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Economic Insights

Why Are Recessions So Hard to Predict? Random Shocks and Business Cycles

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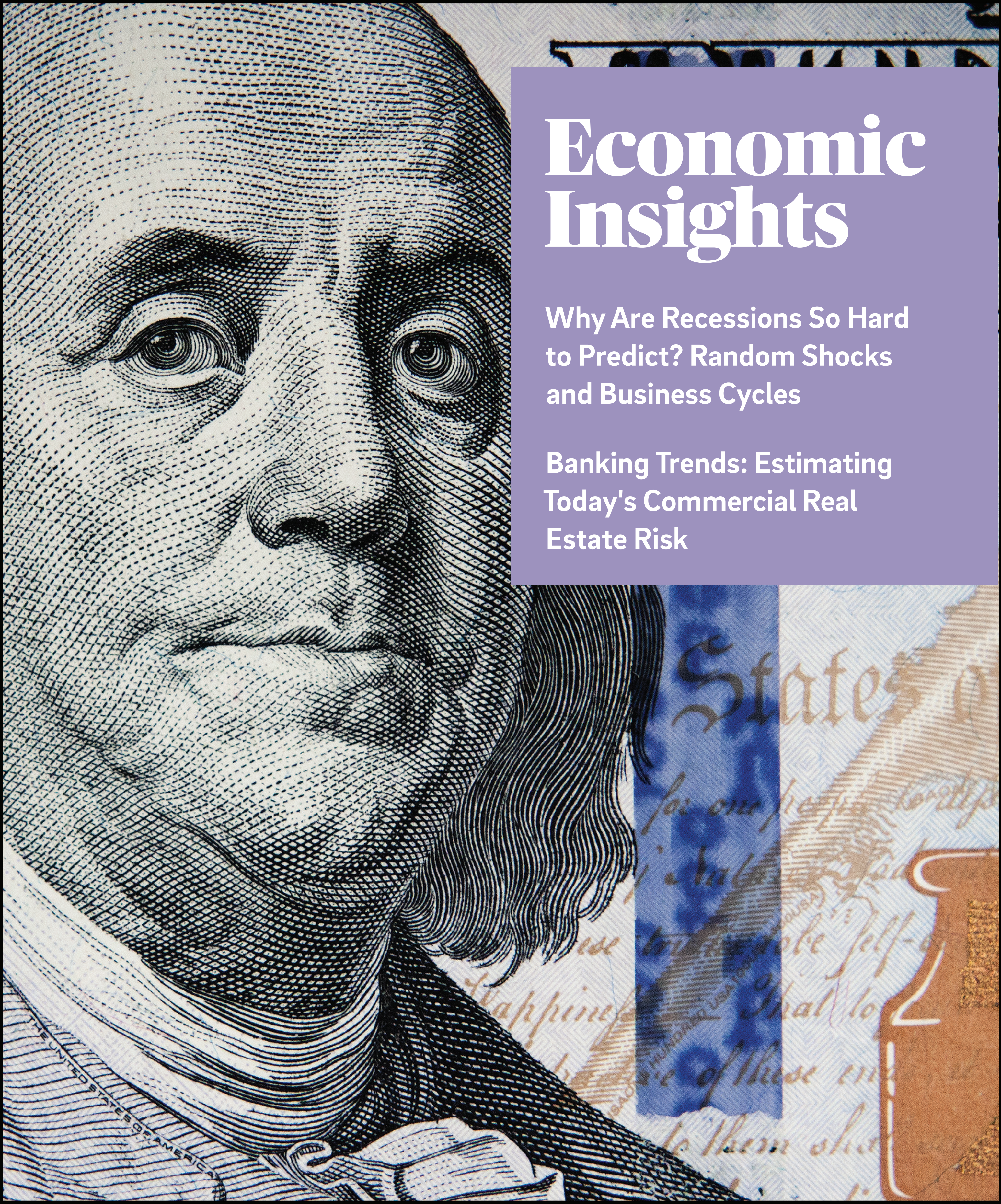

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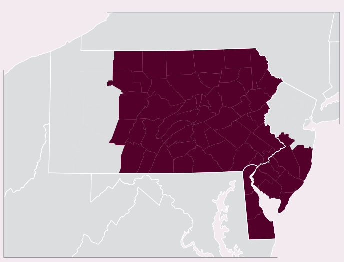

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About the Cover

Philadelphia's most famous citizen, Benjamin Franklin, has graced the $100 bill since the newly created Federal Reserve began issuing "Federal Reserve Notes" in 1914. This particular image is taken from H.B. Hall's engraving of Joseph-Siffred Duplessis's 1785 portrait of Franklin, which is currently on view at the National Portrait Gallery in Washington, D.C. In the background are details from the 2009 redesign of the $100 bill, including a reproduction of the Declaration of Independence. Franklin served on the "Committee of Five" that drafted the Declaration and presented it to the Second Continental Congress, then meeting at the Pennsylvania State House, on July 4, 1776. The State House still stands today, just two blocks from the Federal Reserve Bank of Philadelphia, and is now known as Independence Hall.

Photo by Rich Wood.

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Why Are Recessions So Hard to Predict? Random Shocks and Business Cycles

Economists are like doctors, not soothsayers. They can't predict recessions, but they can help us understand why one is happening. And that can make all the difference for policymaking.

Thorsten Drautzburg is a senior economist at the Federal Reserve Bank of Philadelphia. The views expressed in this article are not necessarily those of the Federal Reserve.

BY THORSTEN DRAUTZBURG

> *Economists can't tell you when the next downturn is coming [...]. Expansions don't die of old age: They're murdered by bubbles, central-bank mistakes or some unforeseen shock to the economy's supply (e.g., energy price spike, credit disruption) and/or demand slide (e.g., income/wealth losses).*
> *–Jared Bernstein, Washington Post, 7/5/2018*

Economists cannot predict the timing of the next recession because forecasting business cycles is hard. For example, at the onset of the 2001 recession, the median forecaster in the Survey of Professional Forecasters (SPF) expected real U.S. gross domestic product (GDP) growth of 2.5 percent over the next year, while in reality output barely grew. Again, on the eve of the Great Recession, forecasters were expecting GDP to grow 2.2 percent over the next four quarters, and we all know how that worked out.[1] Why is it so hard to predict downturns–even while they are happening?

Most economists view business cycle fluctuations–contractions and expansions in economic output–as being driven by random forces–unforeseen shocks or mistakes, as Bernstein writes. As I will show, a model in which purely random events interact with economic forces can resemble U.S. business cycles. This randomness of economic ups and downs poses a challenge for macroeconomic forecasters because random events, by their very nature, are unpredictable.

One might be tempted to conclude that if the origins of business cycles are random forces, then analyzing business cycles must be a pointless endeavor. However, not all random forces are alike. For our purposes, economists distinguish between two main types of random forces–demand shocks and supply shocks.[2] As the term implies, shocks are surprise events that, when put into a mathematical model of the economy, generate patterns in economic variables that resemble those of business cycles. Because the economy responds differently depending on which type of random shock has occurred, knowing which type it was, even after the fact, is important for getting economic models right. And creating the right economic model is important for choosing the right policy response if the economy is in the midst of a recession.

If designing better models is the key, how is that research progressing? What has prompted the recent thinking on the importance of shocks? I will summarize why early research focused on productivity shocks (an important supply shock), and then discuss why later models emphasized demand shocks. Perhaps unsurprisingly after the Great Recession, more recent research has focused on incorporating shocks to financial conditions. I will also look beyond the mainstream research to two recent critical contributions to traditional macroeconomic modeling. First, though, let's consider more carefully what a business cycle is, what the key characteristics of U.S. business cycles have been over time, and just how random they have been.

What Is a Business Cycle?

Business cycles are recurrent expansions and contractions that are common to large parts of the economy. The National Bureau of Economic Research (NBER)–the private organization that is the de facto arbiter of U.S. business cycle dating–defines a recession as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales."[3]

But even though business cycles recur, they are unpredictable because the length of the expansions and contractions varies. In the post-WWII era, expansions have lasted between one and 10 years. When the longest expansion ended after 10 years in 2001, SPF forecasters were still surprised.

On a more practical level, we typically measure cycles as the difference between the data as currently observed and the longer-run trend, defined as a movement that lasts eight or more years.[4] Figure 1 illustrates this by plotting the level of real per capita GDP and its estimated trend in the top panel. The difference between the level and the trend is the estimate of the cycle, shown in the bottom panel. Qualitatively, economists typically focus on how volatile such a detrended series is and how it comoves. We typically measure volatility by the standard deviation, often expressed relative to that of output. The correlation captures the comovement, specifically that with the business cycle (as measured by GDP) and its own past realizations of a series (Figure 2).[5]

What characterizes U.S. business cycles? Three qualitative properties of key economic indicators over the business cycle are robust and form the key features that business cycle models try to explain. First, investment and consumption are both procyclical. They rise in expansions and fall in recessions. This makes economic sense because output and income are higher in expansions. Second, hours worked are strongly procyclical, while unemployment shows the opposite pattern. In contrast, labor productivity is only moderately procyclical, and real wages are nearly acyclical. Third, investment is about three times more volatile than GDP, whereas private consumption is one-third less volatile, which makes sense if households prefer to smooth their consumption—that is, to keep their rate of spending steady through good times and bad.

Can Chance Drive Business Cycles?

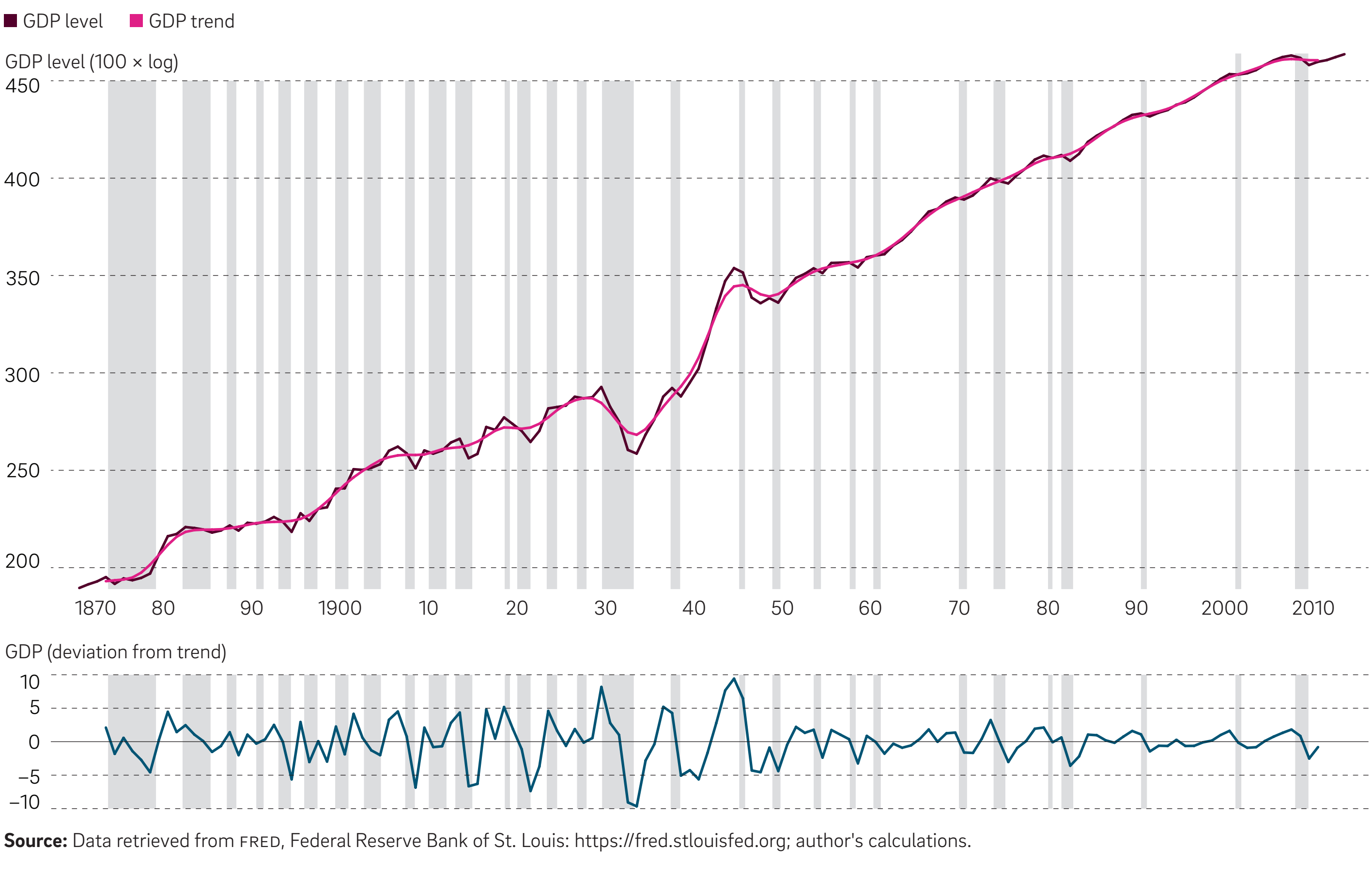
Recall that even though business cycles are recurrent, they are unpredictable because the length of expansions and contractions varies. Economists have formalized this notion by building models of business cycles that are driven by random events.

Mainstream economics views business cycles as comparable to the "random summation of random causes," to quote Eugen Slutzky (1927, in English 1937). What does this mean, though? Back in 1927, Slutzky observed that summing random numbers, such as the last digits from the Russian state lottery, can generate patterns that have properties similar to those we see in business cycles. (See Figure 4 for his experiment.) Around the same time, George Yule observed that other cyclical patterns, such as those of actual sunspots, are well described by random shocks that are fed into a simple linear model, again implying that we can think of business cycles as random shocks that are averaged over time. In 1933, Ragnar Frisch, the first Nobel laureate in economics, took these insights about how random shocks can combine to produce cyclical patterns to build a business cycle model. Following Frisch, most economists now contend that good models of the business cycle rely on combinations of current and past shocks to accurately account for business cycle elements such as those in Figure 2.

Broadly speaking, the models serve two purposes. First, they provide a way to think about the economic origins of shocks. To fix ideas, assume we observe data on prices and quantities.

FIGURE 1

Level and Trend (top) and Cycle (bottom) in U.S. Real GDP Per Capita Since 1870



Source: Data retrieved from FRED, Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org; author's calculations.

Picture the famous "scissors" representing demand and supply, as in Figure 3. The economy moves from origin to the new equilibrium at point A, the intersection of demand D0 and supply S0. Identifying the origin of shocks corresponds to dissecting this change in prices and quantities. Here, a supply shock moved the supply curve from the line labeled S0 to the S1 line. By itself, it would have lowered prices and increased quantities, moving the economy from point A to point B. A demand shock, from D0 to D1, accounts for the remaining movement from B to C. We need models to give us the correct slope of the curves because otherwise we cannot decompose the price-quantity change into demand and supply changes even in this simple example.[6] The business cycle model analogous to this example typically implies that negative supply shocks cause rising inflation and falling output. In contrast, falling inflation and falling output may point to a negative demand shock. Further details, for example on the composition of output changes or on relative prices, allow models to be even more specific.

The second benefit that models bring is that they allow us to have a mapping from current and past shocks to observed macroeconomic data: The models' assumptions on preferences and technologies imply how individual firms and households will respond to economic shocks. For the models discussed here, these individual responses can be averaged to provide us with a linear relationship between shocks and macroeconomic data. This also allows one to compute counterfactuals.

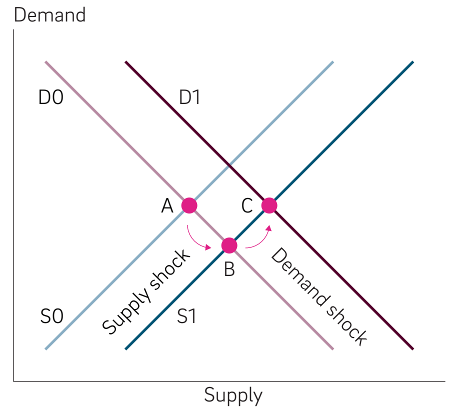
The Search for Shocks

While accepting the paradigm set out by Frisch, economists differ on which models and shocks are most useful for understanding business cycles. Identifying shocks that cause movements in economic variables is not just of academic interest. It is important for policymakers such as the Federal Reserve and other central banks to know whether inflation falls because of, say, a shock that leads to unexpectedly high productivity, or because of a shock that leads households to unexpectedly increase the rate at which they save.

So, what specific shocks, when put into a model, might generate patterns that look like business cycles? Most economists think that economic cycles are the result of multiple shocks, although a single shock may dominate specific episodes such as the Great Recession.[7] The two theories that currently dominate research emphasize different types of shocks. Real business cycle (RBC) theory focuses on real (as opposed to monetary) factors and supply-side shocks. New Keynesian (NK)

FIGURE 3

Disentangling Changes in a Price-Quantity Pair into Demand and Supply Shocks



Source: Following Uhlig 2017.

theory also incorporates nominal factors and stresses the role of demand-side shocks.

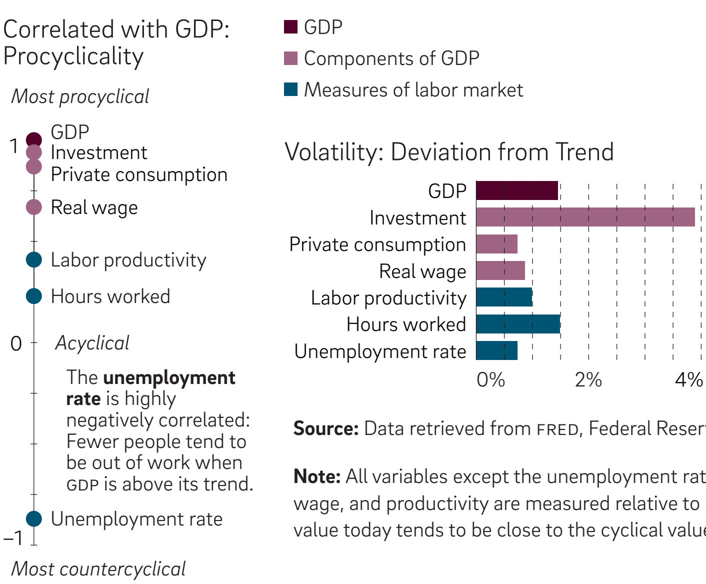
In addition to allowing us to think about the origins of shocks, these theories and their implied models allow us to map these shocks to data counterparts, such as output or wages. This is necessary to allow us to compare them to the data and validate them, albeit indirectly.

Real Business Cycles

The RBC paradigm[8] proposes that random changes in total factor productivity relative

FIGURE 2

Volatility, Cyclicality, and Persistence of GDP and Other Key Macroeconomic Indicators

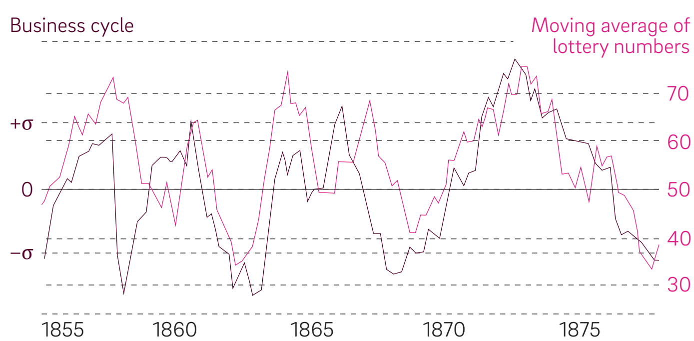


Source: Data retrieved from FRED, Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org; author's calculations.

Note: All variables except the unemployment rate are %-deviations from trend. The volatility of investment, consumption, the real wage, and productivity are measured relative to GDP. All series are persistent, with autocorrelations around 0.9 or higher: Their cyclical value today tends to be close to the cyclical value yesterday.

FIGURE 4

Index of UK Business Cycle, 1855 to 1877 vs. Moving Average of Lottery Numbers



Source: Slutzky (1927, in English 1937).

to its trend are the key shock. Total factor productivity determines how much firms and, ultimately, the economy can produce given inputs such as capital and labor. These random changes can reflect both actual changes in technology, such as self-driving cars, and, more broadly, changes in the legal or regulatory environment.[9] To map these shocks to the data, the model makes certain assumptions about how willing households are to forgo consumption today in order to consume more tomorrow and how willing they are to work more in response to higher wages.[10]

This simple model—with only productivity driving business cycles and a few linear equations—matches most of the qualitative behavior of the U.S. economy described in Figure 2, including the procyclicality and relative volatility of consumption. Because households prefer smooth consumption, they respond to economic conditions by adjusting their investment more than their consumption. This explains the relatively low volatility of consumption. Procyclical hours worked result from households' rational choice to work more while the economy is more productive, even though they like leisure.[11]

However, the basic RBC model has difficulty explaining changes in wages and employment. In this type of model, firms pay their workers according to how productive they are, implying a high correlation between wages and productivity and output—in contrast to their low correlation in the data (Figure 2).[12]

New Keynesian Economics

The NK extension of the RBC model adds nominal, or price-related, elements that nevertheless have real, quantity-related effects. Jordi Galí (1999) argued that nominal factors are key to understanding that people work less after a positive productivity shock: Because firms initially cannot lower prices when productivity rises, their labor demand falls temporarily. That is, firms use the higher productivity to economize on labor rather than to lower prices and increase sales and production. This explains why productivity is not more closely correlated with output and employment and allows the NK model to fit the data better than the RBC model does. Similarly, Julio Rotemberg and Michael Woodford (1999) argued that nominal frictions are also important because they help us understand how prices vary relative to the costs of production.

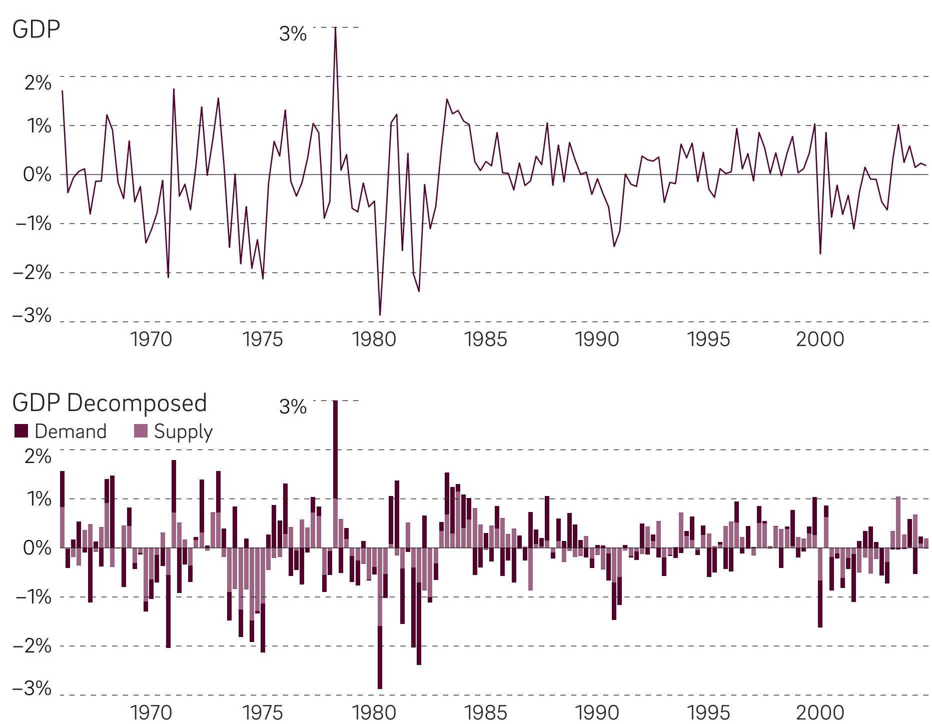
Formally, the NK paradigm adds two elements to the RBC paradigm. First, there is market power, which on the side of firms allows them to set prices and on the side of workers allows them to set wages. Second, there are limits to firms' ability to adjust prices and households' ability to adjust the wages they demand. These limits arise because adjusting prices or wages may be too costly. Or, some firms or households might not have an opportunity to adjust prices or wages, for example due to fixed contract terms. As the example from Galí makes clear, the extra ingredients of the NK model change how shocks affect observables such as output compared with the RBC model. They also give scope to think about new sources of shocks, such as monetary policy shocks to nominal interest rates.

Estimated versions of these models have shaped how central banks today analyze business cycles.[13] These models are also called dynamic stochastic general equilibrium (DSGE) models. They are dynamic because how much people work or consume in the model depends on their assessment of past and current conditions and their expected future paths. They are stochastic because they are driven by random shocks. Absent shocks, the models imply that business cycles are predictable. And they are general equilibrium models because there is full feedback of the choices of individual firms and households onto one another.

In a key breakthrough, Smets and Wouters (2007) showed that such a DSGE model could match state-of-the-art statistical models for forecasting. At the same time, DSGE models allow us to interpret the forces at play in the economy. Other models, such as a no-change forecast or a vector-autoregressive model, also often produce good forecasts. But compared with these purely statistical models, the DSGE model allows us to open up the black box of what had driven an economic forecast and where the forecast fell short. Even in hindsight, this information is important for policymaking and for improving models. For example, as I will discuss, the Great Recession prompted economists to look at shocks to financial conditions.

FIGURE 5

Historical Decomposition of GDP Growth Implied by Smets and Wouters



Source: Author's calculations based on Smets and Wouters.

Note: The demand and supply contributions add up to total real GDP growth per capita in the historical Smets-Wouters data.

New Keynesian DSGE models feature many shocks and decompose business cycles into the effects of these various shocks (Figure 5). With these types of models, it is useful to distinguish between supply shocks that affect the quantity or cost of what can be produced with given inputs and demand shocks that determine how much firms or households want to purchase at a given point in time. These models are therefore useful to monetary policymakers because, to pursue their mandates such as price stability and full employment, central banks may want to lower interest rates in the event of unexpected increases in supply and may have to raise interest rates if demand unexpectedly rises.

Seen through the lens of the Smets and Wouters (2007) model, demand shocks have accounted for most of the variation in GDP growth from 1965 to 2004, as seen in Figure 5. The two largest contributors to short-run fluctuations have been demand shocks: A shock to government consumption and net exports and a shock to the desire to save each accounted for about 25 percent of the fluctuation in GDP growth.[14] Together, four supply shocks have accounted for slightly less than half of the observed GDP growth. The two most important supply shocks have been shocks to the productivity of all firms, as in the RBC model, and shocks specific to firms producing investment goods.

Financial and Uncertainty Shocks

In the aftermath of the financial crisis of 2008 and the subsequent Great Recession, shocks to the financial sector have been proposed as a missing ingredient in business cycle models. At the time, this was new. While economists had long analyzed the effect of the financial sector on the economy, often the question was whether financial institutions strengthen the effects of other shocks, such as demand or supply shocks.[15] After the Great Recession, economists began to ask: Do shocks to the financial sector have important macroeconomic effects?

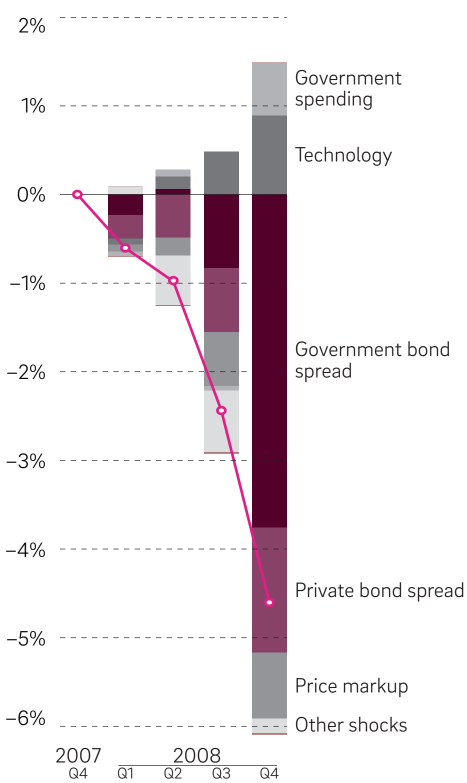
Harald Uhlig and I estimated a DSGE model that includes the spread between the yields on private bonds and government-issued bonds. These spreads are important because firms cannot borrow at the same rate as the government. Since they also pay the spread, both the rate of government bonds and spreads matter for private decisions, while only the former were traditionally modeled in DSGE. Our approach sidesteps modeling the specific drivers of bond spreads, such as, for example, changes in default risk or in how markets price default risk. We found that shocks to bond spreads alone accounted for the drop in output growth at the onset of the Great Recession, even though these shocks usually contribute much less to fluctuations (Figure 6). Incorporating bond spreads can also significantly improve the forecasting performance of these DSGE models.[16]

Christiano et al. (2014) provide a model of the drivers of bond spreads. In their model, bond spreads reflect default risk. They model financial shocks as affecting how much the returns vary between different investment opportunities (within the same asset class). These shocks then move bond spreads. They find that such

FIGURE 6

Bond Spread Shocks Contributed a Significant Amount to the GDP Decline During the Great Recession

Shock contributions to GDP



Source: Drautzburg and Uhlig, 2015.

Note: Real GDP per capita level relative to trend. 2007Q4 normalized to zero.

Micro Shocks Lead to Macro Fluctuations

The approaches discussed so far focus on how aggregate shocks can explain aggregate fluctuations. But the idea also applies to shocks to individual industries or even individual firms. Could these shocks have aggregate effects, too? Detailed data on firms and industries are now readily available to investigate this question. Economists have refined the RBC approach to interpret these microeconomic data.

If an individual firm or industry accounts for a large share of total sales in the economy, it is possible that a shock to only that firm or industry will matter in the aggregate.[17] Using a simple formula to quantify this idea, firm-level shocks may account for about one-third of aggregate fluctuations.[18] More detailed measurement, however, has called this number into question and suggests that firm-level fluctuations are more likely to account for only one-sixth of aggregate fluctuations.[19]

Industry-specific shocks—say, an unexpected advance in drilling techniques for the oil industry—can have outsize weight, too, if the industry is an important supplier or customer for other industries. By one estimate, industry-specific shocks accounted for only one-fifth of fluctuations in postwar U.S. output, although their contribution was higher during the Great Moderation.[20] But if it is hard for industries to switch from one type of input, such as a certain material, to another, shocks to the productivity of the input-producing industry would have a greater impact across the economy. Research that argues that this is the case estimates that industry-specific shocks account for half of aggregate fluctuations.[21]

shocks account for about half of U.S. business cycle fluctuations. Shocks that increase the variance of returns across investors translate into higher borrowing costs and spreads because they make it more likely that borrowers with limited liability may walk away from projects and require lenders to step in. Anticipating this greater likelihood of default, lenders charge higher interest rates to cover expected losses from defaults. Higher borrowing costs discourage firms from investing in their businesses and households from purchasing durable goods, thereby generating drops in output.

Individual uncertainty can also create aggregate fluctuations through another mechanism. Economic activity can contract when uncertainty rises because investors prefer to "wait and see" rather than invest. This behavior is not due to financial frictions but because it is more costly to undo investments than to postpone them.

Is the Search for Shocks the Right Approach?

This article surveys two broad ideas in economics. First, business cycles are driven by random forces. Second, after the fact, we can trace these random forces back to economically meaningful shocks using DSGE models. Both ideas have their critics, however.

Using DSGE models to quantify shocks as the driving forces of business cycles has its limitations. First, shocks can be a measure of our ignorance.[22] In the spirit of "less is more," economists favor models that generate larger effects from small shocks. Second, the way DSGE models and other statistical models are typically estimated implies that they always point to specific shocks to explain the observed changes in economic indicators, without the ability to test whether they have identified the right shocks. My recent research questions whether the identified shocks in DSGE models are correct if one believes established narrative accounts of these shocks.[23] Related research allows us to quantify how important shocks are without taking a stance on how many shocks there actually are.[24]

The idea that business cycle fluctuations are driven purely by random shocks also has its critics. In other business cycle paradigms—for example, in the theories of Karl Marx or Hyman Minsky—each boom carries the seeds of the next downturn. Paul Beaudry and his coauthors have argued that economists should revisit this idea and incorporate it into modern models.

Beaudry and his coauthors motivate their critique by arguing that business cycles are more predictable than typically thought. Using data on all U.S. recessions since the 1850s, they argue that the likelihood of a recession has depended on the time elapsed since the previous recession.[25] Most models today imply that business cycles are driven by the accumulation of positive and negative shocks and that economic indicators such as output or unemployment return smoothly to their long-run trends or averages after a shock. In contrast, business cycles in intrinsically cyclical models—that is, ones that assume that each cycle carries the seeds of the next—could, in the extreme, explain business cycles in the absence of shocks. Of course, Beaudry et al. do not imply that business cycles are perfectly predictable—just that ups and downs are somewhat predictable and that shocks are smaller than commonly believed. EI

Notes

1 In the first quarter of 2001, forecasters expected cumulative GDP growth of 2.5 percent over the next four quarters, whereas actual growth (according to the first releases) averaged 0.5 percent. In the fourth quarter of 2007, forecasters expected cumulative GDP growth of 2.2 percent over the next four quarters, whereas actual growth (according to the first releases) averaged 0.6 percent.

2 Bernstein's "central-bank mistakes," labeled monetary policy shocks later in this article, withdraw demand from the economy and are thus also demand shocks. "Bubbles" could affect the credit supply by easing collateralized borrowing, and their emergence or bursting would then be a supply shock in financial markets.

3 The modern-day NBER definition quoted above (taken from http://www.nber.org/cycles.html) is very similar to the original concept of Mitchell (1927, p. 468), one of the founders of the NBER business cycle research program. He defines a business cycle as a "cycle [that] consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own."

4 See Baxter and King (1999) for a technical exposition.

5 There has recently been debate on the details of detrending procedures (Hamilton 2018; Beaudry et al. 2016). The results here, however, are robust to details of the detrending procedure.

6 See Uhlig (2017) for a discussion of this decomposition and of statistical techniques to identify the slopes.

7 As I will discuss, the Great Recession may have been dominated by a shock to financial intermediation.

8 The RBC paradigm was initiated by Kydland and Prescott in their 1982 article.

9 See the discussion in Stadler (1994).

10 See Hansen and Heckman (1996) for a discussion.

11 See Chatterjee (1999) for more details.

12 Perhaps ironically, labor productivity was more procyclical at the time that Kydland and Prescott invented the RBC paradigm. Before 1982, the correlation of real wages and real GDP was 0.60, as compared with 0.23 for the full post-WWII sample in Figure 2. Huang (2006) also argues that the comovement of real wages with output has changed before and after WWII, consistent with the changing importance of supply shocks. However, he argues that the structure of the economy has changed, not the nature of shocks.

13 See Christiano et al. (2014) and Smets and Wouters (2007) for the original articles and Dotsey (2013) for an overview.

14 A third type of demand shock, a monetary policy shock, has contributed only about 5 percent. However, this does not imply that systematic monetary policy has been irrelevant to the cyclical volatility of economic output, but rather that monetary policy surprises unrelated to the state of the economy have not played a large role in the postwar U.S. economy.

15 See Bernanke et al. (1999).

16 See the handbook chapter by Del Negro and Schorfheide (2013).

17 GDP measures value added (i.e., sales net of intermediate inputs), not sales. One might therefore guess that value added weights matter. However, sales matter because a firm whose value-added is small can still affect large swaths of the economy if it uses inputs from or provides key inputs to many other firms.

18 See Gabaix (2011).

19 See Yeh (2017).

20 See Foerster et al. (2011).

21 See Atalay (2017).

22 See Cochrane (1994).

23 See Drautzburg (2016).

24 See Plagborg-Møller and Wolf (2017).

25 Beaudry and his coauthors also point out that current models miss properties of the business cycle by throwing out too much information in detrending procedures.

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Banking Trends

Estimating Today's Commercial Real Estate Risk

To survive a decline in commercial real estate prices such as occurred during the financial crisis, how much more capital do banks today need?

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PABLO D'ERASMO

Since the mid-1990s, banks have increased their commercial real estate (CRE) lending significantly, allowing the CRE market to almost double as a share of the nation's overall economic output. This growing share of CRE mortgages on bank portfolios presents a financial stability challenge, since CRE exposure has been a key determinant of bank failures in the past. As commercial property prices have climbed back up since the financial crisis, CRE capitalization rates—the expected return to investors in commercial real estate[1]—have fallen to historically low levels. This fall suggests that commercial real estate prices could be poised to tumble again, potentially causing large numbers of CRE borrowers to default, and leaving banks with steeply devalued CRE mortgages on their books and too little capital to match their liabilities.

This article presents evidence of the link between exposure to commercial real estate loans and bank failure, and then estimates how much more capital banks would need to withstand a decline in commercial real estate values like that observed during the financial crisis. Preventing bank failures and keeping capital levels in a position to absorb losses protects taxpayers because it reduces the expected cost to the federal deposit insurance fund and the likelihood of government intervention in the case that the crisis becomes widespread. Moreover, failures at small banks, which are generally more directly exposed to commercial real estate, tend to disproportionally affect small savers and borrowers.

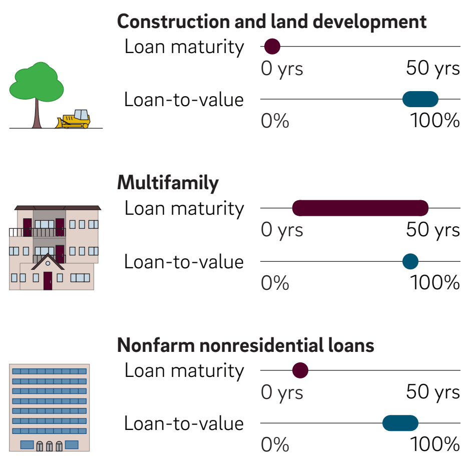
Small Banks Especially Exposed to CRE

CRE loans finance the purchase or development of almost any type of income-producing property, from offices to retail spaces to industrial locations to multifamily residential complexes.[2] There are three types of CRE loans, their use depending on the type of property involved and the buyer's objective for it:[3]

FIGURE 1

Three Types of CRE Loans

Their most common loan maturities and their average loan-to-value ratios.



Source: DiSalvo and Johnston, 2016.

Construction and land development loans cover the cost of acquiring the land and constructing the buildings. Their typical maturity is three years, and their loan-to-value ratio is 75 to 85 percent. This line of credit carries a balloon payment due when construction is completed, and is generally financed by a new loan.

Multifamily loans are used to purchase residential buildings with five or more units. Maturities range from 10 to 40 years, with an average loan-to-value ratio of 75 percent.

Nonfarm nonresidential loans (also referred to as commercial mortgages) are used to buy retail, office, industrial, hotel, and mixed-use properties. The most common length of these loans is 10 years, with a loan-to-value ratio of 65 to 75 percent.

Commercial banks are key players in the commercial real estate market, holding over 50 percent of the outstanding stock of CRE loans on their portfolios in 2016, and are particularly important for the nonfarm nonresidential and construction and land development segments of the market, in which they hold 60.8 percent and 100.0 percent, respectively.[4]

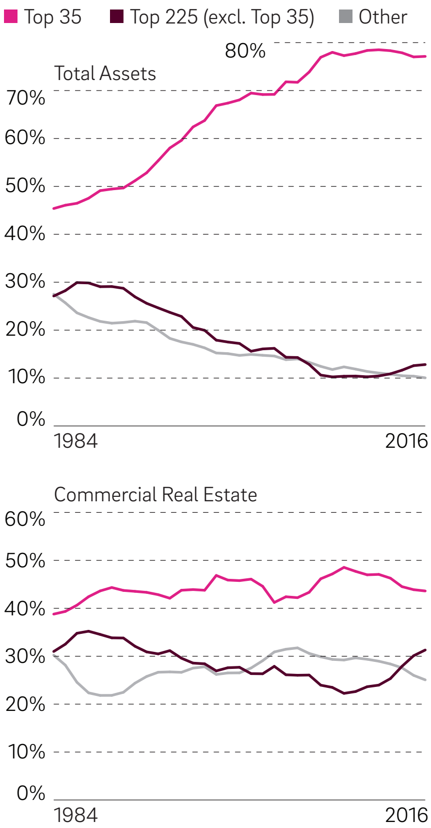
However, within the banking sector, the degree of exposure to commercial real estate mortgages varies substantially by bank size. The top 35 banks hold 75 percent of all bank assets but just 43 percent of the commercial real estate market. The next-largest group of banks—those ranked 36th to 225th in terms of total assets—hold

FIGURE 2

Degree of CRE Exposure Varies

Total assets and CRE exposure.

Market shares by bank size



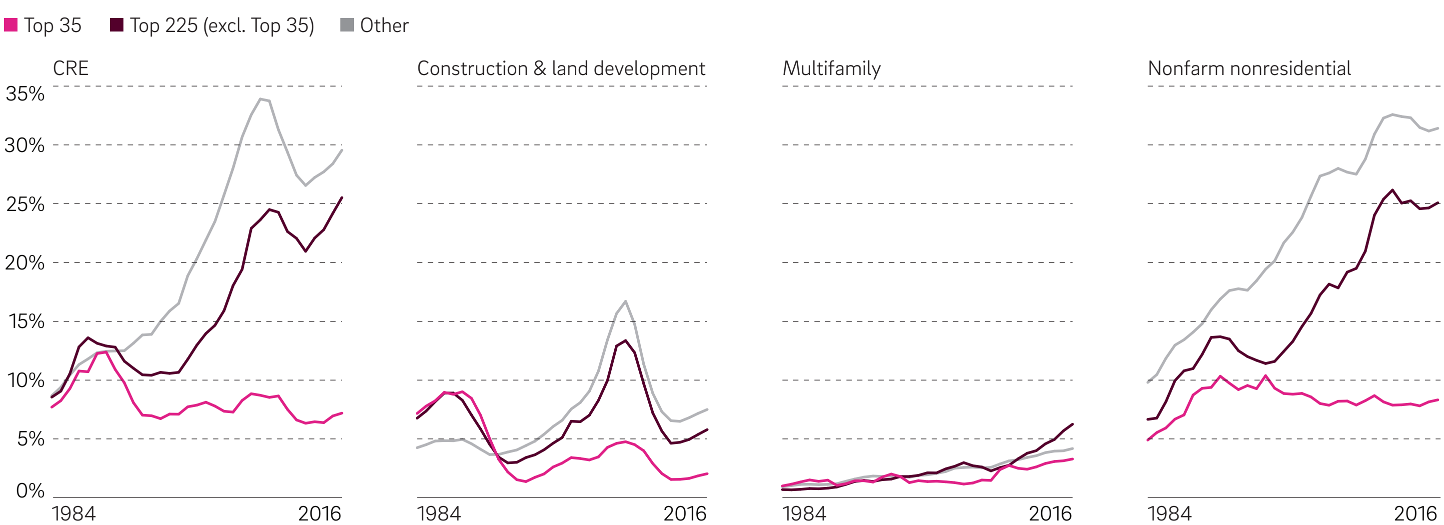
Source: Federal Reserve Call Reports.

FIGURE 3

Postcrisis Exposure to CRE Still Elevated

Loan portfolio specialization by bank size.

Loans-to-assets ratio for different loan types



Source: Federal Reserve Call Reports.

30 percent of CRE assets. Small banks—all those not in the top 225—hold 27 percent of the market (Figure 2).[5]

Although small banks hold the smallest slice of the CRE market, the historical evidence hints that in terms of the share of their loan portfolios, small banks tend to specialize in commercial real estate and are more exposed to this market than large banks are (Figure 3).[6]

Small banks' CRE holdings account for 30 percent of their total assets, compared with just above 5 percent for large banks. And small banks' specialization in commercial real estate has increased over the last few decades. Their specialization in CRE has been driven mostly by construction and land development loans and nonfarm nonresidential mortgages (Figure 3), which have higher rates of default than other commercial real estate loans and, as discussed here, are a main driver of the link between commercial real estate and bank failure.

At the peak of the last financial crisis, commercial real estate loans accounted for almost 50 percent of small banks' total loans. Today, even after the decline of the real estate market during the crisis, that fraction remains above 40 percent, suggesting that concentration in the commercial real estate loan market remains elevated. The largest banks have increased their exposure to multifamily loans since the crisis, but their share of CRE loans as a fraction of their total loans has always been relatively low, just above 15 percent in 2016.

CRE Exposure Determines Bank Failure

Historically, the commercial real estate market has been cyclical, with relatively pronounced oscillations between economic expansions and recessions. Its cyclical properties make banks that concentrate their lending in this sector particularly vulnerable and can amplify business cycles via bank failure and reduced lending.

Evidence shows that high exposure to CRE lending, when coupled with depressed CRE markets, has contributed to significant credit losses and bank failures in the past.[7] Two supervisory criteria—described in a 2006 regulatory guidance by the Board of Governors of the Federal Reserve System, the Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC)—provide good benchmarks for evaluating whether a commercial bank is overexposed to the CRE market:

If its holdings of construction and land development (CLD) loans represent 100 percent or more of its total risk-based capital, then the bank is **High CLD**.

If its holdings of CRE (including CLD) loans represent 300 percent or more of its total risk-based capital and have increased by 50 percent or more during the previous 36 months, then the bank is **High CRE**.

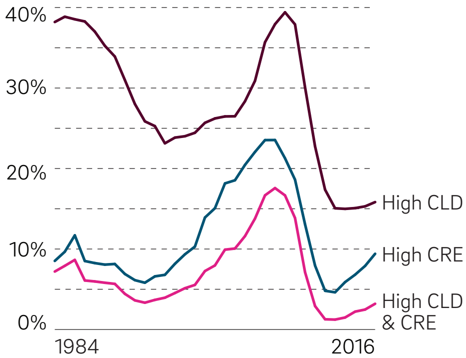
At any point in time, a significant fraction of banks is highly exposed to the fluctuations in CRE prices (Figure 4).[8]

As Figure 4 also makes evident, CRE loan exposure has a local peak in the

FIGURE 4

Significant Share Highly Exposed to CRE

Percentage of banks with high exposure to the CRE market since 1984.



Source: Federal Reserve Call Reports.

Note: High CLD & CRE refers to institutions that satisfy the criteria for High CLD and High CRE.

mid-1980s and another in the mid-2000s. Both peaks were followed by surges in bank failures that, among other factors, the literature has identified with downturns in the CRE market.

To illustrate how relevant CRE exposure has been for bank failures, we can trace the evolution of the number of commercial banks that have failed since 1984 and compare the failure rates for all banks and for banks conditional on their degree of CRE concentration (Figure 5).

The banking crises in the late 1980s and the 2008-2009 financial crisis resulted in a large number of bank failures.[9] In both episodes, there were major differences in failure rates for banks above and below the concentration levels specified in the interagency guidance. Failure rates for banks that exceeded the criteria were three to four times higher than those of the rest of the banks. Most failures in the late 1980s occurred among banks that had high overall CRE exposure, and most failures in the last crisis were among banks with high CLD concentrations.[10]

The Crisis of the Late 1980s and Early 1990s

During a boom in commercial real estate lending in the early 1980s—primarily in the Southwest, Alaska, Arizona, the Northeast, and California—CRE loans tripled, which was followed by a rapid decline in the value of real estate in 1989 and 1990, leading to a large fraction of nonperforming or foreclosed commercial real estate loans in 1991.

What triggered the fantastic increase in CRE lending? One of the factors that the literature has identified (see James Poterba's article) was the tax incentives included in the 1981 tax reform, the Economic Recovery Tax Act of 1981. Total multifamily starts rose from 390,000 in 1981 to 670,000 in 1985, with virtually all of the increase in large buildings. What triggered the decline? Further changes in tax policies had also been identified as the drivers of the decline. The Deficit Reduction Act of 1984 and the Tax Reform Act of 1986 reversed most of the changes of the 1981 tax law. The net effect has been a reduction in the tax incentives to rental construction.[11]

Many of the banks that failed had actively participated in the regional real estate market booms, particularly in commercial real estate. In 1991, the commercial real estate loan-to-asset ratio for banks that failed was close to 30 percent, while the same ratio for banks that continued operating was just above 10 percent. Commercial real estate loan exposure among banks that subsequently failed was significantly higher than for those that did not fail.

The Last Financial Crisis

In response to increased competition in the consumer and residential real estate loan markets during the early 2000s, small banks—generally referred to as community banks—turned increasingly to commercial real estate lending (Figure 3).[12]

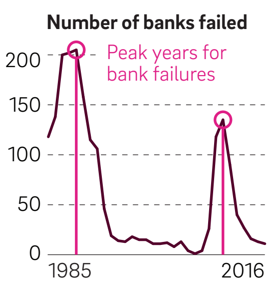
During the early 2000s and until the issuance of the interagency guidance, the fraction of banks with large CRE exposures grew steadily (Figure 4). In 2006, just before the crisis, 40 percent of all commercial banks in the U.S. had high CLD concentrations, and close to 20 percent had high CLD and CRE concentrations. As the crisis deepened, deteriorating conditions in the residential mortgage market that had begun in 2007 spilled over

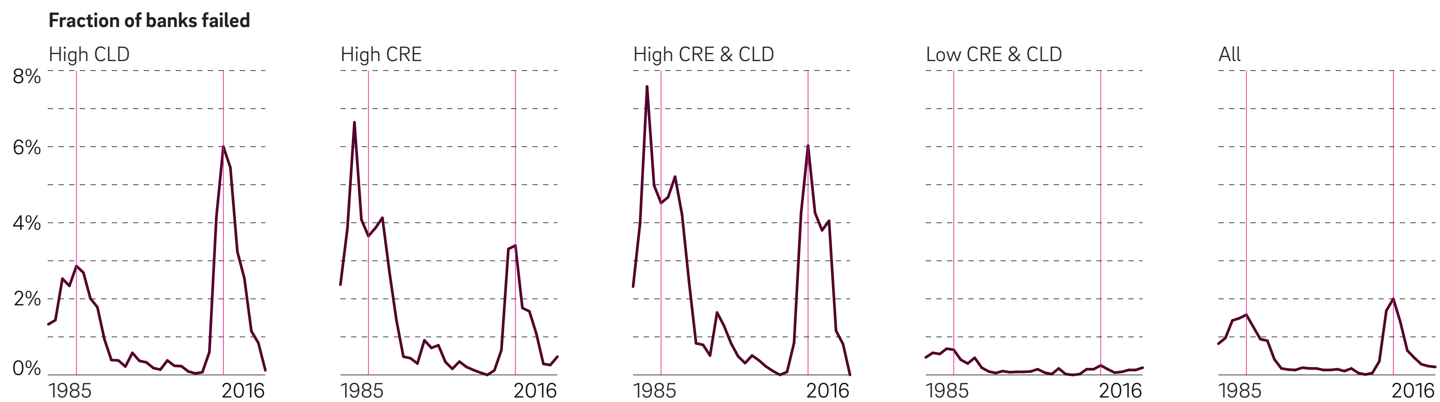
FIGURE 5

High Concentrations Correlate with Bank Failures

Number and rates of bank failures.
1984–2016

Note: High CLD & CRE refers to institutions that satisfy the criteria for High CLD and High CRE, and Low CLD & CRE refers to institutions that do not satisfy either of the criteria.





Source: Federal Reserve Call Reports.

to the CRE market in 2008.[13] One important link between the two markets was that many banks had made loans to developers for the purpose of constructing multifamily residences, and demand for these residences fell sharply in the recession. The CRE price declines—on average, more than 42 percent between the peak in 2007 and 2010—had very negative consequences for the financial sector.

The percentage of CRE loans that banks had to write off from the end of 2007 through the end of 2010 was 10 times higher than it had been between 2000 and 2007. As in the previous crisis, banks that were more exposed to commercial real estate suffered much more. Commercial real estate loan delinquencies were not as high as delinquencies in the residential real estate market but also increased dramatically. Yet, charge-off rates for commercial real estate loans were higher than charge-off rates for residential real estate loans at the peak of the crisis, with CRE charge-offs driven primarily by land, development, and construction loans.

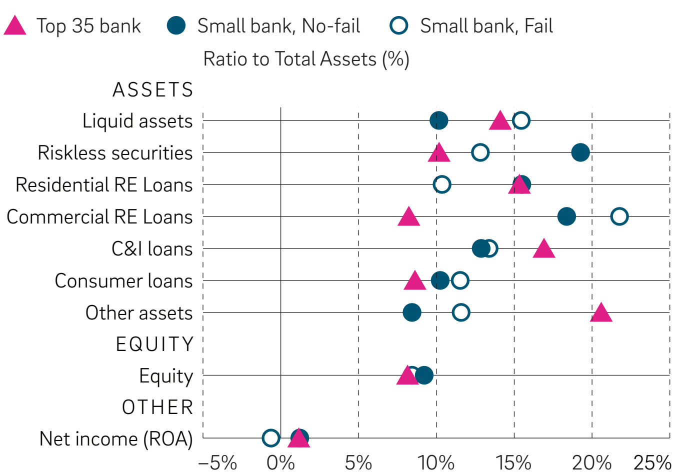
Are there other relevant differences between the banks that failed and those that did not? To shed some light on the factors influencing bank failure—and in particular whether there are significant differences in commercial real estate exposure—we can compare the balance sheet composition for large versus small banks, and in the case of the small banks, for those that failed versus those that did not fail during the financial crisis (Figure 6).

As Figure 6 shows, small banks held more safe assets (liquid assets such as cash plus riskless securities such as U.S. Treasury securities) and were more exposed to commercial real estate. Their higher holdings of securities derives from differences in the cost of borrowing between small and big banks, geographic diversification, and the volatility of their deposit base, as small banks are more exposed to local fluctuations. Moreover, those that failed were more exposed to commercial real estate than those that did not fail and had a negative net income, or return on assets (ROA).

FIGURE 6

Small Banks That Failed Were More Exposed to CRE

Balance sheet composition by bank size and small bank failure. 1984–2016



Source: Federal Reserve Call Reports.

Note: We define large banks as those in the top 35 of the asset distribution and small banks as all the rest.

Current Vulnerability: Stress-Testing CRE Exposure

Although commercial real estate valuations have increased considerably since the end of the crisis and capitalization rates have declined to historical lows, the recovery in CRE prices and sales volumes is beginning to slow. There are indications that demand for CRE loans has weakened and that lenders are tightening lending standards, according to recent Senior Loan Officer Opinion Survey results.

Even though capital regulations have been strengthened and bank risk-weighted capital ratios have increased in recent years, the rise in real estate prices and declines in capitalizations raise questions about the vulnerability of banks exposed to the CRE market.[14] In addition, declines in CRE market values could reduce overall small business lending by community banks.

But how can we quantify the current level of risk in the system posed by CRE lending? To estimate this risk, I perform an experiment that computes capital losses across banks using CRE delinquency rates and loss-given-default rates observed during the last crisis.[15] With a measure of delinquencies and losses at hand, it is possible to estimate the losses that banks would stand to incur in their CRE holdings under circumstances similar to those of the last crisis and from this estimate derive the reduction in bank equity that banks would sustain (Figure 7).[16]

For example, if a bank's CRE holdings equal $100, and 10 percent of those loans default, with an average recovery rate of 70 percent, the bank's portfolio will be reduced by $3. If its ratio of CRE loans over risk-weighted assets is 33 percent—its risk-weighted assets equal $300—then its ratio of risk-weighted capital due to the losses suffered in the CRE portfolio is reduced by 0.01 (=$3/$300). Then, if the bank's capital buffer over and above the minimum required is less than 1 percent, its capital ratio will slip below the minimum.

This approach uses as a starting point the 4Q2016 distribution of CRE loans and capital ratios, and provides a distribution of bank capital losses.

FIGURE 7

Stress Effects

Predicted losses in 4Q2016.

Capital Losses

0.4%	0.1%
AVERAGE	MEDIAN

Buffer over Minimum

5.6%	5.3%
AVERAGE	MEDIAN

Source: Call Reports Federal Reserve Bank.

Note: Uses CRE delinquency and loss-given-default rates across banks during 2008–2009. Capital Losses is ratio of capital to risk-weighted assets lost due to CRE losses. Buffer over Minimum is amount of excess capital over minimum that banks hold after sustaining CRE losses.

While similar in spirit, this experiment differs from the formal stress test that the Federal Reserve conducts, since it does not use loan-level data or an explicit model to calculate loan losses, and it evaluates the losses suffered only during one period as opposed to an extended period. In this respect, the results of the exercise should be viewed as a lower bound on potential losses.[17] While informative, this experiment is not designed to capture the effects of a protracted crisis in the CRE market, in which case banks are hit with repeated, consecutive losses, including those deriving from the linkages across banks, commercial real estate markets, and other asset markets.[18]

One question that arises when performing this type of experiment is whether CRE loans are particularly toxic. The results show that losses in this portfolio have the potential to affect a large swath of small banks. On average, banks currently have enough capital to remain adequately capitalized even after suffering losses as large as those observed during the last crisis (Figure 7).

The average bank has a capital buffer of more than 5 percent. However, this statistic paints over wide differences in CRE exposure and capital ratios similar to those documented for previous crises. A more in-depth analysis shows that when exposed to this stress scenario, 117 banks—2.3 percent of the total number of banks, holding 0.4 percent of the aggregate value of assets and 1.3 percent of the value of CRE credit—would fall below the 7.25 percent Tier 1 capital ratio required.[19]

This number should be understood as a lower bound on the potential effects of a stress scenario, not only because of the static nature of the experiment but also because, as Figure 6 shows, banks with capital ratios that were well above the minimum required had failed. For example, the value of the bank for its shareholders can become negative before capital reaches the minimum required.

Moreover, banks that are vulnerable to CRE price declines do not overlap exactly with those that have the largest CRE concentrations. Approximately 50 percent of those that go below the 7.25 percent capital threshold in the experiment have high concentration ratios. Other banks with high concentrations have capital ratios substantially above 7.25 percent and are able to absorb the losses, but their reduction in capital ratios also has the potential to reduce lending.

This stress experiment induces a clear shift in the distribution of risk-weighted capital closer toward the minimum. If banks are currently operating at or close to their optimal level of capital, this shift implies that losses in the CRE market could curtail lending or other asset markets and impede the normal operation of most banks in the industry.

Conclusion

This experiment shows that while the financial system appears to be better prepared for a shock in the CRE market now than it was leading up to the financial crisis, in the event of another such crisis, most banks would be affected, and many might fail. The CRE sector remains a potential source of instability for the banking sector.

Notes

1 More specifically, capitalization rate refers to the ratio of a property's annual net operating income to its price.

2 I use a conservative definition that excludes loans secured by farmland.

3 See James DiSalvo and Ryan Johnston's 2016 *Banking Trends* article for a description of the commercial real estate market.

4 The other half of commercial real estate mortgages ends up in the hands of other investors, such as insurance companies, government agencies, and private investors, or in a pool of mortgages such as commercial mortgage-backed securities (CMBS).

5 Banks in the top 35 have assets above $50 billion, banks ranked 36th to 225th have assets between $3 billion and $50 billion, and all those not in the top 225 have assets below $3 billion (measured in 2016 dollars).

6 Large banks originate a large fraction of CRE loans, but they tend to securitize a much larger fraction of these loans than small banks do.

7 See the Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency, and the Board of Governors of the Federal Reserve System's "Guidance on Concentrations in Commercial Real Estate Lending, Sound Risk Management Practices" and the Federal Deposit Insurance Corporation's 1997 "History of the Eighties—Lessons for the Future," https://www.fdic.gov/bank/historical/history/.

8 See Keith Friend, Harry Glenos, and Joseph Nichols's article, "An Analysis of the Impact of the Commercial Real Estate Concentration Guidance," for a detailed description of the guidance and its implications for loan growth and bank failure.

9 The estimate of bank failure is very conservative. Mergers are separated from clear failures, since the reasons banks fail can be different from those that result in a bank merger. However, several bank mergers were driven by the same fundamentals that drive bank failures—low returns on assets, declines in charter value, and exposure to risky assets. Similarly, a number of banks would have failed but for government bailouts. All the banks that actually failed were outside the top 35.

10 The Eliana Balla, Laurel Mazur, Edward Prescott, and John Walter article analyzed the factors driving bank failures during the crisis of the late 1980s and the most recent financial crisis extensively. Consistent with previous literature (for example, the articles by David Wheelock and Paul Wilson, George Fenn and Rebel Cole, and Rebel Cole and Lawrence White), they find that CRE, and in particular construction land and development loans, is the main factor driving failure probabilities.

11 The Tax Reform Act of 1986 created the Real Estate Mortgage Investment Conduit, facilitating the issuance of mortgage securitizations, including commercial mortgage-backed securities (CMBS).

12 In 2003, banks with assets of $100 million to $1 billion had commercial real estate portfolios equal to 156 percent of their total risk-based capital, and this ratio increased to 318 percent in 2006.

13 Adonis Antoniades' article describes the link between residential real estate and commercial real estate.

14 Besides cyclical fluctuations in commercial real estate prices, other risk factors include fluctuations in the CMBS market and softness in the retail sector that could impact the value of collateral used in CRE loans.

15 For each commercial bank, the delinquency rate on CRE loans during the crisis is computed as the maximum (yearly) delinquency rate on CRE loans observed during years 2008, 2009, and 2010. The values reported in Figure 5 refer to the average (or the median) across banks. The loss-given-default is computed as the average during the crisis.

16 In addition to delinquency rates and the loss-given-default, estimating capital losses requires a measure of the loan loss provision (the ratio of the provision for loan losses over total loans), the ratio of CRE loans to risk-weighted assets, and the current level of capital over risk-weighted assets for each bank. At the height of the last crisis, average nonperforming CRE loans was 7.75 percent, and loss-given-default CRE loans was 30.27 percent.

17 See the Jihad Dagher, Giovanni Dell'Ariccia, Luc Laeven, Lev Ratnovski, and Hui Tong article for a similar approach used to estimate appropriate levels of bank capital during a crisis.

18 These factors include the spillovers from one commercial real estate market to another via securities prices or a reduction in lending by banks affected by the initial shock as well as linkages across banks that disrupt the normal flow of credit when one of the links in the network is in distress.

19 The minimum Tier 1 risk-weighted capital required is 6 percent plus a 1.25 percent conservation buffer in 2017. The conservation buffer will increase to 2.5 percent in 2019.

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Research Update

These papers by Philadelphia Fed economists, analysts, and visiting scholars represent preliminary research that is being circulated for discussion purposes.

Firm Wages in a Frictional Labor Market

This paper studies a labor market with directed search, where multi-worker firms follow a firm wage policy: They pay equally productive workers the same. The policy reduces wages, due to the influence of firms' existing workers on their wage-setting problem, increasing the profitability of hiring. It also introduces a time-inconsistency into the dynamic firm problem, because firms face a less elastic labor supply in the short run. To consider outcomes when firms reoptimize each period, I study Markov perfect equilibria, proposing a tractable solution approach based on standard Euler equations. In two applications, I first show that firm wages dampen wage variation over the business cycle, amplifying that in unemployment, with quantitatively significant effects. Second, I show that firm-wage firms may find it profitable to fix wages for a period of time, and that an equilibrium with fixed wages can be good for worker welfare, despite added volatility in the labor market.

Working Paper 19-05. Leena Rudanko, Federal Reserve Bank of Philadelphia.

How Big Is the Wealth Effect? Decomposing the Response of Consumption to House Prices

We investigate the effect of declining house prices on household consumption behavior during 2006–2009. We use an individual-level dataset that has detailed information on borrower characteristics, mortgages, and credit risk. Proxying consumption by individual-level auto loan originations, we decompose the effect of declining house prices on consumption into three main channels: wealth effect, household financial constraints, and bank health. We find a negligible wealth effect. Tightening household-level financial constraints can explain 40–45 percent of the response of consumption to declining house prices. Deteriorating bank health leads to reduced credit supply both to households and firms. Our dataset allows us to estimate the effect of this on households as 20–25 percent of the consumption response. The remaining 35 percent is a general equilibrium effect that works via a decline in employment as a result of either lower credit supply to firms or the feedback from lower consumer demand. Our estimate of a negligible wealth effect is robust to accounting for the endogeneity of house prices and unemployment. The contribution of tightening household financial constraints goes down to 35 percent, whereas declining bank credit supply to households captures about half of the overall consumption response, once we account for endogeneity.

Working Paper 19-06. S. Borağan Aruoba, University of Maryland and Federal Reserve Bank of Philadelphia Research Department Visiting Scholar; Ronel Elul, Federal Reserve Bank of Philadelphia; Şebnem Kalemli-Özcan, University of Maryland.

Incumbency Disadvantage of Political Parties: The Role of Policy Inertia and Prospective Voting

We document that postwar U.S. elections show a strong pattern of "incumbency disadvantage": If a party has held the presidency of the country or the governorship of a state for some time, that party tends to lose popularity in the subsequent election. To explain this fact, we employ Alesina and Tabellini's (1990) model of partisan politics, extended to have elections with prospective voting. We show that inertia in policies, combined with sufficient uncertainty in election outcomes, implies incumbency disadvantage. We find that inertia can cause parties to target policies that are more extreme than the policies they would support in the absence of inertia and that such extremism can be welfare reducing.

Supersedes Working Paper 17-43.
Working Paper 19-07. Satyajit Chatterjee, Federal Reserve Bank of Philadelphia; Burcu Eyigungor, Federal Reserve Bank of Philadelphia.

The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform

Fintech has been playing an increasing role in shaping financial and banking landscapes. There have been concerns about the use of alternative data sources by fintech lenders and the impact on financial inclusion. We compare loans made by a large fintech lender and similar loans that were originated through traditional banking channels. Specifically, we use account-level data from LendingClub and Y-14M data reported by bank holding companies with total assets of $50 billion or more. We find a high correlation with interest rate spreads, LendingClub rating grades, and loan performance. Interestingly, the correlations between the rating grades and FICO scores have declined from about 80 percent (for loans that were originated in 2007) to only about 35 percent for recent vintages (originated in 2014–2015), indicating that nontraditional alternative data have been increasingly used by fintech lenders. Furthermore, we find that the rating grades (assigned based on alternative data) perform well in predicting loan performance over the two years after origination. The use of alternative data has allowed some borrowers who would have been classified as subprime by traditional criteria to be slotted into "better" loan grades, which allowed them to get lower-priced credit. In addition, for the same risk of default, consumers pay smaller spreads on loans from LendingClub than from credit card borrowing.

Supersedes Working Paper 17-17.
Working Paper 18-15 Revised. Julapa Jagtiani, Federal Reserve Bank of Philadelphia; Catharine Lemieux, Federal Reserve Bank of Chicago.

From Incurred Loss to Current Expected Credit Loss (CECL): A Forensic Analysis of the Allowance for Loan Losses in Unconditionally Cancelable Credit Card Portfolios

The Current Expected Credit Loss (CECL) framework represents a new approach for calculating the allowance for credit losses. Credit cards are the most common form of revolving consumer credit and are likely to present conceptual and modeling challenges during CECL implementation. We look back at nine years of account-level credit card data, starting with 2008, over a time period encompassing the bulk of the Great Recession as well as several years of economic recovery. We analyze the performance of the CECL framework under plausible assumptions about allocations of future payments to existing credit card loans, a key implementation element. Our analysis focuses on three major themes: defaults, balances, and credit loss. Our analysis indicates that allowances are significantly impacted by specific payment allocation assumptions as well as downturn economic conditions. We also compare projected allowances with realized credit losses and observe a significant divergence resulting from the revolving nature of credit card portfolios. We extend our analysis across segments of the portfolio with different risk profiles. Interestingly, fewer risky segments of the portfolio are proportionally more impacted by specific payment assumptions and downturn economic conditions. Our findings suggest that the effect of the new allowance framework on a specific credit card portfolio will depend critically on its risk profile. Thus, our findings should be interpreted qualitatively, rather than quantitatively. Finally, the goal is to gain a better understanding of the sensitivity of allowances to plausible variations in assumptions about the allocation of future payments to present credit card loans. Thus, we do not offer specific best practice guidance.

Working Paper 19-08. José J. Canals-Cerdá, Federal Reserve Bank of Philadelphia.

Investigating Nonneutrality in a State-Dependent Pricing Model with Firm-Level Productivity Shocks

In recent years, there has been an abundance of empirical work examining price-setting behavior at the micro level. First-generation models with price-setting rigidities were generally at odds with much of the microprice data. A second generation of models, with fixed costs of price adjustment and idiosyncratic shocks, have attempted to rectify this shortcoming. Using a model that matches a large set of microeconomic facts, we find significant nonneutrality. We decompose the nonneutrality and find that state dependence plays an important part in the responses of output and inflation to a monetary shock. We also examine how aggregating firm behavior can generate flat hazards. Last, we find that the steady state statistic developed by Alvarez, Le Bihan, and Lippi (2016) is an imperfect guide to characterizing nonneutrality in our model.

Working Paper 19-09. Michael Dotsey, Federal Reserve Bank of Philadelphia; Alexander L. Wolman, Federal Reserve Bank of Richmond.

Frictional Intermediation in Over-the-Counter Markets

We extend Duffie, Gârleanu, and Pedersen's (2005) search-theoretic model of over-the-counter (OTC) asset markets, allowing for a decentralized interdealer market with arbitrary heterogeneity in dealers' valuations or inventory costs. We develop a solution technique that makes the model fully tractable and allows us to derive, in closed form, theoretical formulas for key statistics analyzed in empirical studies of the intermediation process in OTC markets. A calibration to the market for municipal securities reveals that the model can generate trading patterns and prices that are quantitatively consistent with the data. We use the calibrated model to compare the gains from trade that are realized in this frictional market with those from a hypothetical, frictionless environment, and to distinguish between the quantitative implications of various types of heterogeneity across dealers.

Supersedes Working Paper 15-22.
Working Paper 19-10. Julien Hugonnier, EPFL and Swiss Finance Institute; Benjamin Lester, Federal Reserve Bank of Philadelphia; Pierre-Olivier Weill, UCLA and Visiting Scholar, Federal Reserve Bank of Philadelphia Research Department.

The Paper Trail of Knowledge Spillovers: Evidence from Patent Interferences

We show evidence of localized knowledge spillovers using a new database of U.S. patent interferences terminated between 1998 and 2014. Interferences resulted when two or more independent parties submitted identical claims of invention nearly simultaneously. Following the idea that inventors of identical inventions share common knowledge inputs, interferences provide a new method for measuring knowledge spillovers. Interfering inventors are 1.4 to 4 times more likely to live in the same local area than matched control pairs of inventors. They are also more geographically concentrated than citation-linked inventors. Our results emphasize geographic distance as a barrier to tacit knowledge flows.

Working Paper 17-44 Revised. Ina Ganguli, University of Massachusetts–Amherst; Jeffrey Lin, Federal Reserve Bank of Philadelphia; Nicholas Reynolds, Brown University.

Toward a Framework for Time Use, Welfare, and Household-Centric Economic Measurement

What is meant by economic progress, and how should it be measured? The conventional answer is growth in real GDP over time or compared across countries, a monetary measure adjusted for the general rate of increase in prices. However, there is increasing interest in developing an alternative understanding of economic progress, particularly in the context of digitalization of the economy and the consequent significant changes Internet use is bringing about in production and household activity. This paper discusses one alternative approach, combining an extended utility framework considering time allocation over paid work, household work, leisure, and consumption with measures of objective or subjective well-being while engaging in different activities. Developing this wider economic welfare measure would require the collection of time use statistics as well as well-being data and direct survey evidence, such as the willingness to pay for leisure time. We advocate an experimental set of time and well-being accounts, with a particular focus on the digitally driven shifts in behavior.

Working Paper 19-11. Diane Coyle, University of Cambridge; Leonard Nakamura, Federal Reserve Bank of Philadelphia.

A Dynamic Model of Intermediated Consumer Credit and Liquidity

We construct a model of consumer credit with payment frictions, such as spatial separation and unsynchronized trading patterns, to study optimal monetary policy across different interbank market structures. In our framework, intermediaries play an essential role in the functioning of the payment system, and monetary policy influences the equilibrium allocation through the interest rate on reserves. If interbank credit markets are incomplete, then monetary policy plays a crucial role in the smooth operation of the payment system. Specifically, an equilibrium in which privately issued debt claims are not discounted is shown to exist provided the initial wealth in the intermediary sector is sufficiently large relative to the size of the retail sector. Such an equilibrium with an efficient payment system requires setting the interest rate on reserves sufficiently close to the rate of time preference.

Working Paper 19-12. Pedro Gomis-Porqueras, Deakin University; Daniel Sanches, Federal Reserve Bank of Philadelphia.

A Shortage of Short Sales: Explaining the Underutilization of a Foreclosure Alternative

The Great Recession led to widespread mortgage defaults, with borrowers resorting to both foreclosures and short sales to resolve their defaults. I first quantify the economic impact of foreclosures relative to short sales by comparing the home price implications of both. After accounting for omitted variable bias, I find that homes selling as short sales transact at 9.2% to 10.5% higher prices on average than those that sell after foreclosure. Short sales also exert smaller negative externalities than foreclosures, with one short sale decreasing nearby property values by 1 percentage point less than a foreclosure. So why weren't short sales more prevalent? These home price benefits did not increase the prevalence of short sales because free rents during foreclosures caused more borrowers to select foreclosures, even though higher advances led servicers to prefer more short sales. In states with longer foreclosure timelines, the benefits from foreclosures increased for borrowers, so short sales were less utilized. I find that one standard deviation increase in the average length of the foreclosure process decreased the short sale share by 0.35 to 0.45 standard deviation. My results suggest that policies that increase the relative attractiveness of short sales could help stabilize distressed housing markets.

Working Paper 19-13. Calvin Zhang, Federal Reserve Bank of Philadelphia.

Banking Regulation with Risk of Sovereign Default

Banking regulation routinely designates some assets as safe and thus does not require banks to hold any additional capital to protect against losses from these assets. A typical such safe asset is domestic government debt. There are numerous examples of banking regulation treating domestic government bonds as "safe," even when there is clear risk of default on these bonds. We show, in a parsimonious model, that this failure to recognize the riskiness of government debt allows (and induces) domestic banks to "gamble" with depositors' funds by purchasing risky government bonds (and assets closely correlated with them). A sovereign default in this environment then results in a banking crisis. Critically, we show that permitting banks to gamble this way lowers the cost of borrowing for the government. Thus, if the borrower and the regulator are the same entity (the government), that entity has an incentive to ignore the riskiness of the sovereign bonds. We present empirical evidence in support of the key mechanism we are highlighting, drawing on the experience of Russia in the run-up to its 1998 default and on the recent Eurozone debt crisis.

Working Paper 19-15. Pablo D'Erasmo, Federal Reserve Bank of Philadelphia; Igor Livshits, Federal Reserve Bank of Philadelphia; and Koen Schoors.

We Are All Behavioral, More or Less: Measuring and Using Consumer-Level Behavioral Sufficient Statistics

Can a behavioral sufficient statistic empirically capture cross-consumer variation in behavioral tendencies and help identify whether behavioral biases, taken together, are linked to material consumer welfare losses? Our answer is yes. We construct simple consumer-level behavioral sufficient statistics—"B-counts"—by eliciting 17 potential sources of behavioral biases per person, in a nationally representative panel, in two separate rounds nearly three years apart. B-counts aggregate information on behavioral biases within-person. Nearly all consumers exhibit multiple biases, in patterns assumed by behavioral sufficient statistic models (a la Chetty), and with substantial variation across people. B-counts are stable within-consumer over time, and that stability helps to address measurement error when using B-counts to model the relationship between biases, decision utility, and experienced utility. Conditional on classical inputs—risk aversion and patience, life-cycle factors and other demographics, cognitive and non-cognitive skills, and financial resources—B-counts strongly negatively correlate with both objective and subjective aspects of experienced utility. The results hold in much lower-dimensional models employing "Sparsity B-counts" based on bias subsets (a la Gabaix) and/or fewer covariates, illuminating lower-cost ways to use behavioral sufficient statistics to help capture the combined influence of multiple behavioral biases for a wide range of research questions and applications.

Working Paper 19-14. Victor Stango, University of California, Davis and Federal Reserve Bank of Philadelphia Visiting Scholar; Jonathan Zinman, Dartmouth College and Federal Reserve Bank of Philadelphia Visiting Scholar.

Forthcoming

Exploring the Economic Effects of the Opioid Epidemic

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