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Monetary Policy and Intangible Investment

By Cooper Howes and Alice von Ende-Becker

Since 1980, the share of business investment in "intangible" goods, such as software or research and development, has tripled. This shift in the composition of investment may have important implications for monetary policy. For example, some research suggests intangible investment is far less sensitive than tangible investment to changes in interest rates, both because intangible investment is less likely to be financed through bank loans and because intangible goods have a shorter useful lifespan. As a result, monetary policy could become less effective as intangible investment continues to gain prominence in the economy.

Cooper Howes and Alice von Ende-Becker provide a simple framework to explain how the financing structure and depreciation rate of intangible investment cause it to respond differently to changes in interest rates and then analyze what these properties imply for the efficacy of monetary policy. Building on the findings of Döttling and Ratnovski (2021), they show that monetary policymakers may need to adjust their approach to managing the economy as the share of intangible investment continues to grow.

The Increasing Brick-and-Mortar Efficiency of Community Banks

By Stefan Jacewitz

The number of community banks in the United States has been declining steadily for decades, as has the share of total industry assets held by these banks. Because community banks play an outsized role in originating loans to small businesses, a continued decline in their numbers and asset holdings could constrain entrepreneurs' access to credit—and, accordingly, constrain growth in the overall economy.

One possible explanation for the declining number of community banks is that larger banks have benefitted from economies of scale and outpaced them in efficiency. Stefan Jacewitz examines how the efficiency of community banks has changed since the 2008 global financial crisis. He finds that community banks have in fact seen substantial improvements in efficiency, partially attributable to a relative decline in their brick-and-mortar expenses. His results suggest that community banks have made and continue to make meaningful gains even as the banking landscape evolves.

Considering Bank Age and Performance for De Novo Status

By Stephen Jones, Forest Myers, and Jim Wilkinson

Newly formed or "de novo" banks provide important benefits to banking markets, but they are also considered more financially fragile than established banks and are thus subject to a period of enhanced supervision. Currently, federal banking agencies impose more stringent supervision on de novo banks for at least three years, during which de novos may have more frequent examinations, more intensive surveillance, higher standards for capital levels, and limits on capital distributions. However, whether this three-year period effectively balances risk mitigation with regulatory burden is an open question.

Stephen Jones, Forest Myers, and Jim Wilkinson evaluate the appropriate length of the enhanced supervisory period by analyzing de novo bank financial performance over time. They find that the typical de novo bank's financial performance differs substantially from that of established banks during their first three years; by the end of three years, the financial performance of de novo banks more closely resembles older and more mature banks. Their results suggest that the three-year enhanced supervisory period is likely appropriate for mitigating risk without excessively burdening new banks.

Monetary Policy and Intangible Investment

By Cooper Howes and Alice von Ende-Becker

Prior to 1980, about 90 percent of investment in the United States was in "tangible" physical capital goods such as airplanes or office buildings. But over the past four decades, the share of business investment in non-physical or "intangible" goods, such as software or research and development (R&D), has tripled; currently, intangible products account for almost 30 percent of all investment spending.

This shift in the composition of investment may have important implications for monetary policy. Interest rates have historically been a crucial tool through which policymakers affect firms' investment behavior. However, Döttling and Ratnovski (2021) suggest intangible investment is far less sensitive than tangible investment to changes in interest rates, both because intangible investment is less likely to be financed through bank loans and because intangible goods have a shorter useful lifespan. As a result, monetary policy could become less effective as intangible investment continues to gain prominence in the economy.

In this article, we provide a simple framework to explain how the financing structure and depreciation rate of intangible investment cause it to respond differently to changes in interest rates and then analyze what these properties imply for the efficacy of monetary policy. Our framework, which builds on the findings of Döttling and Ratnovski (2021), highlights that monetary policymakers may need to adjust their

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approach to managing the economy as the share of intangible investment continues to grow.

Section I documents the rise in intangible investment. Section II highlights research that suggests that the rise in intangible investment has made the economy less responsive to monetary policy. Section III establishes a simple framework for understanding how an asset's financing structure and longevity affect its sensitivity to changes in interest rates.

I. The Rise of Intangible Investment

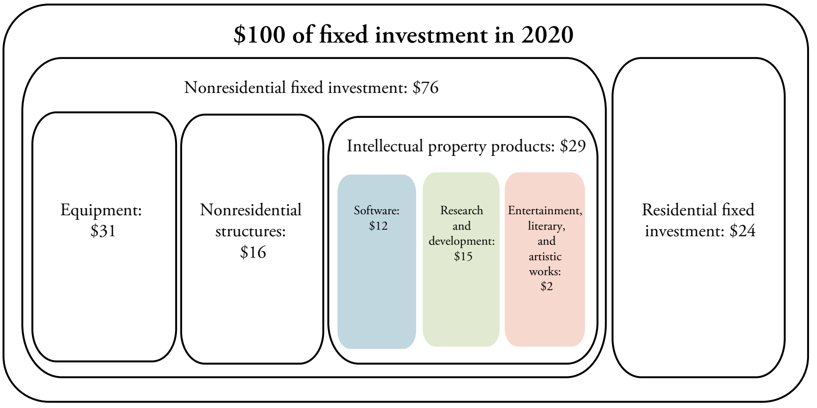
Several different types of investment factor into calculations of GDP. In this paper, we focus on productivity-enhancing business expenditures, such as a mixer for a bakery, sales software for a retailer, or a warehouse for a delivery company. This type of expenditure is classified by the U.S. Bureau of Economic Analysis (BEA) as nonresidential fixed investment. As shown in Figure 1, nonresidential fixed investment accounts for roughly three-quarters of all fixed investment, with housing (residential investment) accounting for the remaining share.[1]

The inclusion of intangible intellectual property products such as software in these calculations is a relatively recent development. Until the late 1990s, the BEA limited its definition of nonresidential fixed investment to two categories: equipment and structures. In 1999, recognizing that technological developments had increased the importance of intangible investment, the BEA created a third category of nonresidential fixed investment—intellectual property products—and released retroactive estimates for these products as far back as 1929.

This category includes software, R&D, and entertainment, literary, and artistic works. Throughout this article, we follow the BEA and use these three groups as our definition of intangible investment.[2] As Chart 1 shows, the share of investment coming from these intangible products has increased steadily over the past four decades, from about 10 percent in 1980 to almost 30 percent in 2020.

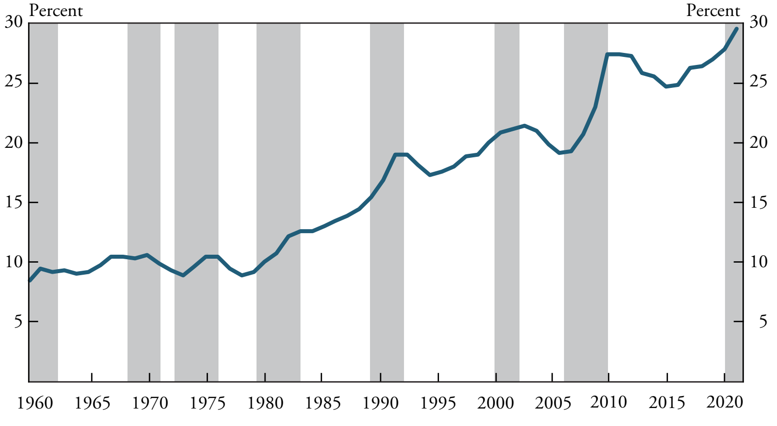
The rising investment share in part reflects the rapid growth of the information technology and professional service sectors, which tend to rely more on intellectual property products. The share of investment in the professional and information services sectors rose by almost 8 percentage points from 1980 to 2020, with similar increases in the shares of employment (5 percentage points) and GDP (9 percentage points)

Figure 1
Breakdown of $100 Fixed Investment in 2020



Source: BEA.

Chart 1
Share of Intangible Investment in Total Nonresidential Fixed Investment, 1960–2020



Note: Gray bars indicate National Bureau of Economic Research (NBER)-defined recessions.
Sources: BEA and NBER.

coming from these sectors. For context, this increase in the investment share for intangible producers is larger than the 2020 investment shares for the agriculture, mining, and construction sectors combined.

However, much of the increase in intangible investment has also come from changes *within* industries over time. Table 1 shows the changes in intangible investment shares across sectors. Much of the growth over the past few decades has come from sectors that previously did not

Table 1
Changes in Shares of Intangible Investment across Sectors, 1960–2020

	Intangible investment share (percent)				
Sector	1960	1980	2000	2020	Total change
Mining	0.0	0.9	8.5	8.8	8.8
Construction	0.0	0.0	7.2	11.9	11.9
Manufacturing	30.9	30.1	49.4	62.3	31.5
Wholesale trade	0.0	2.3	19.3	36.9	36.9
Retail trade	0.0	2.1	10.1	28.6	28.6
Transportation	0.0	0.8	8.2	8.8	8.8
Information	29.8	24.3	41.1	58.8	29.0
Finance, insurance, and real estate	0.0	10.5	22.5	48.9	48.9
Professional and business services	25.0	45.8	58.4	68.6	43.6
Educational services	0.0	10.7	14.8	36.9	36.9
Health care	0.0	4.1	9.0	14.0	14.0
Total	8.6	10.2	20.9	29.6	21.0

Source: BEA.

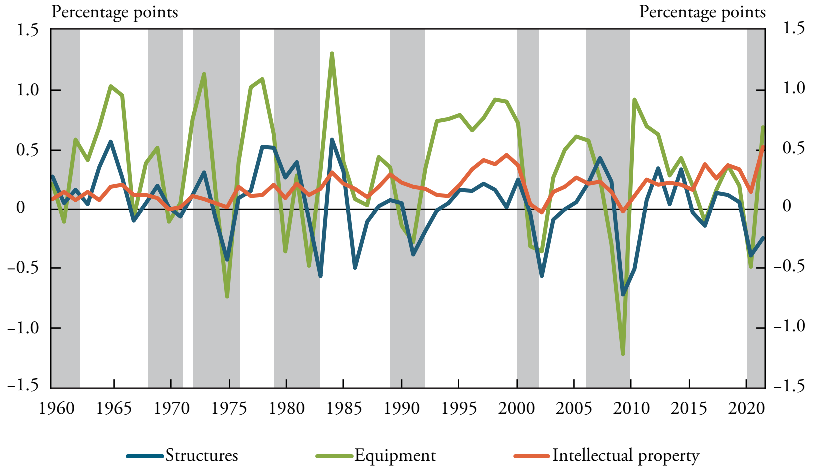
have sizable intangible investment shares. For example, industries such as wholesale trade and retail trade, which have historically used almost exclusively physical assets, now have more than one-third (36.9 percent) and one-quarter (28.6 percent) of their investment, respectively, in intangibles. In other words, while the greater role of intangible investment since 1980 has been driven in part by the rise of companies like Amazon and Google, much of the change has also come from retailers, manufacturers, schools, and hospitals modernizing their operations.

These changes have helped reduce volatility in economic activity. Chart 2, which plots the contribution of each category of investment to real GDP growth over time, shows that intangible investment (orange line) tends to provide a much more stable contribution to real GDP growth than equipment (green line) or structures (blue line). Even during the depths of the Great Recession, when equipment and structures combined to depress real GDP growth by two percentage points, intangible investment dampened GDP growth by only –0.02 percentage points.

Intangible investment in most sectors is likely to continue increasing in the future. Although reduced investment volatility may help smooth business cycles and contribute to a more stable economy, the

Chart 2

Investment Contribution to Real GDP Growth, 1960–2020



Note: Gray bars indicate NBER-defined recessions.
Sources: BEA and NBER.

increased stability from intangible investment may come with costs for monetary policymakers.

II. Understanding the Effects of Intangible Investment on Monetary Policy

Traditionally, central banks have attempted to influence investment activity through changes in interest rates. As a result, changes in the characteristics of investment could alter the transmission of interest rate policy to economic activity. Given these concerns, many academic researchers have studied the rise of intangible investment and how it might affect monetary policy.

Research has consistently found that a greater share of intangible investment reduces monetary policymakers' influence on investment activity. Döttling and Ratnovski (2021) show that aggregate tangible investment declines by up to 3 percent in the three years following a contractionary monetary policy shock, while intangible investment declines just 1 percent in response to the same shock.[3] When they look at firm-level data, they find an even starker difference: tangible investment rates for the average firm fall by up to 6 percent in response to a contractionary monetary policy shock, while intangible investment rates decline by just 1 percent. As the share of intangible investment continues to grow, central banks may have greater difficulty stimulating economic activity during downturns or reining in inflationary pressures during expansions.

What makes intangible investment less responsive to monetary policy? To answer this question, we develop a simple framework to illustrate how investment responds to changes in interest rates. Although our approach is far simpler than the models used in academic papers, it highlights the same fundamental channels that drive the results documented by Döttling and Ratnovski (2021). In addition, our approach highlights the implications for central banks operating in a world with a large and growing share of intangible investment.

A theory of investment

Investment is unique relative to other types of expenditures because it can have effects on production long after the initial purchase is made. For example, a firm might decide to purchase a new office building if they expect business to pick up in the coming years even if their current sales are slow. In contrast, the decision to purchase office supplies such as pens or paper is much more likely to be based on short-term needs. This means that investment decisions must often take a much wider range of factors into account than other purchases.

Many of the considerations influencing investment decisions can be summarized by a single measure known as the *user cost of capital* (Jorgensen 1963; Hall and Jorgensen 1967). A profit-maximizing firm will choose to invest if the user cost of an investment good is less than or equal to the additional revenue it provides—the marginal product of capital. Holding all else equal, if the user cost of an investment good increases, it needs to have a higher marginal product of capital to break even, and thus investment will fall. If the user cost decreases, the threshold required for an investment project to be profitable will decrease, and investment will rise. In this sense, the user cost of capital can be thought of as the true "price" of investment for a firm.

In its simplest form, the user cost can be expressed as the sum of the firms' financing costs and the investment good's depreciation rate.[4] Changes in either of these variables will affect firms' investment decisions. For example, higher financing costs act as an additional outlay that must be paid each period that the investment good is in use, making investment less appealing when financing is more expensive. Similarly, a slower depreciation rate means that a smaller share of the investment good breaks down in each period, and thus the good will provide value further in the future. This relationship suggests that investment goods with shorter lifespans need to be either cheaper or more useful.

The effects of monetary policy on investment

Because the central bank conducts monetary policy primarily through changes in interest rates, the degree to which monetary policy will affect a particular investment good will depend on how responsive that investment good's financing costs are to changes in interest rates. If firms rely more on investment goods whose financing costs are less sensitive to interest rates, then changes in monetary policy will have a smaller effect on investment.

To illustrate this relationship, we highlight two extreme examples. First, consider a firm that finances the entirety of its investment with bank debt. The financing cost of debt is simply the interest rate on that debt, so as the central bank raises interest rates, the firm's financing expenses will increase one-for-one. In contrast, consider a second firm that does not have access to bank loans and must instead finance all investment expenditure through its own cash holdings. Changes in interest rates will have a much smaller effect on this firm because it is not borrowing. In reality, most firms rely on a wide range of financing sources and are likely to fall between these two extremes, but these examples highlight why greater reliance on bank debt can make a firm's investment decisions more sensitive to monetary policy.

In contrast to financing costs, which depend on interest rates and can thus be directly affected by monetary policy, depreciation is a fundamental property of an investment good and does not respond to changes in interest rates. However, depreciation rates can still affect the transmission of monetary policy because the *percentage change* in the user cost, rather than its level, is what determines the magnitude of investment responses to changes in the user cost. Just as saving \$1 on a gallon of gasoline will have a far bigger effect on demand than saving \$1 on a house, a reduction in financing costs for an investment good with a high depreciation rate will have a much smaller effect on investment demand than a good with a low depreciation rate.

Table 2
Financing and Depreciation Influence How Interest Rates Affect Investment

Financing cost (percent)	Depreciation rate (percent)	Total user cost (percent)	Percent change in user cost from a 1 percentage point increase in the interest rate
r	δ	$r + \delta$	$\frac{1}{r+\delta}$
5	3	8	$\frac{1}{8} = 12.5$
5	10	15	$\frac{1}{15} = 6.7$
5	25	30	$\frac{1}{30} = 0.3$

Table 2 offers several numerical examples of how the user cost of capital determines how interest rates affect investment. For example, if a firm pays a 5 percent annual interest rate on an investment good that depreciates at a rate of 10 percent per year, then the user cost will be 15 percent. If the interest rate were to increase by 1 percentage point, the new user cost would be 16 percent, which would represent a 6.7 percent increase from its original level. If the depreciation rate increases to 25 percent per year, then the user cost would increase to 30 percent, and the same 1 percentage point increase in the interest rate would only raise the user cost by 0.3 percent.

The user cost of capital, expressed as the sum of an investment's financing costs and its depreciation rate, thus illustrates how monetary policy transmits to investment. Investment is less sensitive to changes in monetary policy if it depends less on bank debt and has higher depreciation rates—two properties of intangible investment.

III. Intangibles and the Transmission of Monetary Policy

As noted in the previous section, Döttling and Ratnovski (2021) find that intangible investment is between one-third and one-sixth as responsive to monetary policy compared with tangible investment. The authors test several channels and conclude that their empirical findings can primarily be explained by differences in financing costs and depreciation rates. In this section, we incorporate BEA data on intangible investment into our user cost framework to show where these results come from.

First, we consider financing costs. Researchers have found that intangible investment is less likely to be financed through bank loans and more likely to be financed through firms' cash holdings.[5] This tendency largely reflects that many bank loans require collateral. If banks know that they can seize an asset in the event the borrower cannot repay the loan, they will be more likely to extend credit. Just as many homeowners are only able to borrow the funds to buy a house by pledging the house as collateral, many firms fund purchases of investment goods through loans that pledge them as collateral.

Intangible investment, unlike equipment or structures, is generally not useful as collateral because it is likely to have a lower resale value. If a manufacturer defaults on the loan collateralized by an office building, the bank knows that it can sell the building to a law firm or technology company because a wide range of industries require offices. In contrast, a custom piece of software written for a manufacturing firm may not be useful to other firms even within the same narrow industry. This specificity can explain why firms are more likely to fund intangible investments through internal cash holdings. Because the financing costs of investments funded through bank loans will be more responsive to changes in interest rates than investments funded through internal cash holdings, this channel can help explain why intangible investment is less responsive to monetary policy.

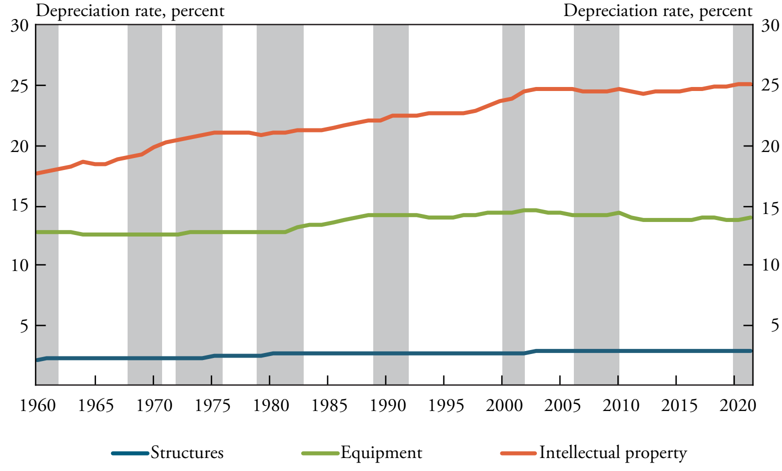
Another distinguishing feature of intangible investment that affects its sensitivity to monetary policy is its faster depreciation rate. Panel A of Chart 3 shows the BEA's annual depreciation rates for equipment, structures, and intellectual property. Approximately 13 percent of the value of the stock of equipment (green line) depreciates per year, as machines break down or become obsolete over time. This number is even lower for structures (blue line), which depreciate at a rate of about 3 percent per year. In contrast, intangible investment—which does not deteriorate physically, but can lose its usefulness as new and improved software is released or research becomes outdated—currently depreciates at a rate of about 24 percent per year (orange line).

Panel B of Chart 3 shows that the average age of the capital stock of both structures (14 years) and equipment (seven years) are higher

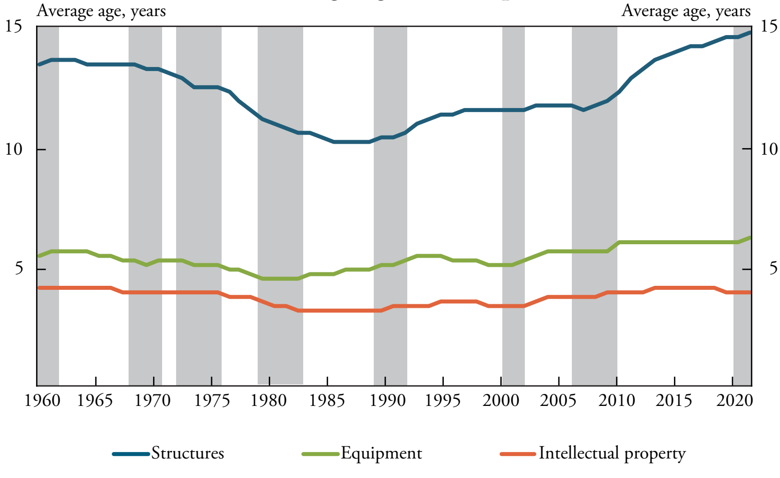
Chart 3

Depreciation Rates and Average Age of Investment by Category, 1960–2020

Panel A: Depreciation



Panel B: Average Age of the Capital Stock



Note: Gray bars indicate NBER-defined recessions.
Sources: BEA and NBER.

than for intellectual property (four years). Because investments with shorter lifespans tend to be repaid over shorter periods, the durability of an investment can affect its sensitivity to interest rates. Because the depreciation rate represents the fraction of an investment good that deteriorates each period, investments with shorter lifespans will have higher depreciation rates. As we showed in the previous section, a higher depreciation rate means that changes in interest rates will have a proportionately smaller effect on the user cost, and as a result investment goods with higher depreciation rates will be less sensitive to monetary policy.

Conclusion

The effect of interest rates on investment activity is one of the primary channels through which monetary policy affects the broader economy. Since 1980, however, the nature of investment has changed significantly, with almost one-third of investment now consisting of intangible products. Researchers have argued that this shift has made the economy less sensitive to monetary policy. We illustrate why the reduced interest rate sensitivity of intangible investment is a natural consequence of its lower reliance on bank financing and higher depreciation rates. Going forward, understanding the unique properties of intangible investment will be crucial for the effective conduct of monetary policy in an increasingly intangible economy.

Endnotes

[1]The BEA defines total investment as fixed investment plus changes in private inventories, which we do not consider in this paper.

[2]A more general definition of investment could include any expenditure today that increases production in the future. This would cover many other intangible assets such as brand loyalty, marketing, or institutional knowledge. Although our empirical analysis focuses on the narrower definition of intangible investment used by the BEA, in principle all our main findings should also apply to these broader categories.

[3]Other examples of papers that analyze the implications of intangible investment include Falato and others (2020), Caggese and Perez-Orive (2021), and Crouzet and Eberly (2021).

[4]In general, the user cost is a complicated object that is derived from a model and will thus change depending on the specific model being considered. With perfect liquidity, no adjustment costs, and constant prices for the investment good, the user cost can be expressed as described in the text: $UC = \delta + r$, where δ is the depreciation rate and r is the interest rate. For many more complex models, however, it is not possible to derive closed-form expressions for the user cost.

[5]Hall and Lerner (2010) analyze empirical patterns in financing arrangements for intangible investment and argue that firms tend to rely on internal funds for these expenditures. More recent work, including Li (2020) and Falato and others (2021), shows that firms that rely more on intangible investment hold more cash and use less debt, making their financing costs less sensitive to changes in interest rates. Hall and Lerner (2010) also argue that small firms, which do not have access to the same levels of internal funds as large firms, are able to offset some of these financial frictions using venture capital but emphasize that it cannot completely close this financing gap. While past work such as Gompers and others (1998) and Romain and van Pottelsberghe (2004) suggests that macroeconomic factors can matter for venture capital markets, very little is known about the ability of monetary policy to influence these markets at the business-cycle frequency.

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The Increasing Brick-and-Mortar Efficiency of Community Banks

By Stefan Jacewitz

Over the last four decades, the number of community banks in the United States has steadily declined, from 15,000 in 1984 to less than 5,000 in 2021. Although community banks still account for more than 91 percent of all banks today, they hold a much smaller share of total industry assets: in particular, their asset share declined from 38 percent in 1984 to less than 12 percent in 2021.

This decline has raised questions about the continued viability of the community bank business model. Community banks play an outsized role in originating loans to small businesses, so a continued decline in their numbers and asset holdings could constrain entrepreneurs' access to credit—and, accordingly, constrain growth in the overall economy. Understanding the source of this decline is thus important for both regulators and policymakers.

One possible explanation for the declining number of community banks is that larger banks have outpaced them in terms of efficiency. Community banks, which have less than $300 million in assets on average, may be less able to benefit from the economies of scale enjoyed by larger banks. In particular, community banks may be less able to afford or adapt to new technologies (such as mobile banking) that make banking more efficient. Moreover, a string of landmark regulatory changes—including the Riegle-Neal Act of 1994, the Gramm-Leach-Bliley Act

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of 1999, and the Dodd-Frank Act of 2010—may have supported an efficiency advantage for large banks, either by removing restrictions on size and activities or by imposing a fixed regulatory burden that large banks can more easily absorb.

In this article, I examine how the efficiency of community banks has changed since the 2008 global financial crisis. I find that community banks have in fact seen substantial *improvements* in efficiency, partially attributable to a relative decline in their brick-and-mortar expenses. Moreover, community banks have been able to reduce their brick-and-mortar expenses relative to income, even as the average number of branches per bank has increased from about 5.5 in 2010 to about 6.5 in 2021. My results suggest that although business models, capital, and the size and quality of assets still matter to banks' overall efficiency, community banks have made and continue to make meaningful gains even as their numbers decline and the mode of banking shifts from being from being branch based to internet and mobile based.

The remainder of the article proceeds as follows. Section I discusses how community banks and efficiency ratios are defined. Section II describes the methodology and provides the key results from a regression analysis showing that community banks have increased their efficiency via a reduction in their brick-and-mortar expenses relative to their income.

I. Community Bank Efficiency

Loosely, a community bank is a "traditional" bank in that it makes loans, funds those loans by taking retail deposits, and operates primarily within a delimited community. Community banks often rely on local clientele, which allows them when making loan decisions to use "soft information" gathered about borrowers through relationships in addition to "hard information" such as credit scores or other financial data (Elyasiani and Goldberg 2004). Relying on relationships gives community banks a comparative advantage in lending to relatively opaque borrowers like small businesses. In fact, around 78 percent of small banks make almost all their commercial and industrial loans to small businesses, compared with less than 12 percent of large banks (FDIC 2018).

Importantly, there is no universally accepted definition of a community bank. A common definition is based on asset size, using a cut-off of $10 billion in consolidated assets. However, I follow the definition used by the Federal Deposit Insurance Corporation (FDIC), which uses a more rigorous definition of a community bank based not only on asset size but also on loan portfolio composition, deposit composition, branches, geographic footprint, and other characteristics (FDIC 2012).[1]

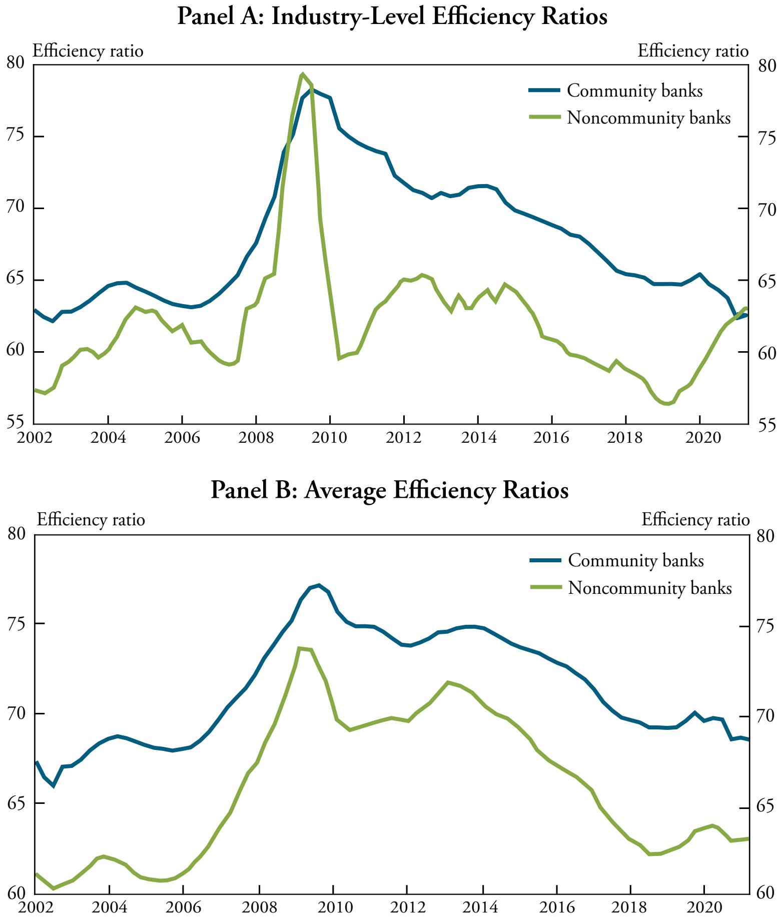
Some of the characteristics of community banks may necessarily place them at an efficiency disadvantage relative to large commercial banks. For example, the smaller asset size may make them less able to invest in technological improvements. Indeed, Berger and DeYoung (2006) show that technological advancement led to geographical expansion in banks. Likewise, in examining internet banking (the precursor to mobile banking), DeYoung, Lane, and Nolle (2007) find that the adoption of this new technology was positively associated with community bank performance.

One common way to measure bank efficiency is through the "efficiency ratio," which represents a bank's spending on operations as a portion of its income.[2] Higher efficiency ratios imply that a bank is less efficient overall. Although there are many slightly different definitions of the efficiency ratio, most share the same basic conceptual framework. I follow the definition from the Federal Financial Institutions Examination Council's (FFIEC) Uniform Bank Performance Report and measure efficiency ratios as total overhead expenses as a percentage of net interest income plus noninterest income. As measured by this efficiency ratio, community banks tend to be less efficient than noncommunity banks. On a per-bank level, the average efficiency ratio for community banks is around 68 percent compared with 63 percent for noncommunity banks.

The current efficiency disadvantage for community banks is not new. Larger banks have a long history of being more efficient than smaller banks, at least as measured by the efficiency ratio. Panel A of Chart 1 shows aggregate efficiency ratios for community and noncommunity banks—that is, total expenses for each group of banks divided by total income for those same groups—while Panel B shows the average efficiency ratios for banks in the same groups.

Both the aggregate and average efficiency ratios for noncommunity banks are smaller than those for community banks, illustrating large banks' efficiency advantage over time. Moreover, both measures of efficiency ratios show that community banks have become steadily

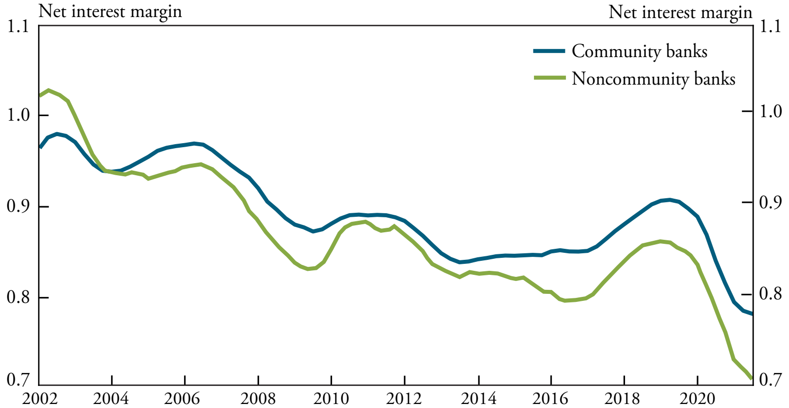
Chart 1
Community and Noncommunity Bank Efficiency Ratios



Note: Values are four-quarter moving averages.
Sources: FDIC, Federal Financial Institutions Examination Council (FFEIC), and author's calculations.

more efficient since 2010. However, the aggregate and average efficiency ratios for noncommunity banks (green lines) deviate in Panels A and B of Chart 1, reflecting that especially large banks can distort aggregate measures of efficiency. Given the heavily skewed distribution of assets in the industry toward a few very large banks, the aggregate efficiency ratio for noncommunity banks is strongly dependent on the largest banks. Therefore, for a more representative view of bank-level

Chart 2
Net Interest Margin as a Portion of Assets



Note: Values are four-quarter moving averages.
Sources: FDIC, FFEIC, and author's calculations.

efficiency, I focus on the average efficiency ratio rather than the aggregate in the subsequent analysis.

Although small banks have, on average, been generally less efficient than larger banks for decades, this disadvantage was partially offset by small banks' relatively higher interest income. For instance, Jacewitz and Kupiec (2012) find that community banks' efficiency ratios relative to larger banks is affected by community banks' advantage in net interest margins. Chart 2 shows that net interest margins, which measure banks' interest income less interest expenses, have been consistently higher at community banks since 2004. This is perhaps unsurprising, as smaller banks' loan rates tend to be higher relative to their deposit rates. This discrepancy between net interest margins at smaller and larger banks is often attributed to community banks' comparative advantage in acquiring soft information, enabling them to make loans that would have otherwise been overlooked by larger banks.

Nevertheless, community banks' persistently lower efficiency has been seen as a major factor contributing to long-run banking industry consolidation (see, for example, Hughes and others 1999, Amel and others 2004, and Kowalik and others 2015). The efficiency ratio is functionally used as a practitioner's version of "economies of scale." Theoretically, larger banks, being able to spread fixed costs across more assets, may exhibit economies of scale and thus report lower average costs compared with smaller banks. Because individual banks have little influence on the federal funds rate and the national wholesale deposit market, most of the variable costs are found in banks' reported "non-interest expense." This logic, combined with observed lower efficiency, is often used as an explanation for why the number of small banks is decreasing. Moreover, it has been used as a motivating factor for mergers and acquisitions, further contributing to consolidation.

II. Quantitative Analysis of Community Bank Efficiency

Although asset size and efficiency are clearly linked, understanding what makes a bank efficient requires delving more deeply into what makes an individual bank unique. For example, community banks with riskier asset portfolios may be less efficient because they face larger monitoring or legal expenses, while community banks with less capital could be more efficient because raising capital to higher levels can be costly. On the other hand, Wall (1985) finds that more profitable small- and medium-size banks had lower interest and noninterest expenses, more transaction accounts, and higher capital. Other research has shown return on assets (ROA), net interest margins, and several other factors play an important role in a bank's efficiency. Hays, De Lurgio, and Gilbert (2009) test a classification model for predicting a community bank's efficiency and find that a bank's ROA, salaries, liquidity, equity, and charge-offs are significant predictors of efficiency. Dreschler, Savov, and Schnabl (2017) show that while there is significant variation in interest expenses (deposit rates) across community banks located in different counties, most of this variation is due to local competitive conditions. Most recently, following the emergence of the COVID-19 pandemic, Sengupta and Xue (2022) and others have shown that net interest margins, a major contributor to community banks' profitability, are now at historic lows for both small and larger banks.

To account for many of these alternatives, I perform a regression analysis that considers asset size, lending specialization, and ROA, among other characteristics. The analysis relies on Call Report data from the FFIEC. The distribution of efficiency ratios and other bank characteristics is generally "heavy tailed," in that extremely high and extremely low values are not rare. As a result, a few observations several orders of magnitude larger or smaller than the rest would tend to dominate all other data. Therefore, for tractability, I drop observations with efficiency ratios, equity ratios, or ROAs below the first or above the 99th percentiles of the distribution from the analysis.

Table 1 provides summary statistics for selected key variables after this procedure. Even after removing extremely high and low values, the range of efficiency ratios for the full sample remains large, from 30 to 220 percent, with high variation. However, the average efficiency ratio of 71 percent is in line with expectations. The average efficiency ratio for community banks is also around 71 percent (as most banks are community banks), while the average for noncommunity banks is closer to 66 percent. Unsurprisingly, Table 1 shows that community banks have a smaller asset size and fewer branches than other banks. Furthermore, it shows that community banks tend to rely more on deposits as a source of funding. Otherwise, the bank characteristics are, on average, generally similar across community and noncommunity banks.

As noted in Section I, the efficiency ratio is defined as a bank's spending on operations as a portion of income. Using data from Call Reports, I decompose banks' overhead spending further into its constituent parts to examine finer, more targeted measures of efficiency. The major components of overhead spending are personnel expenses, such as the cost of salaries and benefits; premises expenses, such as the cost of branches and other buildings; and other expenses, including legal fees and goodwill impairment.[3]

Chart 3 shows how each of these components contributes to the total efficiency ratio over time. Salary expenses are the largest component of noninterest expenses, representing over half (around 58 percent) of the total efficiency ratio. Other expenses are the second-largest component, making up about one-third (around 30 percent) of the total efficiency ratio. Finally, premises expenses are the third-largest component, contributing just under 15 percent.

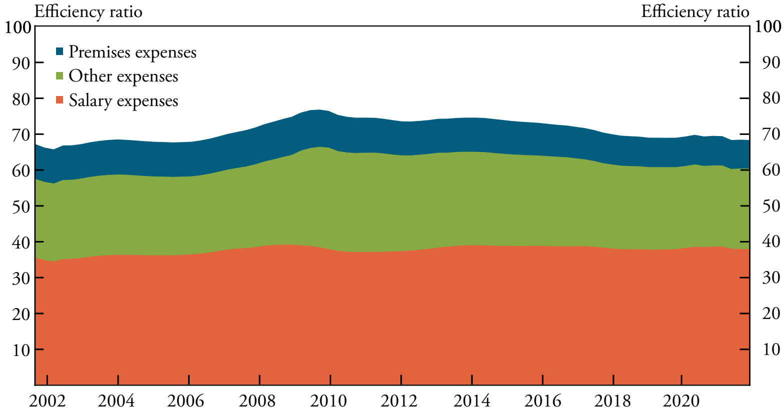
This decomposition allows me to calculate efficiency ratios for each component using expenses from the respective component in the numerator and net interest income plus noninterest income in the denominator. Thus, the "salary efficiency ratio" denotes a bank's spending on personnel per dollar of revenue, and so forth for the other component efficiency ratios.

Table 1
Summary Statistics for Efficiency and Major Related Factors

Independent variable	Dependent variable			
	Mean	Standard deviation	Minimum	Maximum
	(1)	(2)	(3)	(4)
Community banks				
Efficiency ratio	71.37	18.95	30.95	208.92
Total assets ($1,000)	291,529.17	532,215.99	2,157.00	9,984,414.00
Equity-to-assets	11.08	3.47	5.36	39.81
Deposits-to-assets	68.80	8.91	0.00	92.85
Return on assets	0.22	0.22	−1.45	0.98
Interest income	1.21	0.31	−12.92	16.29
Interest expense	0.31	0.23	−2.25	8.05
Noninterest income	0.18	0.33	−63.35	47.40
Noninterest expense	0.76	0.37	−63.05	48.24
Branches	6.23	7.98	1.00	169.00
Observations	478,827			
Noncommunity banks				
Efficiency ratio	65.61	19.92	30.96	208.90
Total assets	20,619,012.79	144,138,456.68	4,749.00	3,290,398,000.00
Equity-to-assets	11.21	4.35	5.37	39.82
Deposits-to-assets	62.08	16.46	0.00	94.26
Return on assets	0.23	0.24	−1.44	0.98
Interest income	1.21	0.51	−6.21	9.22
Interest expense	0.33	0.25	−2.76	3.21
Noninterest income	0.40	0.99	−21.50	48.77
Noninterest expense	0.84	0.95	−17.61	47.45
Branches	220.92	680.30	1.00	6,796.00
Observations	34,354			
All banks				
Efficiency ratio	70.98	19.07	30.95	208.92
Total assets	1,652,406.49	37,642,199.50	2,157.00	3,290,398,000.00
Equity-to-assets	11.09	3.53	5.36	39.82
Deposits-to-assets	68.35	9.75	0.00	94.26
Return on assets	0.22	0.23	−1.45	0.98
Interest income	1.21	0.32	−12.92	16.29
Interest expense	0.31	0.23	−2.76	8.05
Noninterest income	0.20	0.41	−63.35	48.77
Noninterest expense	0.77	0.43	−63.05	48.24
Office branches	20.60	184.17	1.00	6,796.00
Observations	513,181			

Sources: FDIC, FFIEC, and author's calculations.

Chart 3
Decomposition of Community Bank Efficiency Ratios



Note: Values are four-quarter moving averages.
Sources: FDIC, FFEIC, and author's calculations.

Although Panel A of Chart 4 shows that the salary efficiency ratio, the largest component of the overall efficiency ratio, has stayed relatively constant since 2009, Panel B shows that the average premises efficiency ratio has consistently fallen for both community and noncommunity banks. For community banks (blue line), the premises efficiency ratio fell from around 10 percent to around 8 percent. The general decline in premises expenses also follows a secular decline in the number of bank branches (dashed orange line in Panel B), from its most recent high of around 95,000 to its current level of around 70,000. Although the "other efficiency" ratio has also declined for both community and noncommunity banks (Panel C), I do not focus on this decline in the subsequent analysis due to the idiosyncratic nature of these expenses (for example, legal settlements and goodwill impairments). In sum, even though premises expenses are the smallest component of the overall efficiency ratio—representing less than 15 percent of noninterest expenses—improvements in premises efficiency have accounted for nearly 30 percent of the total gains in efficiency for community banks.

Much of community banks' steadily improving premises efficiency—and consequently overall efficiency—since 2009 can be attributed to a reduction in brick-and-mortar spending without an equivalent reduction in income. This steady reduction in brick-and-mortar

Chart 4
Expense Component Efficiency Ratios and Total Branches

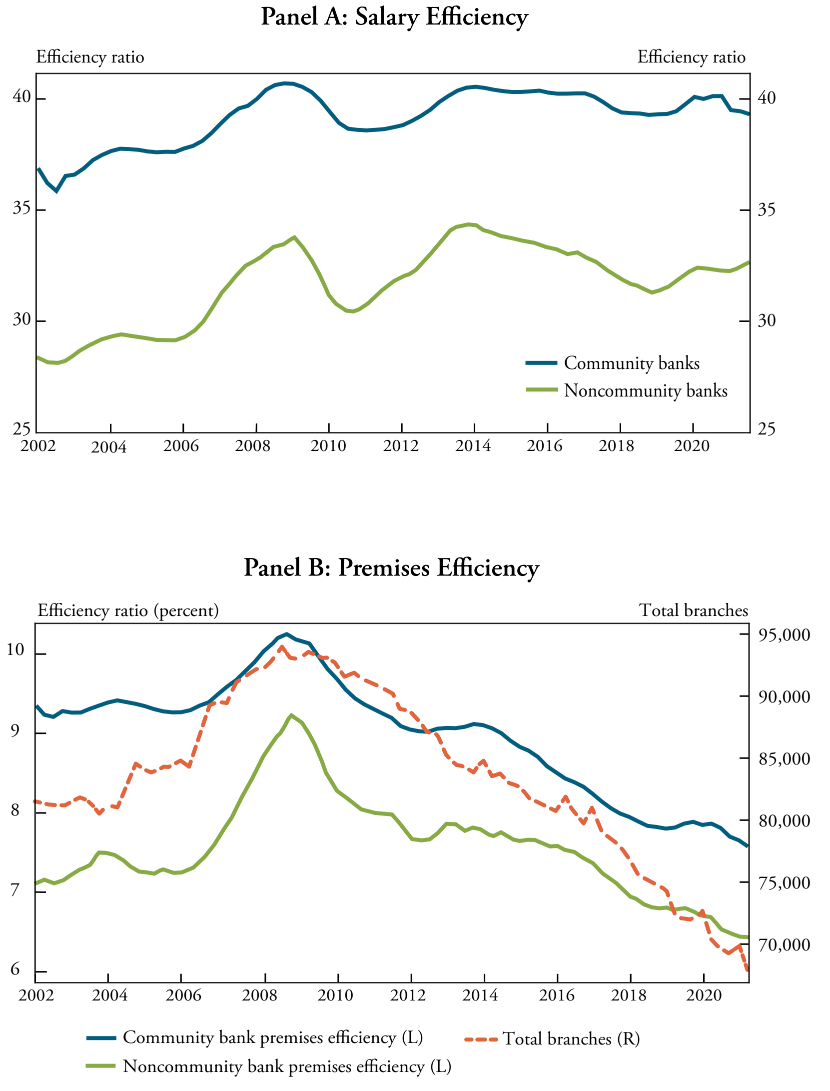
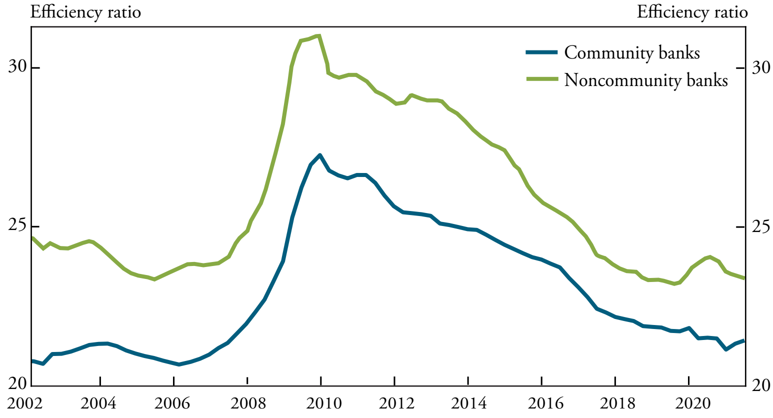


Chart 4 (continued)

Panel C: Other Expenses Efficiency



Notes: The value of the ratios are four-quarter moving averages. The value of the total number of branches is unmodified.
Sources: FDIC, FFEIC, and author's calculations.

spending has coincided with the widespread adoption of internet and mobile banking, suggesting that community banks (as well as noncommunity banks) have benefited from advances in internet and mobile banking, something we might have assumed they were less equipped to do. In fact, according to the Conference of State Banking Supervisors, community banks have nearly a 96 percent adoption rate for mobile banking (CSBS 2021).

Using Call Report data, I examine the relationship between community banks' core characteristics and efficiency ratios, as well as their component efficiency ratios, in Table 2.[4] The table provides the results of a statistical model relating the efficiency ratio and the component efficiency ratios to asset size as well as several other common bank characteristics that loosely follow regulatory CAMELS ratings (capital adequacy, asset quality, management, earnings, liquidity, and sensitivity). Positive coefficients indicate that higher values of that characteristic are associated with worse efficiency, and vice versa for negative coefficients. The table highlights that size, specialization (especially in agricultural lending), number of branches, and delinquency rate have the clearest relationships with efficiency at community banks.

Table 2

Estimated Relationships between Community Bank Characteristics and Bank Efficiency Ratios

Independent variable	Dependent variable			
	Efficiency ratio	Salary efficiency ratio	Premises efficiency ratio	Other expenses efficiency ratio
	(1)	(2)	(3)	(4)
log(assets)	−6.680***	−2.436***	−1.231***	−2.990***
	(−27.50)	(−15.71)	(−19.64)	(−21.80)
Brokered-to-deposits	−0.0132	−0.0189*	−0.00844	0.0135
	(−1.33)	(−1.81)	(−1.56)	(1.49)
Listing-to-deposits	0.155***	0.0489**	0.0186**	0.0863***
	(3.41)	(2.57)	(2.51)	(3.37)
CLD-to-assets	−0.343***	−0.105***	−0.0491***	−0.186***
	(−8.65)	(−4.10)	(−5.10)	(−8.65)
Farm-to-assets	−0.650***	−0.193***	−0.0974***	−0.364***
	(−23.79)	(−12.30)	(−15.04)	(−23.90)
SFR-to-assets	0.0686***	0.0430***	0.000648	0.0265***
	(5.64)	(5.39)	(0.20)	(3.95)
CRE-to-assets	0.0514***	0.0306***	0.0261***	−0.00554
	(2.92)	(2.85)	(5.85)	(−0.58)
CI-to-assets	−0.221***	−0.0778***	−0.0424***	−0.105***
	(−8.52)	(−4.82)	(−6.83)	(−7.75)
Leverage ratio	−0.588***	−0.146***	−0.119***	−0.321***
	(−9.68)	(−4.15)	(−8.11)	(−10.22)
Delinquent-to-assets	1.564***	0.159**	0.176***	1.221***
	(13.07)	(2.39)	(7.17)	(17.03)
ALLL-to-assets	−0.874*	−0.998***	−0.362***	0.608**
	(−1.78)	(−3.23)	(−3.57)	(2.57)
log(branches)	3.298***	0.852***	1.289***	1.002***
	(12.84)	(5.42)	(19.95)	(7.29)
Dividends-to-assets	−8.468***	−4.086***	−1.354***	−3.024***
	(−10.73)	(−10.93)	(−11.70)	(−8.77)
Constant	159.1***	72.02***	23.78***	62.92***
	(58.72)	(41.01)	(32.69)	(40.93)
Observations	17,7562	17,7562	17,7562	17,7562
Adjusted R^2	0.233	0.100	0.131	0.212

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Notes: Table provides parameter estimates yielded from regressing efficiency ratios on the independent variables listed for community banks. Columns 1–4 provide the estimates for the corresponding efficiency ratio. Below each estimate are *t*-statistics in parentheses. All regressions include time fixed effects. Errors are clustered to allow for arbitrary patterns of correlation within bank observations.
Sources: FDIC, FFIEC, and author's calculations.

A bank's asset size, irrespective of whether it is a community bank, is still closely related to its efficiency. A community bank that is 1 percent larger, on average, has more than a 7 percentage point better (lower) overall efficiency ratio. However, the premises efficiency ratio is only one point lower, suggesting that asset size may matter less to efficiency gains from brick-and-mortar savings.

Capital is correlated with efficiency, but perhaps in a surprising way. Community banks with a higher leverage ratio, after accounting for the other common factors, are on average significantly more efficient than banks with lower capital. Dividend payments, as a fraction of assets, also have a statistically significant correlation with efficiency. Although paying additional dividends will, all else equal, decrease capital, community banks with more capital *and* community banks with higher dividends tend to be more efficient overall. One possible explanation is that due to regulatory oversight, larger dividend payments are approved only for banks that are otherwise especially well managed, safe, and sound. It is worth noting that higher dividends are most closely related to salary efficiency. This relationship aligns with a compensation decision faced by many family-owned community banks: should owners, who at the smallest banks are often also managers and part of the staff, be compensated via salary or cash dividends? If community banks compensate owners via dividends, they can reduce salaries by a commensurate amount, thereby reducing expenses and mechanically increasing efficiency.

A community bank's lending portfolio composition is also related to efficiency. Portfolios with a higher proportion of construction and land development (CLD), farm, and commercial and industrial (C&I) loans tend to be significantly more efficient. In contrast, community banks that are more concentrated in single family residential (SFR) and commercial real estate (CRE) loans tend to be less efficient. In conjunction, these two relationships may be a bit puzzling, as these two loan types are quite different from one another. SFR real estate credit tends to be heavily commoditized and trades on a national market, whereas CRE credit tends to be relatively heterogeneous and local. As one might expect, the total value of delinquencies as a fraction of assets is strongly associated with worse efficiency. However, once problem assets have been accounted for, community banks with higher allowances for loan and lease losses (ALLL) as a fraction of assets are more efficient, on average. Thus, while more problem loans are clearly negative for a bank, appropriately provisioning for possible problem loans is actually correlated with more efficient banks.

Brokered and listing service deposits are both typically associated with a higher dependence on a type of internet-based deposits that tend to be more expensive and less stable. However, a higher use of brokered deposits is not significantly related to efficiency ratios, and listing service deposits are significantly related to worse efficiency, both in total efficiency and across all the individual subcomponents.

Finally, and consistent with the rise of mobile banking contributing to community banks' efficiency gains, more branches are significantly associated with worse efficiency. The relationship is strongest for premises efficiency, but also strong for overall, salary, and other efficiency. The estimate suggests that a 1 percent reduction in the number of branches is associated with a 3 percentage point better (lower) efficiency ratio.

Conclusion

Community banks play a central role in credit allocation to small businesses and small communities in the United States economy. However, the number of community banks has been steadily decreasing for decades. Although this decline has often been attributed to community banks' relative inefficiency compared with noncommunity banks, community banks have actually seen steadily improving efficiency since the end of the 2008 global financial crisis. I separate the standard efficiency ratio into its individual components and show that much of community banks' efficiency gains can be attributed to improvements in brick-and-mortar expenses. Although some improvement in average efficiency may be attributed to higher survival rates among relatively efficient banks, the mechanism for this progress has been disproportionately through premises efficiency. Coinciding with the rise of internet and mobile banking, community banks have been able to maintain profitability even while decreasing costs devoted to premises. When compared with the experience of larger banks, this suggests that community banks have benefited similarly from these technological developments. Although a bank's business model, asset size and quality, and capital still matter to efficiency, community banks have made and continue to make meaningful and significant gains even as the mode of banking shifts from being branch based to mobile and internet based.

From a regulatory perspective, policy primarily predates internet and mobile banking and has therefore traditionally relied on the geographical distribution of branches in the approval of mergers and for Community Reinvestment Act assessments. However, the decreasing importance of a bank's branches for servicing the needs of the public has mirrored the rise of internet and mobile banking. The results here suggest that branch restrictions are likely now less costly to community banks, though given internet and mobile banking, community banks may also be less effective in ensuring adequate credit allocation to local communities.

As mobile banking is likely to continue growing, my results suggest that community banks will continue to reap benefits from gains in brick-and-mortar efficiencies, while still being able to maintain similar relative levels of net income. Any mobile-oriented investments made by community banks over the course of the COVID-19 pandemic may act to fortify or increase these efficiency gains. Indeed, Kutzbach and Pogach (2022) find that technological investments made before the pandemic expanded banks' reach to new borrowers. However, as the efficiency gains have been similar for noncommunity banks, it is unlikely that the gains experienced by community banks will materially affect current long-term trends in consolidation. The risk remains that technological advancements, as well as a continued transition away from physical locations, will further reduce community banks' traditional advantage in soft information acquisition, fundamentally cutting into the community bank business model.

Endnotes

[1]All results presented in subsequent sections are qualitatively identical to those from the same analysis using a cutoff of $10 billion in total assets, another commonly used alternative definition of a community bank.

[2]Throughout this paper, the term "efficiency" refers to the "efficiency ratio," and the two are used interchangeably.

[3]Berger and Mester (2003) point out that analyzing both the numerator and the denominator of the efficiency ratio is important to a full understanding of bank efficiencies. However, to keep the analysis as simple as possible, I focus on differences in the numerator (overhead expenses).

[4]These relationships represent correlations only and should not be interpreted as causal.

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Considering Bank Age and Performance for De Novo Status

By Stephen Jones, Forest Myers, and Jim Wilkinson

Newly formed or "de novo" banks promote vitality and competition in their local markets and may provide access to banking services for underserved communities and groups. However, as with any newly formed business, de novo banks are likely to be more financially fragile than more established banks, especially during periods of economic stress. A central challenge for federal banking regulators is mitigating this risk through supervisory attention without discouraging new bank formation.

Currently, federal banking agencies use several strategies to mitigate de novo bank risk, including application requirements and more stringent operating and examination standards. For example, when de novo banks begin operations, they are subject to more frequent examinations, more intensive surveillance, higher standards for capital levels, and limits on capital distributions for at least three years. However, whether this three-year period effectively balances risk mitigation with regulatory burden is an open question.

One way to evaluate the suitability of this threshold is to examine de novo banks' performance as they mature. If a de novo bank's financial performance is comparable to the performance of established banks, enhanced regulatory treatment may not be needed. In this article, we evaluate the appropriate length of the enhanced supervisory period by

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analyzing de novo bank financial performance over time. We find that the typical de novo bank's financial performance differs substantially from that of established banks during their first three years. By the end of three years, the financial performance of de novo banks more closely resembles older and more mature banks. Our results indicate the three-year enhanced supervisory period is likely appropriate.

Section I provides background information on de novo bank activity. Section II summarizes supervisory policy pertaining to de novo banks. Section III presents our research approach. Section IV summarizes study results.

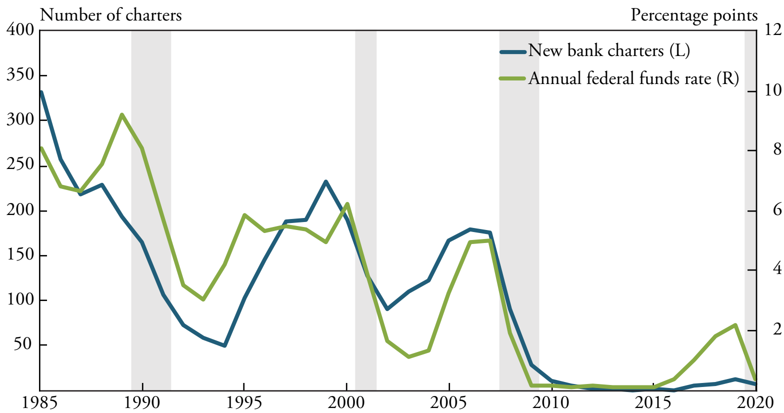
I. De Novo Bank Formation and Economic Conditions

De novo banks are an important feature of the U.S. banking system. Their entry into local banking markets helps maintain banking competition (Adams and Gramlich 2014). They also help provide financial and credit services to underserved communities with limited access to banking products (Bowman 2021). Furthermore, de novo banks can be an especially important source of small business lending because, relative to larger banks, they are more likely to rely on relationship banking—that is, they are more likely to use a more personalized touch in their customer dealings and give weight to intangibles in credit requests as well as financial factors.

De novo bank formation has always been cyclical, increasing in economic expansions and declining during recessions. The number of new bank charters increases when interest rates rise because higher interest rates increase banks' net interest margins, the primary earnings component for small banks; the number of charters declines when interest rates fall and net interest margins are compressed (Adams and Gramlich 2014; Lee and Yom 2016).[1] Indeed, Chart 1 shows that new charter activity has largely moved with the federal funds rate.

From 1985 to 2009, there were 3,870 new bank charters issued in the United States. Following the Great Recession, the number of new bank charters remained low even as economic growth strengthened and bank profitability improved starting in 2010.[2] One potential explanation for the paucity of new banks after the Great Recession is an increase in regulatory burden, as new and changing laws, supervisory policies, and regulations can all affect operating costs and shareholder returns.

Chart 1
New Bank Charters and Annual Federal Funds Rate by Year, 1985–2020



Note: Gray bars indicate National Bureau of Economic Research (NBER)-defined recessions.
Sources: FDIC, Board of Governors of the Federal Reserve System, and NBER.

The Dodd-Frank Act, passed in 2010, led to a substantial increase in new regulations. Moreover, a Federal Deposit Insurance Corporation (FDIC) count of substantive regulatory changes applicable to smaller banks or community banks found 157 changes, or one every 28 days from 2008 to 2019 (FDIC 2020).[3]

Although the goal of these regulatory changes is to mitigate financial risks, at the margin, they may also discourage new bank formation. Regulatory burden has been a long-running concern for banks. Most recently, the dearth of new bank charters has called attention to supervisory policy pertaining to bank charters and de novo banks. Whether enhanced supervision of de novo banks is appropriate or overly stringent is a question critical to both regulators and banks.

II. De Novo Bank Formation and Supervisory Policy

De novo banks are subject to additional supervisory requirements because they are considered more financially fragile than established banks for several reasons (Lee and Yom 2016). First, de novo banks may be organized by investor groups with limited familiarity or experience with bank operations, resulting in a weaker governance chain for management than that of more established banks. Second, even when management teams are experienced, that experience may be at established banks and may not directly translate to managing a newly formed bank. Third, the customer composition may differ between mature and de novo banks. For example, some loan customers denied credit by established banks may seek credit at de novos, believing these institutions will be more driven to build a customer base to achieve profitability. In other instances, new banks may be established to capture presumed market opportunities within a particular sector. However, the banks may develop sectoral concentrations, creating greater credit risk should these sectors experience economic hardship. Fourth, new banks may not have the same financial wherewithal as established institutions. De novos are likely to have lower earnings while building out their loan portfolio and may have lower margins by making loan rate concessions to attract borrowers while paying out higher deposit rates or relying on wholesale funding.[4] Fifth, de novo banks may not have settled risk management practices, and bank managers may have to refine policies, procedures, and risk limits over time, especially if the business model changes.

Because of these risk factors, regulatory agencies—specifically, the Office of the Comptroller of Currency (OCC), the FDIC, and the Federal Reserve System—view de novo banks as riskier than established banks. The agencies mitigate these risks by instituting requirements in the application process for new bank charters and imposing higher initial operating and examination standards.[5]

Organizers of de novo banks must complete applications for both chartering and deposit insurance. The applications request similar information from the organizers about financial and management resources and ask how the proposed bank will meet the credit needs of the community served. In addition, organizers must meet certain requirements set by the agencies—for example, including experienced senior managers in their leadership group and having a board of directors with diverse and relevant backgrounds, including two outside directors with banking experience. Bank organizers must also include with their applications a sound and comprehensive business plan that covers the first three years of operation and demonstrates that the bank will be able to meet supervisory expectations for capital levels over this period.

Once the application is approved, newly chartered banks are subject to more intensive supervision by banking agencies. De novo banks receive more frequent safety and soundness examinations than established banks. Typically, healthy community banks receive an examination every 18 months.[6] Newly chartered banks, however, are subject to a targeted examination within six months and a full-scope examination within 12 months of their opening. These banks will continue to receive full-scope examinations every 12 months until they have had three full-scope examinations and been in operation for at least three years. In addition, regulatory agencies encourage de novo banks to engage an independent public accountant to audit their annual financial statements during the first three years of operation. Newly chartered banks are also expected to maintain capital ratios well above regulatory minimums. To help achieve these ratios, banking agencies limit de novo banks' capital distributions.

Currently, banking agencies impose these higher supervisory standards for a three-year period. However, this period has varied over time and across agencies. In 2009, for example, the FDIC extended its heightened supervisory period for de novo banks to seven years in response to a high failure rate after the Great Recession for banks younger than eight years. In 2016, the FDIC returned to a three-year de novo period. In contrast, the Federal Reserve maintained a five-year de novo period until 2020, when it moved to a three-year de novo period.

Whether the enhanced supervisory period for de novo banks is an appropriate length is an important question, as it influences supervisory costs for both banks and banking supervisors. Furthermore, application costs and associated supervisory requirements may play a role in the slowdown in de novo bank formations to the detriment of an innovative, competitive banking system.

III. Measuring the Financial Performance of De Novo Banks

Currently, banking agencies consider a de novo bank an established bank after three years of operations. The appropriateness of this period depends on whether the financial performance of most de novo banks has sufficiently "matured" within three years so that their risk profiles are comparable to established banks.

To test the appropriateness of the three-year period, we use a statistical model to estimate the probability of a bank being a de novo bank. Specifically, we use a probit model to predict the likelihood that a bank is three years old or less based on their financial characteristics and performance.[7] This approach allows us to observe how banks' probabilities of being de novo change over time and identify when banks "mature" into established banks. The model's dependent variable, de novo status, is based on the three-year regulatory de novo period. The explanatory variables are financial performance measures aligned with the capital, asset quality, earnings, and liquidity components from the regulatory agencies' CAMELS examination rating systems.[8] We include growth rates as well as levels of these financial variables given that the financial composition and performance of de novo banks is expected to change significantly in their early years of operation. In addition, we control for bank operating conditions including market characteristics (such as local economic health and whether a bank is urban or rural) and corporate structure (specifically, whether a bank is part of a bank holding company). Table 1 provides a complete categorization of these independent variables.

Data on bank financial performance are from annual (year-end) Call Report data for domestic commercial U.S. banks from 1995 to 2018. The economic health index is constructed at the Federal Reserve Bank of Kansas City and estimated from various measures of economic activity available at the county level. Appendix A contains more complete information on the sample of banks and the variable definitions and calculations, and Appendix C provides further information on the economic health index.

We divide the data into two groups using randomly selected bank identification numbers. We use half of the observations to estimate model parameters and the other half to predict de novo status. In the parameter estimation process, we use banks with three or fewer years of operation and banks with 14 or more years of operation. This ensures that non-de novo banks are clearly "established" banks.[9] We then use the estimated parameters to predict de novo status for banks of all ages in the second half of the observations and analyze the distribution of de novo probabilities by bank age.

Additionally, we apply k-means clustering on the predicted de novo probabilities to determine an appropriate cutoff point for assigning each observation to either a de novo or an established bank group. The

Table 1
Variables Grouped by Financial Performance Categories

Capital	Asset quality	Earnings	Liquidity	Operating characteristics
Tier 1 capital ratio	Loans to asset ratio	Pre-tax net income as a percentage of average assets	Noncore funding percentage	Indicator for bank headquartered within a rural market
Annual Tier 1 capital ratio growth	Non-performing asset ratio	Efficiency ratio	Deposits to assets	Economic health index
Annual Tier 1 capital ratio growth squared	Annual loan growth	Annual efficiency ratio growth	Annual deposits to assets growth	Indicator for bank operating under a bank holding company
	Annual loan growth squared	Annual efficiency ratio growth squared	Annual deposits to assets growth squared	

k-means clustering algorithm works iteratively to assign observations into a prespecified number of groups—two groups, in this case. The algorithm minimizes the distance between each observation's predicted probability and the cluster centroids. In effect, our observations are optimally grouped into two categories in which the probabilities are nearest to the mean of their neighbors. Once grouped, we can analyze the composition of banks in the false positive and false negative categories.

IV. Results Support a Three-Year De Novo Period

Our results provide confidence that the regression model successfully reflects the behavior of de novo banks during their early operating years. Table 2 presents selected coefficients from our parameter estimation process. (Complete regression results, including each variable's average marginal effect, are provided in Appendix A.)

Overall, the table suggests that the results are consistent with the financial performance of de novo banks. Specifically, the results show that banks with lower income, lower efficiency, high but declining capital ratios, high loan growth, and fewer nonperforming assets are more likely to be within their first three operating years. The coefficients on these variables are statistically significant, indicating they are important in distinguishing between de novo and established banks.

Table 2
Regression Coefficients for Selected Variables

Variable	Level	Growth
Pre-tax net income to average assets	–24.45***	N/A
Efficiency ratio	0.56***	–3.48***
Capital + ALLL to total assets	6.62***	–1.57***
Loans to total assets	0.65***	3.10***
Nonperforming assets ratio	–8.28***	N/A

*** Significant at the 1 percent level

Note: "N/A" indicates the growth variable is not included in the model.

The negative coefficient on the first variable shown in the table, net income to average assets, indicates that banks with losses or low income are more likely to be de novo banks. De novo banks are expected to incur losses in their initial years because their asset base does not generate sufficient income to cover noninterest expenses.

The next variable shown in the table, the efficiency variable, is the ratio of noninterest expense to earnings. Informally, this ratio can be thought of as the cost of earning a dollar of income. Thus, a high ratio indicates a bank is less efficient in generating earnings. The positive coefficient on the efficiency variable suggests that less efficient banks are more likely to be de novo banks, consistent with de novo banks not yet reaching their planned asset size during their initial operating years. Furthermore, the negative coefficient on the efficiency ratio growth variable shows that banks with improving efficiency ratios are more likely to be de novo banks, which is consistent with de novo banks trying to grow into their planned asset size.

The positive capital ratio coefficient and negative capital growth coefficient suggest that banks with high but declining capital ratios have a higher probability of being de novo banks. This estimate is unsurprising: as discussed previously, de novo banks are required to hold capital ratios well above regulatory minimums, and these ratios tend to decline over time due to negative or low earnings and an increasing asset base.

The coefficients on the loans-to-total-assets level and growth variables are positive and significant, suggesting banks with high loan growth are more likely to be de novos. This result is in line with expectations, as de novo banks need to grow their loan portfolios to support their net interest margins.

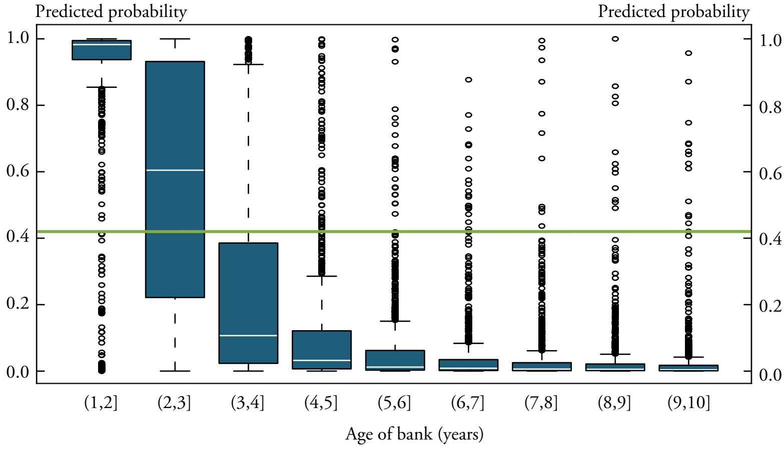
Finally, the coefficient on the nonperforming assets variable is negative, indicating that banks with fewer nonperforming assets are more likely to be de novo banks. Although this parameter estimate might seem counterintuitive, it too is consistent with de novo banks. Initially, all new loans perform well. Repayment problems generally appear after loans have seasoned, which will occur after the de novo period for some loans.

The estimated parameters of the statistical model are consistent with expectations for de novo bank financial performance, suggesting our model can accurately predict which banks have the characteristics of de novo banks. Thus, we use the estimated model parameters to measure the likelihood that banks in the remainder of our sample are de novo banks. Specifically, we assess the distributions of de novo bank probabilities by bank age to determine when de novo banks mature sufficiently to be considered established banks.

The box-and-whisker plots in Chart 2 show the range of time it takes for de novos to reach an established state.[10] The boxes contain 50 percent of the predicted probabilities, or those banks with probabilities within the lower and upper quartiles, and the line within the box indicates the median value of the probabilities at each age. Thus, for banks with two to three years of operation, for example, the black horizontal line within the box at 0.6 indicates that the median bank in this age group has a 60 percent probability of being a de novo bank (based on financial performance), while 50 percent of banks in this age group had de novo probabilities between 22 and 93 percent. The dashed lines (or "whiskers") outside of the box represent probabilities as far out as 1.5 times the interquartile range, while data points outside of these whiskers, denoted as dots, are considered potential outliers.

To assess whether banks in each age group are de novo banks or established banks, we use a cluster analysis that divides banks into these two categories based on their projected de novo probabilities. The cluster analysis chooses a probability level to divide the banks so that each bank's probability is closer to its own group's average probability than to the other group's average probability. Our analysis includes banks with a probability of 42 percent or higher into the de novo bank cluster. Those with a lower probability are put in the established bank cluster. The green line in Chart 2 provides a visual reference for this dividing line.

Chart 2
Probability of De Novo-Like Financial Characteristics by Age



Source: Authors' calculations.

The results show that most banks in our sample reach maturity after three years of operation. As expected, during the first one to two years of operation, almost all banks have a high probability of being classified as a de novo bank. At the two- to three-year age range, however, de novo probabilities become widely dispersed, as evidenced by the large interquartile range. In other words, the financial maturity of banks in this age group varies widely. After three years of operation, most banks have become established—that is, they have a low probability of being a de novo. Thus, our results suggest that the three-year cutoff defined by current regulatory guidance is reasonable overall.

However, our results also show that some banks are maturing much faster than expected, and that some banks are taking much longer than anticipated to reach an established state. For example, the box for banks with two to three years of operation extends below the 42 percent level, indicating banks in that zone already have the performance of established banks. In contrast, the upper tail for the three- to four-year cohort shows that many banks are maturing more slowly and have not reached an established state after the three-year regulatory timeframe. The high probability outliers in the older cohorts are likely poorly performing established banks with low earnings and high loan growth, leading our model to mistakenly classify them as de novo banks. Nevertheless, focusing on performance metrics in addition to age when determining de novo status may be beneficial, given that many banks appear to be reaching an established state before or after three years of operation,

To quantify the volume of banks that are reaching maturity within a shorter or longer timeframe than the three-year de novo period, we construct a confusion matrix that compares the actual and predicted de novo status of banks in our sample. Rather than arbitrarily setting a cutoff probability (or dividing line), we separate de novo and established banks using the cluster analysis, which gives us a cutoff value of 42 percent.

The results from the confusion matrix, shown in Table 3, suggest that nearly 99 percent of the banks in our sample were classified correctly. The 544 false positive observations represent banks that have not yet reached maturity (as measured by our financial performance variables) after three years. These observations may include both newer banks that are taking longer than expected to mature and established banks with risk characteristics that make their financial performance appear similar to de novo banks. The false positive observations account for less than 1 percent of the established banks in our sample. The 403 false negative observations represent banks that reached maturity in less than three years—that is, banks that have the financial characteristics of established banks but that are in their first three years of operation. Overall, 23 percent of de novo banks in our sample reached an established state sooner than the three-year regulatory period. If regulatory agencies included financial performance in their assessment of de novo status, the de novo period could be shortened for these banks, reducing costs for both the banks and the agencies. However, the period of reduced burden would be very short—less than one year for most of these banks. De novo banks achieved a greater reduction in regulatory burden when the FDIC shortened its de novo period from seven to three years in 2016 and when the Federal Reserve reduced its de novo period from five to three years in 2020.

Our results may depend on the three-year assumption used to assign banks to the de novo group. Although this choice mirrors banking agencies' current practice, it may bias the statistical results relative to using a longer assignment period. To account for this possibility, we

Table 3
Comparison of Actual and Predicted De Novo Status

	Actual classification	
Predicted classification	Established	De novo
Established	72,753	403
De novo	544	1,353

repeat the analysis using five-year and seven-year de novo periods. The longer period results have very similar probability distributions to our base three-year results. However, the five-year and seven-year confusion matrices show higher false positive and false negative rates, suggesting the three-year model performs better. The results for the alternatives are discussed in Appendix B.

Conclusion

De novo banks provide important benefits to the banking markets they enter. However, as with any new and growing entities, de novo banks are generally riskier than established banks. To mitigate these risks, banking agencies require a rigorous process for applying for a bank charter and deposit insurance and impose more stringent supervision on new banks for the first three years of operation. Whether this three-year duration is appropriate is an important question, as the enhanced supervision creates additional regulatory burden for de novos during their initial years of operation.

This paper attempts to assess the appropriate length of the enhanced supervisory period by estimating the probability that a bank is a de novo bank based on its financial performance. Our analysis shows that banks with weak earnings, high loan growth, and high capital ratios have a higher de novo probability. We observe the distribution of these probabilities by bank age and find the probabilities of being a de novo bank decline during the third year. Further, most banks have a low de novo probability in their fourth year. Our results support the regulatory agencies using a three-year trial period for de novo banks.

However, our results also suggest that considering financial performance in addition to age could lower regulatory burden for some de novos. Specifically, a cluster analysis shows that some banks older than three years had a high de novo probability, while a substantial proportion of banks younger than three years had a low de novo probability, indicating they should be included in the established bank cluster. These outliers suggest that banking agencies may be able to use financial performance analysis to shorten the de novo window and reduce regulatory burden for some banks.

This research did not analyze the costs and benefits from the regulatory requirements of the application process. It may be possible to reduce regulatory burden associated with applying for a new charter and deposit insurance. However, banks that successfully complete the current application processes appear to be well poised to achieve the financial performance of established banks by the end of three years of operation.

Appendix A

Data and Banks Used in the Analysis

This study uses annual (year-end) data from the Reports of Income and Condition (Call Reports) for the years 1985–2018. We collect data only for U.S. commercial banks and exclude credit unions, savings and loans, savings banks, industrial loan companies, deposit national banks, and U.S. subsidiaries of foreign banking organizations.[11] The data are adjusted to reflect the effect of mergers to ensure the growth rate variables used in the analysis are calculated correctly (English and Nelson 1998). Because growth rate calculations in a given year require data from the previous year, we cannot use the initial annual observation for each bank in the analysis.

For this study, we consider de novo banks to be newly chartered banks up to three years of age, reflecting banking agencies' presumption of de novo status. We only include new entities with no previous operating experience. Thus, we exclude newly chartered banks that 1) result from an established bank changing its charter, 2) are the product of a merger between banks that results in a new charter, 3) facilitate an ownership change of an existing bank, or 4) are the second or subsequent subsidiary of multibank holding companies.

Table A-1 provides full definitions for each variable in our model. Table A-2 provides descriptive statistics for each of our bank samples. Table A-3 presents our complete probit regression results.

Table A-1

Variable Definitions

Variable	Definition
Loans to assets	The ratio of total loans to total assets
Pre-tax net income to average assets	Net income to average assets on a pre-tax basis
Efficiency ratio	The ratio of noninterest expenses to operating revenue, or the overhead required to generate a dollar of revenue
Tier 1 + ALLL to total assets	Tier 1 capital and loan loss reserve as a percentage of total assets
Brokered borrowings and fed funds purchased to average assets	The percentage of average assets funded by non-core funding including brokered deposits and federal funds purchased
Deposits to assets	The ratio of total customer deposits to total assets
Nonperforming assets ratio	The ratio of loans 90+ days past due or on nonaccrual to total assets
Annual loan growth	The simple annual growth rate of total loans
Annual loan growth squared	The square of annual loan growth
Deposits to assets growth	The simple annual growth rate of deposits to assets
Deposits to assets growth squared	The square of deposits to assets growth
Tier 1 + ALLL to total assets growth	Simple annual growth rate of Tier 1 + ALLL to total assets
Tier 1 + ALLL to total assets growth squared	The square of Tier 1 + ALLL to total assets growth
Efficiency ratio growth	Simple annual growth rate of the efficiency ratio
Efficiency ratio growth squared	The square of the efficiency ratio growth
Economic health index	A measure of the economic health of each county
BHC indicator	1 if bank operates under a holding company, 0 otherwise
Rural indicator	1 if bank is headquartered in a rural market, 0 otherwise

Table A-2
Descriptive Statistics

Variable	Overall		De novo		Established	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
De novo	0.023	0.150	1.000	0	0	0
Loans to assets	0.623	0.152	0.681	0.144	0.622	0.152
Pre-tax net income to average assets	0.012	0.012	−0.008	0.019	0.012	0.011
Efficiency ratio	0.693	0.202	1.068	0.424	0.685	0.184
Tier 1 ALLL to total assets	0.111	0.034	0.143	0.055	0.110	0.033
Brokered and FFP to total assets	0.063	0.083	0.076	0.101	0.063	0.083
Deposits to assets	0.002	0.071	0.818	0.085	0.841	0.070
NPA ratio	0.014	0.019	0.006	0.015	0.014	0.019
BHC_1	0.829	0.377	0.490	0.500	0.837	0.369
Rural_1	0.495	0.500	0.162	0.369	0.503	0.500
Loan growth	0.119	0.262	1.014	0.626	0.098	0.204
Loan growth squared	0.083	0.378	1.419	1.328	0.051	0.247
Deposits to assets growth	0.002	0.043	0.087	0.091	0.000	0.039
Deposit to assets growth squared	0.002	0.005	0.016	0.016	0.002	0.004
Tier 1 ALLL to total assets growth	−0.002	0.107	−0.232	0.178	0.008	0.098
Tier 1 ALLL to total assets growth squared	0.011	0.026	0.086	0.063	0.010	0.021
Efficiency ratio growth	0.002	0.124	−0.247	0.183	0.008	0.116
Efficiency ratio growth squared	0.015	0.038	0.095	0.071	0.013	0.035
Economic health index	0.002	0.892	0.599	0.754	0.289	0.893

Table A-3
Complete Probit Regression Results

Independent variables	Probit model	Average marginal effect
(Intercept)	–5.28*** (0.50)	
Loans to assets	0.65*** (0.15)	0.010
Pre-tax net income to average assets	–24.45*** (3.15)	–0.396
Efficiency ratio	0.56*** (0.14)	0.009
Tier 1 + ALLL to total assets	6.62*** (0.69)	0.107
Brokered borrowings and fed funds purchased to average assets	1.41*** (0.30)	0.023
Deposits to assets	1.60*** (0.49)	0.026
Nonperforming assets ratio	–8.28*** (2.33)	–0.134
Annual loan growth	3.10*** (0.16)	0.050
Annual loan growth squared	–1.50*** (0.09)	–0.024
Deposits to assets growth	0.61 (0.52)	0.010
Deposits to assets growth squared	6.63 (3.99)	0.011
Tier 1 + ALLL to total assets growth	–1.57*** (0.20)	–0.025
Tier 1 + ALLL to total assets growth squared	3.05*** (0.73)	0.049
Efficiency ratio growth	–3.48*** (0.17)	–0.056
Efficiency ratio growth squared	3.80*** (0.51)	0.062
Economic health index	0.05* (0.02)	0.001
BHC indicator	–0.51*** (0.04)	–0.010
Rural indicator	–0.33*** (0.05)	–0.005
N	64677	
AIC	4037.59	
BIC	4210.05	
Pseudo R^2	0.77	

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Appendix B

Sensitivity to Alternative Measurement of De Novo Status (Five-Year and Seven-Year Results)

Our main results show that most de novo banks have a low probability of being de novo (or a high probability of being an established bank) in three to four years. However, this result may depend on the decision to define de novo banks as banks up to three years in age. Defining a longer period for de novo banks might produce different results. To test this sensitivity, we rerun the analysis using assigned de novo periods of five and seven years. Below are the de novo probability distributions using the three-year, five-year, and seven-year de novo periods.

Comparing the three panels of Chart B-1 shows that the probability distributions are higher in the five-year (Panel B) and seven-year (Panel C) periods. However, the three panels show a similar pattern over time, with the distributions of the probability of being a de novo bank declining in the third, fourth, and fifth years.

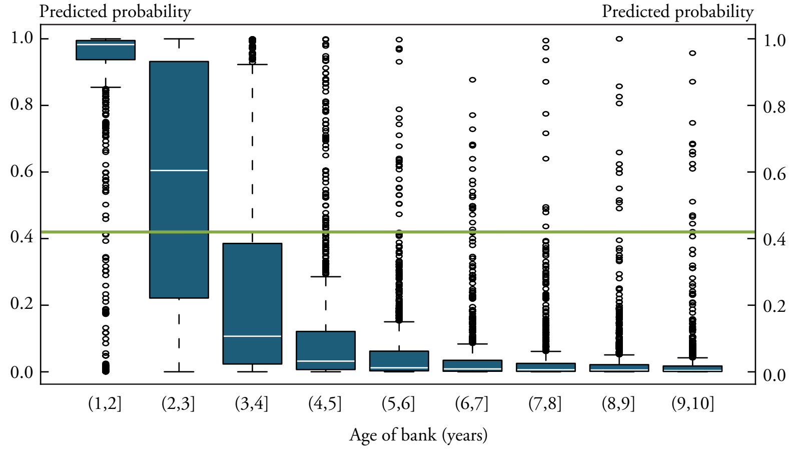
We then use cluster analysis to assign banks to de novo and established bank clusters. The cutoff level is similar in each case: 42 percent, 40 percent, and 38 percent for the three-year, five-year, and seven-year scenarios. When these cutoff levels are applied to the probability distributions, the median de novo probability is below the cutoff levels by the end of the fourth year for the five-year and seven-year analyses. This means the majority of banks are in the established bank cluster by this time, which is before the end of the de novo window.

Table B-1 shows the confusion matrices for the three scenarios. The three-year confusion matrix shows that the model projects a higher percentage of true established banks and a higher percentage of true de novo banks. With a longer de novo period, the model assigns more of the true de novos to the established bank cluster. In the three-year analysis, 23 percent of de novo banks are shown as established banks (403 out of 1,756), while the corresponding percentages for the five-year and seven-year analyses are 42 percent and 49 percent. This result supports the idea that longer periods are "too long," because a much higher percentage of banks become established before the end of the de novo period.

Chart B-1

Probability of De Novo-Like Financial Characteristics by Age

Panel A: Using Three-Year De Novo Period and 42 Percent Cutoff



Panel B: Using Five-Year De Novo Period and 40 Percent Cutoff

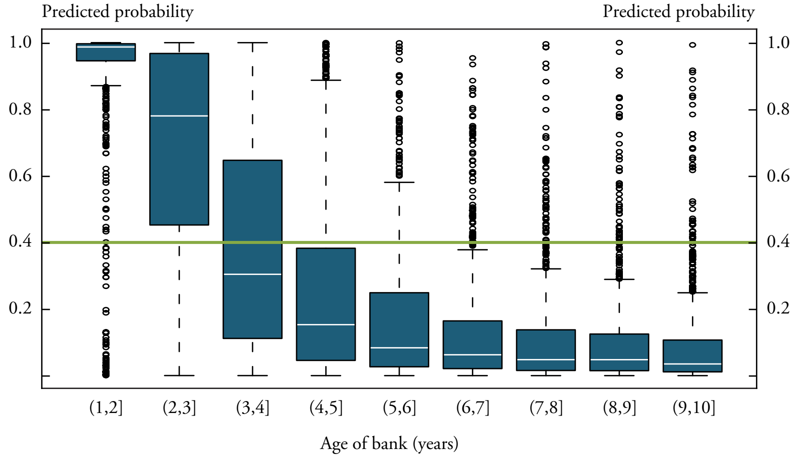
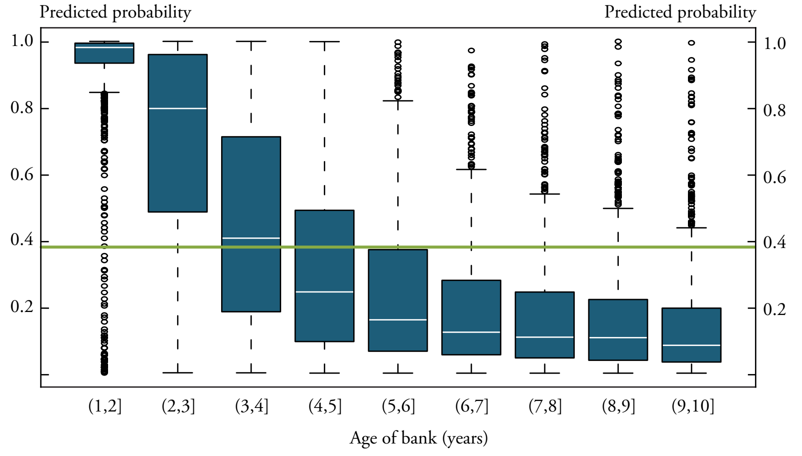


Chart B-1 (continued)

Panel C: Using Seven-Year De Novo Period and 38 Percent Cutoff



Source: Authors' calculations.

In addition, when there is a longer time period for de novo status (five years or seven years), the model assigns a broader range of banks to the de novo bank cluster, including a higher proportion of established banks. Of the banks where the model projects a high de novo probability, 28.7 percent (544 of 1,897) are established banks in the three-year analysis, while 29.4 percent (882 of 2,999) and 32.9 percent (1,332 of 4,047) are established banks in the five-year and seven-year analyses, respectively. Using the longer period for de novos causes the model to cast too wide a net looking for de novo banks.

Table B-1

De Novo Period Sensitivity Analysis

Three-year de novo period			
	Actual classification		
Predicted classification	Established	De novo	Total
Established	72,753	403	73,156
De novo	544	1,353	1,897
Total	73,297	1,756	75,053
Five-year de novo period			
	Actual classification		
Predicted classification	Established	De novo	Total
Established	70,550	1,504	72,054
De novo	882	2,117	2,999
Total	71,432	3,621	75,053
Seven-year de novo period			
	Actual classification		
Predicted classification	Established	De novo	Total
Established	68,389	2,617	71,006
De novo	1,332	2,715	4,047
Total	69,721	5,332	75,053

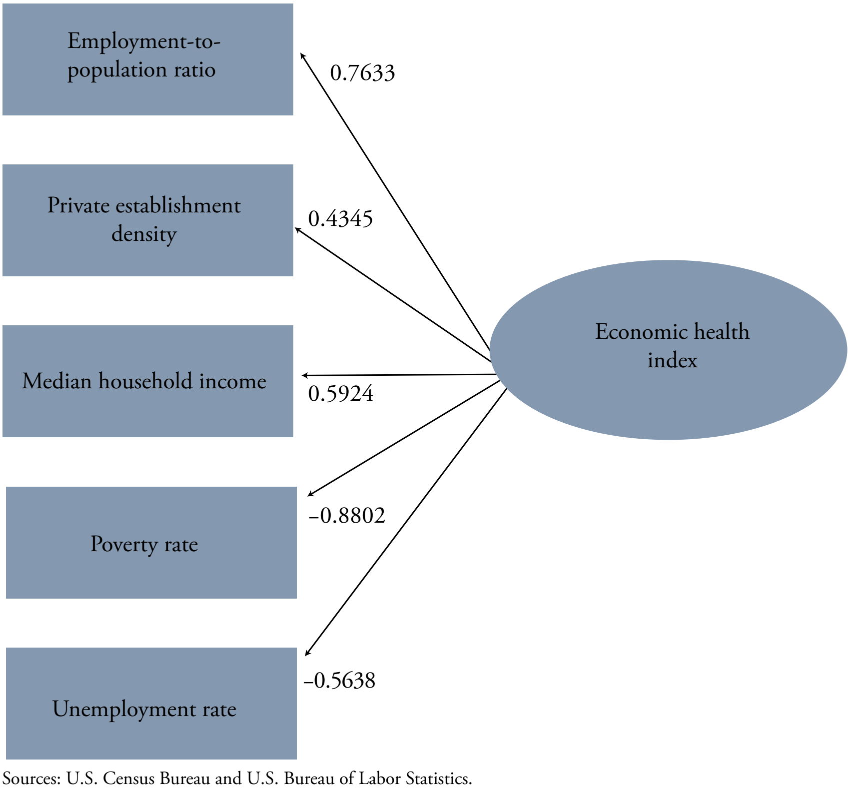
Appendix C

Economic Health Index Variable

The economic health index variable is a latent construct produced through factor analysis intended to track the economic well-being of U.S. counties over the timespan of our data. The approach was modeled after The Hamilton Project's Economic Vitality Index presented in Nunn, Parsons, and Shambaugh (2018). The index considers the employment-to-population ratio, private establishment density, median household income, poverty rate, and unemployment rate, which were obtained from the U.S. Census Bureau and the U.S. Bureau of Labor Statistics. Figure C-1 shows the applicable factor loadings. Much like linear regression coefficients, variables with positive factor loadings have a positive correlation with economic health, while variables with negative factor loadings have a negative correlation with economic health. We limit variables incorporated in the construct to those that can capture small counties and that have a data history that spans the length of our study.

Chart C-1 shows the distribution of the economic health index variable. Resulting index values have been normalized to a mean of 0 and a standard deviation of 1 so that the average county in an average year over the time horizon will have an index value of 0. The 1st and 99th percentile values of the index are –2.70 and 2.13, respectively; however, minimum and maximum values range as low as –5.54 and as high as 5.30.

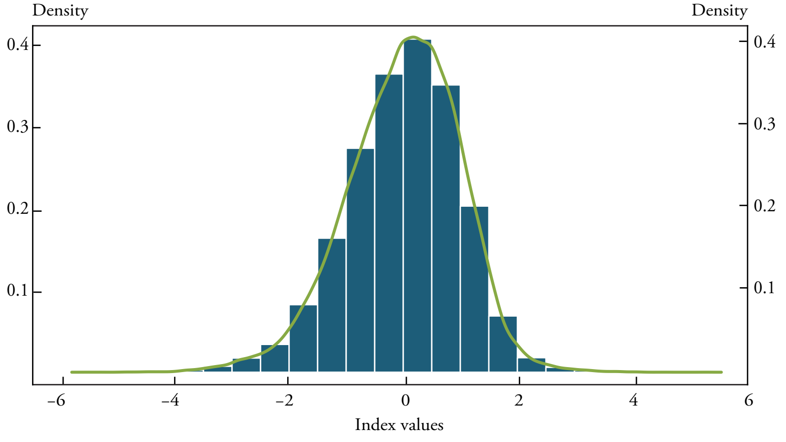
Figure C-1
Economic Health Index Factor Loadings



Sources: U.S. Census Bureau and U.S. Bureau of Labor Statistics.

Chart C-1

Distribution of Economic Health Index



Source: Authors' calculations.

Endnotes

[1]Net interest margins (interest income minus interest expenses) are generally higher when the yield curve is steeper. However, net interest margins also increase or widen as interest rates rise, due primarily to the interest on earning assets rising faster than the interest rates paid on retail deposits, the primary liabilities for new and smaller banks.

[2]Only 18 new bank charters were issued from 2010 through 2015 and only 32 were issued from 2016 through 2020. The process for chartering a bank may take over a year to complete (Board of Governors of the Federal Reserve System 2013). Therefore, there may be some delay before increased profit opportunities in banking translate into new charters.

[3]Substantive changes included final rules and federal programs of the FDIC, Board of Governors of the Federal Reserve System, Office of the Comptroller of the Currency, Consumer Financial Protection Bureau, and the Department of the Treasury (FDIC 2020). The changes did not include accounting standards, tax laws, supervisory guidance, statements of policy, and state laws or regulations.

[4]Wholesale funds include brokered deposits, federal funds purchased, Federal Home Loan Bank advances, and other borrowings. These deposits usually have higher interest rates than retail deposits (FDIC 2019).

[5]The OCC charters and supervises national banks. The FDIC administers the Deposit Insurance Fund and jointly supervises state nonmember banks with state banking agencies. The Federal Reserve is the nation's central bank: it acts as the federal government's bank, is responsible for monetary policy, and is supervisor of state member banks along with state banking agencies and bank holding companies.

[6]Banks that are not in satisfactory condition are subject to more intensive oversight. For example, the banking agencies may examine banks in weak condition as frequently as every six months.

[7]Probit regressions are especially suitable for estimating probabilities because they use a mathematical transformation that keeps the estimated probabilities in the range of zero to one (which is not the case with ordinary least squares regressions).

[8]CAMELS is a summary rating given to banks after a commercial bank examination and stands for Capital, Asset quality, Management, Earning, Liquidity, and Sensitivity to market risk.

[9]DeYoung (1999) finds that de novo bank financial performance lagged more established banks for up to 14 years. We also estimate parameters using banks four years and older as established banks. The resulting probability distributions are very similar to results reported here.

[10]The chart only includes banks 10 years of age or younger.

[11]Deposit national banks are special-purpose banks established by the FDIC to resolve failed banks that could not be sold to or merged with an existing bank.

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