

# 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.

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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.<sup>1</sup> 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.<sup>2</sup> 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.”<sup>3</sup>

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.<sup>4</sup> 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).<sup>5</sup>

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?

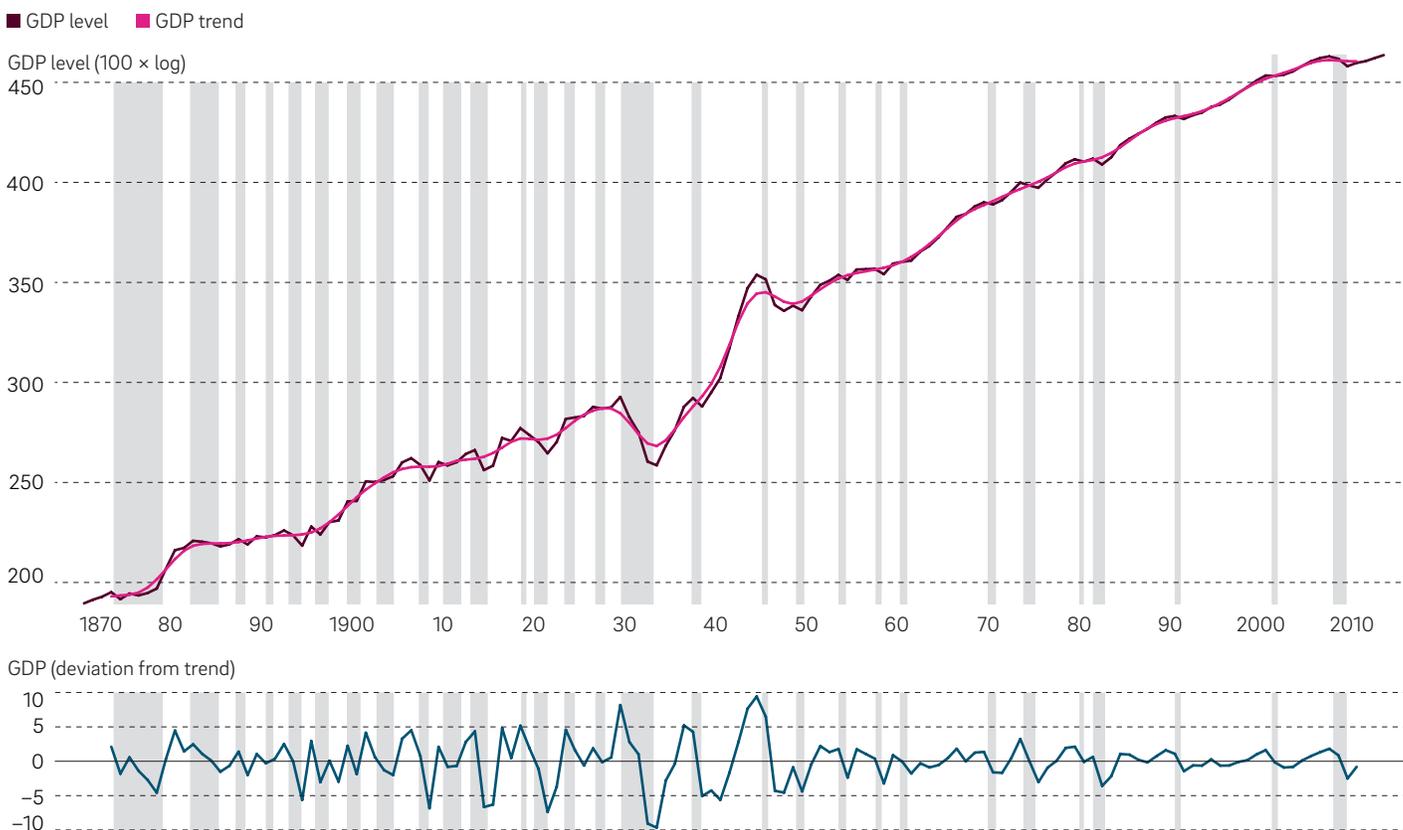
Recall that even though business cycles are recurrent, they are unpredictable because the length of expansions and contractions varies. Economists have formalized this notion by building models of business cycles that are driven by random events.

Mainstream economics views business cycles as comparable to the “random summation of random causes,” to quote Eugen Slutsky (1927, in English 1937). What does this mean, though? Back in 1927, Slutsky 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  $D_0$  and supply  $S_0$ . 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  $S_0$  to the  $S_1$  line. By itself, it would have lowered prices and increased quantities, moving the economy from point A to point B. A demand shock, from  $D_0$  to  $D_1$ , 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.<sup>6</sup> 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

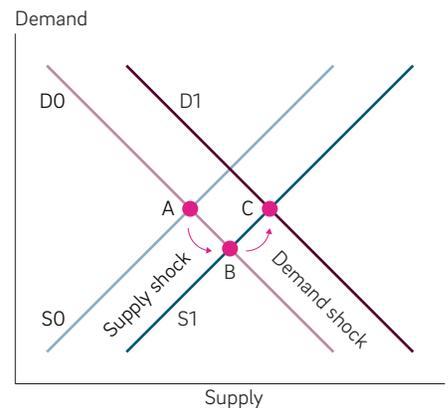
respond to economic shocks. For the models discussed here, these individual responses can be averaged to provide us with a linear relationship between shocks and macroeconomic data. This also allows one to compute counterfactuals.

### 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.<sup>7</sup> 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.

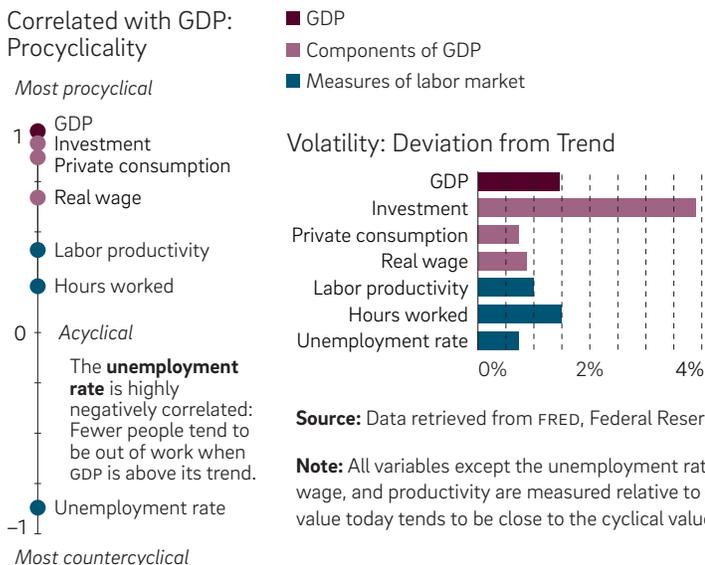
theory also incorporates nominal factors and stresses the role of demand-side shocks.

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.

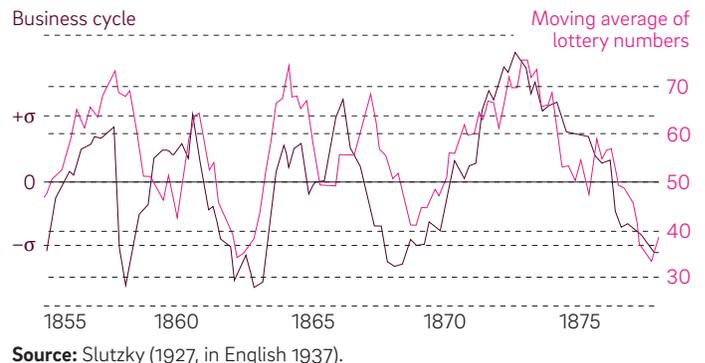
### Real Business Cycles

The RBC paradigm<sup>8</sup> proposes that random changes in total factor productivity relative

**FIGURE 2**  
Volatility, Cyclicity, and Persistence of GDP and Other Key Macroeconomic Indicators



**FIGURE 4**  
Index of UK Business Cycle, 1855 to 1877 vs. Moving Average of Lottery Numbers



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.

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.<sup>9</sup> 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.<sup>10</sup>

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.<sup>11</sup>

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).<sup>12</sup>

## 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.

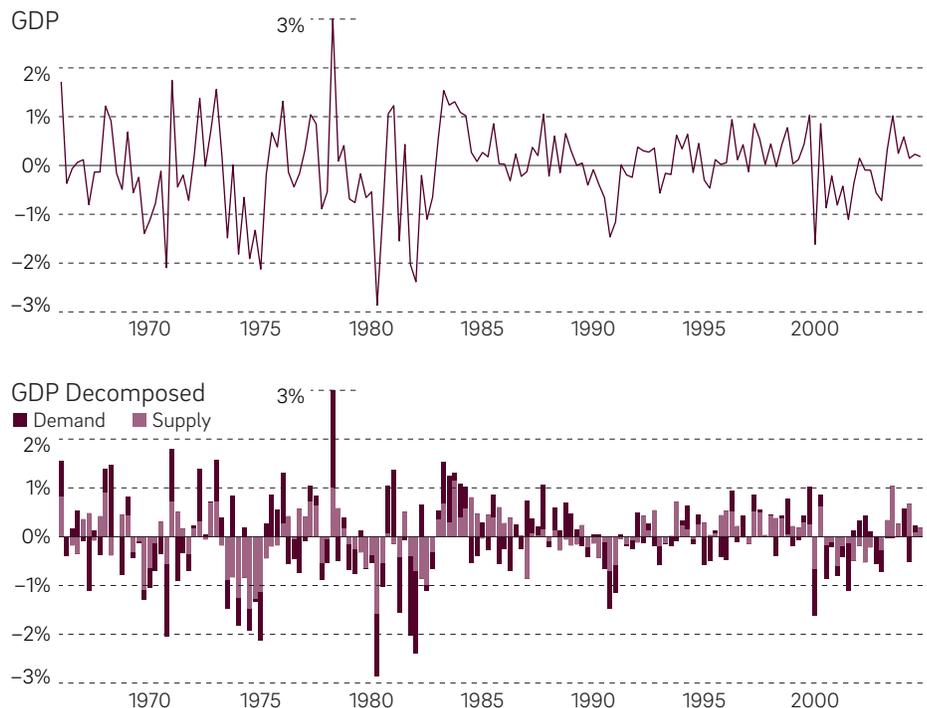
Estimated versions of these models have shaped how central banks today analyze business cycles.<sup>13</sup> These models are also called dynamic stochastic general equilibrium (DSGE) models. They are

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.<sup>14</sup> 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

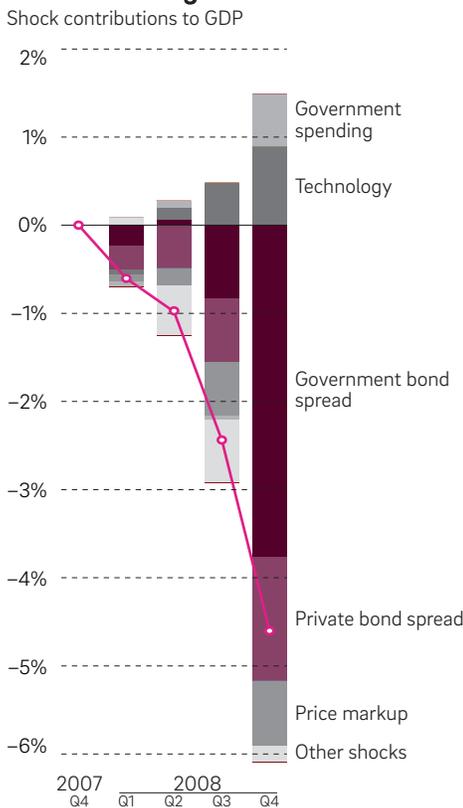
In the aftermath of the financial crisis of 2008 and the subsequent Great Recession, shocks to the financial sector have been proposed as a missing ingredient in business cycle models. At the time, this was new. While economists had long analyzed the effect of the financial sector on the economy, often the question was whether financial institutions strengthen the effects of other shocks, such as demand or supply shocks.<sup>15</sup> 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.<sup>16</sup>

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**



**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.<sup>17</sup> Using a simple formula to quantify this idea, firm-level shocks may account for about one-third of aggregate fluctuations.<sup>18</sup> 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.<sup>19</sup>

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.<sup>20</sup> 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.<sup>21</sup>

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.<sup>22</sup> 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.<sup>23</sup> Related research allows us to quantify how important shocks are without taking a stance on how many shocks there actually are.<sup>24</sup>

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.<sup>25</sup> 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. 

## 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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