Note: Figure 2 displays the distributions of deposit interest expense and interest income. The red shaded histogram plots the distribution of deposit interest expense divided by assets. The blue shaded histogram plots the distribution of interest income divided by assets. Both deposit interest expense and interest income are annualized (multiplied by 4).

Figure 3: Market-to-Book



Note: Figure 3 displays a binned scatter plot of each bank's market value versus the model implied estimate. The binned scatter plot includes time fixed effects. We calculate the model implied market-to-book as the predicted value from the regression $M/B_{jt} = \beta_0 + \frac{\lambda}{r}\widehat{\varpi_{jt}} + \mu_t + \epsilon_{jt}$. The term $\widehat{\varpi_{jt}}$ measures bank excess per-period returns as a function of its deposit and asset productivity. We estimate $\widehat{\frac{\lambda}{r}} = 4.28$. We calculate $\widehat{\varpi_j} = \left[exp(\hat{\phi}_j)exp(\Gamma \bar{X}_j)\bar{A}_j^{\theta-1} + \overline{Deposits/A} \times \frac{\hat{\delta}_j}{\alpha}\right]$. The deposit productivity estimates $(\hat{\delta})$ correspond to the specification reported in column (2) of Table 2. The asset productivity estimates $(\hat{\phi})$ correspond to the specification reported in column (5) of Table 3.

Figure 4: Deposit Productivity Share



Note: Figure 4 displays the distribution of the deposit value share of each bank. The deposit value share reflects the percentage of bank value that is generated by deposit productivity relative to asset productivity. We censor those observations with negative deposit value shares at zero and those observations with deposit value shares greater than 1 at 1. To construct Figure 4 we normalize the level of asset productivity relative to five year constant maturity treasury rates such that the small set of banks earning risk adjusted returns below the five year treasury rate have negative asset productivity. Similarly, we also normalize the deposit productivity distribution relative to 3-month LIBOR such that the small set of banks that offer deposit rates above 3-month LIBOR have negative deposit productivity. The deposit and asset productivity estimates correspond to the specifications reported in columns (2) of Table 2 and (5) of Table 3.

Tables

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Deposit Int. Expense	26,742	2.18%	1.34%	0.11%	6.53%
Deposit Int. Expense (Net of Fees)	26,742	1.73%	1.36%	-0.46%	6.16%
Non Int. Expense (Millions)	26,742	142.44	517.53	1.27	3,662.00
No. Branches	26,742	119.50	307.73	1.00	2,024.00
No. Employees	26,742	3,456.47	10,511.54	54.00	68,396.00
Assets (Billions)	26,742	26.50	161.00	0.10	2,580.00
Interest Income (Millions)	26,742	281.85	1,524.57	1.50	33,000.00
Deposits (Billions)	26,742	14.20	78.90	0.01	1,370.00
Leverage	26,742	0.91	0.04	0.19	1.02
Beta	26,742	0.63	0.58	-0.66	2.46
Std. Dev. ROA	26,742	0.14%	0.18%	0.01%	0.91%
Market-to-Book	26,742	1.71	0.85	0.18	5.30
Liabilities (Relative to Total Liabilities)					
Deposits	26,742	0.83	0.13	0.00	1.00
Small Time Deposits	26,736	0.20	0.11	0.00	0.68
Large Time Deposits	26,736	0.13	0.08	0.00	0.89
Savings Deposits	24,633	0.34	0.15	0.00	0.89
Transaction Deposits	24,627	0.15	0.10	-0.30	0.81
FF+Repo	18,051	0.04	0.06	0.00	0.69
Assets (Relative to Total Assets)					
Loans	26,742	0.65	0.13	0.00	0.96
RE Loans	24,633	0.46	0.16	0.00	0.91
C&I Loan	23,685	0.11	0.07	0.00	0.58
Loan Commitments	26,742	0.14	0.17	0.00	21.10
Securities	26,713	0.22	0.12	0.00	0.94
Cash	26,732	0.02	0.04	0.00	0.41
FF+Repo	18,047	0.01	0.03	0.00	0.45

Note: Table 1 reports the summary statistics for our sample. Observations are at the bank by quarter level over the period 1994-2015. Deposit interest expense and deposit interest expense net of fees are both annualized (multiplied by 4). The following variables are winsorized at the 1% level: Deposit Int. Expense, Deposit Int. Expense (Net of Fees), Non Int. Expense, No. Branches, No Employees, Assets, Interest Income Deposits, Leverage, Beta, and Std. Dev. ROA.

Table 2: Deposit Demand

	(1)	(2)
Deposit Rate	12.61***	20.88***
	(1.848)	(4.620)
No. Branches (hundreds)	0.0405***	0.0441***
	(0.0093)	(0.0096)
No. Empl (thousands)	0.0271***	0.0278***
	(0.0082)	(0.0084)
Non-Int. Exp. (billions)	-0.0886	-0.120
	(0.101)	(0.104)
Time Fixed Effects	X	X
Bank Fixed Effects	X	X
IV-1		X
IV-2		X
Observations	26,742	26,742
R-squared	0.981	0.981

Note: We report our demand estimates (Eq. 6). In Table 2, we define the market for deposits at the aggregate US by quarter level. The unit of observation is at the bank by quarter level over the period 1994-2015. The key independent variable of interest is the deposit rate offered for each bank. We measure the deposit rate as the bank's total quarterly deposit interest expense net of fees (scaled by 4) divided by the bank's level of deposits. Because of the potential endogeneity of the deposit rate, we instrument for the deposit rate using two sets of instruments. We construct our first instrument (IV-1) as the estimated deposit rate from a bank-specific pass-through regression of deposit rates on 3-month LIBOR. We construct our second instrument (IV-2) as the average of the product characteristics offered by a bank's competitors in the previous quarter (branches, employees, non-interest expense, and fees). Specifically, we calculate the average product characteristics of a bank's competitors in each county the bank operates in in a given year, and we then calculate the average across all counties the bank operates in. We winsorize all independent variables at the 1% level to help control for outliers in the sample. Standard errors are clustered by bank and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Bank Production Function (Asset Income)

	(1)	(2)	(3)	(4)	(5)	(6)
ln A_{kt} (θ)	0.848***	0.845***	0.837***	0.887***	0.885***	0.859***
	(0.0132)	(0.0132)	(0.0144)	(0.0454)	(0.0477)	(0.0504)
Beta		-0.00149	-0.00667		-0.00331	-0.00762
		(0.00496)	(0.00575)		(0.00527)	(0.00605)
Beta (fwd 2 yr)			0.0173***			0.0164***
			(0.00494)			(0.00521)
SD ROA		-0.0275***	-0.0258***		-0.0283***	-0.0261***
		(0.00302)	(0.00338)		(0.00302)	(0.00336)
SD ROA (fwd 2 yr)			0.00295			0.00217
			(0.00292)			(0.00348)
No. Branches (hundreds)		0.0124	0.00927		0.0108	0.00843
		(0.0105)	(0.00976)		(0.0109)	(0.0102)
No. Empl (thousands)		0.00172	0.00233		0.000735	0.00189
		(0.00475)	(0.00459)		(0.00460)	(0.00449)
Non-Int. Exp. (billions)		-0.0639	-0.0308		-0.0613	-0.0301
		(0.0441)	(0.0419)		(0.0422)	(0.0408)
Bank F.E.	X	X	X	X	X	X
Time F.E.	X	X	X	X	X	X
IV				X	X	X
Observations	26,742	26,742	21,289	26,742	26,742	21,289
R-squared	0.992	0.992	0.992	0.992	0.992	0.992

Note: We report our asset income production function estimates (Eq. 9) in Table 3. The unit of observation is at the bank by quarter level over the period 1994-2015. The dependent variable is the logged value of interest income earned by the bank. The key independent variable of interest is the log value of a bank's assets lagged by one year. Because of the potential endogeneity of assets, we instrument for assets in columns (4)-(6). Specifically, we instrument for assets using the weighted average of the deposit product characteristics of a bank 's competitors as described in Section 3.3. We also control for the bank's equity beta, standard deviation of return on assets (standardized), and leverage. We measure beta on a rolling basis using monthly equity returns over the previous 24 months with data from CRSP and Kenneth French. We measure the standard deviation of return on assets on a rolling basis using quarterly income statement/balance sheet data over the previous eight quarters. Standard errors are clustered at the bank level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Market to Book vs. Bank Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Productivity	0.236***	0.496***			0.200***	0.451***
	(0.0188)	(0.101)			(0.0355)	(0.105)
Asset Productivity			0.240***	0.154***	0.0967***	0.113***
			(0.0264)	(0.0276)	(0.0294)	(0.0309)
Time F.E.	X	X	X	X	X	X
Other Controls		X		X		X
Observations	26,742	26,742	26,742	26,742	26,742	26,742
R-squared	0.420	0.453	0.386	0.438	0.425	0.459

Note: Table 4 displays the estimation results corresponding to a linear regression model (Eq.10). The dependent variable is the bank's market-to-book ratio. The key independent variables of interest are deposit and asset productivity. Both deposit and asset productivity are standardized. The deposit productivity estimates correspond to the specification reported in column (2) of Table 2. The asset productivity estimates correspond to the specification reported in column (5) of Table 3. The unit of observation is at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Deposit and Asset Productivity Subcategories

Dep. Var	Deposit Productivity		Asset Productivity		Market to Book	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Prod.:						
Savings	0.734***	0.628***			0.237***	0.344***
	(0.0490)	(0.0616)			(0.0419)	(0.0751)
Small Time	0.125***	0.0945***			-0.242***	-0.194***
	(0.0338)	(0.0252)			(0.0461)	(0.0601)
Large Time	0.179***	0.156***			0.0257	0.0602**
	(0.0289)	(0.0171)			(0.0290)	(0.0294)
Transaction	0.414***	0.371***			0.0626*	0.102***
	(0.0342)	(0.0295)			(0.0337)	(0.0358)
Asset Prod.:						
Loans			0.163***	0.149***	0.115***	0.110***
			(0.0294)	(0.0227)	(0.0274)	(0.0319)
Securities			0.0364	0.00783	0.0608***	0.0788***
			(0.0275)	(0.0116)	(0.0230)	(0.0237)
Time F.E.	X	X	X	X	X	X
Other Controls		X		X		X
Observations	22,345	22,345	18,323	18,323	16,724	16,724
R-squared	0.979	0.981	0.666	0.684	0.466	0.497

Note: Table 5 displays the relationship between our more refined measures of productivity, overall productivity, and market-to-book. Overall deposit productivity is the dependent variable columns (1) and (2) and is standardized. We measure overall deposit productivity using the demand estimates reported in column (2) of Table 2. Overall asset productivity is the dependent variable columns (3) and (4) and is standardized. We measure overall asset productivity using the production function estimates reported in column (5) of Table 3. Market-to-book is the dependent variable in columns (5) and (6). We measure deposit productivity for savings deposits, small time deposits, large deposits, and transaction deposits using the corresponding demand estimates reported in Table A1a. We measure asset productivity for loans and savings deposits using the corresponding production function estimates reported in Table A1b. These subcategory measures of deposit and asset productivity are standardized. Observations are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), 3-month returns (lagged by one quarter), equity beta, and sd of roa. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Productivity vs. Composition of Assets and Liabilities

(a) Composition of Liabilities and Deposit Productivity

Dep. Var	Leverage	$\frac{\text{Deposits}}{\text{Liabilities}}$	$\frac{\text{Small Time}}{\text{Liabilities}}$	$\frac{\text{Large Time}}{\text{Liabilities}}$	$\frac{\text{Savings}}{\text{Liabilities}}$	$\frac{\text{Trans.}}{\text{Liabilities}}$	$\frac{\text{FF+Repo}}{\text{Liabilities}}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deposit Prod.	0.0225***	1.773***	-0.347*	0.137	1.354***	0.432**	-0.320
	(0.00843)	(0.255)	(0.186)	(0.146)	(0.199)	(0.177)	(0.290)
Time F.E.	X	X	X	X	X	X	X
Other Controls	X	X	X	X	X	X	X
Observations	26,742	26,742	26,736	26,736	24,633	24,627	18,051
R-squared	0.969	0.558	0.376	0.160	0.383	0.232	0.142

(b) Composition of Assets and Asset Productivity

Dep. Var	$\frac{\text{RE Loans}}{\text{Assets}}$	$\frac{\text{C\&I Loan}}{\text{Assets}}$	$\frac{\text{Loan Commit.}}{\text{Assets}}$	$\frac{\text{Securities}}{\text{Assets}}$	$\frac{\text{Cash}}{\text{Assets}}$	$\frac{\text{FF+Repo}}{\text{Assets}}$
	(1)	(2)	(3)	(4)	(5)	(6)
Asset Prod.	0.319***	0.134***	0.0805**	-0.460***	-0.308***	-0.248**
	(0.0427)	(0.0438)	(0.0378)	(0.0678)	(0.0315)	(0.0985)
Time F.E.	X	X	X	X	X	X
Other Controls	X	X	X	X	X	X
Observations	24,633	23,685	26,742	26,713	26,732	18,047
R-squared	0.346	0.054	0.133	0.145	0.226	0.106

Note: Table 6 panels (a) and (b) display the relationship between a bank's productivity and its liability and asset structure. In Table 6a, we regress bank leverage and the composition of its deposits on deposit productivity. We measure deposit productivity using the demand estimates reported in column (2) of Table 2. In Table 6b, we regress the composition of a bank's assets on asset productivity. We measure asset productivity using the estimates reported in column (5) of Table 3. Observations in both Tables 6a and 6b are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Demographic Characteristics

(a) Productivity and Demographic Characteristics

Dep. Var.	Asset Productivity		Deposit Productivity	
	(1)	(2)	(3)	(4)
ln(Population)	0.244***	0.208***	0.593***	0.351***
	(0.0347)	(0.0100)	(0.0558)	(0.00889)
ln(Population)^2	-0.0457***	-0.00952**	-0.119***	-0.0366***
	(0.0158)	(0.00461)	(0.0244)	(0.00408)
ln(Wage)	-0.194***	-0.149***	-0.163**	0.00630
	(0.0505)	(0.0132)	(0.0753)	(0.0118)
ln(Wage)^2	-0.0522*	-0.0372***	0.0241	0.00665*
	(0.0280)	(0.00391)	(0.0237)	(0.00344)
ln(Branch Age)	-0.00132	-0.0938***	0.383***	0.138***
	(0.0259)	(0.00501)	(0.0371)	(0.00448)
ln(House Prices)	0.141***	0.0849***	0.103	0.0198**
	(0.0459)	(0.00866)	(0.0661)	(0.00770)
HMDA HHI	0.108***	0.0701***		
	(0.0246)	(0.00748)		
Deposit HHI			0.177***	0.0744***
			(0.0334)	(0.00500)
			(0.0352)	(0.0250)
Time F.E.	X	X	X	X
MSA F.E.		X		X
Observations	23,617	23,617	23,617	23,617
R-squared	0.547	0.705	0.330	0.773

(b) Controlling for Geography

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.330***	0.506***	0.417**	0.654**
	(0.0607)	(0.108)	(0.178)	(0.323)
Asset Productivity	0.171***	0.169***		
	(0.0389)	(0.0382)		
Time F.E.	X	X	X	X
MSA F.E.	X	X	X	X
Demographic Controls	X	X	X	X
Other Controls		X		X
Observations	23,617	23,617	23,617	23,617
R-squared	0.608	0.628	0.748	0.756

Note: In Table 7a we show how deposit and asset productivity correlate with the geographic characteristics of areas where banks operate. In Table 7b, we replicate our baseline set of results controlling for fixed effects for each MSA a bank operates in. We measure deposit and asset productivity using the estimates reported in columns (2) of Table 2 and (5) of Table 3. Observations are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. Standard errors in panel (a) are clustered at the bank level and are reported in parentheses. The demographic controls used in panel (b) are the same variables shown in panel (a). The standard errors in panel (b) are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure for the independent variables. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Productivity and Quality

	Deposit Productivity		Asset Productivity	
	(1)	(2)	(3)	(4)
CFPB Complaints	-0.274**	-0.0961***	0.0627	-0.0148
	(0.108)	(0.0247)	(0.172)	(0.152)
Time F.E.	X	X	X	X
Other Controls		X		X
Observations	222	222	222	222
R-squared	0.100	0.923	0.036	0.195

Note: Tables 8 displays the relationship between productivity and the quality of services a bank offers. The dependent variable in columns (1) and (2) is deposit productivity and the dependent variable columns (3) and (4) is asset productivity. We measure deposit and asset productivity using the estimates reported in columns (2) of Table 2 and (5) of Table 3.. The key independent variable of interest is CFPB Complaints. CFPB Complaints measures the number of complaints a bank receives in a given year per dollar of deposits collected and is standardized. Observations are at the bank by year level. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. Standard errors are clustered at the bank level and are reported in parentheses. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Productivity and Rate Setting Technology

Dep. Var	Deposit Productivity		Asset Productivity	
	(1)	(2)	(3)	(4)
Variation in Deposit Rates (σ_{CD})	0.237***	0.0299**		
	(0.0359)	(0.0131)		
Variation in Mortgage Rates (σ_{MTG})			0.132***	0.0215
			(0.0465)	(0.0193)
Time F.E.	X	X	X	X
Other Controls		X		X
Observations	3,141	3,141	1,282	1,282
R-squared	0.059	0.910	0.368	0.633

Note: Table 9 displays the relationship between productivity and the variation in rates set by banks. Each column corresponds to a separate linear regression. The dependent variable in columns (1)-(2) is deposit productivity as measured using the demand estimates reported in column (2) of Table 2. The dependent variable in columns (3)-(4) is asset productivity as measured using the production function estimates reported in column (5) of Table 3. The independent variables Variation in Deposit Rates and Variation in Mortgage Rates are standardized and measure the standard deviation of deposit and mortgage rates offered by a bank across the counties it operates in a given year. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Deposit and Asset Synergies

(a) Market to Book and Synergies

	(1)	(2)
Deposit Productivity	0.198***	0.501***
	(0.0355)	(0.114)
Asset Productivity	0.0817***	0.0882***
	(0.0292)	(0.0306)
Deposit Productivity × Asset Productivity	0.0349*	0.0536***
	(0.0181)	(0.0155)
Time F.E.	X	X
Other Controls		X
Observations	26,742	26,742
R-squared	0.427	0.464

Note: Table 10a displays the estimation results corresponding to Eq. (12). The dependent variable is the bank's market-to-book ratio. The key independent variables of interest are deposit and asset productivity. Both deposit and asset productivity are standardized. The deposit productivity estimates correspond to the specification reported in column (2) of Table 2. The asset productivity estimates correspond to the specification reported in column (5) of Table 3. Observations are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Deposit and Asset Synergies (Continued)

(b) Deposit vs. Asset Productivity

Dep. Var	Asset Productivity		Loan Productivity		Sec. Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Productivity	0.368***	0.404**	0.436***	0.500	0.633***	0.326
	(0.121)	(0.188)	(0.121)	(0.414)	(0.0589)	(0.204)
Time F.E.	X	X	X	X	X	X
Other Controls		X		X		X
Observations	26,742	26,742	18,360	18,360	19,467	19,467
R-squared	0.639	0.650	0.364	0.380	0.573	0.582

(c) Deposit vs. Asset Productivity - Subcategory Measures

Dep. Var	Asset Productivity		Loan Productivity		Sec. Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Prod.:						
Savings	0.164**	0.264***	0.162	0.291*	0.403***	0.158
	(0.0713)	(0.0751)	(0.101)	(0.160)	(0.0549)	(0.0974)
Small Time	0.167***	0.186***	0.274***	0.316***	0.0934**	0.0184
	(0.0549)	(0.0687)	(0.0758)	(0.114)	(0.0460)	(0.0577)
Large Time	0.136***	0.132**	0.132**	0.156*	0.105***	0.0573
	(0.0469)	(0.0581)	(0.0603)	(0.0894)	(0.0373)	(0.0452)
Transaction	-0.0220	0.0220	-0.0535	-0.0111	0.0666*	-0.0180
	(0.0439)	(0.0381)	(0.0563)	(0.0723)	(0.0396)	(0.0489)
Time F.E.	X	X	X	X	X	X
Other Controls		X		X		X
Observations	22,345	22,345	16,753	16,753	17,269	17,269
R-squared	0.657	0.673	0.552	0.565	0.556	0.575

Note: Tables 10b and 10c display the relationship between deposit productivity and asset productivity (Eq. 13). Each column corresponds to a separate linear regression. All independent and dependent variables are standardized. The dependent variable in columns (1)-(2) is overall productivity as measured using the production function estimates reported in column (5) of Table 3. The dependent variable in columns (3)-(4) is loan productivity as measured using the production function estimates reported in column (1) of Table A1b. The dependent variable in columns (5)-(6) is securities productivity as measured using the production function estimates reported in column (2) of Table A1b. The key independent variable of interest is deposit productivity. We measure overall deposit productivity using the demand estimates reported in column (2) of Table 2 and deposit productivity for each type of deposit using the demand estimates reported in Table A1a. Observations are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Productivity vs. Composition of Assets and Liabilities

(a) Composition of Assets and Deposit Productivity

Dep. Var	$\frac{\text{RE Loans}}{\text{Assets}}$ (1)	$\frac{\text{C\&I Loan}}{\text{Assets}}$ (2)	$\frac{\text{Loan Commit.}}{\text{Assets}}$ (3)	$\frac{\text{Securities}}{\text{Assets}}$ (4)	$\frac{\text{Cash}}{\text{Assets}}$ (5)	$\frac{\text{FF+Repo}}{\text{Assets}}$ (6)
Deposit Prod.	0.165	0.705***	0.255**	-0.0280	-0.131*	-0.665**
	(0.141)	(0.146)	(0.119)	(0.167)	(0.0785)	(0.276)
Time F.E.	X	X	X	X	X	X
Other Controls	X	X	X	X	X	X
Observations	24,633	23,685	26,742	26,713	26,732	18,047
R-squared	0.314	0.090	0.136	0.068	0.193	0.123

(b) Composition of Liabilities and Asset Productivity

Dep. Var	Leverage (1)	$\frac{\text{Deposits}}{\text{Liabilities}}$ (2)	$\frac{\text{Small Time}}{\text{Liabilities}}$ (3)	$\frac{\text{Large Time}}{\text{Liabilities}}$ (4)	$\frac{\text{Savings}}{\text{Liabilities}}$ (5)	$\frac{\text{Trans.}}{\text{Liabilities}}$ (6)	$\frac{\text{FF+Repo}}{\text{Liabilities}}$ (7)
Asset Prod.	0.00305	0.118***	0.0899**	0.293***	0.00414	-0.192***	-0.104
	(0.00447)	(0.0410)	(0.0383)	(0.0374)	(0.0453)	(0.0462)	(0.0673)
Time F.E.	X	X	X	X	X	X	X
Other Controls	X	X	X	X	X	X	X
Observations	26,742	26,742	26,736	26,736	24,633	24,627	18,051
R-squared	0.969	0.282	0.369	0.190	0.232	0.229	0.137

Note: Table 11 (a) and (b) display the relationship between productivity and a bank's liability and asset structure. In Table 11a, we regress the composition of a bank's assets on deposit productivity. We measure deposit productivity using the demand estimates reported in column (2) of Table 2. In Table 11a, we regress bank leverage and the composition of its deposits on asset productivity. We measure asset productivity using the estimates reported in column (5) of Table 3. Observations in both Tables 11a and 11b are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. The symbols *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Online Appendix – Estimation Procedure for Figure 3

As discussed in Section 2, our two productivity measures directly affect bank cash flows. For example, if a bank's ability to collect deposits increases from δ^0 to δ^1, the bank can offer a lower deposit rate and still collect the same amount of deposits. The cost savings of increasing deposit productivity are given by

$$Cost\,Savings = Deposits \times \frac{\Delta\delta}{\alpha} \tag{15}$$

where α is the elasticity of demand for deposits. Similarly, if a bank's ability to invest assets and make loans increases from ϕ^0 to ϕ^1, its returns increase by

$$\Delta Y = \left[exp(\phi^1) - exp(\phi^0)\right] exp(\Gamma X_j) A_j^{\theta}. \tag{16}$$

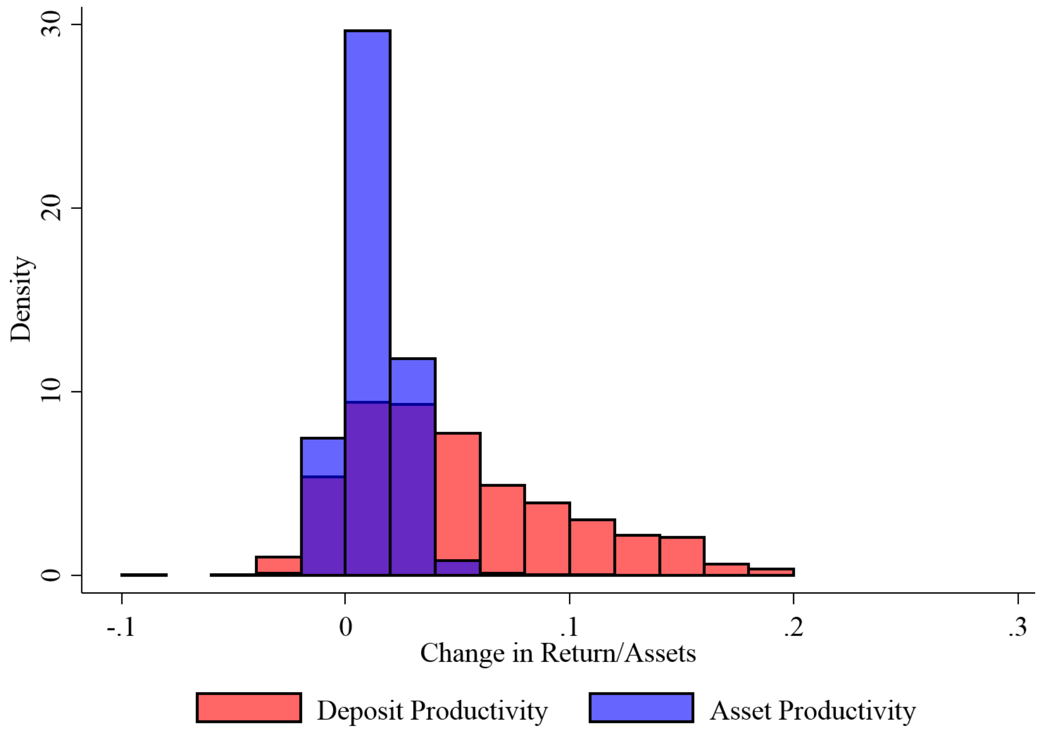
Variation in a bank's ability to collect and invest deposits translates directly into bank value. Assuming a fixed payout ratio λ, discount rate r, and growth rate g, and keeping size fixed, we can write a bank's market-to-book as a function of its deposit and asset productivity plus some constant C.

$$\begin{aligned}\frac{M}{B} &= \frac{\lambda}{r-g}\left[\frac{exp(\phi_j)exp(\Gamma X_j)A_j^{\theta} + Deposits \times \frac{\delta_j}{\alpha}}{A}\right] + C \\ &= \frac{\lambda}{r-g}\varpi_j + C\end{aligned}$$

where the term ϖ_j measures the variation in bank profitability attributable to variation in asset and deposit productivity. We use the model estimates of $\hat{\phi}$ and $\hat{\delta}$ to calculate the model implied market-to-book. Specifically, we calculate the term $\widehat{\varpi_j} = \left[exp(\hat{\phi}_j)\frac{exp(\Gamma \bar{X}_j)\bar{A}_j^{\theta}}{\bar{A}} + \frac{\overline{Deposits}}{A} \times \frac{\hat{\delta}_j}{\alpha}\right]$ for each bank, keeping size fixed. We then regress a bank's market-to-book on the term $\widehat{\varpi_j}$ and time fixed effects in order to recover an estimate of $\widehat{\frac{\lambda}{r-g}}$. We estimate a positive and statistically significant coefficient (p<0.01) of $\widehat{\frac{\lambda}{r-g}} = 4.28$. Assuming a fixed payout ratio of $\lambda = 28\%$ based on historical averages, the estimate of $\widehat{\frac{\lambda}{r-g}}$ implies an $r - g$ value of 6.5%, which is consistent with an average cost of equity of 8-9% (King, 2009) and an average growth rate of 1.5-2.5%. Hence, the estimates from our simple quantitative framework seem to match the observed M/B data quite well.

Online Appendix – Figures and Tables

Figure A1: Value Creation: Asset Productivity vs. Deposit Productivity



Note: Figure A1 displays the distributions of our empirical Bayes estimates of asset and deposit productivity as discussed in Section 5.3.2. Specifically, we "shrink" the estimated distribution of asset and deposit productivity to account for measurement error. The red shaded histogram plots the distribution of our empirical Bayes estimates of bank deposit productivity weighted by $\frac{\overline{Deposits}}{Assets}\frac{1}{\alpha}$. The blue histogram displays the distribution of our empirical Bayes estimates of asset productivity $\frac{\overline{Assets}^{\theta}}{Assets}exp(\phi_{jt}+\overline{\Gamma X_{jt}})$. We normalize the level of asset productivity relative to five year constant maturity treasury rates such that the small set of banks earning risk adjusted returns below the five year treasury rate have negative asset productivity. Similarly, we also normalize the deposit productivity distribution relative to 3-month LIBOR such that the small set of banks that offer deposit rates above 3-month LIBOR have negative deposit productivity. The deposit productivity estimates correspond to the specification reported in column (2) of Table 2. The asset productivity estimates correspond to the specification reported in column (5) of Table 3.

Table A1: Refined Demand and Production Function Estimates

(a) Demand for Deposits by Type of Deposit

	Deposit Type			
	Savings	Small Time	Large Time	Transaction
	(1)	(2)	(3)	(4)
Deposit Rate	-9.594	63.17***	75.39***	-1.188
	(12.73)	(23.21)	(18.25)	(12.51)
No. Branches (hundreds)	0.0825***	0.113***	0.0265	0.0142
	(0.0211)	(0.0412)	(0.0263)	(0.0143)
No. Empl (thousands)	0.00932	0.0241	0.0479***	0.0377***
	(0.0102)	(0.0185)	(0.0135)	(0.0104)
Non-Int. Exp. (billions)	-0.192	-0.920***	-0.656***	0.0724
	(0.154)	(0.347)	(0.247)	(0.0881)
Time Fixed Effects	X	X	X	X
Bank Fixed Effects	X	X	X	X
IV	X	X	X	X
Observations	24,609	24,500	24,556	22,345
R-squared	0.970	0.868	0.809	0.941

(b) Bank Production Function by Asset Type

	Asset Type	
	Loans	Securities
	(1)	(2)
ln(Loans$_{kt}$) (θ_L)	0.837***	
	(0.0203)	
ln(Securities$_{kt}$) (θ_S)		0.748***
		(0.0215)
Beta	-0.0101	-0.00335
	(0.00618)	(0.0104)
SD ROA	-0.0303***	-0.0226***
	(0.00375)	(0.00703)
Bank F.E.	X	X
Time F.E.	X	X
Observations	18,360	19,467
R-squared	0.989	0.978

Note: Table A1a reports our baseline demand estimates for each type of deposit. The key independent variable of interest is the deposit rate offered for each bank. Because of the potential endogeneity of the deposit rate, we instrument for the deposit rate using two sets of instruments. We construct our first instrument (IV-1) as the estimated deposit rate from a bank-specific pass-through regression of deposit rates on 3-month LIBOR. We construct our second instrument (IV-2) as the average of the product characteristics offered by a bank's competitors in the previous quarter (branches, employees, non-interest expense, and fees). Specifically, we calculate the average product characteristics of a bank's competitors in each county the bank operates in a given year, and then we calculate the average across all counties the bank operates in. We winsorize all independent variables at the 1% to help control for outliers in the sample. Standard errors are clustered by bank and are reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
Table A1b reports our asset production function estimates for loans and securities. The unit of observation is at the bank by quarter level over the period 1994-2015. The dependent variable in column (1) (column 2) is the logged value of loan (securities) interest income earned by the bank. The key independent variable of interest in column (1) (column 2) is the log value of the bank loans (securities) lagged by one year. We also control for the bank's equity beta, standard deviation of return on assets (standardized), and leverage. We measure beta on a rolling basis using monthly equity returns over the previous 24 months with data provided by CRSP and Kenneth French. We measure the standard deviation of return on assets on a rolling basis using quarterly income statement/balance sheet data over the previous eight quarters. Standard errors are clustered at the bank level and are reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A2: Alternative Demand Estimates

(a) County Level Demand Estimates

	(1)	(2)	(3)
Deposit Rate	20.33	18.19**	21.02**
	(13.59)	(8.213)	(8.812)
Deposit Rate × Avg. Weekly Wage			11.78***
			(2.353)
Deposit Rate × Pct College			-10.87***
			(1.762)
Deposit Rate × Pct Over 65			6.013***
			(1.916)
No. of Branches (County Level)		1.257***	1.256***
		(0.0272)	(0.0269)
County×Year Fixed Effects	X	X	X
Bank Fixed Effects	X	X	X
IV	X	X	X
Observations	260,881	260,881	254,662
R-squared	0.659	0.779	0.777

(b) Alternative Demand Estimates - County Level Demand

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.123***	0.138***	0.441***	0.212***
	(0.0323)	(0.0387)	(0.0383)	(0.0416)
Asset Productivity	0.0785**	0.0806**		
	(0.0345)	(0.0368)		
Time F.E.	X	X	X	X
Other Controls		X		X
Observations	3,045	3,045	3,045	3,045
R-squared	0.436	0.487	0.499	0.525

Table A2: Alternative Demand Estimates (Continued)

(c) Market to Book and Average Elasticity

	(1)	(2)
Deposit Productivity	0.129***	0.154***
	(0.0332)	(0.0392)
Deposit Productivity × Deposit Rate Sensitivity	-0.0606***	-0.0617***
	(0.0203)	(0.0192)
Deposit Rate Sensitivity	-0.0185	-0.0101
	(0.0274)	(0.0259)
Asset Productivity	0.0782**	0.0830**
	(0.0346)	(0.0372)
Time F.E.	X	X
Other Controls		X
Observations	3,045	3,045
R-squared	0.441	0.492

Note: We report our demand estimates (Eq. 6) in Table A2a where we define the market for deposits at the county by year level. The unit of observation is at the bank by county by year level over the period 2002-2012. We instrument for the deposit rate using the estimated deposit rate from a bank by county specific pass-through regression of deposit rates on 3-month LIBOR. We winsorize all independent variables at the 1% to help control for outliers in the sample.

In Table A2b, we replicate our baseline set of results using our alternative measure of deposit productivity. We measure deposit productivity using the demand estimates reported in column (3) of Table A2a. The asset productivity estimates correspond to the specification reported in column (5) of Table 3.

Table A2c displays the relationship between a bank's market to book ratio and productivity (Eq. 10). The key independent variable of interest is the interaction between Deposit Productivity and Deposit Rate Sensitivity. Deposit Rate Sensitivity is standardized and measures the average deposit rate demand sensitivity $\bar{\alpha}_{jt}$ faced bank j in year t as per the demand estimates reported in column (3) of Table A2a. Observations in Tables A2b and A2c are at the bank by year level over the period 2002-2012. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. Standard errors are clustered at the bank level and are reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A3: Alternative Asset Production Fuction Estimates

(a) Alternative Production Function Estimates - Spline

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.233***	0.329***	0.543***	0.511**
	(0.0315)	(0.128)	(0.0507)	(0.238)
Asset Productivity	0.0467	0.131***		
	(0.0326)	(0.0350)		
Time F.E.	X	X	X	X
Other Controls		X		X
Observations	21,362	21,362	21,362	21,362
R-squared	0.414	0.455	0.664	0.708

(b) Alternative Production Function Estimates - Asset Composition

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.193***	0.467***	0.383**	0.421**
	(0.0518)	(0.117)	(0.161)	(0.203)
Asset Productivity	0.169***	0.166***		
	(0.0394)	(0.0437)		
Time F.E.	X	X	X	X
Other Controls		X		X
Observations	18,564	18,564	18,564	18,564
R-squared	0.436	0.468	0.703	0.708

(c) Alternative Production Function Estimates - Alt. Measure of Income

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.170***	0.449***	0.556***	0.394**
	(0.0300)	(0.103)	(0.115)	(0.167)
Asset Productivity	0.118***	0.129***		
	(0.0189)	(0.0204)		
Time F.E.	X	X	X	X
Other Controls		X		X
Observations	18,564	18,564	18,564	18,564
R-squared	0.436	0.468	0.703	0.708

Note: In Tables A3a, A3b, and A3c, we replicate our baseline set of results using our alternative measures of asset productivity. To construct the measure of asset productivity reported In Table A3a, we estimate the bank's asset income production function using a spline with five knot points as discussed in Section 5.1.2. To construct the measure of asset productivity reported In Table A3b, we estimate the bank's asset income production function where we control for the Fama French risk factors and the proportion of a bank's assets held in both loans and securities (both lagged by one year). To construct the measure of asset productivy reported in Table A3c, we estimate a bank's asset income production function where we measure a bank's output as interest income net of realized gains/losses on its securities and loan portfolios as described in Section 5.1.4. We measure deposit productivity using the demand estimates reported in column (2) of Table 2. Observations in Tables A3a, A3b, and A3c are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Alternative Measures of Value

(a) Tobin's q

	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Productivity	0.232***	0.527***			0.244***	0.515***
	(0.0228)	(0.108)			(0.0306)	(0.116)
Asset Productivity			0.141***	0.0772***	-0.0329	0.0309
			(0.0303)	(0.0299)	(0.0376)	(0.0379)
Time F.E.	X	X	X	X	X	X
Other Controls		X		X		X
Observations	26,742	26,742	26,742	26,742	26,742	26,742
R-squared	0.388	0.462	0.346	0.442	0.388	0.462

(b) Return on Equity

	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Productivity	0.113***	0.313***			0.0726***	0.264***
	(0.0129)	(0.0795)			(0.0257)	(0.0907)
Asset Productivity			0.161***	0.151***	0.110***	0.128***
			(0.0208)	(0.0217)	(0.0234)	(0.0256)
Time F.E.	X	X	X	X	X	X
Other Controls		X		X		X
Observations	26,742	26,742	26,742	26,742	26,742	26,742
R-squared	0.194	0.223	0.195	0.223	0.198	0.228

(c) ln(Market Cap)

	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Productivity	1.718***	0.590***			1.690***	0.507***
	(0.0564)	(0.0941)			(0.0637)	(0.0943)
Asset Productivity			1.284***	0.252***	0.0784	0.206***
			(0.225)	(0.0233)	(0.0795)	(0.0236)
Time F.E.	X	X	X	X	X	X
Other Controls		X		X		X
Observations	26,742	26,742	26,742	26,742	26,742	26,742
R-squared	0.863	0.945	0.275	0.944	0.864	0.950

Note: In Tables A4a, A4b and A4c, we replicate our baseline set of results from eq. (10) using alternative measures of bank value and return. The dependent variable in Table A4a is Tobin's q, the dependent variable in Table A4b is the bank's return on equity (ROE), and the dependent variable in Table A4c is ln(Market Cap). We calculate Tobin's q as equity market capitalization plus book value of liabilities divided by its book value of assets. Tobin's q, ROE, and ln(Market Cap) are standardized. The key independent variables of interest are deposit and asset productivity. Both deposit and asset productivity are standardized. The deposit productivity estimates correspond to the specification reported in column (2) of Table 2. The asset productivity estimates correspond to the specification reported in column (5) of Table 3. The unit of observation is at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), and equity beta. We also control for standard deviation of return on assets in Table A4a and A4c. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Measurement Error - Instrumental Variables

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.184***	0.508***	0.393***	0.533***
	(0.0331)	(0.106)	(0.0265)	(0.130)
Asset Productivity	0.0692	0.0933**		
	(0.0461)	(0.0458)		
Time F.E.	X	X	X	X
Other Controls		X		X
IV	X	X	X	X
Observations	16,724	16,724	22,345	22,345
R-squared	0.428	0.470	0.633	0.646

Note: In Table A5, we replicate our baseline set of results using instrumental variables to address potential measurement error issues. Specifically, we instrument for deposit productivity using the subcategory deposit productivity measures that we construct from the estimates reported in Table A1a. Similarly, we instrument for asset productivity using the subcategory asset productivity that we construct from the estimates reported in Table A1b. We measure deposit and asset productivity using the estimates reported in columns (2) of Table 2 and (5) of Table 3.. Observations are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. Standard errors are clustered at the bank level and are reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A6: Subsample Analysis

(a) Subsample Analysis - Excluding the Largest Banks

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.218***	0.458***	0.378***	0.973***
	(0.0350)	(0.115)	(0.116)	(0.251)
Asset Productivity	0.103***	0.112***		
	(0.0294)	(0.0337)		
Time F.E.	X	X	X	X
Other Controls		X		X
IV	X	X	X	X
Observations	24,881	24,881	24,881	24,881
R-squared	0.427	0.459	0.655	0.686

(b) Subsample Analysis - Excluding the Financial Crisis

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.205***	0.463***	0.370***	0.416**
	(0.0374)	(0.105)	(0.121)	(0.189)
Asset Productivity	0.117***	0.127***		
	(0.0299)	(0.0311)		
Time F.E.	X	X	X	X
Other Controls		X		X
Observations	24,211	24,211	24,211	24,211
R-squared	0.403	0.433	0.650	0.659

(c) Subsample Analysis - Traditional Banks

Dep. Var.	Market-to-Book		Asset Productivity	
	(1)	(2)	(3)	(4)
Deposit Productivity	0.156***	0.761***	0.425***	0.568***
	(0.0355)	(0.105)	(0.121)	(0.188)
Asset Productivity	0.204***	0.199***		
	(0.0294)	(0.0309)		
Time F.E.	X	X	X	X
Other Controls		X		X
Observations	23,942	23,942	23,942	23,942
R-squared	0.467	0.534	0.706	0.710

Note: In Tables A6a, A6b, and A6c we replicate our baseline set of results using different subsets of the data. In Table A6a, we replicate our baseline set of results where we exclude the largest banks from our sample. Specifically, we drop all observations of those banks that appear among the top 5% of the sample in terms of assets at any point in time. In Table A6a, we replicate our baseline set of results where we exclude all observations from the years surrounding the financial crisis (years 2008 and 2009). In Table A6c we replicate our baseline set of results where we restrict our data set to those banks who follow a traditional deposit taking and lending business model. Specifically, we restrict the data set to those observations in which a bank has at least two branches and generates roughly 2/3s (90% of obs.) of its income in the form of interest income. We measure deposit and asset productivity using the estimates reported in columns (2) of Table 2 and (5) of Table 3.. Observations are at the bank by quarter level over the period 1994-2015. Other controls include assets (lagged by one year), leverage (lagged by one quarter), three-month returns (lagged by one quarter), equity beta, and the standard deviation of return on assets. The standard errors are reported in parentheses and are cluster bootstrapped at the bank level (n=1,000) to account for the two stage estimation procedure. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A7: Alternative Deposit Demand Estimates - Extended Data Set

	(1)	(2)	(3)	(4)
Deposit Rate	13.66***	8.943**	48.25***	19.67***
	(1.721)	(4.363)	(9.091)	(4.664)
No. Branches (hundreds)	0.0330***	0.0328***	0.0338***	0.0320***
	(0.00955)	(0.00949)	(0.0100)	(0.00925)
No. Empl (thousands)	0.0366***	0.0345***	0.0527***	0.0403***
	(0.0109)	(0.0111)	(0.0117)	(0.0106)
Non-Int. Exp. (billions)	-0.163	-0.148	-0.254**	-0.165
	(0.117)	(0.117)	(0.127)	(0.115)
Time Fixed Effects	X	X	X	X
Bank Fixed Effects	X	X	X	X
IV-1		X		X
IV-2			X	X
Observations	33,145	33,145	32,083	32,083
R-squared	0.976	0.976	0.971	0.977

Note: We report our demand estimates (Eq. 6) in Table A7. Here we re-estimate demand using our extended data set of over 32,000 bank by quarter observations. In our baseline demand estimates (Table 2), we restrict our data set to the 26,742 bank/quarter observations for which data is available to estimate both deposit demand and the asset production function. The unit of observation is then at the bank by quarter level over the period 1994-2015. We define the market for deposits at the aggregate US by quarter level. The key independent variable of interest is the deposit rate offered for each bank. We measure the deposit rate as the bank's quarterly deposit interest expense net of fees (scaled by 4) divided by the bank's level of deposits. Because of the potential endogeneity of the deposit rate, we instrument for the deposit rate using two sets of instruments. We construct our first instrument (IV-1) as the estimated deposit rate from a bank-specific pass-through regression of deposit rates on 3-month LIBOR. We construct our second instrument (IV-2) as the average of the product characteristics offered by a bank's competitors in the previous quarter (branches, employees, non-interest expense, and fees). Specifically, we calculate the average product characteristics of a bank's competitors in each county the bank operates in in a given year, and we then calculate the average across all counties the bank operates in. We winsorize all independent variables at the 1% level to help control for outliers in the sample. Standard errors are clustered by bank and are reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A8: Alternative Production Function Estimates

	(1)	(2)	(3)
$\ln A_{kt}$ (θ)	0.879***	0.885***	0.771***
	(0.0369)	(0.0585)	(0.0631)
θ_1	-0.00276		
	(0.0447)		
θ_2	-0.00527		
	(0.0326)		
θ_3	0.0190		
	(0.0282)		
θ_4	-0.108***		
	(0.0297)		
Beta	-0.00656		-0.00943
	(0.00500)		(0.00891)
Beta (fwd 2 yr)		0.0140***	
		(0.00517)	
SD ROA	-0.0290***		-0.0690***
	(0.00299)		(0.00704)
SD ROA (fwd 2 yr)		0.00201	
		(0.00350)	
SMB (fwd 2 yr)		0.00430	
		(0.00274)	
HML (fwd 2 yr)		-0.00101	
		(0.00247)	
$Securities_{t-4}/Assets_{t-4}$		0.295***	
		(0.101)	
$Loans_{t-4}/Assets_{t-4}$		0.799***	
		(0.108)	
Bank F.E.	X	X	
Time F.E.	X	X	
IV		X	
	-0.0290***		
	(0.00299)		
Observations	26,742	18,564	26,317
R-squared	0.992	0.993	0.973

Note: Table A8 displays our alternative production function estimates. The unit of observation is at the bank by quarter level over the period 1994-2015. The dependent variable in columns (1) and (2) is the logged value of interest income earned by the bank. The dependent variable in column (3) is logged interest income net of realized gains/losses on loans/securities. The key independent variable of interest is the log value of a bank's assets lagged by one year. In column (1) we estimate a bank's asset production function using a spline with five knot points (Eq. 14) as described in Section 5.1.2. In column (2) and (2) we estimate a bank's asset production function using our basline log-linear specification and instrument for assets using the weighted average of the deposit product characteristics of a bank 's competitors as described in Section 3.3. In each specification, we control for the number of branches, number of employees and non-interest expenditures. In column (2), we also control for the other Fama French Factors, HML and SMB, and asset composition. We measure betas on a rolling basis using monthly equity returns over the previous 24 months with data provided by CRSP and Kenneth French. We measure the standard deviation of return on assets on a rolling basis using quarterly income statement/balance sheet data over the previous eight quarters. Standard errors are clustered at the bank level and are reported in parentheses. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.