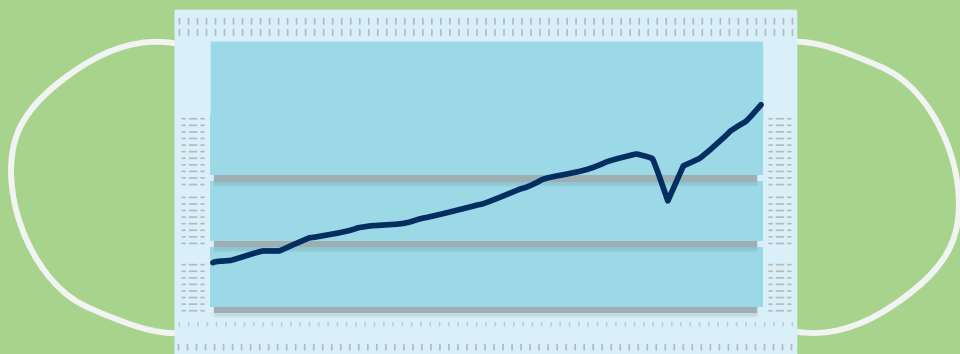# RECESSION REMEDIES

Lessons Learned from the U.S. Economic Policy Response to COVID-19

Edited by

Wendy Edelberg, Louise Sheiner, and David Wessel

Recession Remedies

Lessons Learned from the U.S. Economic Policy Response to COVID-19

Edited by
Wendy Edelberg, Louise Sheiner, and
David Wessel

THE HAMILTON PROJECT

Hutchins Center
on Fiscal & Monetary Policy
at BROOKINGS

BROOKINGS

CHAPTER 9

Lessons Learned from the Use of Nontraditional Data during COVID-19

Tomaz Cajner, Laura Feiveson, Christopher Kurz, and Stacey Tevlin[1]

Introduction

Over the last decade, an explosion of data collection has led to a robust set of nontraditional data sources for both monetary and fiscal policymakers to incorporate into their decision-making. In normal times, existing and time-tested datasets compiled by government statistical agencies often do a good job of capturing the evolution of the economy at a monthly or quarterly frequency accurately and without bias. However, when the economy turns quickly—times when policymakers need to be particularly responsive—nontraditional data sources may be able to fill important gaps. The COVID-19 crisis provided a test case of the usefulness of these alternative data sources. In this chapter, we explore how nontraditional data sources aided—or, in some cases, did not aid—policy decision-making during the pandemic recession and what lessons we can learn for future crises.

We organize the chapter around examples that highlight the three main potential benefits of nontraditional data sources relative to their government counterparts. The first possible benefit we call *timely measurement* of the economy, meaning the use of nontraditional datasets to learn in close to real time

about aggregate developments in the economy that will be reflected only later in statistics released by the government. We argue that the benefit of such timely measurement is important to policymakers, especially in times of sharp contractions, such as March 2020.

The second benefit that we highlight is *granularity*, that is, that due to their nature some nontraditional data sources may provide reads on aspects of firm or consumer behavior for which there is no standard government data source (even with a lag). The finer granularity could be related to frequency (e.g., daily data), geography (e.g., data broken down by region), or individual characteristics. Generally, being able to do granular analyses in almost real time could allow for faster evaluations of the costs of shocks or the benefits of policies, which in turn could serve to fine-tune subsequent policy actions.

The final benefit of nontraditional data that we discuss is *crisis-specific data gathering*. The availability of data from so many different sources allows policymakers to answer specific, unanticipated questions that are unique to a particular crisis. For these unique uses, it is not clear that investment in generating these statistics during normal times would be even worth the cost, underscoring the importance of quick access in times when they are.

The last section dives into the pitfalls of nontraditional data and how we can learn from what did not go well in their use during the COVID-19 crisis. Unlike government statistics, most alternative data sources are not designed with the purpose of generating statistics but are instead a byproduct of another use (such as card transactions). As such, the data are not designed to be representative of consumers or firms and may be hard to interpret or, worse, misleading. It is from these pitfalls that we take some of the most useful lessons of where effort is needed to be ready for the next crisis.

To assist in the discussions of measurement, granularity, data gathering, and pitfalls, we compiled a summary table at the end of this chapter of examples of nontraditional data sources that would have been available to policymakers during this crisis (Table 9.1). The table, while certainly not exhaustive, contains a list of indicators from five categories, covering spending and consumer confidence, employment, health, mobility, and "other."

Timely Measurement of the Economy

We start by considering how the timely measurement benefit of nontraditional data may have influenced both monetary and fiscal policy decisions in the spring of 2020—a time of historically acute economic change. As Figure 9.1 shows, as events rapidly unfolded, many critical policy decisions were made before the release of any government data. In fact, the Federal Reserve's (Fed) emergency rate cuts, resumption of large-scale asset purchases, announcement of new facilities, and Congress' passage of the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) came before any government data containing sign of the downturn were released. As we describe below, nontraditional data sources were likely essential in guiding the writing of policy during the latter part of this period.

TABLE 9.1

Summary Table of High Frequency Indicators

High-Frequency Indicator	Indicator	Length of Time Series	Frequency	Standard Statistics Analog	Other Information	Additional Granularity by
1. Spending and Consumer Confidence Indicators						
Affinity	Consumer spending	2020–present	Daily	Census Retail Sales; BEA PCE	Card data from Opportunity Insights	Geography; industry; income
BoxOfficeMojo	Movie spending	1977–present	Weekly	Census QSS; BEA NIPAs		Country
Fiserv	Consumer spending	2010–present	Daily	Census Retail Sales; BEA PCE	formerly First Data	Industry; state
JD Power	Motor vehicle sales	2002–present	Weekly	Wards Light Vehicle Sales; BEA PCE		
MorningConsult	Consumer confidence	2018–present	Daily	Michigan Survey		Future/current conditions; state
NPD	Consumer spending	2020–present	Weekly	Census Retail Sales; BEA PCE		Geography; spending category
OpenTable reservations	Restaurant spending	2020–present	Daily	Census QSS; BEA NIPAs		City
Ramussen	Consumer confidence	2004–present	Daily	Michigan Survey		
Redfin	Home sales	2017–present	Weekly	Census New Home Sales; NAR Existing Home Sales		Pending and existing sales
Smith Travel Research	Hotel spending	2020–present	Weekly	Census QSS; BEA NIPAs		City; state
Womply	Small business revenue	2020–present	Daily	n/a	Businesses open	Sectors
2. Employment Indicators						
ADP-FRB	Payrolls; wages; business exit	2002–present	Weekly	BLS Current Employment Statistics	Can measure business exit	Industry; state
Homebase	Payrolls; hours worked	2020–present	Daily	BLS Current Employment Statistics	Businesses open; Can measure percent change since February 2020.	Small business
Burning Glass	Job postings	2020–present	Weekly	BLS JOLTS		Industry; demographics
Indeed	Job postings	2018–present	Daily	BLS JOLTS		
Census Household Pulse	Employment	2020–present	Weekly	BLS Current Employment Statistics		Industry; demographics

(continued)

TABLE 9.1 (CONTINUED)

Summary Table of High Frequency Indicators

High-Frequency Indicator	Indicator	Length of Time Series	Frequency	Standard Statistics Analog	Other Information	Additional Granularity by
Federal Reserve Bank of Dallas Real-Time Population Survey	Employment	2020–present	Weekly	BLS Current Employment Statistics		
Yale Labor Survey	Employment	2020–2021	Weekly	BLS Current Employment Statistics		
3. Health Indicators						
Covid Tracking Data	Hospitalization; testing	2020–2021	Daily	n/a		State
Department of Health and Human Services	Cases; deaths; hospitalizations; testing	2020–present	Daily	n/a		Demographics
Johns Hopkins University	Cases; deaths	2020–present	Daily	n/a		County
National Public Radio	Contact tracing	2020–2021	Weekly	n/a		State
New York Times	Cases; deaths	2020–present	Daily	n/a		County
4. Mobility Indicators						
Apple Mobility	Mobility	2020–present	Daily	n/a	Index of activity from navigation requests	Location
Descartes Labs	Mobility	2020–2021	Daily	n/a	Index of distance travelled based on smartphone GPS location devices	Location
Flightstats	Spending; travel	2020–present	Daily	n/a	Flight cancellations	Airport
Google Mobility	Mobility	2020–present	Daily	n/a	Visits to select destinations	Sectors
Metropolitan Transit Authority	Mobility	2011–present	Weekly	n/a	MTA turnstiles	Location
Safegraph	Spending; mobility	2018–present	Daily	Census Retail Sales; BEA PCE	Share staying at home	Location; industry
Safegraph	Business exit	2018–present	Daily	Census Business Dynamic Statistics; BLS Business Employment Dynamics	Inactivity at business location	Location; industry
Transportation Security Administration	Spending; travel	2019–present	Daily	Census QSS; BEA NIPAs	Airport passenger departures	

(continued)

TABLE 9.1 (CONTINUED)

Summary Table of High Frequency Indicators

High-Frequency Indicator	Indicator	Length of Time Series	Frequency	Standard Statistics Analog	Other Information	Additional Granularity by
				5. Other Indicators		
American Iron and Steel Institute	Raw steel production	1971–present	Weekly	n/a		
						(continued)
Association of American Railroads	Railcar loads	1988–present	Weekly	n/a	Indicator for industrial activity	
Burbio	School closures	2020–present	Weekly	n/a	Share of students; school count	
Census Bureau Small Business Pulse Survey	Activities; expectations	2020–present	Weekly	n/a	Outlook; financial situation; employment; revenue	Industry
Census Household Pulse	Household impacts of COVID	2020–present	Weekly	n/a	Food security; housing; health and healthcare; education disruption	Industry; demographics
CoStar Real Estate Vacancies	Business closures	2015–present	Daily	Census Business Dynamic Statistics; BLS Business Employment Dynamics		Geography
Education Week	School closures	2020–present	Weekly	n/a	Share of students, schools	
Epiq	Bankruptcies	2011–present	Monthly	n/a		
Federal Reserve Bank of New York Weekly Economic Index (WEI)		2008–present	Weekly	BEA NIPAs	Index based on ten indicators of economic activity that is scaled align with the historical four-quarter GDP growth rate	
Google Trends	Firm exits; employment claims	2004–present	Daily	n/a	Internet search queries	
Kastle Return to Office Barometer	Return to the office	2020–present	Weekly	n/a		
Opportunitiy Insights	Economic tracker	2020–present	Weekly	n/a	Businesses; employment; education; public health	State; county; metro area
Optimal Blue	House prices	2018–present	Weekly	n/a		
Oxford Stringency Index	COVID-related restrictions	2020–present	Daily	n/a	Index based on government COVID mitigation policies	
Paynet	Small business deliquencies	2005–present	Monthly	n/a		

TABLE 9.1 (CONTINUED)

Summary Table of High Frequency Indicators

High-Frequency Indicator	Indicator	Length of Time Series	Frequency	Standard Statistics Analog	Other Information	Additional Granularity by
The Eviction Lab, Princeton University	Evictions	2020–present	Weekly	n/a		
Weekly Business Formation Statistics (BFS)	Business formation	2005–present	Weekly	Quarterly BFS	EIN applications with information on business formation	Industry; region; state

Note: "n/a" implies there is no applicable official analog of the HFI data.

THE HAMILTON PROJECT

Hutchins Center on Fiscal & Monetary Policy at BROOKINGS

However, it is also worth noting that the nontraditional data could not have possibly filled the entire information vacuum since some of the very first policy actions were necessarily taken before there was any material effect on the economy at all. In particular, the Fed's emergency rate cuts were made in early and mid-March, before there was a U.S. lockdown, and the discussions about facilities and the CARES Act were underway before the effects of COVID-19 had taken hold of the U.S. economy. During these times, policymakers mostly relied on nongovernment sources to guide these initial actions—financial movements and news of shutdowns in China and Italy—as well as on analysis by epidemiologists regarding the likely spread of COVID-19, along with calibrations by economists on the resulting impact on the economy.[2] This can be seen from the minutes of the Federal Open Market Committee (FOMC)'s videoconference meeting on March 2nd, which cited that "the virus was at an earlier stage in the United States and its effects were not yet visible in monthly economic indicators, although there had been some softening in daily sentiment indexes and travel-related transactions."[3]

Still, once the pandemic did take hold in the U.S., nontraditional data sources filled in a crucial gap in corroborating the enormous effects of the pandemic on employment and on spending before official statistics were released.

Figure 9.2 shows how the use of ADP-FRB employment data from a large payroll processor—cleaned and refined by economists at the Federal Reserve Board— revealed the labor market damage in real time.[4] The Bureau of Labor

---

2. For example, in the first half of March, the near-complete shutdowns of motor vehicle production in Italy and Spain, and lower production rates in Germany and France, provided guidance for forecasts of domestic light motor vehicle production.

3. See FOMC (2020). Both Rasmussen and Morning Consult indexes of consumer sentiment had softened at the end of February. Similarly, hotel occupancy and restaurant reservations were moving down at the start of March.

4. The ADP-FRB data were available in real time to policymakers in the Federal Reserve System. For more details, see Cajner et al. (2018, 2020a, 2022). The ADP data contain two measures
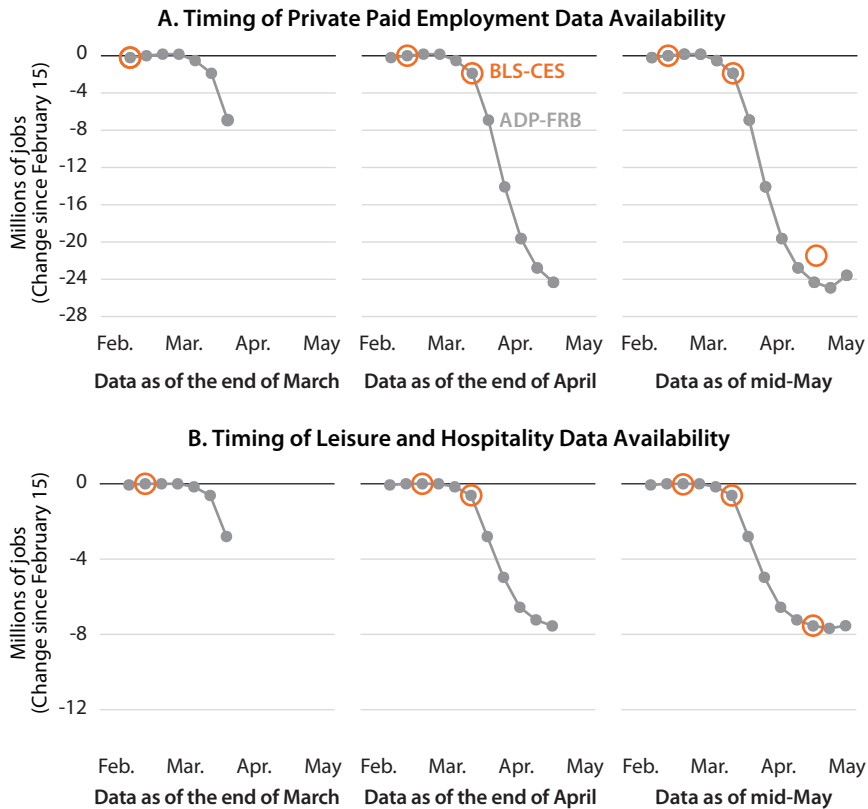
FIGURE 9.1

Timeline of Data Releases and Early Policy Responses to COVID-19, January to July 2020

• Health news   • Monetary policy   • Fiscal policy   • Data release

Jan. 2020
- Jan. 21: First reported COVID-19 case in U.S.
- Jan. 23: China lockdown

Feb.
- Feb. 22: Italy lockdown

Mar.
- Mar. 3: Fed emergency rate cut by 1/2 percentage point
- Mar. 13: President declares national emergency
- Mar. 15: Large-scale asset purchases
- Mar. 15: Fed emergency rate cut to 0 percent
- Mar. 17: First announcement of new Fed facilities
- Mar. 19: First state-wide lockdown order in the U.S.
- Mar. 19: Opening discussion of CARES Act
- Mar. 26: Initial UI claims data
- Mar. 27: CARES Act passage

April
- Apr. 9: Last announcement of new Fed facilities
- Apr. 13: First stimulus checks/UI go out
- Apr. 15: March retail sales report
- Apr. 24: Paycheck Protection Program and Health Care Enhancement Act

May
- May 8: April employment situation
- May 15: April retail sales report
- May 28: U.S. death toll surpasses 100,000

June
- Jun. 16: May retail sales report

July
- Jul. 30: First read of GDP in Q2

Source: BEA 2020; BLS 2020; Census Bureau 2020a–c; Center for Disease Control and Prevention 2020; Congress 2020; Department of Labor 2020; Department of the Treasury 2020; Federal Reserve Board 2020; Reuters 2020.

THE HAMILTON PROJECT

Hutchins Center on Fiscal & Monetary Policy at BROOKINGS

FIGURE 9.2

Snapshots of Employment Data in 2020

A. Timing of Private Paid Employment Data Availability

Data as of the end of March   Data as of the end of April   Data as of mid-May

B. Timing of Leisure and Hospitality Data Availability

Data as of the end of March   Data as of the end of April   Data as of mid-May

Source: ADP, Inc. 2020, Bureau of Labor Statistics BLS n.d.; authors' calculations.

Note: For ADP-FRB, paid employment concept is plotted.

Statistics (BLS) report released at the beginning of April only covered the week including March 12th and did not reflect these declines. It was not until the beginning of May that these employment losses were visible in official

of business-level employment. The first, referred to as "paid" employment, measures the number of employees issued a paycheck by an ADP client in each pay period. The second, referred to as "active" employment, measures the number of employees in employer payroll databases. At the height of the pandemic, the ADP-FRB indexes based on paid employment were extremely useful for studying short-term temporary job dislocation.

estimates.[5] In contrast, by the end of March and the beginning of April, when the final Fed facilities were decided upon and announced, policymakers with access to the ADP-FRB data could already see the staggering amount of job loss occurring, driven in large part by employment declines in the leisure and hospitality sector.[6]

Note that the ADP-FRB data for a given week are available with a lag of about one week, which translates into learning information about the week of the BLS Current Employment Statistics survey about two weeks before the BLS releases its data. Even by the end of March, it was apparent that private paid employment was declining sharply. By the end of April, the ADP-FRB data clearly portrayed an unprecedented collapse. These readings from the ADP-FRB data were available well before the official BLS publication dates and proved quite accurate in portraying the scale of the employment devastation.

The nontraditional data on consumer spending filled in a similar gap. Figure 9.3 shows some of the spending data that were in hand at three snapshots in time: the end of March, mid-April, and mid-May. The high-frequency data shown are retail sales data derived from Fiserv card swipe data, restaurant reservations from OpenTable, and airport departures from the Transportation Security Administration.[7] The Census series shown are monthly and released two weeks after a month's end. Like the ADP-FRB data, the nontraditional spending data were able to capture the severe downturn in spending in COVID-sensitive categories by the time policy decisions were taken at the end of March.

Furthermore, even by mid-May, the available government data were incomplete in that they covered only a narrow portion of COVID-sensitive services—food services and drinking places—in addition to the sales of retail goods, which were of less concern since they were much less affected by social distancing than services categories.[8] The nontraditional data shown here and others—such as announced school closures, tracking estimates of light vehicle sales, hotel occupancy, movie ticket receipts, transit ridership, flight cancellations, and Google Trends searches for both unemployment insurance and layoffs—were crucial for quantifying the impact on the economy during that time.[9]

---

5. While initial claims for Unemployment Insurance were available at a weekly frequency, essentially in real time, during the pandemic recession, the translation of initial claims into employment losses was not straightforward because initial claims overstated true employment losses. For more details, see Cajner et al. (2020b).

6. While the ADP-FRB data are available on an ongoing basis only to policymakers in the Federal Reserve System, Cajner et al. (2020c) published the ADP-FRB data from February through April 2020, which indicated job losses of 18 million through April 4th.
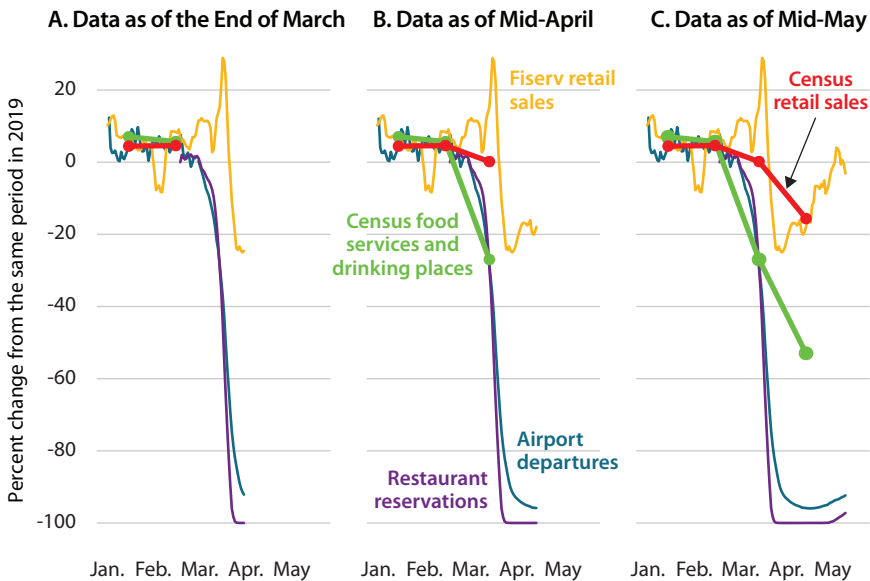
7. For details on the construction of the Fiserv card swipe data index, see Aladangady et al. (2022).

8. Government data on other services spending—such as the Census' Quarterly Services Survey—come out with even more of a lag. The first and second quarters of 2020 preliminary services spending data were released on May 20 and August 19, 2020, respectively.

9. School closure information is from Education Week and Burbio; light vehicle sales tracking information from J.D. Power; hotel occupancy from Smith Travel Research; movie ticket

FIGURE 9.3

Snapshots of Consumer Spending Data in 2020

A. Data as of the End of March **B. Data as of Mid-April** **C. Data as of Mid-May**

Source: Census Bureau n.d.a.; Fiserv 2020; OpenTable 2020; Transportation Security Administration 2020.

Note: Airport departures, restaurant reservations, and Fiserv retail sales are seven-day moving averages.

THE HAMILTON PROJECT

Hutchins Center on Fiscal & Monetary Policy at BROOKINGS

So, even though the initial policy actions and the discussions of further actions kicked off before the economic slump began, the corroboration provided by nontraditional data sources may have hastened Congress' decisions on the CARES Act (and a supplementary Paycheck Protection Program and Health Care Enhancement Act, which was passed in late April 2020) and Federal Reserve deliberations on Fed facilities.[10,11] Had policymakers been forced

---

receipts from Box Office Mojo; transit ridership from the New York Metropolitan Transportation Authority; and flight cancellations from flightstats.com.

10. The first pandemic-era facilitates were announced shortly after the FOMC meeting of March 15. At the time, FOMC participants cited reports on the pandemic's impact on business sectors, such as air travel, cruise lines, hotels, tourism services, sports and recreation, entertainment, hospitality, and restaurants. See FOMC (2020). Additional facilities were announced in late March and in mid-April. For a summary of Fed actions during the COVID-19 crisis, see Milstein and Wessel (2021).

11. The January 2021 Economic Report of the President, put together by the Council of Economic Advisors, cites numerous nontraditional data sources to describe the economic landscape and to support the passage of various pieces of legislation. Similarly, congressional press

to wait until May for the release of government data to fully understand the magnitude of the impact of social distancing, it is possible that some of their policy actions may have been smaller, less well targeted, or delayed.

Had that delay occurred, what might have been the cost? It is hard to know for sure, and it is possible that the costs would not have been that high. However, there are risks that would have been heightened by a smaller policy response or a delay.[12] Regarding the Fed, it is likely that a delay in some of the facilities would have led to greater disruptions in the financial system, as uncertainty and a loss of confidence would have worsened. Even just the announcement of the facilities led to rapid improvements in financing conditions in bond markets, narrowing spreads, and increased access to markets for many issuers. If the Fed had been delayed, a flood of defaults on loans to businesses may have led more businesses to close their doors permanently, leading to costly reallocation that might have greatly slowed the recovery. As we learned from the Great Recession, this type of dislocation is hard to reverse and can have lasting impacts on the economy.

On the fiscal policy side, the CARES Act provided needed assistance to individuals who lost their jobs in the pandemic and was essential for households with little savings or outside support. The longer these households went without support, the longer they might have gone without food or other necessities. They might also have cut back sharply on discretionary spending, slowing the economy more. Furthermore, without the prospect of immediate support, some vulnerable households may have felt the need to liquidate longer-term assets such as retirement funds or housing, which, in turn, could have had long-lasting and negative effects on their economic well-being and led to further fragility in financial markets. Finally, without the prospect of immediate and substantial support, some workers might have returned to unsafe working conditions too early and, in doing so, may have worsened the pandemic.

Thus, nontraditional data likely played some role, and possibly a consequential one, in supporting both monetary and fiscal policy actions. But the sharp downturn of March 2020 is an anomaly in the modern era. Specifically, private nonfarm payrolls posted their largest decline of the downturn in the second month of the recession. By contrast, it took 26 months to reach the maximum employment decline during the Great Recession. Given this disparity between the pandemic recession and other downturns, can a case be made more generally that the timely measurement benefit of alternative data is worth investing in?

Even in more normal times or more typical downturns, nontraditional data allowing for timely measurement can still provide policymakers with

---

releases oftentimes cited nontraditional data during the discussion surrounding pandemic-related legislation.

12. See Doniger and Kay (2021) for estimates of the employment implications of a delay in the provision of Paycheck Protection Program loans.

an important tool. Although the benefits are hard to quantify, they may be substantial. First, government data are revised and measured with noise, and the alternative data provide means for policymakers to know the state of the economy with greater precision. Second, the timely aspect of the data— they lead the government data by a few weeks to a few months—is important for policymaker decision-making. It could also be important for communication since describing the state of the economy accurately in real time can only help policymakers' credibility. Third, nontraditional data sources can substitute for government statistics at times when government data themselves are delayed, such as during a government shutdown.[13]

An example from the Great Recession helps make the first point. The constellation of data the Fed observed in mid-2007 provided a markedly different signal from what we now view as the economic situation before the Great Recession started.[14] Specifically, at the August 7, 2007, meeting of the FOMC, the committee had in hand—among other indicators—the first print of the July employment data from the BLS and estimates of second-quarter GDP from the Bureau of Economic Analysis. For employment, the July employment report reported a gain of 92,000 for nonfarm payroll employment and the Greenbook—the Board staff's forecast document at the time—noted that "labor demand has continued to run slightly ahead of our expectations, with private nonfarm payrolls up an average of 115,000 per month over the last three months." In terms of GDP, at the time the Bureau of Economic Analysis had published an estimate of real GDP growth of 3.4 percent in the second quarter, and policymakers were looking at a first half growth rate of roughly 2 percent. Overall, in real time growth appeared to be holding up in the two primary indicators of an economy's well-being.

In retrospect, and with fully revised data in hand, the economic landscape was somewhat less supportive of growth than was thought at the time of the August 2007 FOMC meeting. Specifically, fully revised employment decreased by 33,000 in July, and the average growth over the three-month period mentioned above was 93,000. In terms of total output, the latest estimate of average real GDP growth over the first half of 2007 was 1.2 percent, roughly ¾ percentage points lower than the estimate available in August 2007. Had the revised data, or an expansive set of nontraditional data, been in policymakers' hands at the time of the August meeting, a better picture of a less robust state of the economy might have assisted policymakers. That is, more information could have pulled forward the view that broader economic conditions were weakening. Focusing on the subsequent year, Cajner et al. (2022) show that
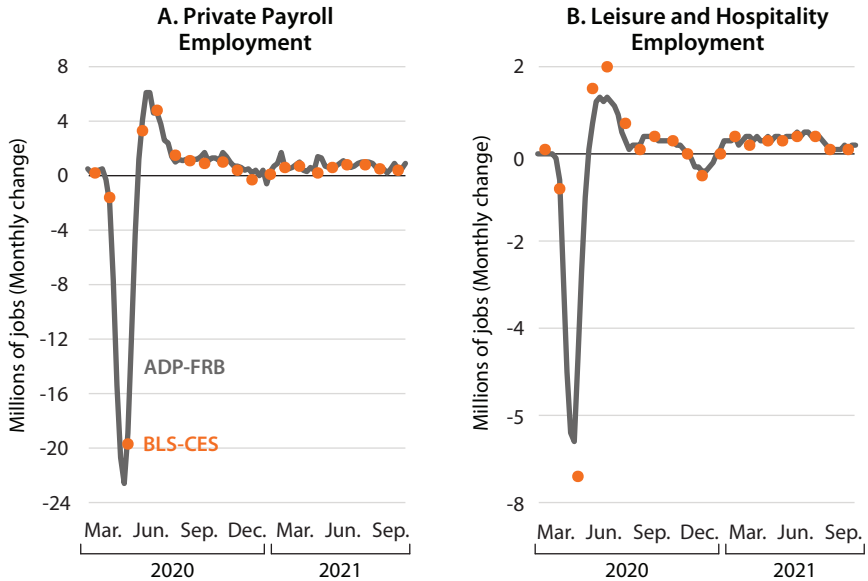
---

13. Given that there have been three government shutdowns in the past 10 years, two of which led to delays in government data releases, even outside the window of the actual shutdown, this benefit is not trivial.

14. The National Bureau of Economic Research dates the Great Recession from December of 2007 to June of 2009.

FIGURE 9.4

Timing of ADP-FRB and BLS CES Employment Data Releases for Change in Employment, March 2020–July 2021

A. Private Payroll Employment

B. Leisure and Hospitality Employment

Source: ADP, Inc. n.d.; Bureau of Labor Statistics (BLS) n.d.; authors' calculations.

Note: For ADP-FRB, paid employment concept is plotted.

THE
HAMILTON
PROJECT

Hutchins Center
on Fiscal & Monetary Policy
at BROOKINGS

ADP-FRB data would have provided a better real-time signal of employment losses than BLS data. By August 2008, real-time BLS estimates showed private sector job losses totaling about 750,000, while ADP-FRB was at approximately 1 million—closer to the current vintage estimate of 1.4 million jobs lost.

As shown above in Figure 9.4, during the COVID-19 crisis, the ADP-FRB data have done a terrific job of tracking the employment gains seen in the BLS employment report, suggesting that both these datasets are useful for shedding light on employment changes in the economy. But they are not always exactly aligned, in which case analysts can better approximate the true state of the world using both; this is particularly important when they temporarily diverge (Cajner et al. 2022).

Granularity

In addition to providing timely information about aggregate statistics, nontraditional data often also allow for more detailed measurement, which we refer to as granularity. Examples of granularity include economic measurement across geographic areas (e.g., states or counties), industries, different individual characteristics (e.g., income), and high-frequency time periods. Sometimes such granular information is available in official statistics but typically only with very long lags. In this section, we will discuss three main benefits of granular data. First, by adding information that is not included in aggregate statistics, granular data can lead to a better understanding of real-time developments. Second, this understanding could lead to a more targeted policy response. Third, timely analysis with granular data can lead to essentially real-time policy evaluation, which can, in turn, also inform follow-on policy actions. We will illustrate these benefits with examples from the COVID-19 pandemic recession.

Granularity and Understanding of Real-Time Developments

During the early weeks of the first wave of the pandemic, northeastern parts of the country—in particular, New York, New Jersey, and Connecticut—experienced more severe COVID-19 outbreaks than the rest of the country (Figure 9.5a). At that point, the economic effects of the pandemic could not be well assessed with aggregate statistics. Instead, the geographical variation available in nontraditional data helped to better understand links between health shocks and the responses of economic variables. For example, many analysts turned to data on public transportation in New York City (Figure 9.5b) to get a better understanding of how individuals and businesses would react to rising COVID-19 cases.

Similarly, employment data at the state level were used to better link job losses to COVID-19 outbreaks. Many papers, which started appearing in the summer of 2020, used state- and county-level employment data to distinguish between the economic effects of voluntary responses and state-mandated restrictions (Gupta, Simon, and Wing 2020). The availability of granular data for the early affected areas allowed policymakers to get a better estimate of how severe the pandemic was likely to be for the country as a whole; indeed, at that point, aggregate data would not have picked up the severity.[15] In addition, the availability of granular geographic data would have enabled state and local governments to decide on policy responses that were tailored to their specific needs.
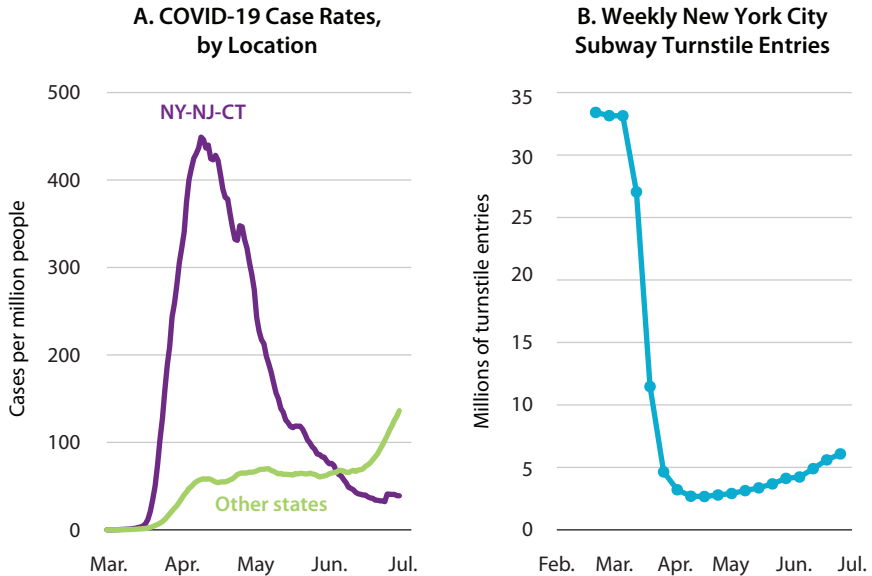
---

15. The geographic breakdown available in the Fiserv data is another example of such granularity. Because the data are broken down by state, it was possible to track the effect of the pandemic on spending as waves of cases hit different parts of the country.

FIGURE 9.5

COVID-19 Case Rates and New York City Subway Turnstile Entries, March–July 2020

A. COVID-19 Case Rates, by Location

B. Weekly New York City Subway Turnstile Entries

Source: Metropolitan Transportation Authority 2020; New York Times n.d.

Note: Seven-day moving averages of COVID-19 data are depicted. Weekly estimates of transportation data are seasonally adjusted.
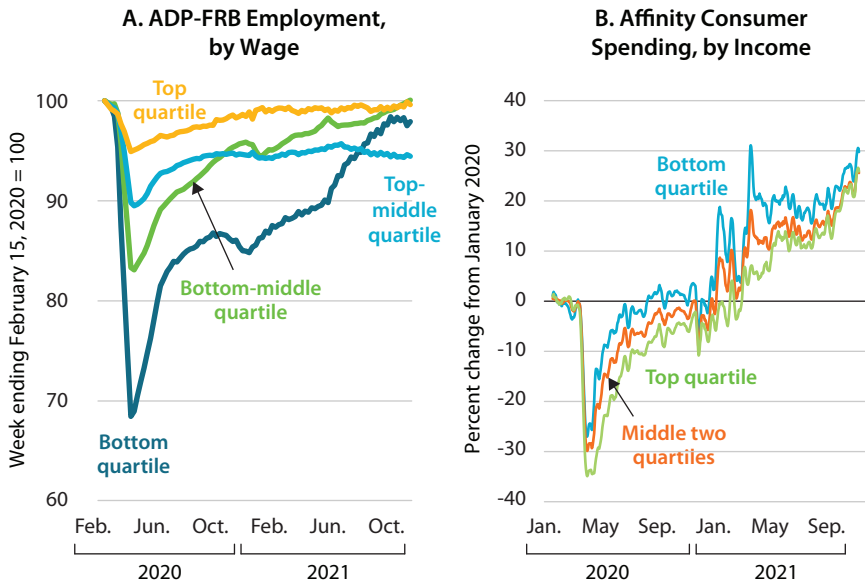
THE **HAMILTON** PROJECT

Hutchins Center on Fiscal & Monetary Policy at BROOKINGS

Granularity and Policy Design

Another important example of granularity is the distribution of job losses during the pandemic recession, which was relevant for the design of many policies during that period. For example, the pandemic recession had much larger employment effects on some service industries, such as leisure and hospitality, mostly due to voluntary and mandatory social distancing. Those industries are also more likely to employ low-wage workers. As a result, the employment of workers in the bottom quartile of the wage distribution fell substantially more than the employment of workers with higher incomes (Figure 9.6a). Knowing the distribution of employment losses by wage may have helped to better design policy responses for Unemployment Insurance compensation and better target stimulus checks. In turn, these policies helped to support consumer spending for the low-income group (Figure 9.6b).

FIGURE 9.6

Employment and Consumer Spending by Income, Indexed to February 2020

A. ADP-FRB Employment, by Wage

B. Affinity Consumer Spending, by Income

Source: ADP, Inc 2020–21; Affinity via Opportunity Insights 2020–21; authors' calculations.

Granularity and Real-Time Policy Evaluation

Finally, access to real-time granular data opens the door to real-time policy analysis. In turn, this analysis can be used to fine-tune subsequent policy actions. One of the clearest examples of this in the pandemic recession is the analysis done to study the three rounds of stimulus checks that went out in April 2020, January 2021, and March 2021. One granular dimension that was immediately useful to track the effectiveness of the stimulus checks in promoting spending was the high-frequency nature of some of the nontraditional data. As Figure 9.7 shows, the Fiserv daily spending index was able to highlight surges in spending associated with stimulus check receipt that would not have otherwise been evident from the monthly data reported by Census.

Other types of granular household-level data led to even more detailed estimates of the response to the stimulus checks. Using household balance sheet data, some researchers were able to publish estimates of the response to the first round of stimulus checks within a few months of the disbursement (Baker

FIGURE 9.7

Fiserv and Census Consumer Spending

Source: Census Bureau n.d.a.; Fiserv 2020-21; authors' calculations.

Note: Vertical dashed lines indicate the week in Economic Impact Payment (EIP) direct deposits commenced. Physical checks continued to be disbursed for three to four weeks after these dates.

et al. forthcoming; Chetty et al. 2020; Cox et al. 2020). These early analyses of the response to stimulus checks showed that even when services spending was very constrained due to social distancing, households, especially lower-income ones, still managed to spend significantly out of their stimulus checks. When the second and third rounds of stimulus checks were planned, these analyses were already available to inform policymakers of expected outcomes. Other important examples of real-time analysis done, but not discussed here, were on the Paycheck Protection Program (Autor et al. forthcoming; Chetty et al. 2020; Hubbard and Strain 2020) and on Unemployment Insurance benefits (Coombs et al. 2021; Ganong et al. 2021).

These types of real-time analyses are not a panacea for policy design. They are only useful to the extent that they are accurate, available to, and acted on by policymakers. When the analysis is conducted by researchers outside of the government using privately sourced data, it is both difficult for policymakers to control the subject of the analysis and time-consuming for government actors to vet the data and the quality of the analysis. Still, in the case of the pandemic recession, there is some evidence that policymakers leaned on the work of

Opportunity Insights to determine the income thresholds in the second and third rounds of stimulus checks.[16]

An additional forward-looking benefit is that the availability of granular data opens the door for future policymakers to condition policy on the outcome of real-time analysis; government agencies could contract with nontraditional data sources such that they are prepared to do some of this analysis in house or if they could contract with outside researchers to carry out and report the analysis. This type of analysis could even be an explicit part of a policy's design and legislation. For example, the Council of Economic Advisors was legislated to provide quarterly reports on the effectiveness of the American Recovery and Reinvestment Act after the Great Recession.

Crisis-Specific Data Gathering

The information policymakers needed during the pandemic differed markedly from the indicators used in a typical economic downturn. As a result, substantial crisis-specific data gathering was carried out by not only government agencies but also private data providers. Most notably, during the pandemic policymakers paid particular attention to health-related indicators such as COVID-19 cases, hospitalizations, deaths, disease reproduction rates, variants, and vaccinations—since those were highly informative about possible disruptions to the economy. The importance of health-related data was, for example, reflected in FOMC statements that said "the Committee's assessments will take into account a wide range of information, including *readings on public health*, labor market conditions, inflation pressures and inflation expectations, and financial and international developments (emphasis added; Board of Governors 2022)."

At the start of each COVID-19 wave, policymakers tried to understand how fast a particular COVID-19 variant would spread and how severe the associated health outcomes could be. This information was used to predict possible behavioral responses of consumers and businesses, which in turn allowed for an assessment of the possible economic effects of each COVID-19 wave. While the importance of health-related indicators is obviously specific to the pandemic recession, other nontypical economic downturns could require gathering crisis-specific data. For example, a climate disaster leading to a recession would likely require gathering timely, granular data on agriculture, migration, or weather patterns to better understand the possible evolution of the economy in real time.

Most of the health-related indicators that were informative during the pandemic did not exist before it. While official health agencies worked hard to provide the necessary health-related data during the pandemic, it is important to

---

16. See The Economist (2021).

also emphasize the role that the private sector played. For example, institutions such as Johns Hopkins University, the *New York Times*, and the collaborative, volunteer-run COVID Tracking Project provided high-quality and regularly updated health data, including at very granular levels (e.g., by state or county and by demographic characteristics).

To better understand some specificities of the pandemic and the related downturn, several new statistics were developed. First, school instruction policy had important consequences for the labor supply decisions of parents with young children. Thus, policymakers closely followed data on shares of schools with in-person, hybrid, and remote instruction policy (Figure 9.8a). As school districts varied in terms of their school instruction policies, these data were not readily available and were thus gathered by private sector companies, such as *Education Week* and Burbio.

Second, soon after the pandemic started, office occupancy dropped precipitously, either because businesses switched to remote work or because they laid off their employees. The aforementioned data on transit ridership and new data on office occupancy (Figure 9.8b), such as those provided by Kastle Systems, were used to measure in real time how quickly employees stopped coming to offices and, later during the pandemic, how quickly businesses returned to in-person work. These measures indirectly relay information about the state of the labor market and the location and form of the majority of white-collar employment. Aside from the pandemic, these metrics should eventually return to their pre-pandemic norms and likely have little intrinsic informational content going forward.

The next three categories of new nontraditional data have a higher likelihood of being leveraged to extract information about economic outcomes after the pandemic. Mobility measures, our third category, obtained, for example, from SafeGraph, Google Mobility, and Apple Mobility Trends data, were used to infer activity from the location of requests to mapping software or from the geolocation of a particular cellphone. These data were able to shed light on how many people were socially distancing by staying at home or visiting service-providing businesses or parks.
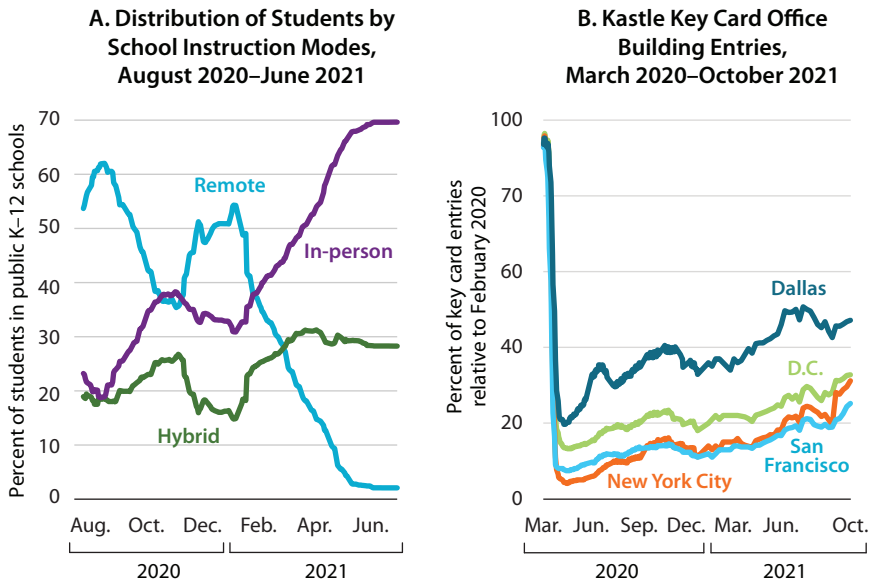
Fourth, many analysts and policymakers initially feared that the social distancing and dislocation of the pandemic would lead to a burst of business exits and thus leave permanent damage to the productive capacity of the economy. Official statistics on business exit and entry are available with lags of at least a year or even more; but, data from private data sources, such as ADP, SafeGraph, Womply, Yelp, and Homebase, allowed the measurement of business exit and entry in real time and thus allowed a better assessment of potential scarring effects in the economy.[17] These data thus had the potential to affect

---

17. The ADP payroll data can be employed to look at inactive payroll accounts; Safegraph geolocation data can be leveraged to measure businesses that no longer have active visits;

FIGURE 9.8

School Instruction Mode and Keycard Office Entries, 2020–2021

A. Distribution of Students by School Instruction Modes, August 2020–June 2021

B. Kastle Key Card Office Building Entries, March 2020–October 2021

Source: Burbio, Inc 2020–21; Kastle Systems 2020–21; authors' calculations.

Note: Based on employee key card entries into office buildings. 7-day average through January 6, 2021, and weekly readings thereafter.

THE HAMILTON PROJECT

Hutchins Center on Fiscal & Monetary Policy at BROOKINGS

forward-looking policy or decisions about extensions of different policies, such as the Paycheck Protection Program.

Fifth, and finally, beginning in early 2021, supply bottlenecks severely impacted the ability of the economy to recover and led to notable inflation pressures. Nontraditional data, such as container dwell times and counts of ships waiting to unload at port, were helpful to measure the extent of bottlenecks in real time.

Two new products from the Census Bureau—the Small Business Pulse Survey and the Household Pulse Survey—stand out as excellent examples of traditional data providers implementing a flexible production framework to provide valuable nonstandard information.[18] The Small Business Pulse Survey

Womply exits are based on card transactions; and data on clock ins and clock outs from Homebase can be used to measure business exits. See Crane et al. (2020).

18. See Buffington, Fields, and Foster (2021) for more details on the Pulse surveys.

provided timely, high-frequency, granular data on the effect of the pandemic on small, single-location employer businesses in the United States. The survey covered questions on overall effect, operations, challenges, finances, and expectations. The Household Pulse Survey brought high-frequency data on households to bear during the pandemic. Specifically, it provided timely data on a range of ways in which lives were impacted by the COVID-19 pandemic: employment status, spending, food security, housing, physical and mental health, access to health care, and educational disruption.[19] Importantly, the flexibility exhibited by the Census Bureau in the rollout of the Pulse surveys can and should be applied in future emergency situations.

To summarize, there are some variables that do not provide much (or any) information about the overall path of the economy during normal times, which we would not advocate tracking even with an unlimited budget for data. However, during the pandemic, they proved to be crucially important because they provided qualitative and, at times, quantitative understanding of current developments, and thus they informed the policymaking process. Gathering these crisis-specific data often required substantial resources. If subsequent economic downturns differ from typical recessions, it might be helpful to plan how to improve the necessary crisis-specific data collection and allocate the resources to do so.

Pitfalls in Using Alternative Data

Statistical agencies are staffed with statisticians, data scouts, economists, analysts, and surveyors because of the complexity and rigor necessary to produce timely and reliable statistics. While data storage, manipulation, digitized collection, and the addition of metadata have dramatically decreased the cost of data processing and collection, these aspects are only a small fraction of the investment needed to collect and provide reliable estimates over time. The costs of nontraditional data are substantial and include the cost of purchasing data by policymaking institutions along with the expertise necessary to address pitfalls that arise from these data. These pitfalls include limited history and seasonal adjustment issues, sample representativeness, methodological consistency, the possible untimely cessation of data collection, and substantial variability that may diminish the signal value to the content of a given data release. This section will detail each of these complications in the context of the pandemic recession.[20]

Nontraditional data can be expensive to government agencies. Moreover, the costs of purchasing data have increased dramatically over the past several years as voluminous amounts of information have become valuable assets to

---

19. Importantly, and in contrast to most of the nontraditional data gathered and published during the pandemic, the Household Pulse Survey provided demographic characteristics for their measures of the economic impacts of the pandemic, such as race.

20. Two costs we do not address here, but are nevertheless worth consideration, are "hold-up costs" and private companies trading on "insider" information from a nontraditional data release.

organizations' core operations.[21] Importantly, firms differ in how willing they are to consider the public policy and academic benefits of their data, and they price accordingly. Many data purveyors charge a lower price for academic use than for nonacademic use, which often includes government agencies. As a result, the government is sometimes priced out of important data assets when the pricing offered is comparable to what might be charged to a private organization, such as a hedge fund, that can use the data profitably.

Perhaps the most important drawback to using nontraditional data is that many of these data sources do not have long time series, which leads to several disadvantages. First, it makes seasonal adjustment difficult or sometimes impossible, as typical approaches used to remove seasonality effectively from a time series require at least five or more years of data.[22] To deal with seasonal adjustment in the absence of a long time series, most analysts adjusted how they presented their data, such as taking the percentage change between same time period in 2020 and 2019. One downside of this approach is that week-to-week fluctuations in the percentage change are heavily influenced by idiosyncratic fluctuations in the 2019 level. For instance, there are sharp movements in the weekly series when holidays move from one day or one week to another. We can see this in some of the spending indexes mentioned earlier, where the timing of Labor Day leads to substantial jumps in the spending series.[23] This is especially easy to see in Figure 9.9, which presents the plot of restaurant reservations (i.e., a proxy for spending) alongside leisure and hospitality employment.

One can easily see the imprint of the Labor Day holidays in 2020 and 2021, which at the time might have led the casual observer to expect a burst in restaurant and services spending or possibly a spike in leisure and hospitality employment, neither of which materialized. These differences are not easily solved by an overarching methodology, as different series exhibit substantially different seasonal patterns: for example, health care spending in March is impacted by the expiration of flexible spending accounts, an event that does not influence other spending.

A second disadvantage of not having a long time series is that it hinders the ability of data users to contextualize a particular reading relative to historical trends or prior business cycles. A good example of this comes from the new COVID Impact Survey and the Household Pulse Survey, both of which presented numbers of critical importance but had a limited basis of comparison. For instance, the food insecurity rate, a good metric for determining household distress, was surveyed in the COVID Impact Survey, which started in April of

---

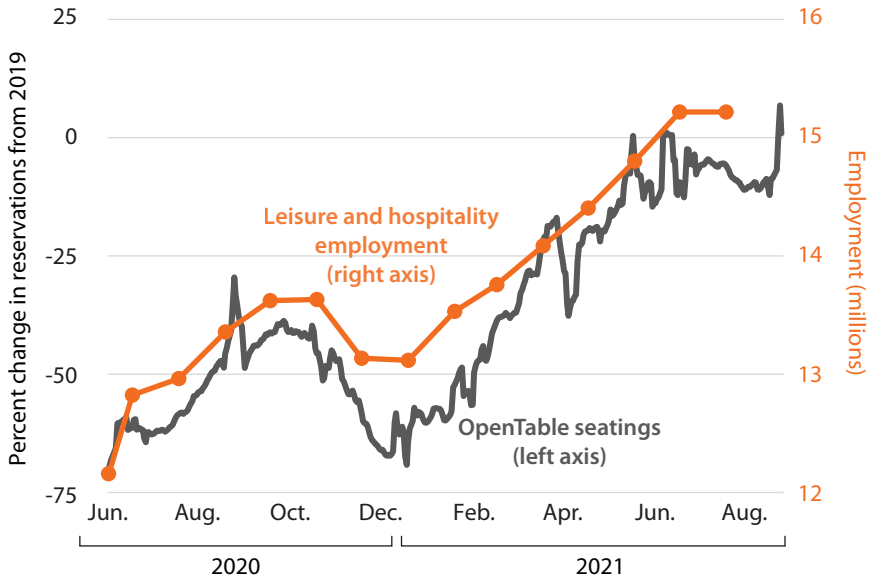21. Moreover, many private data providers have consolidated (Laney 2020).

22. According to Census, the proper identification and estimation of seasonal and calendar effects requires a span of 10 to 15 years of data or a minimum of 5 years to properly estimate a seasonal pattern and 7 years for calendar effects and moving holidays. See Dagum (1988) and U.S. Census Bureau (2008).

23. Holiday effects can also be found in COVID-19 health data, including cases, hospitalizations, and deaths.

FIGURE 9.9

Open Table Reservations and BLS Leisure and Hospitality Employment, June 2020–September 2021

Source: Bureau of Labor Statistics (BLS) n.d.; OpenTable 2020–21; authors' calculations.

2020. However, it was hard to know whether the resulting insecurity rate was elevated without earlier readings. Researchers spliced the data with similar information from the quarterly National Health Interview Survey, but the measured change was difficult to interpret.[24]
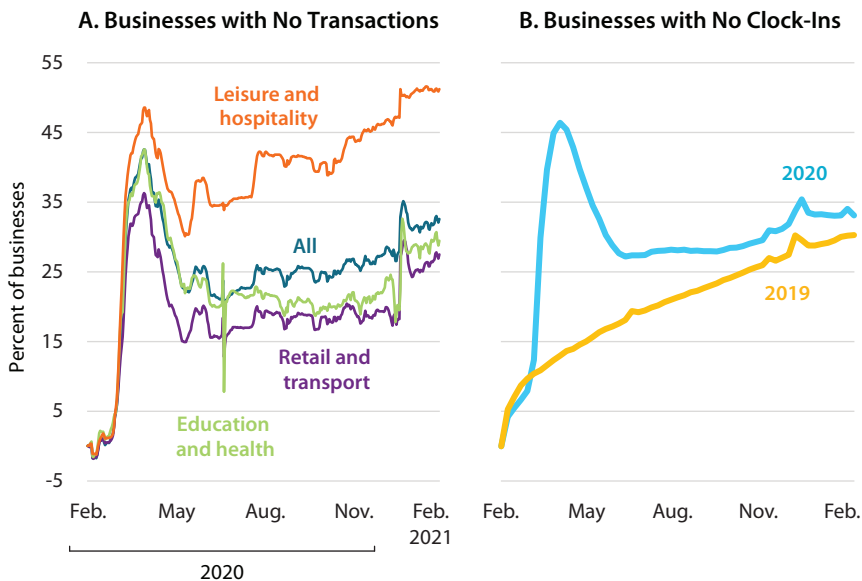
Another example comes from using nontraditional data to measure business exits and closures. As described by Crane et al. (2020), payroll information from ADP, card transactions from Womply, and data on clock-in and clock-out tracking from Homebase can be used to measure business exits a year or two before the standard data sources from the Census and BLS are released.[25] How-

---

24. Similarly, the Census Pulse data were spliced with historical data from supplementary Current Population Survey questions (Bitler, Hoynes, and Schanzenbach 2020).

25. Womply is a credit card processor and provides a measure of firms that have ceased point-of-sale transactions, while the Homebase clock-in and clock-out software facilitates tracking

FIGURE 9.10

Measures of Small Business Closures

A. Businesses with No Transactions

B. Businesses with No Clock-Ins

Source: Womply via Opportunity Insights 2020–21; Homebase 2020–21; authors' calculations.

Note: The samples are limited to businesses with a transaction on February 15th, 2020, for figure A., and businesses with a clock-in on February 15th, 2020, for figure B.

THE
HAMILTON
PROJECT

Hutchins Center
on Fiscal & Monetary Policy
at BROOKINGS

ever, the resulting closure patterns are also driven by client attrition rather than business shutdown, confounding the measurement of true business closures.

The 2020 Womply data are hard to interpret as it is difficult to translate what a near 40 percent closure rate says about true business exits (Figure 9.10a). In contrast, the longer time series we have for Homebase allows a comparison with 2019 figures (Figure 9.10b). By February of 2021, exit in the Homebase series was a striking 33 percent. But once that number is compared to the 2019 attrition rate, excess exits were only about 3 percentage points higher, a much less worrisome picture.[26]

A third disadvantage of the lack of historical data for many nontraditional data series is that there often is little to no track record to see how these data

firms that have not had clock-in events over a given period of time.

26. Ideally, the comparison would contain multiple years of early attrition rates to average over so as not to draw too many conclusions from just 2019, which could reflect a particular year effect.

translate to or predict standard data sources. A good example of this can be found in leveraging nontraditional data to predict rental price movements. The Zillow Rent Index, ApartmentList, and CoreLogic rental price indexes can all be used to track rental prices at a high frequency in a timely manner. However, both the Zillow Rent Index and ApartmentList have short time spans, with the Zillow Rent Index's current methodology starting in 2019 and the ApartmentList data starting in 2017. Most importantly, the nontraditional data tracks rents for new leases by a new tenant, which is conceptually different from the change in shelter cost for all renters. Moreover, any statistical relationship between the Consumer Price Index for renting and the nontraditional data such as ApartmentList and CoreLogic will be difficult to estimate due to the nontraditional data's short history.

Even if there are sufficient time series, past relationships may no longer hold due to the pandemic's reshuffling of the economic landscape. A good example of this is high-propensity business applications from the weekly Business Formation Statistics from the Census Bureau. The Business Formation Statistics depend on the historical relationship between business applications (Employment Identification Numbers) and establishment formation.

The series in Figure 9.11 show that Employment Identification Number applications increased sharply in the second year of the pandemic. In normal times, this would imply healthy growth in new business entry.[27] Unfortunately, the relationship between Employment Identification Numbers and new establishments with active payroll might no longer hold. This could result from business applications covering an entirely new form of venture or new work-from-home businesses that do not employ workers expanding rapidly during the pandemic.[28] Due to lags in the publication of official data on business entry—a similar problem to the data on exit mentioned above—it could be years before we know if the businesses identified by the Business Formation Statistics show up in official data.

Beyond short histories, nontraditional data face additional hurdles that may make them unreliable. The fact that they may be nonrepresentative presents one of the largest hurdles. Many of the databases that were most helpful during the pandemic recession were sampled from client bases and firms' administrative records that represent only a small fraction of the overall population of activity one would want to track. Small samples are not necessarily an insurmountable hurdle to representative aggregates because low-level aggregates could be weighted and benchmarked to properly reflect a particular population. For example, the ADP-FRB series—which is roughly based on a sample of 20 percent of employment—is stratified to characteristics derived from the
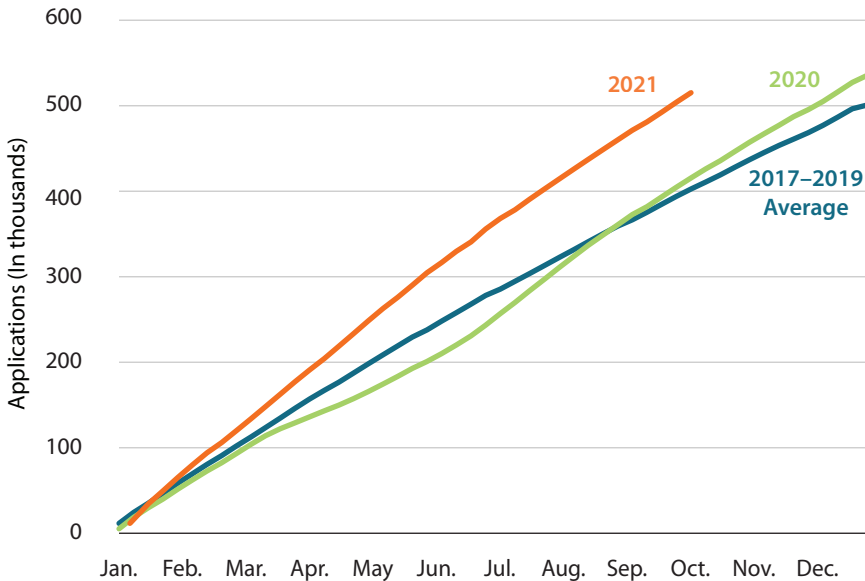
---

27. See Bayard et al. (2018).

28. For example, this could happen if the average employment count of payroll-maintaining establishments changes. One possibility during the pandemic could be a wholesale shift toward microbusinesses (Hartman and Parilla 2022).

FIGURE 9.11

Cumulative New Business Applications, Select Years

Source: Census Bureau n.d.b.

Note: Business applications with planned paid employees.

Quarterly Census of Employment and Wages to improve its reliability for measuring employment changes.

The ADP-FRB series approach is similar to the BLS use of Quarterly Census of Employment and Wages weights for its payroll data. This contrasts with Homebase data, which have become an important indicator for small business employment and activity during the pandemic.[29] Homebase is a scheduling and time-tracking tool used mostly by small businesses—it covers just 2 percent of employment and 1 percent of establishments in the accommodation and food services industry. And this comparison is within a sector Homebase covers well. For other services, the coverage is much smaller—in the tenths of a percent.[30] Unfortunately, the small sample issue is compounded with sample

---

29. See Kurmann, Lalè, and Ta (2021), Bartik et al. (2020), Bartlett and Morse (2020), and Granja et al. (2020).

30. These nontraditional indicators should be employed for aggregative forecasting with caution, as a Homebase-based indicator predicted a job loss of more than 800,000 jobs in September

selection issues, since the sample is just the customer base and there is a significant amount of churn within the sample of firms employing Homebase. This is typical of most opportunity surveys, and researchers generally lack a way to weigh the data to make it represent the whole economy. Representativeness problems are exacerbated when attempting to delve into the industry, geographic, or demographic heterogeneity of the data series.

Another hurdle for nontraditional data is methodological changes. For traditional data, these are typically folded into federal statistical releases during annual or comprehensive revisions and most often are accompanied by a revision to the historical data so that the time series is consistent. This is not necessarily the case with nontraditional data, as the data collection and provision of statistics are fundamentally not the focus of the enterprise that releases the data. Two examples illuminate this situation. Kastle occupancy reports, which used keycards as a metric of employees return to work in person, changed its methodology from daily to weekly data in March 2021. Fortunately, it re-estimated the entire time series with the new methodology. On the other hand, SafeGraph, a company that aggregates anonymized location data from numerous mobile device applications to provide insights about physical places, changed its methodology for imputing devices' locations in March 2021. Because SafeGraph did not re-estimate the historical data, the series suggests there was an abrupt change in social distancing measures in March of 2021 when that is likely not the case.

Sometimes nontraditional data series just cease. As the pandemic has dragged on, several organizations have stopped reporting data. For example, the Yale Labor Survey, an online survey of households akin to the Current Population Survey that started collecting and publishing data in April 2020, provided rapid and inexpensive information on employment, unemployment, and other labor market measures that tracked the official measures well but provided more frequent and timelier data. The last Yale Labor Survey covers the week ending February 27, 2021 (Tobin Center 2021). Somewhat similarly, portions of the Census' Small Business Pulse Survey and Household Pulse Survey started, paused, or stopped altogether as the Census revised the survey and added new questions. For example, data items that were rotated off the Small Business Pulse Survey—series that would have been useful in all phases—included questions about temporary closures, supply chain questions, planned capital expenditures, rehiring, and remote work. Last, the COVID Tracking Project—a well-organized, formatted, and consistent purveyor of COVID-19 health data—stopped collecting new data in March 2021. And while the federal health data improved over the course of the pandemic, the sources and structure varied tremendously, leading researchers and policy officials scrambling for alternative sources of information.

---

of 2020, whereas employment increased by more than 300,000 jobs that month.

One final hurdle for nontraditional data is that they are sometimes so noisy that they provide little signal for economic indicators of interest. Moreover, even indicators that did well at the height of the pandemic, such as the ability of Google Trends to predict unemployment claims and Homebase to provide insight into overall employment, might be less helpful once the period in which dramatic swings in activity were all highly correlated moves further into the past. To gauge their value, all these measures should be evaluated for their signal content outside of the dramatic 2020 months and when the forecasting framework includes additional indicators of economic activity.[31]

Conclusions

Nontraditional economic data were an important resource for policymakers during the pandemic downturn and recovery. These alternative data sources provided a view into economic activity weeks or months before most traditional data would become available. They also illuminated household and business activity at a granular level, helping to clarify the mechanisms affecting the pandemic economy. Having access to nontraditional data specific to this episode also allowed policymakers insight into how the virus and associated health policies were evolving. One important question is whether these data were valuable only because of the unusual and rapid nature of the recent downturn or whether they will be important in future economic crises.

At the onset of any crisis, economic policymakers must identify whether they are confronting a demand shock or a supply shock and the magnitudes and likely persistence of those shocks. As the episode unfolds, policymakers also want to understand how the shocks are propagating to the broader economy. Consequently, many of the series used in the pandemic recession will likely prove useful in most downturns: daily point-of-sale card swipe data, surveys of consumer sentiment, credit card data, and weekly automotive transactions should give an early warning of shocks to demand. And understanding the propagation of shocks to the rest of the economy may be aided by nontraditional data on payrolls, business exits/entries, or supply chain disruptions. Furthermore, these are some of the series policymakers need to have and understand for every crisis, and they should plan for the next crisis by investing in nontraditional data sources now—to build longer time series of timely indexes to supplement traditional data sources, to improve the usability of existing data, to validate the granular details that may be available and become important during a downturn, and to hone their skills in working with these data. Even if these nontraditional data sources have limited use during an expansion, it is

---

31. While there is evidence that nontraditional data inputs like credit card data and Google Trends improve forecasting (see Chapman and Desai 2020 and D'Amuri and Marcucci 2017), the gains are likely minimal when combined with the full suite of possible economic data that can be folded into a model (Li 2016).

worth developing them to be prepared for the next crisis, the next government shutdown, or the unexpected.

Some shocks, often supply shocks, seem more idiosyncratic across episodes, and so the relevant data are as well. In the 1970s, timely data on global oil markets and inflation expectations would have been valuable but were largely unavailable. In the most recent recession, data on COVID-19 hospitalizations and public shutdowns were valuable but seem unlikely to be important in future cyclical events. It is hard to know what types of idiosyncratic series will be valuable in future episodes, but a culture that embraces transparency and data sharing can only help.

It is also important to understand the pitfalls of using nontraditional data. The absence of a long time series in many of these series hinders seasonal adjustment, makes levels difficult to interpret, and impedes comparisons at a business cycle frequency. These data can also be unreliable because they are nonrepresentative, methodologically inconsistent, highly variable or noisy, or susceptible to discontinuation. The resources to develop the human capital to address these issues are large—and that is over and above the cost of the data itself.

Nonetheless, we view the benefits of nontraditional data as much greater than the costs. And some of the learning is still ahead of us. As the COVID-19 crisis is still evolving, a full accounting is still to come. High-frequency, granular data will probably continue to reveal aspects of business cycle dynamics that we can learn from for many years.

References

Aladangady, Aditya, Shifrah Aron-Dine, Wendy Dunn, Laura Feiveson, Paul Lengermann, and Claudia Sahm. 2022. "From Transactions Data to Economic Statistics: Constructing Real-Time, High-Frequency, Geographic Measures of Consumer Spending." In *Big Data for Twenty-First-Century Economic Statistics*, edited by Katharine G. Abraham, Ron S. Jarmin, Brian Moyer, and Matthew D. Shapiro. 115-46. Chicago, IL: University of Chicago Press.

Autor, David, David Cho, Leland D. Crane, Mita Goldar, Byron Lutz, Joshua Montes, William B. Peterman, David Ratner, Daniel Villar, and Ahu Yildirmaz. Forthcoming. "An Evaluation of the Paycheck Protection Program Using Administrative Payroll Microdata." *Journal of Public Economics.*

Baker, Scott, R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis. Forthcoming. "Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments." *Review of Finance.*

Bartik, Alexander W., Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matthew Unrath. 2020. "Measuring the Labor Market at the Onset of the COVID-19 Crisis," *Brookings Papers on Economic Activity* (Summer): 239–68.

Bartlett, Robert P. III, and Adair Morse. 2020. "Small Business Survival Capabilities and Policy Effectiveness: Evidence from Oakland," NBER Working Paper 27629, National Bureau of Economic Research, Cambridge, MA.

Bayard, Kimberly, Emin Dinlersoz, Timothy Dunne, John Haltiwanger, Javier Miranda, and John Stevens 2018. Early-Stage Business Formation: An Analysis of Applications for Employer Identification Numbers," NBER Working Paper 24364, National Bureau of Economic Research, Cambridge, MA.

Bitler, Marianne P., Hilary W. Hoynes, and Diane Whitmore Schanzenbach. 2020. "The Social Safety Net in the Wake of COVID-19." *Brookings Papers on Economic Activity* (Summer): 119–58.

Board of Governors of the Federal Reserve System. 2022. "Federal Reserve issues FOMC statement, January 26, 2022." *Press Release.* Board of Governors of the Federal Reserve System. Washington, D.C.

Buffington, Catherine, Jason Fields, and Lucia Foster. 2021. "Measuring the Impact of COVID-19 on Businesses and People: Lessons from the Census Bureau's Experience." *AEA Papers and Proceedings 111*: 312–16.

Bureau of Economic Analysis (BEA). 2020. "Gross Domestic Product, 2nd Quarter 2020 (Advance Estimate) and Annual Update." Press Release, July 30, 2020, Bureau of Economic Analysis, Suitland, MD.

Bureau of Labor Statistics (BLS). n.d. "Current Employment Statistics." Bureau of Labor Statistics, U.S. Department of Labor, Washington, D.C.

———. 2020. "Employment Situation News Release." Press Release, May 8, 2020, Bureau of Labor Statistics, U.S. Department of Labor, Washington, D.C.

Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, Adrian Hamins-Puertolas, Christopher Kurz, and Tyler Radler. 2018. "Using Payroll Processor Microdata to Measure Aggregate Labor Market Activity." Working Paper 2018-005, Board of Governors of the Federal Reserve System, Washington, D.C.

Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, Adrian Hamins-Puertolas, and Christopher Kurz. 2022. "Improving the Accuracy of Economic Measurement with Multiple Data Sources: The Case of Payroll Employment Data." In *Big Data for Twenty-First-Century Economic Statistics*, edited by Katharine G. Abraham, Ron S. Jarmin, Brian Moyer, and Matthew D. Shapiro. 147-72. Chicago, IL: University of Chicago Press.

Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz. 2020a. "The U.S. Labor Market during the Beginning of the Pandemic Recession." *Brookings Papers on Economic Activity* (Summer): 3–33.

Cajner, Tomaz, Andrew Figura, Brendan M. Price, David Ratner, and Alison Weingarden. 2020b. "Reconciling Unemployment Claims with Job Losses in the First Months of the COVID-19 Crisis." Finance and Economics Discussion Series 2020-055, Board of Governors of the Federal Reserve System, Washington, D.C.

Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, Adrian Hamins-Puertolas, and Christopher Kurz. 2020c. "Tracking Labor Market Developments during the COVID-19 Pandemic: A Preliminary Assessment." Finance and Economics Discussion Series 2020-030, Board of Governors of the Federal Reserve System, Washington, D.C.

Census Bureau. n.d.a. "Advance Retail Sales." U.S. Census Bureau, Suitland, MD.

———. n.d.b. "Business Formation Statistics." U.S. Census Bureau, Suitland, MD.

———. 2008. X-12-ARIMA Reference Manual. U.S. Census Bureau, Suitland, MD.

———. 2020a. "Advance Monthly Sales for Retail and Food Services, March 2020." Press Release, April 15, 2020. U.S. Census Bureau, Suitland, MD.

———. 2020b. "Advance Monthly Sales for Retail and Food Services, April 2020." Press Release, May 15, 2020. U.S. Census Bureau, Suitland, MD.

———. 2020c. "Advance Monthly Sales for Retail and Food Services, May 2020." Press Release, June 16, 2020. U.S. Census Bureau, Suitland, MD.

Chapman, James, and Ajit Desai. 2020. "Using Payment Data to Nowcast Macroeconmic Variable During the Onset of COVID-19." *Journal of Market Infrastructure* 9(1).

Chetty, Raj, John Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team. 2020. "How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data." Working Paper 26463, National Bureau of Economic Research, Cambridge, MA.

Coombs, Kyle, Arindrajit Dube, Calvin Jahnke, Raymond Kluender, Suresh Naidu, and Michael Stepner. 2021. "Early Withdrawal of Pandemic Unemployment Insurance: Effects on Earnings, Employment and Consumption." Working Paper 22-046, Harvard Business School, Cambridge, MA.

Cox, Natalie, Peter Ganong, Pascal Noel, Joseph Vavra, Arlene Wong, Diana Farrell, Fiona Grieg, and Erica Deadman. 2020. "Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data." *Brookings Papers on Economic Activity* (Summer): 35–82.

Crane, Leland D., Ryan A. Decker, Aaron Flaaen, Adrian Hamins-Puertolas, and Christopher Kurz. 2020. "Business Exit during the COVID-19 Pandemic: Non-Traditional Measures in Historical Context." Finance and Economics Discussion Series 2020-089, Board of Governors of the Federal Reserve System, Washington, D.C.

Dagum, Estela B. 1988. *The X11ARIMA/88 Seasonal Adjustment Method: Foundations and User's Manual.* Ottawa, ON: Statistics Canada, Time Series Research and Analysis Division.

D'Amuri, Francesco, and Juri Marcucci. 2017. "The predictive power of Google searches in forecasting U.S. unemployment." *International Journal of Forecasting 33*, no. 4: 801-816.

Doniger, Cynthia L., and Benjamin Kay. 2021. "Ten Days Late and Billions of Dollars Short: The Employment Effects of Delays in Paycheck Protection Program Financing." Finance and Economics Discussion Series 2021-003, Board of Governors of the Federal Reserve System, Washington, D.C.

Federal Open Market Committee (FOMC). 2020. "Minutes of the Federal Open Market Committee, March 15, 2020." Federal Open Market Committee, Board of Governors of the Federal Reserve System, Washington, D.C.

Ganong, Peter, Fiona Grieg, Max Liebeskind, Pascal Noel, Daniel Sullivan, Joseph Vavra. 2021. "Spending and Job Search Impacts of Expanded Unemployment Benefits: Evidence from Administrative Micro Data." Working Paper 2021-19, Becker Friedman Institute for Economics, Chicago, IL.

Granja, João, Christos Makridis, Constantine Yannelis, and Eric Zwick. 2020. "Did the Paycheck Protection Program hit the target?" NBER Working Paper 27095. National Bureau of Economic Research, Cambridge, MA.

Gupta, Sumedha, Kosali Simon, and Coady Wing. 2020. "Mandated and Voluntary Social Distancing during the COVID-19 Epidemic." *Brookings Papers on Economic Activity* (Summer): 269–315.

Hartman, Jeremy and Joseph Parilla. 2022. "Microbusinesses flourished during the pandemic. Now we must tap into their full potential." The Brookings Institution, Washington, D.C.

Hubbard, Glenn, and Michael Strain. 2020. "Has the Paycheck Protection Program Succeeded?" *Brookings Papers on Economic Activity* (Fall): 335–90.

Kurmann, Andre, Etienne Lalè, and Lien Ta. 2021. "The Impact of COVID-19 on Small Business Dynamics and Employment: Real-Time Estimates with Homebase Data." SSRN Working Paper.

Laney, Douglas B. 2020. "The Data Land-Grab Continues as S&P Global Acquires IHS Markit For $44 Billion." *Forbes*. December 3, 2020.

Li, Xinyuan. 2016. "Nowcasting with Big Data: is Google useful in the Presence of other Information?" London Business School, London, NW1, United Kingdom

Milstein, Eric and David Wessel. 2021. "What did the Fed do in response to the COVID-19 crisis?" The Brookings Institution, Washington, D.C.

The Economist. 2021. "Enter third wave economics: How the pandemic reshaped the dismal science." *The Economist*. October 23, 2021.

Tobin Center for Economic Policy. 2021. "Yale Labor Survey: Report of March 9, 2021 for the week ending February 27, 2021." Tobin Center for Economic Policy, Yale University, New Haven, CT.

The COVID-19 pandemic posed an extraordinary threat to lives and livelihoods. In the United States, the pandemic triggered a sharp downturn. Yet, the ensuing economic recovery was faster and stronger than nearly any forecaster anticipated due in part to the swift, aggressive, sustained, and creative response of U.S. fiscal and monetary policy. But when the next recession arrives, it most likely won't be triggered by a pandemic.

Recession Remedies examines and evaluates the breadth of the economic-policy response to COVID-19. Chapters address Unemployment Insurance, Economic Impact Payments, loans and grants to businesses, assistance to renters and mortgage holders, aid to state and local governments, policies that targeted children, Federal Reserve policy, and the use of non-traditional data to monitor the economy and guide policy. These chapters provide evidence and lessons to apply to the next recession.

Contributors

Anna Aizer • Robin Brooks • Tomaz Cajner
Gabriel Chodorow-Reich • Wendy Edelberg • Laura Feiveson
Jason Furman • Peter Ganong • Tim Geithner • Michael Gelman
Kristopher Gerardi • Fiona Greig • Laurie Goodman • Ben Iverson
Christopher Kurz • Lauren Lambie-Hanson • Pascal Noel
Claudia Persico • Jonathan Pingle • Louise Sheiner
Melvin Stephens, Jr. • Daniel Sullivan • Adi Sunderam
Stacey Tevlin • Joseph Vavra • Susan Wachter
David Wessel • Paul Willen