FEDERAL RESERVE BANK OF KANSAS CITY

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By Taeyoung Doh and Jaeheung Bae

Measuring the current state of the U.S. economy in real time is an important but challenging task for monetary policymakers. The most comprehensive measure of the state of the economy—real gross domestic product—is available at a relatively low frequency (quarterly) and with a significant delay (one month). To obtain more timely assessments of the state of the economy, the Federal Reserve Bank of Kansas City has developed a GDP tracking model that combines new econometric methods with two conventional approaches to estimating GDP.

Taeyoung Doh and Jaeheung Bae review the KC Fed model's underlying details and illustrate its performance by comparing the model's tracking estimates to those from other real-time tracking models. Their results suggest the KC Fed model provides a useful tool for policymakers by combining estimates and forecasts from factor and accounting-based models.

The Uneven Recovery in Prime-Age Labor Force Participation

By Didem Tüzemen and Thao Tran

The labor force participation rate of prime-age individuals (age 25 to 54) in the United States declined dramatically during and after the Great Recession. Although the prime-age labor force participation rate has been increasing since mid-2015, it remains below its pre-recession level. Understanding the reasons for this decline requires detailed analysis; aggregate statistics on labor force participation may mask potential differences in labor market outcomes by sex or educational attainment.

Didem Tüzemen and Thao Tran identify these differences, finding that prime-age men and women without a college degree experienced larger declines in their labor force participation rates during the recession than their college-educated counterparts. The disappearance of routine jobs over the last few decades may explain these declines. In addition, they find that only prime-age women with a college degree have seen their labor force participation rate fully recover to its pre-recession level, although their participation rate remains well below that of both college-educated and non-college-educated men.

Did Local Factors Contribute to the Decline in Bank Branches?

By Rajdeep Sengupta and Jacob Dice

Although the total number of bank branches in the United States increased from the mid-1990s to 2007, this number has declined since the 2007–08 financial crisis. A loss in bank branches is potentially problematic because it may reduce customers' access to financial services as well as small businesses' access to credit. Changes in local conditions may partly explain this loss: the number of branches varies signficantly across geographic areas, and local conditions have been shown to influence past trends in bank branching.

Rajdeep Sengupta and Jacob Dice examine the relationship between bank branching and local conditions over the last two decades to assess which factors contributed to the decline in bank branches. They find a strong association between the number of branches in a county and that county's population, income, and employment. In addition, they find that the relative influence of local market and competitive factors on branch openings and closings strengthened after the financial crisis, while the influence of local demographic and economic factors weakened.

Tracking U.S. GDP in Real Time

By Taeyoung Doh and Jaeheung Bae

Measuring the current state of the U.S. economy in real time is an important but challenging task for monetary policymakers. A more accurate assessment of the current state of the economy helps policymakers make better projections for the future and, accordingly, set policy best suited to achieving the mandated goals of maximum employment and stable prices. However, capturing the state of the economy in real time is difficult because the most comprehensive measure—real gross domestic product—is available at a relatively low frequency (quarterly) and with a significant delay (one month). While several indicators used to estimate GDP are available at higher frequencies, using them to track GDP in real time requires researchers to make choices about how to combine and weight these indicators. These choices may introduce errors.

Recent advances in econometric methods have made it feasible to track GDP in real time with fewer human judgments using the historical relationship between the official quarterly GDP numbers and economic indicators available at higher frequencies. The Federal Reserve Bank of Kansas City has incorporated these new methods into a GDP tracking model (henceforth referred to as the "KC Fed model") that combines two conventional approaches to estimating GDP to obtain better assessments of the current state of the economy.

In this article, we explain the model's underlying details and illustrate its performance by comparing the model's daily tracking estimates of 2019:Q1 GDP with those from the Federal Reserve Bank of New

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York and the Federal Reserve Bank of Atlanta. Our results suggest that the KC Fed model's tracking estimate is comparable to tracking estimates from the other two Reserve Banks. In addition, our results lend support to the KC Fed model's dynamic weight-shifting assumption, which adjusts the weights placed on GDP estimates from the two approaches as information from monthly indicators accumulates.

Section I explains the policy relevance of tracking GDP in real time as well as some practical challenges. Section II introduces the general methodologies used to track GDP in real time and discusses their pros and cons. Section III reviews the underlying details of the KC Fed model and compares its real-time tracking performance with other Reserve Bank models based on the models' estimates of 2019:Q1 GDP.

I. The Challenges of Tracking GDP in Real Time

Tracking current-quarter macroeconomic conditions based on recent indicators is important for the conduct of monetary policy and medium-term forecasting. Members of the Federal Open Market Committee (FOMC) have increasingly communicated to the public that policy decisions are "data dependent," meaning policymakers take into account new information as economic conditions and the outlook evolve (Powell 2019; Williams 2019). Although most macroeconomic data are released with a lag, incomplete data can provide a reasonable starting point for assessing current-quarter economic conditions. For this reason, the FOMC's post-meeting statement typically begins by discussing the implications of the data released between meetings. In addition, researchers have shown that initial-period forecasts play a key role in the accuracy of forecasts at subsequent horizons in the medium term (Carriero and Clark 2015).

While obtaining an accurate estimate of current-quarter GDP is useful in making policy decisions and medium-term forecasts, the official estimate is released with a significant lag. The Bureau of Economic Analysis (BEA) releases the first estimate of GDP only at a quarterly frequency and with a one-month delay.[1] However, this first estimate is often revised in subsequent months because not all underlying source data are available at the time of the initial release. The final estimate of GDP that incorporates more than 90 percent of the underlying source data is usually released three months after the end of the quarter.

To overcome these data limitations and lags, policymakers consider a wide range of information provided by other economic and financial indicators available at higher frequencies. Some of these indicators are "hard" data that directly feed into the official estimate of GDP— namely, monthly retail sales and industrial production. Others are "soft" data, which include consumer and business surveys or financial asset prices. According to Williams (2019), data-dependent policy means taking into account such policy-relevant data at higher frequencies.

However, considering all available higher-frequency indicators requires policymakers to make substantial judgments. For example, estimating overall consumption in a given quarter may require policymakers to estimate how much a positive surprise in one month's retail sales will persist into the next month's retail sales. In addition, incorporating survey data into an assessment of current macroeconomic conditions may require policymakers to estimate the effect of changes in consumer sentiment on consumer spending. Quantifying this effect can be especially challenging because sentiment sometimes changes even without new information on economic fundamentals.

Recent advances in econometric methods may allow policymakers to automate some of these judgments in a consistent way using statistical models. For example, Giannone, Reichlin, and Small (2008) explain how to address "unbalanced" data sets in which the release dates of monthly data differ by indicator.[2] In particular, they provide the statistical tools used to aggregate various components of GDP with different frequencies and release dates into the tracking estimate of GDP. While these methods do not eliminate all human choices—for example, which criterion function to use to evaluate different models—they allow policymakers to largely automate the process of tracking GDP in real time using mixed-frequency data (Banbura and others 2013).

II. The "Bottom-Up" and "Top-Down" Methods for Tracking GDP

Two popular ways of estimating GDP in real time are the "bottom-up" and "top-down" methods. The bottom-up method aggregates the effect of each economic indicator on each subcomponent of GDP. The top-down method extracts the statistical factors driving the co-movements of economic indicators and predicts GDP or its subcomponents based on estimates of these factors.

Forecasters using the bottom-up method make a current-quarter forecast for each subcomponent of GDP using bridging equations that link monthly indicators with quarterly forecasts of GDP subcomponents. Then, they aggregate the quarterly forecasts of GDP subcomponents to obtain the current-quarter estimate of headline GDP. For example, a forecast of current-quarter services consumption would aggregate forecasts for relevant indicators such as electric and gas utilities in monthly industrial production. The aggregation is typically based on the subcomponents' accounting identities and closely mimics the methodology used by the BEA to calculate each subcomponent of GDP from underlying details.

The bottom-up method offers researchers a few key benefits. Because the bottom-up method makes projections at the indicator level, it can easily identify surprises in data releases and determine their effect on GDP. In this way, the bottom-up method provides transparency in how the tracking estimate of GDP responds to data releases. For example, consider the following autoregressive prediction model for monthly retail sales for food services:

$$x_t = (1-\rho_x)\mu_x + \rho_x x_{t-1} + \epsilon_{x,t},$$

where x_t represents monthly retail sales for food services in month t, ρ_x represents the degree of persistence, μ_x represents the historical average, and $\epsilon_{x,t}$ represents an unanticipated surprise. If the indicator follows a highly persistent autoregressive model (ρ_x close to 1), a positive surprise in the latest reading of the indicator (a big positive realization of $\epsilon_{x,t}$) is more likely to shift up the current-quarter estimate of the services consumption subcomponent of GDP. In contrast, if the indicator follows an autoregressive model with a negative coefficient ($-1 < \rho_x < 0$), one month's strong reading is more likely to shift down the estimate in the following month within the same quarter with relatively little influence on the current-quarter estimate.

The bottom-up method has two key disadvantages. First, the method cannot easily incorporate information from soft data, such as surveys, that are not part of the official GDP estimate. In addition, the method can yield estimates of GDP that are overly sensitive to individual data points early in the quarter, when fewer indicators are available. This sensitivity arises from the fact that the tracking model relies more on extrapolated values than actual data to obtain early-quarter estimates of GDP. As more data become available, the model relies more on the realized data and less on extrapolated values, and the volatility of the tracking estimate tends to decline accordingly.

In contrast, the top-down method tends to generate much smoother and less volatile estimates. In the top-down method, we aggregate information from high-frequency indicators into a few statistical factors before using the factor estimates to predict GDP. We extract the statistical factors by identifying the common components that explain most of the covariations of the high-frequency indicators. This aggregation process smooths out the idiosyncratic volatility of individual indicators. Then, we project current-quarter GDP by regressing headline GDP growth on the factor estimates.

Another benefit of the top-down method is that the statistical factor model is not restricted by accounting identities and can thus include soft data as well as hard data as input variables. This flexibility allows researchers to include hard data such as employment that may help predict GDP but are not a direct input into the calculation of GDP. For example, the BEA uses the monthly employment report to estimate only two components of GDP—services consumption and government spending. However, labor market conditions in the employment report might also influence business investment. The flexibility of the top-down method allows us to examine how hard data might influence variables outside of the bottom-up method's rigid accounting identities.

In addition, researchers have the flexibility to include relevant soft data as additional inputs when releases of hard data are unexpectedly or systematically delayed. Even when hard data releases are not delayed, soft data may offer benefits to researchers. For example, the effect of news about future fiscal policy on current spending may show up in hard data with a delay but in survey and financial market data immediately. This feature can be useful for predicting future macroeconomic conditions beyond the current quarter.

However, the top-down method has one key disadvantage. Because factor estimates are based on a purely statistical relationship, it is difficult to explain why the tracking estimate of GDP changes in response to data releases. For example, a strong data point in the manufacturing survey may change the estimated factor that affects the tracking estimates of GDP components, such as consumption, that are not directly tied to the manufacturing survey. A strong data point in a consumer survey that moves the factor estimate by the same amount can affect consumption to the same degree. The top-down method cannot isolate which data release drove the change in consumption, even though the consumer survey is more likely to affect consumption and the manufacturing survey is more likely to affect investment. For this reason, the top-down method is not a good tool for interpreting the underlying economic forces behind data surprises.

III. The KC Fed Model

Although the bottom-up and top-down approaches have discrete advantages and disadvantages, they are not mutually exclusive. In fact, the two approaches can be combined to generate more accurate forecasts. For example, researchers can take the weighted averages of forecasts generated by the two approaches and incorporate factor estimates into bridging equations.

The KC Fed model follows this process, combining forecasts from two different models.[3] The first model, which follows the bottom-up method, is the accounting-based model. This model generates quarterly forecasts of indicators by filling in observations for missing months and aggregating them to make a quarterly projection for each subcomponent of GDP. The second model, which follows the top-down method, is the factor model. This model generates forecasts for the nine major subcomponents of GDP by aggregating information from high-frequency indicators into a few statistical factors and then making corresponding projections using these factor estimates.[4]

The two models address the varying availability of monthly data used as inputs in different ways. The accounting-based model generates a forecast using a specified selection function for each data series yet to be released. Namely, the model selects its forecasting method based on the recent forecast accuracy of four univariate methods.[5] Whichever method and parameterization produces the smallest root mean square error (RMSE) for its one-step-ahead forecast over the preceding six months is used to forecast missing values for that data series. Under this approach, forecasts are based only on the observed variables so far. In contrast, the factor model can allow the unobserved latent variables to affect forecasts. The factor model has two sets of parameters: those governing the dynamics of observed or unobserved factors and those linking factors with observed variables. To estimate the factor model, we first estimate model parameters from a balanced panel containing data for all input indicators up to the date of the latest common release. Then, the model updates the estimated factor using parameter estimates and monthly indicators already released but not included in the balanced panel. Finally, we run an ordinary least squares (OLS) regression of past quarterly data on past estimates of the factor to produce current-quarter estimates of each subcomponent of GDP. We then aggregate these subcomponent estimates to construct GDP.

Once quarterly forecasts are obtained from both models, we can generate alternative forecasts that combine these forecasts by imputing weights. For example, the KC Fed model aggregates the forecasts from the two models for the nine subcomponents of GDP using calendar-based weights. For each subcomponent (x) in quarter t, the tracking model combines the forecasts from the factor model (x_t^F) and the accounting-based model (x_t^{act}) according to the corresponding weight ($w_{x,t}$) to obtain the final forecast of x_t as follows:

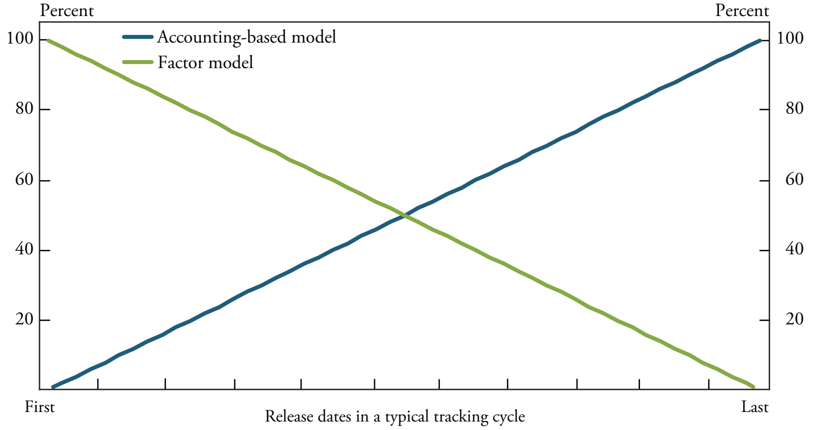
$$x_t = w_{x,t} x_t^{act} + \left(1 - w_{x,t}\right) x_t^F .$$

Chart 1 shows how the KC Fed model weights the forecasts from the two models over time. The horizontal axis shows the calendar dates in which economic indicators for a particular tracking quarter are released. The first date, following the first release date of the BEA's first estimate of the previous quarter GDP, usually occurs early in the second month of the quarter. The last date, corresponding to the last relevant release date, usually occurs in the first month of the subsequent quarter. Table 1 shows the release schedule for some of the key data sources used in the KC Fed model. In a tracking cycle of approximately 12 weeks, three monthly observations of each indicator are incorporated into the model.

The KC Fed model weights forecasts from the factor model more heavily early in the tracking cycle, when many data are not yet available and forecasts from the accounting-based model are more sensitive to surprises in high-frequency indicators. The KC Fed model then increases the weight on forecasts from the accounting-based model over time. One day before the release of the BEA's first estimate of quarterly GDP, the model places the entire weight on the accounting-based model's

Chart 1

Weights Assigned to the Two Models for Components of GDP for a Given Quarter



Notes: The blue and green lines represent the weights assigned to the accounting-based model and factor model, respectively, in computing the final estimate of the subcomponent. The entire weight is assigned to the accounting-based model forecasts one day before the release of the BEA's first estimate of quarterly GDP for the current tracking quarter.
Source: Authors' calculations.

Table 1

Typical Release Weeks for Major Source Data in the KC Fed Model

Week of release	Data
First	Construction spending, factory orders, international trade, motor vehicle sales, employment situation
Second	Wholesale trade, import/export prices, retail sales, consumer price index
Third	Business inventories, producer price index, industrial production, residential construction
Fourth	New home sales, durable goods, personal income and personal outlays

Note: Table represents typical release weeks for the relevant series; the actual week of release may differ from month to month.

forecasts. Because the accounting-based model follows the same guidelines used in the BEA's actual calculation of GDP, the model-based tracking estimate is likely to be a good proxy for the official estimate as the date approaches the release date (given that both estimates include the same amount of information provided by high-frequency indicators).[6]

Table 2 provides summary information for input variables used in each model. The accounting-based model includes 148 indicators, 107 of which are available at a monthly frequency. The factor model includes 198 indicators, 197 of which are available at a monthly frequency. Because it follows the top-down method, 11 of the 198 indicators are soft data.

Table 2
Source Data in the KC Fed Model

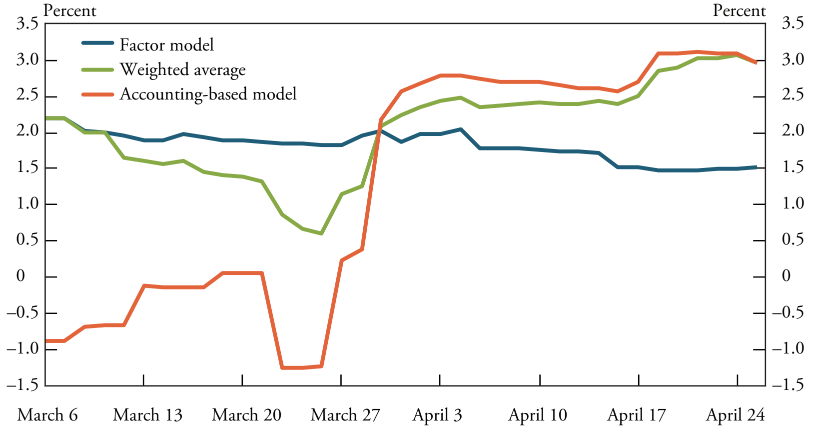
Accounting-based model				Factor model			
Category		Frequency		Category		Frequency	
Personal consumption expenditures	23	Quarterly	38	Soft	11	Quarterly	1
Business fixed investment	40	Monthly	107	Hard	187	Monthly	197
Residential investment	19	Weekly	2				
Change in private inventories	19	Daily	1				
Net exports of goods and services	25						
Government consumption expenditures and gross investment	25						
Total	148		148		198		198

Source: Authors' calculations.

Chart 2 shows the real-time tracking estimates of 2019:Q1 headline GDP growth from the KC Fed model from March 6, 2019, to April 25, 2019. Typically, we would begin tracking first-quarter GDP in late January or early February rather than March. However, due to the partial government shutdown that began in December 2018, the BEA did not release its first estimate of 2018:Q4 GDP until the end of February—one month later than usual. The GDP tracking estimate from the factor model (blue line) slowly moves down from 2.2 percent to 1.5 percent, with a standard deviation of 0.2 percent. In contrast, the estimate from the accounting-based model (orange line) exhibits substantially higher volatility during the same period. Indeed, the corresponding standard deviation is an order of magnitude larger at 1.66 percent. The estimate from the weighted average of the two forecasts (green line) has a standard deviation between the two extremes at 0.67 percent.

The difference in the volatility of the models' forecasts reflects the difference in the models' sensitivity to high-frequency data releases. Although the tracking estimate of 2019:Q1 GDP from the accounting-based model starts below that of the factor model, it quickly rises above the factor model. Specifically, the accounting-based model's estimate of headline GDP growth jumps up by 1.46 percent on March 27, coinciding with the release of January international trade data showing a narrowing of the trade deficit spurred by a substantial decline in imports. The estimate jumps up by another 1.77 percent on March

Chart 2
KC Fed Model Tracking Estimates for 2019:Q1 GDP



Source: Authors' calculations.

29, coinciding with the release of much stronger than expected January manufacturing and wholesale inventories data. In contrast, the factor model estimates change little on these dates.

Table 3 shows that the accounting-based model's final estimates of quarterly inventory investment and international trades (exports and imports) are much closer to the BEA's official estimates than those from the factor model, suggesting the accounting-based model correctly identified the signals from monthly indicators. The accounting-based model also captured the weakness in private domestic final sales masked by the strength in inventory investment and net exports. By generating forecasts for the subcomponents of GDP, the KC Fed model helps isolate the subcomponent that is more likely to be persistent (here, private domestic final sales) before the BEA's official estimate of GDP is available.

However, the sizable adjustments in the accounting-based model on March 27 and 29 suggest that the model might have underestimated the strength of inventories and net exports early in the quarter simply because it lacked relevant monthly data. These adjustments justify the KC Fed model's use of time-varying weights, allowing the factor model to be more influential early in the quarter, when many high-frequency indicators are not available.

To further evaluate the KC Fed model's performance, we compare the model's forecasts to those from other available GDP tracking models.

Table 3
Comparison of 2019:Q1 GDP Tracking Estimates

Component	Factor model (April 25)	Accounting-based model (April 25)	Atlanta GDPNow (April 25)	New York Nowcast (April 25)	BEA (April 26)
GDP	1.5	3.0	2.7	1.4	3.2
Private domestic final sales	3.2	0.9	1.4		1.3
Personal consumption expenditures	3.0	0.6	1.1		1.2
Business fixed investment	3.9	2.3	3.1		2.7
Structures	3.8	−1.6	−0.3		−0.8
Equipment	1.7	1.7	2.0		0.2
Intellectual property products	6.8	5.8	6.8		8.6
Residential investment	−2.0	1.6	1.3		−2.8
Change in private inventories	52.0	128.0	117.0		128.0
Net exports of goods and services		−902.0	−929.0		−899.0
Exports	1.6	4.0	3.4		3.7
Imports	2.9	−3.2	−0.5		−3.7
Government consumption expenditures and gross investment	2.4	3.8	3.2		2.4

Note: All components are annualized quarterly rates of change except net exports and change in private inventories, which are in billions of chained 2012 dollars.
Sources: BEA, Federal Reserve Bank of Atlanta, Federal Reserve Bank of New York, and authors' calculations.

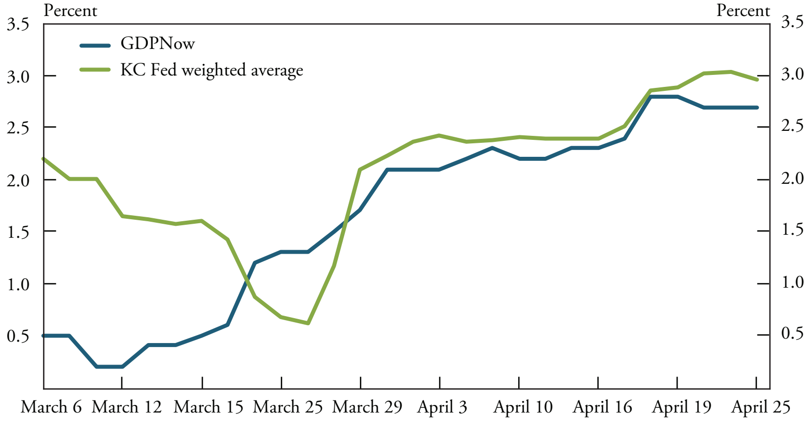
Specifically, we consider two publicly available tracking estimates from the Federal Reserve Bank of Atlanta and the Federal Reserve Bank of New York. These models provide good benchmarks because they use two different approaches to tracking GDP.

Chart 3 compares estimates from the KC Fed model with estimates from the Atlanta Fed's tracking model, also known as "GDPNow." The GDPNow model is similar to the KC Fed model in that it combines a factor model with bridging equations. However, the GDPNow model differs from the KC Fed model in that it adds factor estimates as predictors in the bridging equations (Higgins 2014). In addition, the GDPNow model uses forecasts from a Bayesian vector autoregression of 13 subcomponents of GDP as additional inputs for the tracking model estimates. Despite these differences, the KC Fed model's tracking estimate of GDP closely follows the estimate from GDPNow.

In contrast, Chart 4 shows that estimates from the New York Fed's tracking model appear to differ substantially from estimates from the KC Fed model. This difference can be attributed to different goals. According to Bok and others (2017), the New York Fed's model targets the systematic

Chart 3

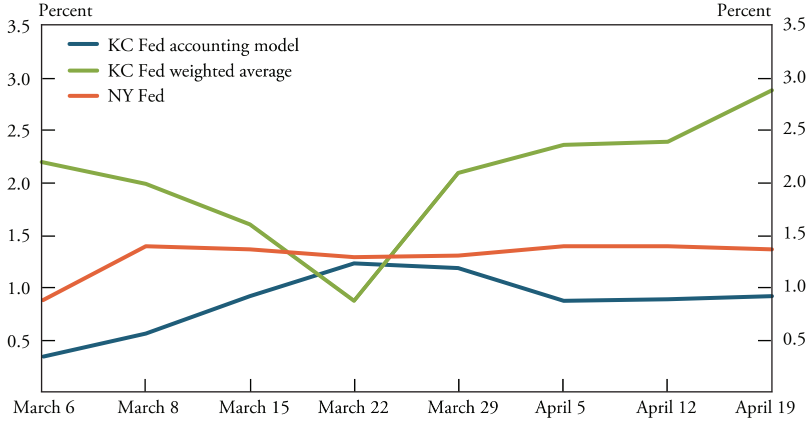
Tracking Estimates of 2019:Q1 GDP from KC Fed Model and GDPNow



Note: Dates correspond to releases of the Federal Reserve Bank of Atlanta's tracking estimates.
Sources: Federal Reserve Bank of Atlanta and authors' calculations.

Chart 4

Tracking Estimates of 2019:Q1 GDP from KC Fed and NY Fed Models



Note: Dates correspond to releases of the Federal Reserve Bank of New York's tracking estimates.
Sources: Federal Reserve Bank of New York and authors' calculations.

component of GDP growth, which can be approximated by growth in private domestic final sales. Indeed, the estimates of private domestic final sales from the KC Fed's accounting-based model (not shown) fairly closely follow the New York Fed's GDP tracking estimates.

Comparing the KC Fed model's tracking estimates with those from other Reserve Bank models suggests that the real-time tracking of GDP is fairly robust to implementation details. The main difference in each model's estimates is which aspect of GDP the models target. If policymakers are more interested in tracking the systematic component of GDP that may persist in the future, a factor model may be more useful to the extent that it smooths out idiosyncratic variations in high-frequency data. However, if policymakers are more interested in understanding current macroeconomic conditions as accurately as possible, information from an accounting-based model may be more appealing. Ultimately, these two approaches are complementary; the KC Fed model allows us to combine estimates from the factor model and accounting-based model, resulting in better predictions of GDP.

Conclusion

Understanding how data releases influence current macroeconomic conditions in real time is important for monetary policymakers who set policy in a data-dependent way. The Federal Reserve Bank of Kansas City has developed a model to track GDP in real time using high-frequency indicators and recent developments in time series econometrics. Specifically, the KC Fed model combines estimates from two different models—an accounting-based model and a factor model—to produce estimates of current-quarter GDP that adjust in response to new data.

We compare estimates from the KC Fed model to estimates from two other real-time tracking models and find that all three models produce relatively consistent estimates provided they share the same target variable (for example, the official estimate of GDP or the underlying trend of GDP more relevant for predicting future macroeconomic conditions). By combining estimates from models with different target variables, the KC Fed model can provide a useful source for understanding both current and future macroeconomic conditions.

Endnotes

[1]In the euro area, the official estimate of quarterly GDP is released six to seven weeks after the end of the quarter. Although GDP is measured on a quarterly basis in the United States and euro area, unofficial estimates of GDP at higher frequencies are available from the private sector (for example, the Monthly GDP series produced by Macroeconomic Advisers in the United States). In addition, some public institutions provide alternative estimates of real activity measures at higher frequencies (for example, the monthly Chicago Fed National Activity Index (CFNAI).

[2]For example, some indicators are released in the first month of the quarter, while others are released in the second month of the quarter.

[3]The KC Fed model does not represent the official view of the Federal Reserve Bank of Kansas City. The model is one input that is included in staff discussion on the current state of the economy.

[4]The nine subcomponents are personal consumption expenditures, business investment in nonresidential structures, business investment in equipment, business investment in intellectual property, residential investment, government spending, exports, imports, and changes in inventories.

[5]The four methods are a moving average from horizons of three to 12 months, exponential smoothing with a smoothing factor between 0.1 and 0.5, a univariate regression with one to 12 lags using the last 24 months of data, and a univariate regression with one to 12 lags using the last 120 months of data.

[6]The BEA's accounting framework used to calculate GDP is available at https://www.bea.gov/resources/methodologies/nipa-handbook, and the KC Fed's accounting-based model follows these guidelines as much as possible.

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The Uneven Recovery in Prime-Age Labor Force Participation

By Didem Tüzemen and Thao Tran

The labor force participation rate of prime-age individuals (age 25 to 54) in the United States declined dramatically during and after the Great Recession. From 2008 to 2015, the share of prime-age individuals either working or actively looking for work decreased from 83.1 percent to 81.0 percent, the lowest rate since the 1980s. In 2008, 21 million prime-age individuals did not participate in the labor force. By 2015, this number had risen to almost 24 million. Although the labor force participation rate of prime-age individuals has been increasing since mid-2015, it remains below its pre-recession level.

Prime-age individuals are in their most productive working years, and a decline in their labor force participation has important implications for the future of the labor market and economic growth. However, understanding the decline requires detailed analysis; aggregate statistics on labor force participation may mask differences in labor market outcomes by sex and educational attainment. Identifying these differences is crucial to both evaluating potential labor market implications and designing targeted policies to encourage labor force participation.

In this article, we use data from the U.S. Census Bureau's Current Population Survey (CPS) to document recent changes in the labor force participation rates of prime-age individuals across sex and education levels during the Great Recession and the subsequent recovery. Our analysis yields two key findings. First, prime-age men and women without a bachelor's degree experienced larger deteriorations in their

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labor force participation rates during the recession than their college-educated counterparts. These rates are still well below their pre-recession levels, likely due to the long-term shift in employment away from routine occupations and toward non-routine occupations. Second, only prime-age women with a bachelor's degree have seen their labor force participation rate fully recover. Notably, although the prime-age participation rate of college-educated women has recovered to its pre-recession level, it still remains well below the participation rates of both college-educated and non-college-educated men. A greater share of women who report caring for family as their reason for nonparticipation may explain this discrepancy.

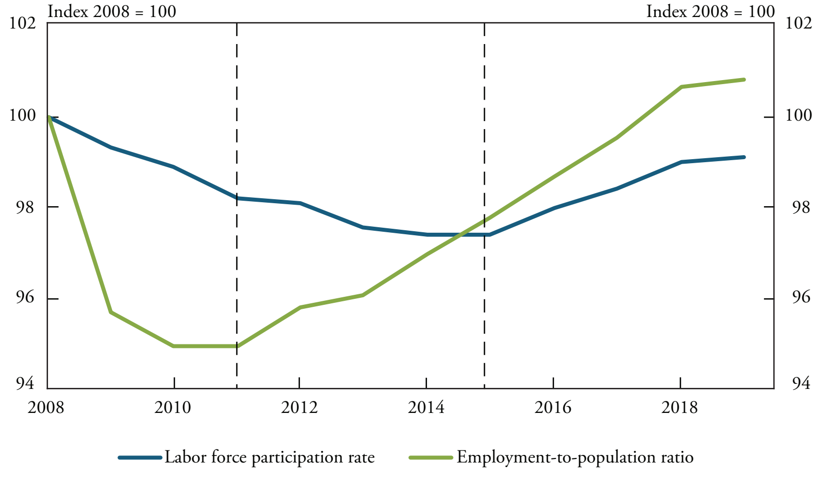
Section I documents the sharp decline and subsequent recovery in the prime-age labor force participation rate during and after the Great Recession, revealing stark differences in the labor market outcomes of prime-age individuals of different sex and education groups. Section II shows how long-term shifts in the composition of jobs have caused declines in employment and labor force participation among prime-age individuals. Section III argues that policies that equip workers with the new skills and education demanded by employers, or that provide help with family care, may support higher labor force participation among prime-age individuals.

I. Patterns in the Prime-Age Labor Force Participation Rate during the Great Recession and Recovery

During the Great Recession, prime-age labor force participation and employment declined dramatically due to large-scale layoffs (Aaronson and others 2015; Van Zandweghe 2012). Chart 1 plots the prime-age labor force participation rate alongside the prime-age employment-to-population ratio, both indexed to their pre-recession levels, using data from the CPS.[1] Both rates show a similar pattern during the recession, declining steeply after 2008. However, in 2011, the two rates diverged: the prime-age employment-to-population ratio began to increase, while the prime-age labor force participation rate continued to decline until 2015. Since 2015, both rates have been increasing, though the employment-to-population ratio has risen much more quickly than the labor force participation rate.

Chart 1

Prime-Age Labor Force Participation Rate and Employment-to-Population Ratio



Notes: All rates correspond to monthly observations averaged for each year. Dashed lines separate the three time periods used in the analysis: recession (2008–11), early recovery (2011–15), and late recovery (2015–19).
Sources: CPS and authors' calculations.

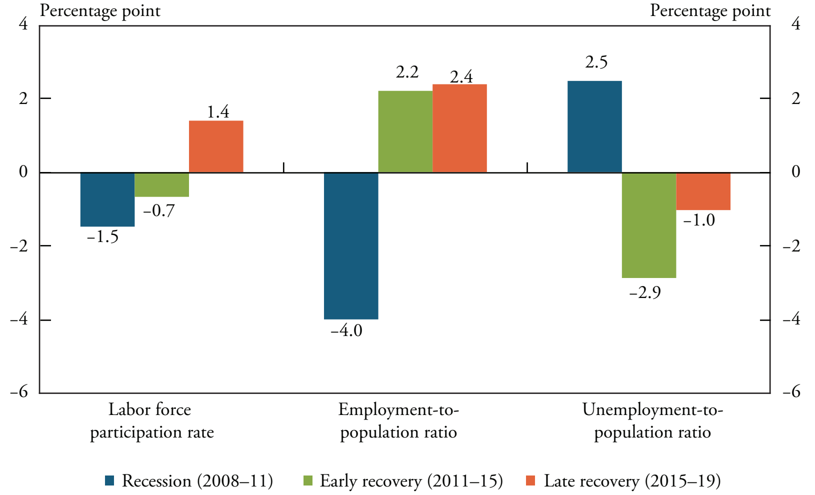
To account for the different trends in the labor force participation rate and employment-to-population ratio over time, we break our sample into three distinct periods, timed to major movements in the rates: recession (2008–11), early recovery (2011–15), and late recovery (2015–19).[2]

The prime-age labor force participation rate corresponds to the share of prime-age population either working (employed) or actively looking for work (unemployed). To provide further insights into the differing patterns in prime-age labor force participation during the three periods, we decompose the changes in the prime-age labor force participation rate into the changes in the prime-age employment-to-population ratio and the changes in the prime-age unemployment-to-population ratio. Chart 2 illustrates this breakdown during the three periods considered, while Table 1 lists the actual employment changes.

Through the recession period (2008–11), the prime-age labor force participation rate declined alongside employment, as 5.7 million prime-age individuals lost their jobs (Table 1). While some of these displaced workers joined the pool of the unemployed, others temporarily or permanently left the labor force. Chart 2 shows that the prime-age

Chart 2

Decomposing Changes in the Prime-Age Labor Force Participation Rate



Note: All rates correspond to monthly observations averaged for each year.
Sources: CPS and authors' calculations.

Table 1

Changes in Prime-Age Employment

Period	Employment changes
Recession (2008–11)	−5,707,615
Early recovery (2011–15)	3,052,145
Late recovery (2015–19)	3,927,883

Note: Employment changes are calculated using annual averages for the corresponding years.
Sources: CPS and authors' calculations.

labor force participation rate declined 1.5 percentage points by 2011, due to a 4.0 percentage point decline in the prime-age employment-to-population ratio and a 2.5 percentage point increase in the prime-age unemployment-to-population ratio.

During the early recovery period (2011–15), the prime-age labor force participation rate declined despite overall improvement in the labor market. For example, the prime-age employment-to-population ratio increased by 2.2 percentage points as about 3 million more individuals found jobs (Chart 2; Table 1). However, some prime-age workers continued to leave the labor force over this period, and the decline in the share of prime-age individuals looking for a job was greater than the increase in the share of prime-age individuals working. More specifically, the prime-age unemployment-to-population ratio declined by 2.9 percentage points, while the prime-age employment-to-population ratio increased by only 2.2 percentage points. As a result, the prime-age labor force participation rate declined by 0.7 percentage point by 2015.

In contrast, during the late recovery period (2015–19), the prime-age labor force participation rate increased alongside a strengthening labor market. The prime-age employment-to-population ratio increased by 2.4 percentage points over this period as nearly 4 million more people found jobs (Chart 2; Table 1). This increase more than offset a small, 1 percentage point decline in the unemployment-to-population ratio. As a result, the prime-age labor force participation rate rose 1.4 percentage points from 2015 to 2019.

While the prime-age employment-to-population ratio recovered to its pre-recession level by 2019, the prime-age labor force participation rate remained 0.7 percentage point below its pre-recession level. This suggests that some prime-age individuals have remained out of the labor force instead of actively searching for jobs or working.

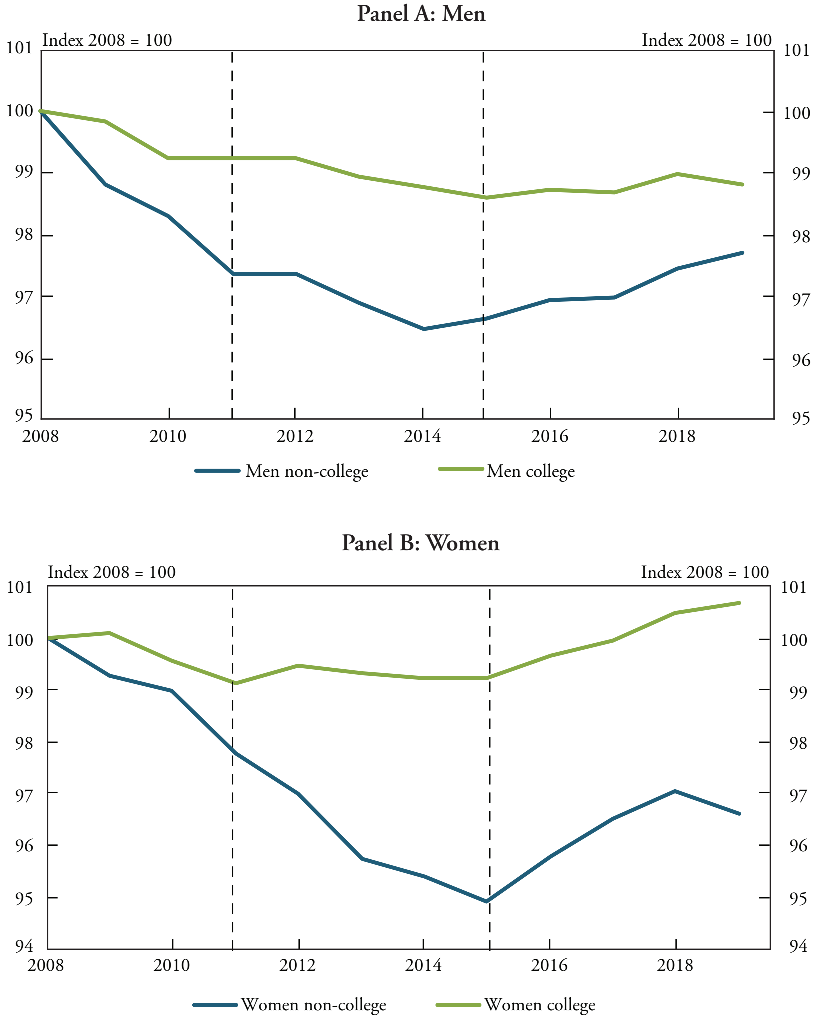
Changes in prime-age labor force participation by sex and education

Changes in the aggregate labor force participation rate and employment-to-population ratio mask large differences across different demographic groups. Women historically have lower participation rates than men, and individuals with lower educational attainment historically have lower participation rates than their more-educated counterparts. To account for these differences, we compare changes in labor market outcomes across sex and education levels. To facilitate comparison, we group prime-age individuals into one of four groups: men with less than a bachelor's degree (non-college men), men with a bachelor's degree or higher (college men), women with less than a bachelor's degree (non-college women), and women with a bachelor's degree or higher (college women).

Chart 3 shows the labor force participation rates over time for all four groups. The chart illustrates three striking results. First, prime-age men and women without a bachelor's degree saw larger deteriorations in their labor force participation rates during the recession than their college-educated counterparts. This result is likely related to the severity

Chart 3

Prime-Age Labor Force Participation Rates by Sex and Education Groups



Notes: All rates correspond to monthly observations averaged for each year. Dashed lines separate the three time periods used in the analysis: recession (2008–11), early recovery (2011–15), and late recovery (2015–19).
Sources: CPS and authors' calculations.

of job losses, as prime-age men and women without a bachelor's degree saw larger employment losses during the recession than college-educated prime-age men and women. Indeed, Table 2 shows that in the non-college group, 2.8 million men and 2.6 million women lost jobs during the recession. In contrast, in the college group, 385,318 men lost jobs during the recession, while 76,456 women actually gained jobs.

Second, the labor force participation rates of prime-age men and women without a bachelor's degree have remained well below their pre-recession levels during the two recovery periods. This, too, is likely related to job losses and lack of new job opportunities for their skill sets: Table 2 shows that sizeable employment losses continued for non-college individuals during the recovery periods, though the losses were particularly steep for women. Non-college men may have been more willing to accept lower wages during this period of high unemployment than their female counterparts, in line with the evidence that women are more likely to stop working if their wages fall (Kimmel and Kniesner 1998).

As a result, during the early recovery, the labor force participation rate of prime-age women without a bachelor's degree declined by 2.1 percentage points, from 70.8 percent in 2011 to 68.7 percent in 2015 (Table 3). In contrast, the labor force participation rate of prime-age men without a bachelor's degree declined by only 0.6 percentage point, from 86.1 percent in 2011 to 85.5 percent in 2015. Interestingly, the labor force participation rate for both groups ticked up during the late recovery, a time when their employment losses continued. The slight increases in labor force participation rates during this period are due not to increasing employment but a declining number of prime-age men and women without a bachelor's degree.

Third, among prime-age individuals with a bachelor's degree, only women have seen their labor force participation rate recover to its pre-recession level. Why has the participation rate for women rebounded more rapidly? While both college-educated men and women faced slight declines in their labor force participation rates during the economic downturn, women's labor force participation remained stable during the early recovery period, a time when men's labor force participation continued to decline. Moreover, prime-age women with a bachelor's degree saw greater employment gains during both recovery

Table 2
Changes in Prime-Age Employment by Sex and Education Groups

Employment changes	Non-college men	College men	Non-college women	College women
Recession (2008–11)	−2,848,038	−385,318	−2,550,715	76,456
Early recovery (2011–15)	−16,977	1,701,656	−949,029	2,316,496
Late recovery (2015–19)	−38,416	1,986,352	−815,653	2,795,598

Note: Employment changes are calculated using annual averages for the corresponding years.
Sources: CPS and authors' calculations.

Table 3
Prime-Age Labor Force Participation Rates

Prime-age group	2008 (percent)	2011 (percent)	2015 (percent)	2019 (percent)	Change 2008–19 (percentage point)
All	83.1	81.6	81.0	82.4	−0.7
Non-college men	88.4	86.1	85.5	86.4	−2.0
College men	95.2	94.5	93.9	94.1	−1.1
Non-college women	72.4	70.8	68.7	69.9	−2.5
College women	83.1	82.4	82.4	83.7	0.6

Note: Monthly data are averaged for each year.
Sources: CPS and authors' calculations.

periods, preventing further deterioration in their labor force participation rate. While prime-age men with a bachelor's degree gained 2 million jobs from 2015 to 2019, their female counterparts gained 2.8 million jobs. As a result, the labor force participation rate of prime-age women with a bachelor's degree rose by 1.3 percentage points, from 82.4 percent in 2015 to 83.7 percent in 2019, while the rate for men rose by 0.2 percentage point, from 93.9 percent in 2015 to 94.1 percent in 2019 (Table 3).

In summary, prime-age men and women without a bachelor's degree experienced larger declines in their employment and labor force participation rates during the recession and further deterioration in their labor market outcomes during the recovery. Only prime-age women with a bachelor's degree have seen their labor force participation rate fully recover, though their participation remains lower than men's.

II. Changes in Labor Demand: Job Polarization

Although the decomposition highlights important differences in labor force participation by sex and education, it does not reveal the factors driving changes in employment for these groups across the three periods in our analysis. One possible explanation for these changes could be a shift in labor demand toward jobs that favor the skills and education of prime-age individuals (Tüzemen 2019).

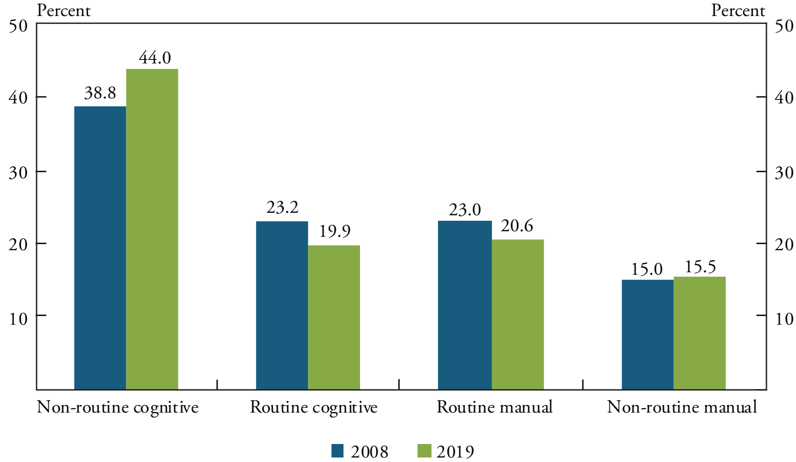
Skills demanded by employers and the composition of job opportunities have changed dramatically over the past several decades. The employment share of middle-skill jobs has declined significantly, while the employment shares of low- and high-skill jobs have increased. This aggregate shift in employment away from middle-skill jobs and toward low- and high-skill jobs is called "job polarization" (Goos and Manning 2007; Autor and others 2006; Autor 2010; Acemoglu and Autor 2011; Tüzemen and Willis 2013; Tüzemen 2018).

Technological advancements help explain why the share of workers employed in middle-skill jobs has fallen so sharply. Middle-skill jobs are considered "routine" jobs, as workers typically perform tasks that are procedural and rule-based. These jobs may be "routine cognitive jobs," such as sales and administrative support occupations, or "routine manual jobs," such as construction and production occupations. The tasks performed in many of these jobs have become automated by computers and machines.

International trade and weakening unions have also contributed to the decline in routine jobs. Many jobs in this category, particularly those in the manufacturing industries, have been off-shored to countries where workers can perform similar tasks for lower wages (Goos and others 2011; Oldenski 2012). In addition, some firms have contracted out portions of their businesses to workers in foreign countries through outsourcing.

In contrast, tasks performed in high- and low-skill jobs are more difficult to automate, making them "non-routine" jobs. Workers in high-skill or "non-routine cognitive" jobs are typically highly educated and perform tasks requiring analytical ability, problem solving, and creativity. Many of these jobs are managerial and technical in nature in fields such as engineering, finance, and medicine. In contrast, workers in low-skill or "non-routine manual" jobs typically have no formal education beyond high school and work in jobs that are physically demanding. Many of these jobs are service-oriented in fields such as food preparation, cleaning, and security and protective services.

Chart 4
Prime-Age Employment Shares by Occupation Groups



Notes: Workers who are self-employed, employed in military or agricultural occupations or industries, and work without pay are excluded from the sample. Monthly data are averaged for each year.
Sources: CPS and authors' calculations.

Effects of job polarization on prime-age employment

Over the past decade, job polarization has led to a large increase in demand for highly educated workers and a decline in demand for less-educated workers, many of whom were employed in routine jobs. Chart 4 shows how prime-age employment in each skill category has changed since the Great Recession. In 2008, 46.2 percent of employed prime-age individuals worked in routine jobs: 23.2 percent worked in routine cognitive jobs, and 23.0 percent worked in routine manual jobs.[3] By 2019, this share had declined to 40.5 percent: 19.9 percent of employed prime-age individuals worked in routine cognitive jobs and 20.6 percent worked in routine manual jobs.

The decline in employment in routine jobs was accompanied by an increase in employment in non-routine cognitive jobs. The share of employed prime-age individuals in non-routine cognitive jobs rose from 38.8 percent in 2008 to 44.0 percent in 2019. Over the same period, the share of employed prime-age individuals in non-routine manual jobs remained around 15 percent.

Non-college individuals bore the brunt of the employment losses during the 2008–11 period, when most employment losses were in routine jobs. The rapid decline in routine employment is in line with the observation that job polarization accelerates during economic downturns (Tüzemen and Willis 2013; Jaimovich and Siu 2012). Table 4 shows that 1.5 million prime-age workers lost jobs in routine cognitive occupations, 1.3 million of whom were non-college women. Over the same period, 2.3 million prime-age workers lost jobs in routine manual occupations, 1.8 million of whom were non-college men.

During the early and late recovery periods, non-college women continued to lose jobs, while non-college men saw only modest improvements. Over 1.6 million non-college women (832,111 + 805,710) lost jobs in routine cognitive occupations over the two periods, more than offsetting slight increases in their employment in non-routine manual occupations (Table 4). In contrast, non-college men recovered some of their losses in routine manual jobs due to the rebound in construction and transportation occupations. Moreover, their employment in non-routine cognitive occupations slightly increased.

Prime-age women and men with a bachelor's degree fared much better across all three periods and were only slightly affected by the decline in routine employment during the recession. Interestingly, college-educated women gained jobs on net during the recession period, as their job gains in non-routine occupations, especially in non-routine cognitive or high-skill occupations, more than offset their job losses in routine manual and routine cognitive occupations. In contrast, college-educated men lost jobs on net during the recession period, as their gains in non-routine manual jobs fell short of offsetting their job losses in all other occupation categories.

College-educated individuals accrued almost all of the job gains during the two recovery periods. As employment opportunities shifted toward high-skill occupations, firms' demand for more-educated workers increased. Employment among college-educated prime-age men and women rose by 3.6 million (1.7 + 1.9) and 4.7 million (2.2 + 2.5), respectively, during the two recovery periods, and three-fourths of these job gains were in non-routine cognitive or high-skill occupations (Table 4). Interestingly, the majority of employment gains in routine employment also accrued to college-educated prime-age individuals. This pattern suggests that firms' demand for more-educated workers increased even for routine occupations. In other words, a large pool of unemployed workers searching for jobs during the recovery periods may have led firms to become more selective.

Table 4
Changes in Prime-Age Employment by Occupation Groups

Prime-age group	Total	Non-routine cognitive	Routine cognitive	Routine manual	Non-routine manual
All prime-age					
Recession (2008–11)	−4,222,147	−613,040	−1,491,980	−2,320,731	203,603
Early recovery (2011–15)	3,083,690	2,832,984	−449,360	451,007	249,060
Late recovery (2015–19)	3,738,653	3,545,176	−443,332	312,272	324,537
Non-college men					
Recession (2008–11)	−2,051,021	−346,031	−149,881	−1,847,200	292,091
Early recovery (2011–15)	−20,443	206,558	−193,965	168,619	−201,655
Late recovery (2015–19)	66,403	113,627	49,184	−9,918	−86,490
College men					
Recession (2008–11)	−109,033	−75,246	−18,294	−73,141	57,648
Early recovery (2011–15)	1,706,947	1,139,123	167,589	253,543	146,693
Late recovery (2015–19)	1,906,219	1,585,596	87,786	131,525	101,312
Non-college women					
Recession (2008–11)	−2,259,293	−429,441	−1,304,880	−360,276	−164,696
Early recovery (2011–15)	−840,523	−129,000	−832,111	−60,786	181,374
Late recovery (2015–19)	−766,279	−187,900	−805,710	120,468	106,863
College women					
Recession (2008–11)	197,199	237,679	−18,924	−40,115	18,559
Early recovery (2011–15)	2,237,709	1,616,304	409,127	89,631	122,648
Late recovery (2015–19)	2,532,310	2,033,853	225,408	70,198	202,852

Notes: Workers who are self-employed, employed in military or agricultural occupations or industries, or who work without pay are excluded from the sample. Employment changes are calculated using annual averages for the corresponding years.
Sources: CPS and authors' calculations.

In summary, the recent economic downturn led to large employment losses in routine occupations that did not return during the recovery. These losses were largely felt by men and women without a bachelor's degree, who lost jobs in routine manual and routine cognitive jobs, respectively. As the demand for workers in routine jobs declined, some displaced workers were able to transition to high-skill jobs, while other workers moved to low-skill service sector jobs. However, a majority of displaced workers without a bachelor's degree were unable to find employment in their skill levels and eventually dropped out of the labor force (Cortes and others 2015; Foote and Ryan 2015; Tüzemen 2018). Therefore, the disappearance of routine occupations contributed to the decrease in the labor force participation rates among prime-age individuals without a bachelor's degree (Tüzemen 2019). In contrast, the shift in the composition of jobs toward high-skill, non-routine cognitive jobs during the recovery increased employment and labor force participation among college-educated individuals, especially women.

Prime-age workers' response to the shift toward high-skill occupations

Prime-age workers have responded to job polarization and shifting employment opportunities toward high-skill occupations by increasing their educational attainment. Both the number and the share of prime-age individuals with a college education have increased over the past decade, especially among women. In 2008, 63.6 million women were prime-age, 32.9 percent of whom had a bachelor's degree or higher (Table 5). By 2019, the population of prime-age women had risen to almost 64 million, while the share with a bachelor's degree or higher had risen to 42.2 percent. Men have followed a similar pattern, though their population and college shares remain below those of women. In 2008, 62.1 million men were prime-age, 30.3 percent of whom had a bachelor's degree or higher. By 2019, the population of prime-age men had increased modestly to 62.3 million, while the share with a bachelor's degree or higher had risen to 36.2 percent. As a result, the total population of college-educated, prime-age men was 22.6 million compared with 27 million for women.

The larger increase in the share of prime-age individuals with a bachelor's degree was accompanied by an increase in their share in the prime-age labor force. The share of college-educated women in the prime-age labor force rose from 16.6 percent in 2008 to 21.7 percent in 2019, while the share of college-educated men rose from 17.1 percent in 2008 to only 20.4 percent in 2019. As a larger share of prime-age women have obtained a bachelor's degree than men, the share of non-college women in the prime-age labor force has subsequently declined by more than the share of non-college men. Specifically, the share of non-college women in the prime-age labor force declined from 29.5 percent in 2008 to 24.8 percent in 2011, while the share of non-college men declined from 36.7 percent in 2008 to 33.0 percent in 2019.[4] Nevertheless, non-college men still have the largest share in the prime-age labor force.

Table 5

Changes in Prime-Age Population, Employment, and Labor Force Compositions by Sex and Education Groups

Sex/education group	2008 (percent)	2019 (percent)	Change 2008–19 (percentage point)
Women			
Population (number)	63,580,812	63,978,852	398,040
College-educated (number)	20,932,984	27,020,544	6,087,560
College share	32.9	42.2	9.3
Men			
Population (number)	62,107,180	62,284,345	177,165
College-educated (number)	18,821,718	22,567,705	3,745,987
College share	30.3	36.2	5.9
Non-college women			
Prime-age employment share	29.3	24.6	–4.7
Prime-age labor force share	29.5	24.8	–4.7
College women			
Prime-age employment share	17.1	22.0	4.9
Prime-age labor force share	16.6	21.7	5.1
Non-college men			
Prime-age employment share	36.1	32.8	–3.3
Prime-age labor force share	36.7	33.0	–3.7
College men			
Prime-age employment share	17.6	20.7	3.1
Prime-age labor force share	17.1	20.4	3.3

Note: Monthly data are averaged for each year.
Sources: CPS and authors' calculations.

The shift toward college education among prime-age men and women appears to have supported the recent uptick in the prime-age labor force participation rate. A simple counterfactual exercise shows that had the population shares of college-educated men and women stayed at their 2008 levels, the prime-age labor force participation rate would be at 81.5 percent instead of 82.4 percent in 2019. In other words, 1.1 million fewer prime-age individuals would be in the labor force.

However, the increasing share of prime-age individuals with a bachelor's degree was not enough to offset the sharp decline in the labor force participation rate of individuals without a bachelor's degree. Non-college men and women have been hit the hardest by the disappearance of routine occupations during the economic downturn. With the exception of college-educated women, the labor force participation rates for all groups have remained below their 2008 levels. A similar counterfactual exercise shows that had the participation rates of all groups stayed at their 2008 levels, 1.8 million more prime-age individuals would be in the labor force.

III. Self-Reported "Situations" of Nonparticipants and Policy Implications

The increased demand for highly educated workers contributed to the labor force participation rate of prime-age women with a bachelor's degree exceeding its pre-recession level. As college-educated women have had historically lower labor force participation rates than men, we might interpret this as college-educated women "catching up" with their male counterparts. However, the labor force participation rate of college-educated women has remained lower than both college-educated and non-college-educated men. While changes in labor demand seem to be a significant factor behind recent patterns in labor force participation, studying the self-reported situations of nonparticipants could provide further insight for policymakers into how to bring more prime-age individuals into the labor force.

The CPS provides a useful way to gauge prime-age individuals' reasons for nonparticipation. Each month, the CPS asks respondents about their labor force status (employed, unemployed, or not in the labor force). Those who report their status as "not in the labor force" also respond to another question, which asks, "what best describes your situation at this time? For example, are you disabled, ill, in school, taking care of house or family, or something else?" Based on responses to these questions, we group prime-age individuals who are not in the labor force into one of five categories: retired, disabled or ill, in school, taking care of family, and other reasons.

Throughout the sample period, the most common situation reported by prime-age women of all education levels was taking care of family. In 2008, 60.2 percent of nonparticipating prime-age women without a bachelor's degree reported they were taking care of family, while 26.6 percent said they were disabled or ill (Table 6). From 2008 to 2019, these shares were mostly unchanged. Even more strikingly, 71.5 percent of nonparticipating women with a bachelor's degree reported they were

Table 6
Situations Reported among Nonparticipating Prime-Age Individuals

Sex/education group	Situations	2008 (percent)	2019 (percent)	Change, 2008–19 (percentage point)
Women				
Non-college	Disabled or ill	26.6	25.6	−1.0
	Family care	60.2	60.2	0.0
	In school	5.3	5.5	0.2
	Retired	4.8	5.3	0.5
	Other	3.1	3.4	0.3
College	Disabled or ill	8.1	9.2	1.1
	Family care	71.5	67.8	−3.7
	In school	8.9	9.5	0.6
	Retired	6.6	7.6	1.0
	Other	4.9	5.9	1.0
Men				
Non-college	Disabled or ill	58.0	53.8	−4.2
	Family care	12.6	15.1	2.5
	In school	8.4	9.6	1.2
	Retired	8.7	9.3	0.6
	Other	12.3	12.2	−0.1
College	Disabled or ill	23.7	20.2	−3.5
	Family care	14.7	15.8	1.1
	In school	28.6	28.0	−0.6
	Retired	17.6	17.5	−0.1
	Other	15.4	18.6	3.2

Note: Monthly data are averaged for each year.
Sources: CPS and authors' calculations.

taking care of family in 2008, while only 8.1 percent said they were disabled or ill. By 2019, the share of college-educated women reporting family care declined to 67.8 percent, countered by small increases in all other categories.

In contrast, the most common situation reported by nonparticipating prime-age men without a bachelor's degree was disability or illness, while the most common situation reported by men with a bachelor's degree was being in school. In 2008, 58.0 percent of nonparticipating prime-age men without a bachelor's degree reported they were disabled or ill, while 12.6 percent said they were taking care of family. By

2019, the share who reported they were disabled or ill declined to 53.8 percent, while the share taking care of family rose to 15.1 percent. For nonparticipating prime-age men with a bachelor's degree, 28.6 percent reported they were in school in 2008 compared with 28.0 present in 2019. The share reporting that they were disabled or ill declined from 23.7 percent in 2008 to 20.2 percent in 2019.

These self-reported responses offer further insights into the reasons for nonparticipation among prime-age individuals. First, consistent with job polarization, prime-age men and women without bachelor's degrees may have a harder time returning to the labor force because they are unable to find jobs suitable for their skills and education levels (Cortes and others 2015; Foote and Ryan 2015; Tüzemen 2018). The stress of long-term unemployment or inactivity could lead to mental or physical problems, which may contribute to the large share of prime-age men reporting disability or illness as their reason for not participating in the labor market. Moreover, some individuals who recovered from disability or illness may have become dependent on pain medication, rendering them unable to work (Krueger 2017). Ending this vicious cycle may require equipping workers with the new skills and higher education demanded by employers in the face of rapid technological advancements.

Second, self-reported responses suggest family care remains a major obstacle for labor force participation among prime-age women, regardless of their educational attainment. Family care could involve taking care of young children or an elderly parent, which are responsibilities more often shouldered by women than men. However, overcoming this obstacle seems plausible given the experiences of other countries. The labor force participation rate of prime-age women is lower in the United States than in other countries in the Organisation for Economic Co-operation and Development (OECD) such as France, Canada, the United Kingdom, and Japan (Black and others 2017). Research shows that family-friendly policies in these countries have been successful in pulling more prime-age women into the labor force, suggesting family-friendly labor market policies could also help increase labor force participation among prime-age women in the United States.

Conclusion

During the Great Recession, large-scale layoffs caused a sharp decline in the employment of prime-age individuals, resulting in a dramatic decline in their labor force participation rate. Although the prime-age labor force participation rate began to recover in 2015, it remains below its pre-recession level. We break down the prime-age labor force participation rate by sex and education level and show that the labor force participation rates are lower than their pre-recession levels for all groups except for college-educated women. Moreover, we emphasize that the disappearance of routine occupations contributed to the decrease in the labor force participation rates among prime-age individuals, especially those without a bachelor's degree (Tüzemen 2019). Had the participation rates for all groups stayed at their 2008 levels, 1.8 million more prime-age individuals would be in the labor force in 2019.

Over the past decade, nonparticipating prime-age men reported disability or illness as the most common situation explaining their participation, while prime-age women reported taking care of family. These situations represent significant barriers to labor force participation. For men, a lack of job opportunities may lead to depression and illness, and these health conditions may, in turn, become further barriers to employment. Similarly, a lack of affordable family care may prevent many prime-age women from joining the labor force. Policymakers may have the scope to address both obstacles. Policies geared toward equipping workers with the new skills and education demanded by employers, or toward providing support for family care, may encourage higher participation among prime-age individuals.

Endnotes

[1]The CPS is the primary source of labor force statistics and demographic data for the U.S. population. The U.S. Census Bureau collects survey data for the Bureau of Labor Statistics at a monthly frequency from approximately 60,000 households. The survey has a response rate ranging from 91 to 93 percent, one of the highest response rates among government surveys.

[2]Our recession period covers a longer horizon than the recession period determined by the National Bureau of Economic Research's Business Cycle Dating Committee, which covers December 2007–June 2009, from the peak of the business cycle to the trough.

[3]In calculating these skill shares, we exclude workers who are self-employed, employed in the military or agricultural industries or occupations, and working without pay.

[4]Similar changes are observed in the sex and education composition of employed prime-age individuals (Table 5).

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Did Local Factors Contribute to the Decline in Bank Branches?

By Rajdeep Sengupta and Jacob Dice

Although the total number of bank branches in the United States increased from the mid-1990s to 2007, this number has declined since the 2007–08 financial crisis. A loss in bank branches is potentially problematic because it may reduce local consumers' access to financial services as well as small businesses' access to credit. National economic conditions, banking regulations, industry trends, and improvements in information technology can all influence a bank's decision to expand or contract its branch network. However, the number of branches varies significantly across geographic areas, suggesting local conditions may also influence bank branching activity. If bank branching adjusts to local factors, then policies that improve local conditions may have the added benefit of attracting bank branches.

In this paper, we examine the relationship between bank branching and local conditions over the last two decades to assess which factors contributed to the decline in bank branches. We find a strong association between the number of branches in a county and that county's population, income, and employment. In addition, we find that the association between local factors and the total number of bank branches has not changed in a meaningful way since the crisis. However, we do find that the relative influence of local competition on branch openings and closings strengthened after the crisis, while the influence of local population, income, and employment weakened.

Section I analyzes trends in bank branching and the factors that likely affect these trends. Section II describes the data used for our

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statistical analysis. Section III examines the factors associated with branch openings and closings as well as whether these associations changed after the crisis.

I. Recent Trends in Bank Branching

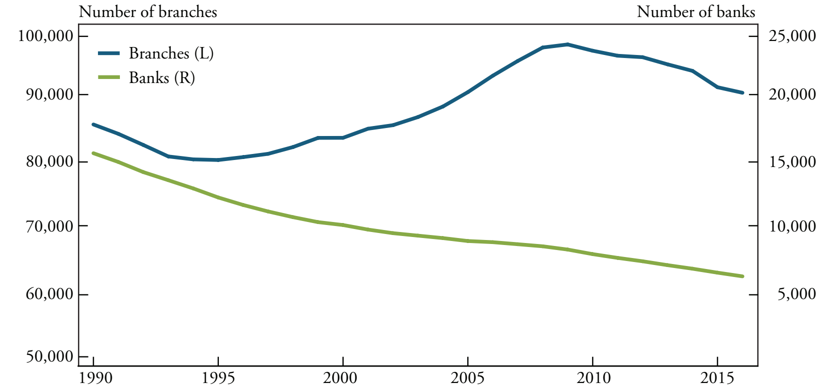
The U.S. banking industry has undergone significant restructuring over the last three decades. The number of banks has declined since the mid-1980s. Before the financial crisis, much of this decline was due to merger and acquisition (M&A) activity rather than bank failures (Janicki and Prescott 2006). But after the financial crisis, bank failures and a collapse in the entry of new banks also became prominent reasons for the decline. Entry by newly created banks, commonly called *de novo* banks, has been minimal in the post-crisis recovery (McCord and Prescott 2014).

The number of bank branches has also declined since the financial crisis, reversing a decade-long trend. Chart 1 shows that throughout the mid-1990s and early 2000s, the number of brick-and-mortar bank branches trended up even as the number of banks continued to decline. The increase in branches during this period helped mitigate concerns about the consequences of bank consolidation (Avery and others 1999).[1] However, the upward trend in bank branches stalled in 2008 and 2009 and then reversed course from 2010 to 2017.

The reversal in branching trends does not appear to be isolated to only rural or only urban counties. While branching patterns likely differ across individual counties, they follow a surprisingly similar pattern across broad spatial classes of counties. Chart 2 shows the aggregate bank branching trends for rural counties, which have a median population of around 11,500; urban-micropolitan counties, which have a median population of around 36,800; all-urban counties, which combine micropolitan and metropolitan areas and have a median population of around 52,000; and urban-metropolitan counties, which have a median population of around 89,300.[2] Across these broad categories, the trends are similar: a post-crisis reversal in branching trends is accompanied by a secular decline in the number of banks.

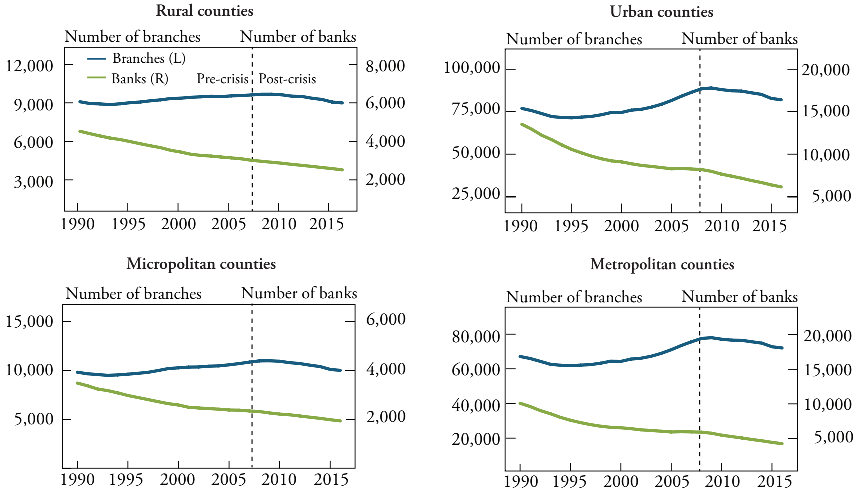
Although multiple factors likely influence bank branching decisions, national factors appear to have gained prominence in recent

Chart 1
U.S. Banks and Branches, 1990–2016



Source: FDIC.

Chart 2
Banks and Branches by County Type, 1990–2016



Source: FDIC.

years. Interest margins declined industry-wide after the crisis, potentially driving banks to contract their branch networks to reduce noninterest expenses. In addition, bank regulation ramped up after the crisis, and several economists and policymakers have argued that this post-crisis regulation imposed a significant burden, especially on smaller community banks. McCord and others (2015) and Ash, Koch, and Siems (2015), for example, argue that regulatory burden has contributed to the dramatic fall of new bank charters since 2010. The lack of new bank formation may have led to fewer branches overall. Increased regulatory costs may also have raised existing banks' operational costs, thereby leaving fewer resources for them to expand their branching network (Feldman, Heinecke, and Schmidt 2013; DiSalvo and Johnston 2016).

In addition, developments in information technology have arguably diminished the influence of local factors. Banks have invested billions in online financial technology (fintech) services over the years, and an increasingly large fraction of banking transactions are now conducted online (Anenberg and others 2018). In nonfinancial industries, the increase of online retail services has led to a decline in the number of establishments whose products and services are also available online. Likewise, an increasing number of new fintech firms with online banking services may have reduced demand for local branches (Jagtiani and Lemieux 2018).

Despite these developments, geographical proximity to customers remains relevant to banking. Anenberg and others (2018) show that most depositors who use online banking services still make in-branch visits. They also document a broad reliance on branch banking, suggesting online banking is an imperfect substitute for branch banking. In addition, local branches continue to be important to small business lending. Although the share of nonlocal lenders to small businesses has risen in recent years, it still remains quite low. Moreover, Nguyen (2019) demonstrates that unanticipated branch closings can lead to "a sharp and persistent decline in credit supply to local small businesses."

Notwithstanding the role of national factors, it is important to know the extent to which local factors also affect bank branching. Prior research has shown that local conditions drove the rapid proliferation of branches before the crisis as demand for banking services increased (Hannan and Hanweck 2008). Whether local factors also contributed to the reversal of this trend is an empirical question.

II. Measuring Branching Trends and Local Factors

Assessing the relationship between bank branches and local factors requires information about branching and local conditions for a given geographical area over time. We define the U.S. county as the geographical unit of our analysis and use annual data from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD) to count the number of banks, branches, branch openings, and branch closings in each county in the 50 U.S. states and the District of Columbia.

For each county, we consider local demographic, economic, and competitive factors that are likely to influence bank branching. For example, demographic factors, such as the number of people in a county, are likely to affect the demand for branches. Economic factors, such as income and employment in a given county, are also likely to affect demand for banking services. Finally, competitive factors, such as the number of nearby credit unions, may also affect the number of branches in a given county.[3]

To capture these factors in our analysis, we use county-level indicators available on an annual basis for the past two decades. We use county population as our local demographic factor, and we use county-level real personal income (measured in thousands of 2012 U.S. dollars) and total employment (number of jobs) as our local economic factors. These data are obtained from the Local Area Personal Income Accounts of the Bureau of Economic Analysis.[4]

We use measures of competition from both banks and nonbanks as our local competitive factors because they can drive branching in different ways. To measure bank competition, we calculate the Herfindahl-Hirschman Index (HHI) for deposits on an annual basis using SOD data. The HHI is calculated using bank deposit shares within each county. Higher HHIs indicate counties with more concentration and less competition. To measure nonbank competition, we use the number of nonbank depository establishments (NBDs) and the number of other nonbank financial establishments (NBFs) operating within each county. Data on nonbank establishments are obtained from the annual County Business Patterns (CBP) series maintained by the U.S. Census Bureau.[5] NBDs include credit unions, which offer similar services to banks but are nonprofit cooperatives organized around individuals with a common bond or "field of membership." NBFs include all other financial establishments involved in nondepository credit intermediation, such as financing and leasing companies for credit cards, sales (auto, equipment, and machinery), consumer lending, real estate (construction, farm, home equity), and trade. Table 1 shows a complete list of variables and their sources. Appendix Table A-1 presents summary statistics for the variables listed in Table 1.

III. Trends in County Bank Branches

Our sample comprises a panel of annual observations on 3,068 counties from 1998 to 2016. To assess whether the relationship between local factors and bank branches changed after the crisis, we divide the sample into two subperiods: the pre-crisis period from 1998 to 2008 and the post-crisis period from 2009 to 2016.

Summary data on branching patterns demonstrate the reversal in trends from the pre-crisis to the post-crisis periods. Column 4 of Table 1 presents differences in the unconditional means of the pre-crisis (column 2) and post-crisis (column 3) samples. The difference in the pre- and post-crisis average in the variable "branch net change," defined as the annual change in branches by county, captures the reversal in branching trends. On average, the net change in branches per county is positive in the pre-crisis period but negative in the post-crisis period. Differences in branch net change over the two periods appear to be driven by differences in branch openings rather than branch closings. Columns 2 and 3 of Table 1 show that branch openings declined by a statistically significant amount between the two periods, while branch closings were little changed. In addition, branch turnover, defined as the sum of openings and closings, was higher in the pre-crisis period.

Local demographic and economic factors appear to have trended up throughout our sample period. In particular, average population, employment, and income are all higher in the post-crisis period. However, these factors vary significantly across counties (the standard deviations of these variables are shown in Appendix Table A-1).

Competitive factors do not always exhibit this upward trend. In particular, the failures and mergers of NBFs after the crisis led to fewer nonbanks in the post-crisis period (columns 2 and 3 of Table 1). At first glance, the marginally higher number of banks per county in the post-crisis period may appear inconsistent with the secular decline of banks nationwide. However, local trends differed from the national trend in

Table 1

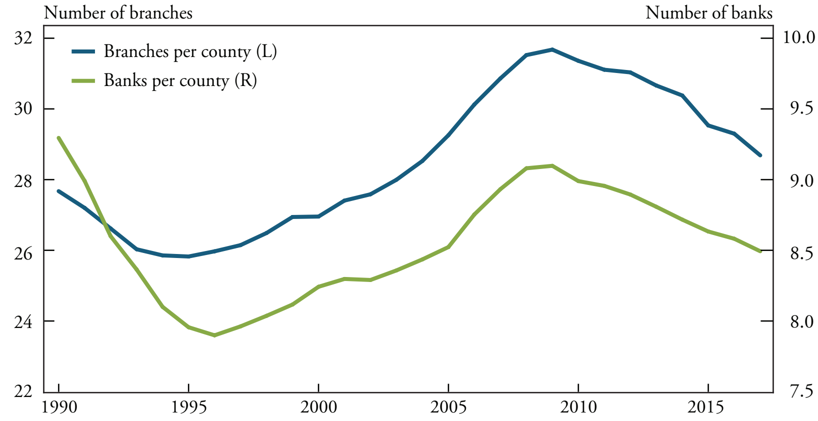
Variables, Sources, and Difference of Means (Pre-Crisis versus Post-Crisis)

Variable	Source	Full sample (mean) (1)	Pre-crisis (mean) (2)	Post-crisis (mean) (3)	Difference (2)–(3) (4)	Standard error
County-level branching						
Branches (county total)	Summary of Deposits (FDIC)	29.54	28.67	30.75	–2.08***	0.61
Branch net change	Summary of Deposits (FDIC)	0.16	0.49	–0.29	0.78***	0.03
Branch turnover	Summary of Deposits (FDIC)	2.19	2.54	1.71	0.83***	0.06
Branch openings	Summary of Deposits (FDIC)	1.13	1.48	0.65	0.83***	0.03
Branch closings	Summary of Deposits (FDIC)	1.04	1.02	1.07	–0.05	0.03
Demographic and economic factors						
Population (number of persons)	Local Area Personal Income Accounts (BEA)	97,157.84	93,815.04	101,749.61	–7934.57**	2,619.19
Employment (number of jobs)	Local Area Personal Income Accounts (BEA)	56,276.01	54,556.40	58,638.12	–4081.72*	1,636.27
Real personal income (thousands of $)	Local Area Personal Income Accounts (BEA)	4,081,711	3,769,983	4,509,910	–739,926.73***	125,000.19
Competitive factors						
Banks	Summary of Deposits (FDIC)	8.62	8.47	8.83	–0.36***	0.08
Nonbank depository (NBD)	County Business Patterns (U.S. Census Bureau)	5.55	5.28	5.91	–0.62***	0.12
Nonbank financial (NBF)	County Business Patterns (U.S. Census Bureau)	25.88	27.64	23.46	4.18***	0.86
Deposit HHI	Summary of Deposits (FDIC)	3,192.00	3,190.46	3,194.12	–3.66	17.62
Observations		58,135	33,643	24,492	58,135	

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

Notes: “Branch net change” reflects the annual change in branches by county averaged over the relevant sample period. “Branch turnover” reflects the sum of a county’s branch openings and closings averaged over the relevant sample period.

Chart 3
Branches and Banks per County, 1990–2016



Source: FDIC.

the pre-crisis period. Chart 3 shows that both the number of banks per county and the number of branches per county climbed steadily from the mid-1990s to 2009. During this period, existing banks expanded into newer counties through M&A activity or *de novo* branching, thereby breaking with the nationwide trend of bank consolidation. As a result, both the average number of banks per county and the average number of branches per county trended up in the pre-crisis period. As Chart 3 shows, both series have reversed course in the post-crisis period. However, the average yearly number of branches per county is still higher in the post-crisis sample than in the pre-crisis sample (Table 1).

Factors associated with bank branches

A review of the summary statistics shows that both banks and branches reversed their respective upward trends after the financial crisis. However, this simple descriptive analysis does not control for differences in county demographic, economic, and competitive factors that may also explain branching patterns.

To account for these factors, we estimate a regression model that regresses the number of branches in county i in year t on county demographic, economic, and competitive factors according to:

$$Branches_{it} = \beta^d X_{it}^{demographic} + \beta^e X_{it}^{economic} + \beta^c X_{it}^{competitive} + \mu_i + \lambda_t + \varepsilon_{it},$$

where $X_{it}^{demographic}$, $X_{it}^{economic}$, and $X_{it}^{competitive}$ are vectors of demographic, economic, and competitive factors, respectively. The demographic factor is county population, the economic factors are county income and employment, and the competitive factors are county-level deposit HHIs and the number of NBDs and NBFs.

The estimated coefficients, β, are factor elasticities indicating the responsiveness of branches to changes in each factor. For the regression analysis, we transform all variables using the inverse hyperbolic sine (IHS) transformation (MacKinnon and Magee 1990).[6] Except for very small values, the IHS transformation can be interpreted in the same way as a standard logarithmic transformation of the variable. Accordingly, the transformation allows us to interpret the coefficients on the independent variables as factor elasticities—the percent change in county-level branches associated with a 1 percent change in the local factor, holding all other factors fixed.

We use county-specific fixed effects, μ_i, in all regressions to account for persistent differences between counties. Accordingly, the estimated coefficients reflect changes in the number of branches as county conditions improve or deteriorate relative to their county-specific averages.

Table 2 reports the estimated associations for two different models. The first column shows the results for the base model. In addition to the factor variables and county fixed effects, the base model also includes year fixed effects as λ_t, a vector of indicator variables for each year. Year fixed effects absorb, among other things, changes in aggregate banking conditions across the United States and aggregate changes in demographic, economic, and competitive conditions. Given our 1998–2016 sample period, the year fixed effects are necessary to account for changes in aggregate conditions across the United States that affected all counties. The second column in Table 2 shows the results for the Post-Crisis Break (PCB) model. The PCB model allows the coefficients on the explanatory variables in the base model to vary across the pre-crisis and post-crisis periods. To do so, we create an indicator variable, *post-crisis*, that takes a value of 1 for all years after 2008 and 0 otherwise. We then interact this variable with all explanatory variables. This interacted regression allows us to examine the difference between pre- and post-crisis estimates of the explanatory variables and thereby assess whether the association between branches and local factors changed.

Table 2

Determinants of County-Level Bank Branches

Variable	Base model (1)	PCB model (2)
Population	0.364*** (11.33)	0.384*** (10.88)
Employment	0.182*** (7.62)	0.0983*** (4.24)
Real personal income	0.0739*** (4.08)	0.0960*** (6.76)
Nonbank depository	–0.0107** (–2.30)	–0.00432 (–0.90)
Nonbank financial	0.00639** (2.15)	0.0133*** (4.31)
Deposit HHI	–0.214*** (–16.28)	–0.226*** (–16.33)
Post-crisis		0.0169 (0.15)
Post-crisis # population		–0.0403*** (–3.41)
Post-crisis # employment		0.0454*** (3.70)
Post-crisis # real personal income		0.00180 (0.13)
Post-crisis # nonbank depository		–0.0128*** (–3.67)
Post-crisis # nonbank financial		0.00854*** (3.11)
Post-crisis # deposit HHI		–0.00988 (–1.62)
Constant	–2.097*** (–5.43)	–1.729*** (–4.52)
County fixed effect	Yes	Yes
Year fixed effect	Yes	No
Log-likelihood	48,858.7	47,825.1
P-value	0	1.39e-236
Counties	3,068	3,068
Observations	58,135	58,135

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

Note: T-statistics are shown in parentheses.

The number of branches in a county tends to increase as local demographic and economic factors improve. The estimated factor elasticities in Table 2 measure the strength of the association between changes in a local factor and changes in the number of branches within a county, where the change is measured as the percentage deviation from its county mean. In the base model (column 1), a 1 percent increase in population from the county mean is associated with a 0.364 percent increase in branches. In the same vein, a 1 percent increase in employment from the county mean is associated with a 0.182 percent increase in branches.

The number of branches in a county tends to vary with local competition as well. The estimated factor elasticities for the two nonbank competition measures show that an increase in NBDs is associated with a smaller number of bank branches, while an increase in the number of NBFs is associated with a larger number of bank branches. One possible explanation for the negative association between NBDs and bank branches is that credit unions increasingly provide services that are similar to banks, potentially reducing demand for additional branches (Anderson and Liu 2013). The estimated factor elasticity for deposit HHIs is negative, indicating that counties where deposits are more concentrated in a few banks tend to have fewer branches.

Our results from the PCB model suggest that the post-crisis decline in bank branches cannot be attributed to a shift in the associations between branches and local factors. The fully interacted coefficients in column 2 of Table 2 test for statistically significant differences in the PCB model coefficients before and after the crisis. While some of the post-crisis changes in these coefficients are statistically different from zero, in most cases, the magnitude of this change is small. For example, the post-crisis branch elasticity of population changed from its pre-crisis estimate of 0.384 to 0.344 (= 0.387 – 0.0403). The smaller estimated post-crisis elasticity indicates that the association between population and the number of branches weakened slightly after the crisis—specifically, a 1 percent change in population was associated with a 0.0403 percent smaller change in the number of branches after the crisis than before the crisis. In contrast, the association between employment and the number of branches in a county appears to have strengthened slightly after the crisis. The post-crisis branch elasticity of employment changed from its pre-crisis estimate of 0.0983 to 0.1437 (= 0.0983 + 0.0454). Moreover, much of the negative association between NBDs and bank branches appears to be a post-crisis phenomenon (DiSalvo and Johnston 2017).[7] Lastly, the association between branches and other competitive factors does not appear to have changed much in the post-crisis period. Overall, the association between bank branches and local factors does not appear to have changed in a meaningful way after the financial crisis. As a result, the decline in branches was more likely driven by changes in local factors themselves rather than changes in the relationship between branches and these factors. See Box for a discussion of how the results for the Tenth Federal Reserve District compare with those for the nation as a whole.

IV. Trends in County Branch Openings and Closings

Our results demonstrate a link between changes in local conditions and changes in the aggregate number of branches in a county. However, they do not reveal whether the associated changes in the number of branches were driven by branch openings, branch closings, or both. To examine the isolated links between local conditions and branch openings and closings, we use data on yearly branch openings and closings for each county in our full sample.[8]

The pattern of openings and closings has changed significantly since the financial crisis. Chart 4 shows a scatterplot of the pre-crisis and post-crisis average yearly openings and closings for each county. Each blue dot shows the average yearly openings and closings for the pre-crisis period, while each orange dot shows the same for the post-crisis period. The blue and orange dashed lines are the lines of fit for each period. The green dashed line is a 45-degree line: dots to the left of this line represent counties where the number of branch openings exceeded the number of branch closings; dots to the right of the line represent counties where closings exceeded openings. The chart clearly shows that before the crisis, openings tended to be higher than closings, leading to a net increase in the number of branches. After the crisis, the opposite is true.

Counties with more branch openings typically also have more branch closings and thereby high branch turnover. Although we might expect branch openings and closings to move in opposite directions,

Box

Local Contributions to Changes in Branches in the Tenth Federal Reserve District

The Tenth Federal Reserve District differs from the nation in terms of banking and local economic conditions. The District—which covers Colorado, Kansas, Nebraska, Oklahoma, Wyoming, and parts of Missouri and New Mexico—has no large banks (with assets above $50 billion) but many community banks with strong ties to the local economy. In addition, many localities in the district are more reliant on the energy and agriculture sectors.

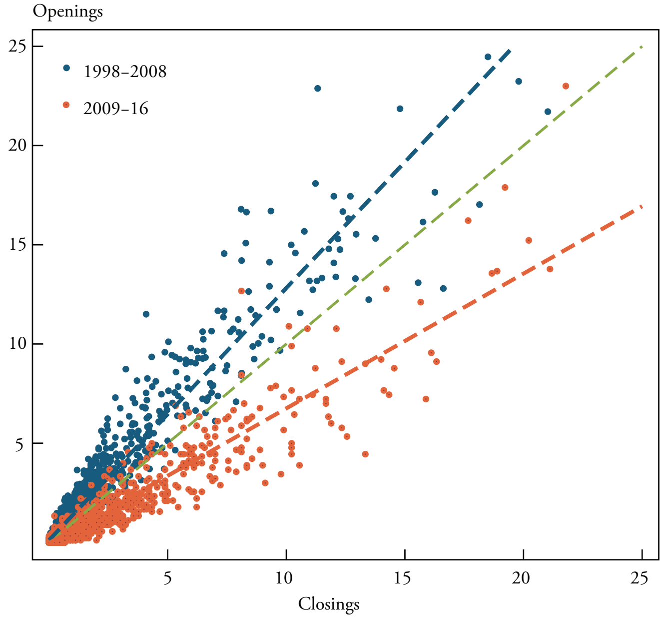
Recognizing these differences, we examine the contributions of local factors to variations in bank branches across Tenth District counties. In unreported results, we find that demographic and competitive factors contributed most to changes in the number of branches in urban counties. For example, changes in county population made the largest contribution to post-crisis changes in the number of branches in Cleveland County (Oklahoma City, OK), Butler County (Wichita, KS), Douglas County (Denver-Aurora-Lakewood, CO), and Clay County (Kansas City, MO). Population increases in these counties contributed positively to the number of bank branches, partly offsetting the post-crisis decline. Competitive forces were more potent in Jefferson County (Denver-Aurora-Lakewood, CO), Wyandotte County (Kansas City, KS), and Jackson County (Kansas City, MO), where an increase in deposit concentration (HHI) after the crisis was associated with a decline in branches.

In contrast, economic factors made the strongest contributions to the number of branches in rural counties. For example, increases in county income in the post-crisis recovery contributed positively to partly offset the decline in branches in Caddo County, OK, and York County, NE. Likewise, *Box (continued)*

increases in employment (jobs) in the post-crisis recovery helped to partly offset the decline in branches in Garvin, OK. These county-level results highlight that improvements in local conditions can help to offset the decline in bank branches within a given county.

Chart 4

Branch Openings versus Closings Pre- and Post-Crisis

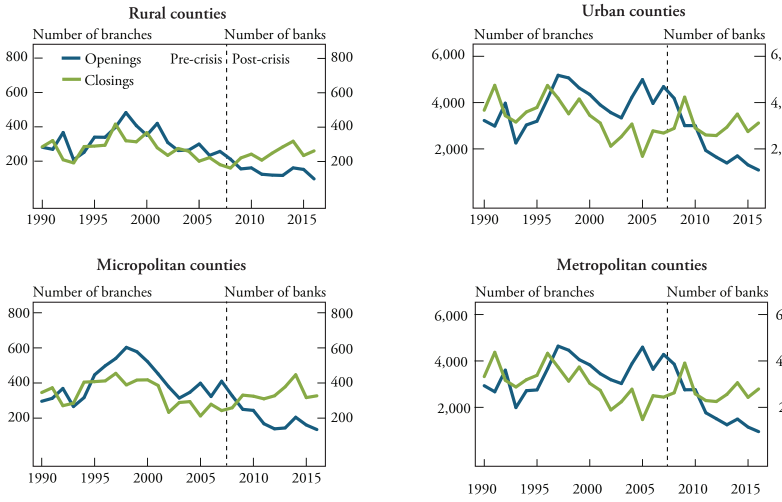


Source: FDIC.

they move in the same direction when turnover is high. In Chart 4, points closer to the bottom-left of the chart indicate low turnover, while those near the top-right indicate high turnover. Most counties in our sample are clustered near the 45-degree line rather than near either axis, implying that most counties have both openings and closings.

The post-crisis trends in branch openings and closings does not appear to be isolated to only rural or only urban counties. Chart 5 shows annual openings and closings by county type from 1990 to 2016. As in Chart 2, openings and closings are similar across county types in

Chart 5
Branch Openings and Closings by County Type, 1990–2016



Source: FDIC.

the post-crisis period. For all county types, branch openings peaked in 2007 and declined steadily thereafter. In contrast, branch closures hit a trough in 2005. Since then, average closures have exceeded their 2005 level each year.

Overall, our summary data reveal that both fewer openings and more closings led to the decline in bank branches. To assess whether these changes were driven by local factors, we run regressions with branch openings and closings as the dependent variables. The regressions use the same demographic, economic, and competitive factors as explanatory variables as in previous sections. We also examine whether the relationship between openings and closings and local factors shifted in the post-crisis period.

Aggregate trends and branch turnover can often confound the estimated association between local factors and branch openings and closings. Table 3 reports the estimated coefficients for the base model and the PCB model with annual branch openings and closings as the dependent variable. The estimated coefficients for some factors in the PCB model are statistically significantly different from those in the base model. This can happen because the PCB model, which does not control for year fixed effects, may pick up the influence of aggregate trends that have little to do with the association between the two variables. As

Table 3
Determinants of Openings and Closings of County-level Bank Branches

Variable	Openings		Closings	
	Base model	PCB model	Base model	PCB model
Population	−1.167*** (−17.41)	−0.0675 (−1.12)	0.243***	0.153**
Employment	−0.0857* (−1.80)	0.163*** (3.68)	0.0533 (1.36)	0.245*** (6.13)
Real personal income	0.499*** (14.37)	−0.261*** (-8.83)	−0.0477* (−1.79)	−0.304*** (-10.74)
Nonbank depository	−0.0338*** (−2.80)	−0.0181 (−1.46)	−0.0101 (−1.00)	−0.0262** (-2.46)
Nonbank financial	0.0733*** (9.39)	0.0188** (2.48)	−0.0237*** (−3.82)	−0.0413*** (−6.27)
Deposit HHI	0.0542** (2.28)	0.0817*** (3.97)	−0.0813*** (−4.31)	−0.0527*** (−2.68)
Post-crisis		1.229*** (4.73)		−0.0337 (−0.14)
Post-crisis # population		0.0147 (0.62)		−0.0657*** (−3.27)
Post-crisis # employment		−0.0865*** (−3.79)		−0.0991*** (−4.57)
Post-crisis # real personal income		−0.0560** (−2.01)		0.135*** (5.27)
Post-crisis # nonbank depository		−0.0237*** (−3.28)		0.0146** (2.06)
Post-crisis # nonbank financial		−0.0139** (−2.48)		0.0144*** (2.65)
Post-crisis # deposit HHI		0.0318** (2.48)		−0.0548*** (−4.29)
Constant	5.528*** (7.34)	3.321*** (5.10)	−1.110* (−1.93)	1.935*** (3.23)
County fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	No	Yes	No
Log-likelihood	−41,180.4	−40,267.3	−41,816.1	−42,099.6
P-value	0	0	9.16e-128	1.35e-54
Counties	3,068	3,068	3,068	3,068
Observations	58,135	58,135	58,135	58,135

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

Note: T-statistics are shown in parentheses.

a result, the base model with year fixed effects is our preferred model for determining the true association of local factors. For some cases in both models, the estimated factor elasticities for branch openings have the same sign as the elasticities for branch closings. In theory, we might expect the estimated elasticities for openings and closings to have opposite signs. For example, if a given factor is associated with a decline in branches, we would expect it to be associated with fewer openings, more closings, or both. In practice, however, the estimated coefficients might reflect the association between high and low turnover and the local factor, leading to coefficients for openings and closings with the same sign.

The results in columns 2 and 4 of Table 3 indicate that the association between demographic and economic factors and branch openings and closings weakened after the crisis. For example, the employment elasticities of openings and closings diminished significantly in the post-crisis period. The income and population elasticities of closings are also significantly lower in the post-crisis period. Taken together, these estimates would suggest that the association of local demographic and economic factors with openings and closings weakened after the financial crisis.

The associations between NBFs and openings and closings also appear to have weakened since the crisis. For example, the negative association between NBFs and closings estimated in the PCB model weakened significantly from –0.0413 in the pre-crisis period to –0.269 in the post-crisis period.

In contrast, the association between other competitive factors and branch openings and closings strengthened in the post-crisis period. Notable among these is the association with deposit HHI, indicating that the same increase in deposit concentration is associated with more openings and fewer closings after the crisis than before the crisis. Moreover, the association between openings and NBDs appears to be largely a post-crisis phenomenon. The estimated coefficient on the uninteracted term in the PCB model is negative but not statistically significant. The coefficient on the interacted term is negative but statistically significant, suggesting the effect is significant in the post-crisis period.

Conclusion

The upward trend in U.S. bank branches from the mid-1990s to the mid-2000s reversed course after the financial crisis. The pattern appears to be widespread across both rural and urban counties. Notwithstanding industry trends and other national factors, understanding how local factors influence branching decisions is important. If branches vary with local conditions, policies aimed at improving local conditions might help reduce the decline in local branches.

Our results show that although local factors are important determinants of bank branching, the relationship between local conditions and the number of bank branches has not changed in a meaningful way since the crisis. Nevertheless, some of the reversal in trends can be attributed to changes in local factors.

Our results also show that the relationship between local factors and branch openings and closings does appear to have shifted since the financial crisis. While the association with demographic and economic factors such as employment appears to have weakened since the crisis, the association with competitive factors such as deposit market concentration strengthened. Taken together, our results suggest that local market competition played a greater role in branch openings and closings after the financial crisis.

The future path of bank branches will depend on both local and national factors. While some trends such as industry consolidation and online banking are likely irreversible, others such as bank performance and bank regulation are more likely to evolve. Improvements in bank profitability and the rollback in post-crisis regulation for small and medium-sized banks might slow or even reverse the current downward trend in branching nationwide. However, local conditions also influence whether a community sheds or retains its local branches, making changes in local policies all the more relevant.

Appendix
Summary Statistics

Table A-1

Summary Statistics of Variables Pre- and Post-Crisis

	Full sample				Pre-crisis			
Variable	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum
County-level branching								
Branches (total)	29.54	72.28	0	1,808	28.67	68.46	0	1,750
Branch net change	0.16	3.03	−137	191	0.49	3.57	−137	191
Branch turnover	2.19	6.77	0	257	2.54	7.64	0	257
Branch openings	1.13	3.80	0	194	1.48	4.55	0	194
Branch closings	1.04	3.39	0	206	1.02	3.54	0	206
Demographic and economic factors								
Population (persons)	97,158	311,845	421	10,200,000	93,815	302,210	421	9,793,263
Employment (jobs)	56,276	194,812	226	6,357,376	54,556	187,970	226	5,693,811
Real personal income (thousands of $)	4,081,711	14,888,199	8,016	545,091,322	3,769,983	13,674,452	8,016	448,616,071
Competitive factors (thousands)								
Banks	8.62	9.54	1	228	8.47	9.62	1	228
Nonbank depository institutions (NBD)	5.55	14.70	0	331	5.28	14.38	0	331
Nonbank financial institutions (NBF)	25.88	102.81	0	3,816	27.64	110.57	0	3,816
Deposit HHI	3,192.00	2,097.55	423.58	10,000	3,190.46	2,103.75	423.58	10,000
Observations	58,135				33,643			

Note: "Branch net change" reflects the annual change in branches by county averaged over the relevant sample period. "Branch turnover" reflects the sum of a county's branch openings and closings averaged over the relevant sample period.
Sources: FDIC, BEA, and U.S. Census Bureau.

Table A-1 (continued)

	Post-crisis			
Variable	Mean	Standard deviation	Minimum	Maximum
County-level branching				
Branches (total)	30.75	77.21	0	1,808
Branch net change	–0.29	2.00	–45	29
Branch turnover	1.71	5.32	0	170
Branch openings	0.65	2.32	0	78
Branch closings	1.07	3.16	0	88
Demographic and economic factors				
Population (persons)	101,750	324,563	442	10,200,000
Employment (jobs)	58,638	203,816	241	6,357,376
Real personal income (thousands of $)	4,509,910	16,400,367	12,112	545,091,322
Market factors				
Banks	8.83	9.43	1.00	174
Nonbank depository institutions (NBD)	5.91	15.12	0.00	312
Nonbank financial institutions (NBF)	23.46	91.02	0.00	2,799
Deposit HHI	3,194.12	2,089.04	468.39	10,000
Observations	33,643			

Notes: “Branch net change” reflects the annual change in branches by county averaged over the relevant sample period. “Branch turnover” reflects the sum of a county’s branch openings and closings averaged over the relevant sample period.
Sources: FDIC, BEA, and U.S. Census Bureau.

Endnotes

[1]Following Avery and others (1999), we define both commercial banks and savings associations as banks in this study. Although they may differ in their offerings of commercial loan services, both institutions offer the same range of retail services at their branches.

[2]Median populations are calculated for all years since 1990. We use 2013 delineation files to determine whether a county is designated as a metropolitan or micropolitan county. However, the county designation does not change over the years in our sample. See https://www.census.gov/programs-surveys/metro-micro/guidance.html for details.

[3]While credit unions provide similar services to banks at their branches, the motivation behind their branch creation and location differs somewhat. Credit unions are nonprofits, and their customer base is typically set by their field of membership, which determines who is eligible to join the credit union (DiSalvo and Johnston 2017). For this reason, we do not consider branches of credit unions in our count of bank branches.

[4]Local economic data for personal income, population, and employment are obtained under the series Economic Profile of the County (CAINC30), available at https://apps.bea.gov/regional/downloadzip.cfm

[5]NBDs include credit unions (NAICS code 522130) and other establishments involved in depository credit intermediation (NAICS code 522190). NBFs include all establishments involved in nondepository credit intermediation (NAICS code 5222) and activities related to credit intermediation (NAICS code 5223).

[6]The IHS transformation allows us to account for the counties in our sample with no openings or closings as well as the presence of outliers in our outcome variable.

[7]Compared with the estimated coefficient on the pre-crisis (uninteracted) term for NBDs, the coefficient on the post-crisis interaction term is larger and also statistically significant.

[8]We define a branch closing as the termination of a bank branch at a given location. We account for situations in which a bank moves a branch from one location to another by tracking branches with their FDIC branch number. In this way, we avoid counting branch relocations and changes of branch ownership as openings or closings.

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