

FEDERAL RESERVE BANK OF ST. LOUIS

# REVIEW

THIRD QUARTER 2022  
VOLUME 104 | NUMBER 3

**The Blockchain Revolution: Decoding Digital Currencies**

David Andolfatto and Fernando M. Martin

**Increasing Employment by Halting Pandemic Unemployment Benefits**

Iris Arbogast and Bill Dupor

**The Murky Future of Monetary Policy**

Mickey D. Levy and Charles Plosser

**Turbulent Years for U.S. Banks: 2000-20**

Paul W. Wilson

**Subjective Assessment of Managerial Performance and  
Decisionmaking in Banking**

Drew Dahl and Daniel C. Coster

# REVIEW

Volume 104 • Number 3



FEDERAL  
RESERVE  
BANK *of*  
ST. LOUIS

CENTRAL TO AMERICA'S ECONOMY®

**President and CEO**

James Bullard

**Director of Research**

Carlos Garriga

**149**

**Deputy Director of Research**

B. Ravikumar

**149**

**Review Editors-in-Chief**

Michael T. Owyang

Juan M. Sánchez

**The Blockchain Revolution:  
Decoding Digital Currencies**

*David Andolfatto and Fernando M. Martin*

**166**

**Special Policy Advisor**

David C. Wheelock

**Increasing Employment by Halting  
Pandemic Unemployment Benefits**

*Iris Arbogast and Bill Duper*

**166**

**Economists**

David Andolfatto

Subhayu Bandyopadhyay

Alexander Bick

Serdar Birinci

Yu-Ting Chiang

YiLi Chien

Riccardo DiCecio

William Duper

Maximiliano Dvorkin

Miguel Faria-e-Castro

Charles S. Gascon

Victoria Gregory

Nathan Jefferson

Kevin L. Kiesen

Julian Kozlowski

Fernando Leibovici

Oksana Leukhina

Fernando M. Martin

Michael W. McCracken

Christopher J. Neely

Serdar Ozkan

Paulina Restrepo-Echavarría

Hannah Rubinton

Ana Maria Santacreu

Guillaume Vandenbroucke

Mark L. J. Wright

Christian M. Zimmermann

**The Murky Future of Monetary Policy**

*Mickey D. Levy and Charles Plosser*

**178**

**Turbulent Years for U.S. Banks: 2000-20**

*Paul W. Wilson*

**189**

**Subjective Assessment of Managerial Performance and  
Decisionmaking in Banking**

*Drew Dahl and Daniel C. Coster*

**210**

**Managing Editor**

Lydia H. Johnson

**Contributing Editors**

George E. Fortier

Jennifer M. Ives

**Designer | Production Coordinator**

Donna M. Stiller

### **Review**

*Review* is published four times per year by the Research Division of the Federal Reserve Bank of St. Louis. Full online access is available to all, free of charge.

### **Online Access to Current and Past Issues**

The current issue and past issues dating back to 1967 may be accessed through our Research Division website: <http://research.stlouisfed.org/publications/review>. All nonproprietary and nonconfidential data and programs for the articles written by Federal Reserve Bank of St. Louis staff and published in *Review* also are available to our readers on this website.

Review articles published before 1967 may be accessed through our digital archive, FRASER: <http://fraser.stlouisfed.org/publication/?pid=820>.

*Review* is indexed in Fed in Print, the catalog of Federal Reserve publications (<http://www.fedinprint.org/>), and in IDEAS/RePEc, the free online bibliography hosted by the Research Division (<http://ideas.repec.org/>).

### **Subscriptions and Alerts**

The *Review* is no longer printed or mailed to subscribers. Our last printed issue was the first quarter of 2020.

Our monthly email newsletter keeps you informed when new issues of *Review*, *Economic Synopses*, *Regional Economist*, and other publications become available; it also alerts you to new or enhanced data and information services provided by the St. Louis Fed. Subscribe to the newsletter here: <http://research.stlouisfed.org/newsletter-subscribe.html>.

### **Authorship and Disclaimer**

The majority of research published in *Review* is authored by economists on staff at the Federal Reserve Bank of St. Louis. Visiting scholars and others affiliated with the St. Louis Fed or the Federal Reserve System occasionally provide content as well. *Review* does not accept unsolicited manuscripts for publication.

The views expressed in *Review* are those of the individual authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors.

### **Copyright and Permissions**

Articles may be reprinted, reproduced, republished, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. In these cases, there is no need to request written permission or approval. Please send a copy of any reprinted or republished materials to *Review*, Research Division of the Federal Reserve Bank of St. Louis, P.O. Box 442, St. Louis, MO 63166-0442; [STLS.Research.Publications@stls.frb.org](mailto:STLS.Research.Publications@stls.frb.org).

Please note that any abstracts, synopses, translations, or other derivative work based on content published in *Review* may be made only with prior written permission of the Federal Reserve Bank of St. Louis. Please contact the *Review* editor at the above address to request this permission.

### **Economic Data**

General economic data can be obtained through FRED®, our free database with over 800,000 national, international, and regional data series, including data for our own Eighth Federal Reserve District. You may access FRED through our website: <https://fred.stlouisfed.org>.

# The Blockchain Revolution: Decoding Digital Currencies

*David Andolfatto and Fernando M. Martin*

Cryptocurrencies and decentralized finance have grown considerably since the publication of the white paper on bitcoin in 2009. This article presents an overview of cryptocurrencies, blockchain technology, and their applications, explaining the spirit of the enterprise and how it compares with traditional operations. We discuss money, digital money, and payments; cryptocurrencies, blockchain, and the double-spending problem of digital money; decentralized finance; and central bank digital currency. (JEL E42, E44, E58, G21, G23, G28, G34)

Federal Reserve Bank of St. Louis *Review*, Third Quarter 2022, 104(3), pp. 149-65.

<https://doi.org/10.20955/r.104.149-65>

---

## INTRODUCTION

Few people took notice of an obscure white paper published in 2009 titled “Bitcoin: A Peer-to-Peer Electronic Cash System,” authored by a pseudonymous Satoshi Nakamoto. The lack of fanfare at the time is hardly surprising given that innovations in the way we make payments are not known to generate tremendous amounts of excitement, let alone inspire visions of a revolution in finance and corporate governance. But just over a decade later, the enthusiasm for cryptocurrencies and decentralized finance spawned by Bitcoin and blockchain technology has grown immensely and shows no signs of abating.

Because cryptocurrencies are money and payments systems, they have naturally drawn the interest of central banks and regulators. The Federal Reserve Bank of St. Louis was the first central banking organization to sponsor a public lecture series on the topic: In March 2014, presenters [outlined the big picture of cryptocurrencies](#) and the blockchain by discussing its possibilities and pitfalls.<sup>1</sup> Since that time, the Bank’s economists and research associates have [published numerous articles and explainers](#) on these topics.<sup>2</sup> This article represents a continuation of this effort to [help educate the public and offer our perspective](#) on the phenomenon as central bankers and economists.<sup>3</sup>

David Andolfatto is a senior vice president and economist and Fernando M. Martin is an assistant vice president and economist at the Federal Reserve Bank of St Louis. This article is derived from their essay published in the 2021 annual report of the Federal Reserve Bank of St Louis: <https://www.stlouisfed.org/annual-report/2021/essay>.

© 2022, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

Understanding how cryptocurrencies work “under the hood” is a challenge for most people because the protocols are written in computer code and the data are managed in an esoteric mathematical structure. To be fair, it’s difficult to understand *any* technical language (e.g., legalese, legislation, and regulation). Because we are not technical experts in this space, we spend virtually no time discussing the technology in detail.<sup>4</sup> What we offer instead is an overview of cryptocurrencies and blockchain technologies, explaining the spirit of the endeavor and how it compares with traditional operations.

In this article, we explore four key areas:

1. Money, digital money, and payments
2. Cryptocurrencies, blockchain, and the double-spend problem of digital money
3. Understanding decentralized finance
4. The makeup of a central bank digital currency

## MONEY, DIGITAL MONEY, AND PAYMENTS

It is sometimes said that money is a form of social credit. One can think of this idea in the following way: When people go to work, they are in effect providing services to the community. They are helping to make others’ lives better in some way and, by engaging in this collective effort, make their own lives better as well.

In small communities, individual consumption and production decisions can be debited and credited, respectively, in a sort of communal ledger of action histories. This is because it is relatively easy for everyone to monitor and record individual actions. A person who has produced mightily for the group builds social credit. Large social credit balances can be “spent” later as consumption (favors drawn from other members of the community).

In large communities, individual consumption and production decisions are difficult to monitor. In communities the size of cities, for example, most people are strangers. Social credit based on a communal record-keeping system does not work when people are anonymous.<sup>5</sup> Producers are rewarded for their efforts by accumulating money balances in wallets or bank accounts. Accumulated money balances can then be spent to acquire goods and services (or assets) from other members of the community, whose wallets and bank accounts are duly credited in recognition of their contributions. In this manner, money—like social credit—serves to facilitate the exchange of goods and services.

The monetary object representing this social credit may exist in physical or nonphysical form. In the United States, physical cash takes the form of small-denomination Federal Reserve bills and U.S. Treasury coins. Cash payments are made on a peer-to-peer (P2P) basis, for example, between customer and merchant. No intermediary is required for clearing and settling cash payments. As the customer debits his or her wallet, cash is credited to the merchant’s cash register, and the exchange is settled. Hardly any time is spent inspecting goods and money in small-value transactions. Some trust is required, of course, in the authority issuing the cash used in transactions. While that authority is typically the U.S. government, there is no law preventing households and businesses from accepting, say, foreign currency, gold, or any other object as payment.

When people hear the word “money,” they often think of cash. But, in fact, most of the U.S. money supply consists of digital dollars held in bank accounts. The digital money supply is created

as a byproduct of commercial bank lending operations and central bank open market operations. Digital money is converted into physical form when depositors choose to withdraw cash from their bank accounts. Most people hold both forms of money. The reasons for preferring one medium of exchange over the other are varied and familiar.

Digital dollar deposits in the banking system are widely accessible by households and businesses. This digital money flows in and out of bank accounts in the form of credits and debits whenever a party initiates a purchase. Unlike with cash, making payments with digital money has traditionally required the services of a trusted intermediary. A digital money payment is initiated when a customer sends an encrypted message instructing his or her bank to debit the customer's account and credit the merchant's account with an agreed-upon sum. This debit-credit operation is straightforward to execute when both customer and merchant share the same bank. The operation is a little more complicated when the customer and merchant do not share the same bank. In either case, clearing and settling payments boils down to an exercise in secure messaging and honest bookkeeping.

## CRYPTOCURRENCIES, BLOCKCHAIN, AND THE DOUBLE-SPEND PROBLEM OF DIGITAL MONEY

One can think of cryptocurrencies as digital information transfer mechanisms. If the information being transferred is used as an everyday payment instrument, it fulfills the role of money. In this case, a cryptocurrency can be thought of as a money and payments system.

Every money and payments system relies on trust. The difference between cryptocurrencies and conventional money and payments systems lies in where this trust is located. In contrast to conventional systems, no delegated legal authority is responsible for managing and processing cryptocurrency information. Instead, the task is decentralized and left open to “volunteers” drawn from the community of users, similar in spirit to how the internet-based encyclopedia Wikipedia is managed. These volunteers—called miners—work to update and maintain a digital ledger called the blockchain. The protocols that govern the read-write privileges associated with the blockchain are enshrined in computer code. Users trust that these rules are not subject to arbitrary changes and that rule changes (if any) will not benefit some individuals at the expense of the broader community. Overall, users must trust the mathematical structure embedded in the database and the computer code that governs its maintenance.

Managing a digital ledger without a delegated accounts manager is not a trivial problem to solve. If just anyone could add entries to a public ledger, the result likely would be chaos. Malevolent actors would be able to debit an account and credit their own at will. Or they could create social credit out of thin air, without having earned it. In the context of money and payments systems, these issues are related to the so-called double-spend problem.

To illustrate the double-spend problem, consider the example of a dollar stored in a personal computer as a digital file. It is easy for a customer to transfer this digital file to a merchant on a P2P basis, say, by email. The merchant is now in possession of a digital dollar. But how can we be sure that the customer did not make a copy of the digital file before spending it? It is, in fact, a simple matter to make multiple copies of a digital file. The same digital file can then be spent twice (hence, a double-spend). The ability to make personal copies of digital money files would effectively grant each person in society his or her own money printing press. A monetary system with this property is not likely to function well.

Physical currency is not immune from the double-spend problem, but paper bills and coins can be designed in a manner to make counterfeiting sufficiently expensive. Because cash is difficult to counterfeit, it can be used more or less worry-free to facilitate P2P payments. The same is not true of digital currency, however. The conventional solution to the double-spend problem for digital money is to delegate a trusted third party (e.g., a bank) to help intermediate the transfer of value across accounts in a ledger. Bitcoin was the first money and payments system to solve the double-spend problem for digital money without the aid of a trusted intermediary. How?

### ***The Digital Village: Communal Record-Keeping***

The cryptocurrency model of communal record-keeping resembles the manner in which history has been recorded in small communities, including in networks of family and friends. It is said that there are no secrets in a small village. Each member of the community has a history of behavior, and this history is more or less known by all members of the community—either by direct observation or through communications. The history of a small community can be thought of as a virtual database living in a shared (or distributed) ledger of interconnected brains. No one person is delegated the responsibility of maintaining this database—it is a shared responsibility.

Among other things, such a database contains the contributions that individuals have made to the community. As we described above, the record of these contributions serves as a reputational history on which individuals can draw; the credit they receive from the community can be considered a form of money. There is a clear incentive to fabricate individual histories for personal gain—the ability to do so would come at the expense of the broader community in the same way counterfeiting money would. But open, shared ledgers are very difficult to alter without communal consensus. This is the basic idea behind decentralized finance, or DeFi.

### ***Governance via Computer Code***

All social interaction is subject to rules that govern behavior. Behavior in small communities is governed largely by unwritten rules or social norms. In larger communities, rules often take the form of explicit laws and regulations. At the center of the U.S. money and payments system is the Federal Reserve, which was created in 1913 through an act of Congress. The Federal Reserve Act of 1913 specifies the central bank's mandates and policy tools. There is also a large body of legislation that governs the behavior of U.S. depository institutions. While these laws and regulations create considerable institutional inertia in money and payments, the system is not impervious to change. When there is sufficient political support—feedback from the American people—changes to the Federal Reserve Act can be made. The [Humphrey-Hawkins Act of 1978](#), for example, provided the Fed with three mandates: stable prices, maximum employment, and moderate long-term interest rates (Steelman, 1978). And the [Dodd-Frank Act of 2010](#) imposed stricter regulations on financial firms following the financial crisis in 2007–09 (Goodwin, 2010).

Because cryptocurrencies are money and payments systems, they too must be subject to a set of rules. In 2009, Satoshi Nakamoto brought forth his aforementioned white paper, which laid out the blueprint for Bitcoin. This blueprint was then operationalized by a set of core developers in the form of an open-source computer program governing monetary policy and payment processing protocols. Adding, removing, or modifying these “laws” governing the Bitcoin money and payments system is virtually impossible.<sup>6</sup> Concerted attempts to change the protocol either fail or result in

breakaway communities called “forks” that share a common history with Bitcoin but otherwise go their separate ways. Proponents of Bitcoin laud its regulatory system for its clarity and imperviousness, especially relative to conventional governance systems in which rules are sometimes vague and subject to manipulation.

### ***How Blockchain Technology Works***

As with any database management system, the centerpiece of operations is the data itself. For cryptocurrencies, this database is called the blockchain. One can loosely think of the blockchain as a ledger of money accounts, in which each account is associated with a unique address. These money accounts are like post office boxes with windows that permit anyone visiting the post office to view the money balances contained in every account.<sup>7</sup> These windows are perfectly secured.<sup>8</sup> While anyone can look in, no one can access the money without the correct password. This password is created automatically when the account is opened and known only by the person who created the account (unless it is voluntarily or accidentally disclosed to others). The person’s account name is pseudonymous (unless voluntarily disclosed). These latter two properties imply that cryptocurrencies (and cryptoassets more generally) are digital bearer instruments. That is, ownership control is defined by possession (in this case, of the private password). It is worth noting that large-denomination bearer instruments are now virtually extinct. Today, bearer instruments exist primarily in the form of small-denomination bills and metal coins issued by governments. For this reason, cryptocurrencies are sometimes referred to as “digital cash.”

As with physical cash, no permission is needed to acquire and spend cryptoassets. Nor is it required to disclose any personal information when opening an account. Anyone with access to the internet can download a cryptocurrency wallet—software that is used to communicate with the system’s miners (the aforementioned volunteer accountants). The wallet software simultaneously generates a public address (the “location” of an account) and a private key (password). Once this is done, the front-end experience for consumers to initiate payment requests and manage money balances is very similar to online banking as it exists today. Of course, if a private key is lost or stolen, there is no customer service department to call and no way to recover one’s money.

Cryptocurrencies have become provocative and somewhat glamorous, but their unique and key innovation is *how* the database works. The management of money accounts is determined by a set of regulations (computer code) that determines who is permitted to write to the database. The protocols also specify how those who expend effort to write to the database—essentially, account managers—are to be rewarded for their efforts. Two of the most common protocols associated with this process are called proof-of-work (PoW) and proof-of-state (PoS). The technical explanation is beyond the scope of this article. Suffice it to say that *some form* of gatekeeping is necessary—even if the effort is communal—to prevent garbage from being written to the database. The relevant economic question is whether these protocols, whatever they are, can process payments and manage money accounts more securely, efficiently, and cheaply than conventional centralized finance systems.

### ***Native Token***

Recording money balances requires a monetary unit. This unit is sometimes referred to as the native token. From an economic perspective, a cryptocurrency’s native token looks like a foreign currency, albeit one whose monetary policy is governed by a computer algorithm rather than the

**Figure 1****Bitcoin in U.S. Dollars**

NOTE: Gray shaded area indicates U.S. recession.

SOURCE: Coinbase via FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/graph/?g=R9Gx>, accessed July 8, 2022.

**Figure 2****Ethereum in U.S. Dollars**

NOTE: Gray shaded area indicates U.S. recession.

SOURCE: Coinbase via FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/graph/?g=R9Gs>, accessed July 8, 2022.

policymakers of that country. Much of the excitement associated with cryptocurrencies seems to stem from the prospect of making money through capital gains via currency appreciation relative to the U.S. dollar (USD). (To see how the prices of bitcoin and ethereum, another cryptocurrency, have changed since 2017, see the FRED® graphs in this article: Figures 1 and 2.) It seems to have less to do with the promise of the underlying record-keeping technology stressed by Nakamoto's white paper. To be sure, the price of a financial security can be related to its underlying fundamentals. It is not, however, entirely clear what these fundamentals are for cryptocurrency or how they might generate continued capital gains for investors beyond the initial rapid adoption phase. Moreover, while the supply of a given cryptocurrency such as Bitcoin may be capped, the supply of close substitutes (from the perspective of investors, not users) is potentially infinite. Thus, while the total market capitalization of cryptocurrencies may continue to grow, this growth may come more from newly created cryptocurrencies and not from growth in the per-unit price of any given cryptocurrency, such as Bitcoin.<sup>9</sup>

In any case, conceptually, there is a distinction to be made between the promise of a cryptocurrency's underlying technology and the market price of its native token. Bitcoin (BTC) as a payments system could, in principle, function just as well at any given BTC/USD exchange rate.

### **Cryptocurrency Applications**

Cryptocurrencies designed to serve as money and payments systems have continued to struggle in their quest for adoption as an everyday medium of exchange. Their main benefit to this point—at least for early adopters—has been as a long-term store of value. But their exchange rate volatility makes them highly unsuitable as domestic payment instruments, given that prices and debt contracts are denominated in units of domestic currency. While year-over-year returns can be extraordinary, it is not uncommon for a cryptocurrency to lose most of its value over a relatively short period of time. How a cryptocurrency might perform as a domestic payments system when it is also the unit of account remains to be seen. El Salvador recently adopted bitcoin as its legal tender, and people will be watching this experiment closely.<sup>10</sup>

A use case touted early in Bitcoin history was its potential to serve as a vehicle currency for international remittances. One of the attractive attributes of Bitcoin is that anyone with access to the internet can access the Bitcoin payments system freely and without permission. For example, a Salvadoran working in the United States can convert his or her USD into BTC at an online exchange and send BTC to a relative in El Salvador in minutes for (usually) a relatively low fee, compared with sending money through conventional channels.

As with any tool, bitcoin may be used for good or ill purposes. Because BTC is a permissionless bearer instrument (like physical cash), it may become a popular way to finance illegal activities, terrorist organizations, and money laundering operations. Recently, it has been used in ransomware attacks, in which nefarious agents blackmail hapless victims and demand payment in bitcoin, thereby bypassing the banking system.

But possibly the most attractive characteristic of Bitcoin is that it operates independently of any government or concentration of power. Bitcoin is a decentralized autonomous organization (DAO). Its laws and regulations exist as open-source computer code living on potentially millions of computers. The blockchain is beyond the (direct) reach of government interference or regulation. There is no physical location for Bitcoin. It is not a registered business. There is no CEO. Bitcoin

has no (conventional) employees. The protocol produces a digital asset, the supply of which is, by design, capped at 21 million BTC. Participation is voluntary and permissionless. Large-value payments can be made across accounts quickly and cheaply. It is not too difficult to imagine how these properties can be attractive to many people.

### ***Policy Considerations of Cryptocurrency***

To a central bank, a cryptocurrency looks very much like a foreign currency. From this perspective, there is nothing revolutionary here. Foreign currency is sometimes seen as a threat by governments. This is not the case for the United States, since the U.S. dollar remains the world's reserve currency, but many other countries often take measures to discourage the domestic use of foreign currency. Citizens may be prohibited, for example, from holding foreign currency or opening accounts in foreign banks. Because cryptocurrencies are freely available and permissionless, it would likely be considerably more difficult to enforce cryptocurrency controls. The cryptocurrency option may also serve to constrain domestic monetary and fiscal policies—in particular, by imposing a more stringent limit on the amount of seigniorage (i.e., the “printing” of more money to finance government spending).

A dominant foreign currency may cause another problem: As it turns out, it is often cheaper to issue debt denominated in a dominant foreign currency. The problem with this activity is that when the domestic currency depreciates, debtors may have trouble repaying, and a financial crisis may ensue. When that dominant foreign currency is the U.S. dollar, the central bank of a foreign country can sometimes find relief by borrowing dollars from the Federal Reserve through a currency-swap line. But if debt instruments are denominated in cryptocurrency, there is no negotiating with the DAO of that cryptocurrency. Because this is the case, domestic regulators might want to regulate the practice of issuing cryptocurrency-denominated debt more stringently if the practice ever became sufficiently widespread to pose significant systemic risk.

## **UNDERSTANDING DECENTRALIZED FINANCE**

Decentralized finance broadly refers to financial activities that are based on a blockchain. Unlike conventional or traditional finance that relies on intermediaries and centralized institutions, DeFi relies on so-called smart contracts. The removal of those intermediaries in transactions between untrusted parties would significantly reduce costs and grant the parties more control over the terms of such agreements. Still, intermediaries oftentimes play meaningful roles beyond verification and enforcement, which means they would not altogether disappear. Here, we examine some of these concepts to explain what DeFi means and implies.<sup>11</sup>

### ***What Are Smart Contracts?***

A smart contract is a computer program designed to execute an agreed-upon set of actions. The concept was first introduced in the mid-1990s by Nick Szabo, who proposed vending machines as a primitive example: A vending machine is a mechanism that dispenses a product in exchange for a listed amount of coins (or bills); anyone with a sufficient amount of money can participate in this exchange.<sup>12</sup> Smart contracts allow interested parties to engage in secure financial transactions without the participation of third parties. As we explain below, their application goes beyond conventional financial transactions.

Ethereum is a blockchain with smart contract capability that was released in 2015. In this case, smart contracts are a type of account, with their own balance and the capability to interact with the network. Rather than being controlled by a user, smart contracts run as programmed, with their code and data residing at a specific address on the Ethereum blockchain. Other platforms may implement smart contracts in different ways.<sup>13</sup>

Like cryptocurrencies, smart contracts overcome security and transparency concerns in transactions between untrusted parties, without the need for a trusted third party. In fact, smart contracts aim to do away with intermediaries such as brokers, custodians, and clearinghouses.

Consider a collateralized loan as an example. In traditional finance, a borrower seeks a bank to lend funds or a broker to find potential lenders. The parties then agree on the terms of the loan: interest rate, maturity, type and value of collateral, etc. The borrower's collateral is placed in escrow. If the borrower fulfills the terms of the contract, the collateral is released and full ownership rights are returned. If the borrower defaults, the collateral is used to fulfill the contract (e.g., repay the remaining principal, interest, and penalties). There are many parties involved in this transaction: financial intermediaries, appraisers, loan servicers, asset custodians, and others.

In a smart contract, the entire agreement is specified as part of the computer program and is stored on a blockchain. The program contains the terms of the loan, as well as the specific actions it will take based on compliance (e.g., the transfer of collateral ownership in the event of default). Since the blockchain handles the faithful execution of the contract, there is no need to involve any parties beyond the borrower and lender.

### **Asset Tokenization**

The example above illustrates an important wrinkle: It may not be possible for all the elements and actions of a contract to be handled by the blockchain—particularly when it comes to collateral. If collateral is not available as an asset in the native protocol (i.e., the specific blockchain where the smart contracts exist), then, as in traditional finance, the contract necessitates a third party to provide escrow services. Naturally, this exposes the contract to counterparty risk. One solution to this problem is asset tokenization.

Asset tokenization consists of converting the ownership of an asset into digital tokens, each representing a portion of the property. If the asset exists in physical form (e.g., a house), then tokenization allows the asset to exist in a blockchain and be used for various purposes (e.g., as collateral). An important issue is how to enforce property rights stored in the blockchain for assets that exist in the physical world. This is an ongoing challenge for DeFi and one that may never be fully resolved.

Tokens also have a variety of nonfinancial applications. For example, they may grant owners voting rights to an organization. This allows for the decentralized control of institutions within a blockchain, as we describe below. Another popular application is the creation of nonfungible tokens (NFTs), which provide ownership of a digital image created and “signed” by an artist. Although the image could in principle be replicated countless times, there is only one version that is verifiably authentic. The NFT serves as a certificate of authenticity in the same way that artists' signatures ensure paintings are originals and not copies. The advantage of an NFT is the security provided by the blockchain—signatures can be forged, whereas the authenticity of the NFT is validated by a decentralized communal consensus algorithm.

### ***Decentralized Autonomous Organizations***

Smart contracts could transform the way we organize and control institutions. Applications may range from investment funds to corporations and perhaps even the provision of public goods and services.

A DAO (decentralized autonomous organization) is an organization represented by a computer code, with rules and transactions maintained on a blockchain. Therefore, DAOs are governed by smart contracts. A popular example is MakerDAO, the issuer of the stablecoin Dai, whose stakeholders use tokens to help govern decisions over protocol changes.

The concept of governance refers to the rules that balance the interests of different stakeholders of an institution. For example, a corporation's stakeholders may include shareholders, managers, creditors, customers, employees, the government, and the general public, among others. The board of directors typically plays the critical role in corporate governance. One of the main issues corporate governance is designed to mitigate is agency problems: when managers do not act in the best interest of shareholders. But governance extends beyond regulating internal matters and may, for example, manage the role of a corporation inside a community or relative to the environment.

DAOs may be created for ongoing projects, such as a DeFi entity, or for specific and limited purposes, such as public works. Because they offer an alternative governance model by encoding rules in a smart contract, they replace the traditional top-down structure with a decentralized consensus-based model. Two prominent examples—the decentralized exchange Uniswap and the borrowing and lending platform Aave—started out in the traditional way, by having their respective development teams in charge of day-to-day operations and development decisions. They eventually issued their own tokens, which distributed governance to the wider community. With varying details, holders of governance tokens may submit development proposals and vote on them.

### ***Centralized and Decentralized Exchanges***

Currently, the most popular way in which cryptoassets are traded is through a centralized exchange (CEX), which works like a traditional bank or a broker: A client opens an account by providing personal identifiable information and depositing funds. With an account, the client can trade cryptoassets at listed prices in the exchange. The client does not own these assets, however, as the exchange acts as a custodian. Hence, clients' trades are recorded on the exchange's database rather than on a blockchain. Binance and Coinbase are CEXs that offer accessibility to users. However, since they stand between users and blockchains, they need to overcome the same trust and security issues as traditional intermediaries.

Decentralized exchanges (DEXs), on the other hand, rely on smart contracts to enable trading among individuals on a P2P basis, without intermediaries. Traders using DEXs keep custody of their funds and interact directly with smart contracts on a blockchain.

One way to implement a DEX is to apply the methods from traditional finance and rely on order books. These order books consist of lists of buy and sell orders for a specific security that display the amounts being offered or bid on at each price point. CEXs also work in this way. The difference with DEXs is that the list and transactions are handled by smart contracts. Order books can be “on-chain” or “off-chain,” depending on whether the entire operation is handled on the blockchain. In the case of off-chain order books, typically only the final transaction is settled on the blockchain.

Order-book DEXs may suffer from slow execution and a lack of liquidity. That is, buyers and sellers may not find adequate counterparties, and individual transactions may affect prices too much. DEX aggregators alleviate this problem by collecting the liquidity of various DEXs, which increases the depth of both sides of the market and minimizes slippage (i.e., the difference between the intended and executed price of an order).

An automated market maker (AMM) is another way to solve the liquidity problem in DEXs. Market makers are also derived from traditional finance, where they play a central role in ensuring adequate liquidity in securities markets. AMMs create liquidity pools by rewarding users who “deposit” assets in the smart contract, which then can be used for trades. When a trader proposes an exchange of two assets, the AMM provides an instant quote based on the relative availability (i.e., liquidity) of each asset. When the liquidity pools are sufficiently large, trades are easy to fulfill and slippage is minimized. AMMs are currently the dominant form of DEXs, because they resolve the liquidity problem better than alternative mechanisms and thus provide speedier and cheaper transactions.

### ***What Are Stablecoins?***

As we described earlier, cryptocurrencies are subject to extreme exchange rate volatility, which makes them highly unsuitable as payment instruments. A stablecoin is a cryptocurrency that ties its value to an asset outside of its control, such as the U.S. dollar.<sup>14</sup> To accomplish this, the stablecoin must effectively convince its liability holders that its liabilities can be redeemed on demand (or on short notice) for U.S. dollars at par (or at some other fixed exchange rate). The purpose of this structure is to render stablecoin liabilities more attractive as payment instruments. Pegging to the U.S. dollar is attractive to people living in the U.S. because the U.S. dollar is the unit of account. Those outside the U.S. may be attracted to the product because the U.S. dollar is the world’s reserve currency. This structure serves to increase demand for the stablecoin. But why would someone want to make U.S. dollar payments using a stablecoin instead of a regular bank account?

The answer ultimately rests on which product offers its clients the services they desire at a price they find attractive. A stablecoin is likely to be attractive at the wholesale level, where firms would be able to make USD payments at each point in an international supply chain without the need for conventional banking arrangements. Stablecoins market themselves as leveraging blockchain technology to deliver safer and more efficient account management and payment processing services. These efficiency gains can then be passed along to customers in the form of lower fees. A more cynical view ascribes these purported lower costs to regulatory arbitrage (i.e., sidestepping certain costs by relocating the transaction outside of the regulatory environment), rather than technological improvements in database management.

### ***Financial Stability Concerns***

U.S. dollar-based stablecoins are similar to money market funds that peg the price of their liabilities to the U.S. dollar. They also look very much like banks *without deposit insurance*. As the financial crisis of 2007–09 showed, even money market funds are subject to runs when the quality of their assets is questioned. Unless a U.S. dollar-based stablecoin is backed fully by U.S. dollar reserves (it needs an account at the Federal Reserve for this) or by U.S. dollar bills (the maximum denomination is \$100, so this seems unlikely), it is potentially prone to a bank run. If a stablecoin

cannot dispose of its assets at fair or normal prices, it may fail to raise the U.S. dollars it needs to meet its par redemption promise in the face of a wave of redemptions. In such an event, the stablecoin would turn out to be not so stable.

If the adverse consequences of a stablecoin run were limited to the owners of stablecoins, then standard consumer protection legislation would be sufficient. But regulators also are concerned about the possibility of systemic risk. Consider, for example, the commercial paper market, where firms regularly borrow money on a short-term basis to fund operating expenses. Then consider a stablecoin (or any money market fund) with large holdings of commercial paper. A stablecoin run in this case may compel a fire sale of commercial paper to raise the funds needed to meet the wave of redemptions. This fire sale would likely have adverse economic consequences for firms that make regular use of the commercial paper market: As commercial paper prices decline, the value of commercial paper as collateral falls, and firms may find it more difficult to borrow the funds they normally access with ease. If the fire sale spills over into other securities markets, credit conditions may tighten significantly and lead to the usual woes experienced in an economic recession (missed payments, worker layoffs, etc.). These events are sufficiently difficult for a central bank to handle when the entities involved are domestic money market funds. The problem is compounded if the stablecoin is an unregulated “offshore” DAO. Will offshore stablecoins that are “too big to fail” be able to take advantage of the implicit insurance provided by central bank lender-of-last-resort operations? If so, this would be an example of how the private benefits of DeFi arise from regulatory arbitrage and not from an inherent technological advantage. This possibility presents a significant challenge for national and international regulators.

On the other hand, it may be possible for stablecoins to be rendered “run-proof” by employing smart contracts to design more resilient financial structures. For example, real-time communal monitoring of balance sheet positions is a possibility—a feature that could shine light on what are traditionally opaque financial structures.<sup>15</sup> Furthermore, because redemption policies can potentially manifest themselves as computer code, their design can be made more elaborate (state-contingent) and credible (contractual terms that can be credibly executed and not reversed). These features can potentially render stablecoins run-proof in a manner that is not possible with conventional banking arrangements.

### ***Regulators and Stablecoins***

The regulatory concerns with stablecoins are similar to age-old concerns with the banking industry. Banks are in the business of creating money and do so by issuing deposit liabilities that promise a fixed (par) exchange rate against U.S. dollar bills and dollar credits held in Federal Reserve accounts. Lower-yielding liabilities are used to acquire higher-yielding assets. Because commercial banks normally hold only a very small fraction of their assets in the form of reserves, they are called fractional reserve banks. Since the introduction of federal deposit insurance, retail-level bank runs have been practically nonexistent. Banks also have access to the Federal Reserve’s emergency lending facilities. These privileges are matched by a set of regulatory constraints on bank balance sheets (both assets and liabilities) and other business practices.

Some stablecoin issuers would undoubtedly like to base their business models on those of banks or prime institutional money market funds. The motivation is clear: Issuing low-cost liabilities to finance high-yielding assets can be a profitable business. (Until, of course, something goes wrong.)

Then, regulators and policymakers face blame for permitting such structures to exist in the first place.) This business model naturally involves non-negligible risk and could make for a potentially unstable stablecoin. As stablecoins with these properties interact with off-chain financial activity, they introduce risks that may spill over to other markets and, therefore, prompt some form of regulation.

Other stablecoin issuers are likely to focus on delivering payment services, which can be accomplished by holding only safe assets. These stablecoins would be more akin to government money market funds. Stablecoins that submit to government regulations may be permitted to hold only the safest of securities (e.g., U.S. Treasury securities). If they could, they might even hold only interest-bearing reserves, thereby becoming “narrow banks.” The business model in these cases would be based on generating profits through transaction-processing fees and/or net interest margins enhanced by what stablecoin users would hope to be a wafer-thin capital requirement.

## THE MAKEUP OF A CENTRAL BANK DIGITAL CURRENCY

The Board of Governors of the Federal Reserve System (BOG), in its recent paper “[Money and Payments: The U.S. Dollar in the Age of Digital Transformation](#),” defines a central bank digital currency (CBDC) as a “digital liability of the Federal Reserve that is widely available to the general public” (BOG, 2022, p. 3). This essentially means allowing the general public to open personal bank accounts at the central bank. How might a CBDC work?

Today, only financial institutions defined as depository institutions by the Federal Reserve Act and a select number of other agencies (including the federal government) are permitted to have accounts at the Federal Reserve. These accounts are called reserve accounts. The money balances that depository institutions hold in their reserve accounts are called bank reserves. The money account held by the federal government at the Federal Reserve is called the Treasury General Account. In a sense, a CBDC already exists, but only at the wholesale level and only for a small group of agencies. The question is whether to make it more broadly accessible and, if so, how.

As explained above, the general public already has access to a digital currency in the form of digital deposit liabilities issued by depository institutions. Most households and businesses have checking accounts with private banks. The general public also has access to a central bank liability in the form of physical currency (cash). While banks are obligated to redeem their deposit liabilities for cash on demand, deposits are not legally central bank or government liabilities. To put it another way, CBDC is (or would presumably be made) legal tender, while bank deposits represent claims to legal tender.

### ***Federal Deposit Insurance***

Bank accounts in the United States are presently insured up to \$250,000 by the Federal Deposit Insurance Corp. From a political-economic point of view, bank deposits at the retail level are a de facto government liability. Moreover, given the role of the Federal Reserve as lender of last resort, one could make a case that large-value bank deposits are also a de facto government liability. To the extent this is so, the legal status of CBDC versus bank money may not be important as far as the ultimate safety of money accounts is concerned.

### ***The Question of Counterparty Risk***

Safety is only one of the many concerns surrounding money and payments. There is also the question of how counterparty risk may affect access to funds. For example, even if money in a bank account is insured, access to those funds may be delayed if a bank is suddenly subject to financial stress. This type of risk may be one reason corporate cash managers often turn to the repo market, where deposits are typically collateralized with Treasury securities that can be readily liquidated in the event deposited cash is not returned on time. If there is no restriction on the size of CBDC accounts, the product would effectively provide fully insured money accounts for corporations with no counterparty risk. Such a product, if operated effectively, could very well disintermediate (i.e., eliminate) parts of the money market.

### ***Potential for Efficiency Gains***

There is also the question of how a CBDC might improve the overall efficiency of the payments system. This is a difficult question to answer. Proponents often compare a well-designed CBDC with the payments system as it exists today in the United States, which has not caught up to developments in other jurisdictions, including in many developing economies. The U.S. payments system, however, is evolving rapidly to a point that may make CBDC a less attractive proposition. For example, The Clearing House now offers a 24/7 [real-time payment services platform](#).<sup>16</sup> The [Federal Reserve's FedNow platform](#) will provide a similar service (BOG, 2021).

There may be no single best way to organize a payments system. A payments system is all about processing payment requests and debiting/crediting money accounts. Conceptually, bookkeeping is very simple, even if the actual implementation and operation of a payments system are immensely challenging endeavors. Any arrangement would need mechanisms that guard against fraud.

Messaging must be made fast and secure. Institutions (or DAOs) must be trusted to manage the ledgers containing money accounts and related information. Property rights over data ownership would need to be specified and enforced. Some have advocated strongly for a CBDC (e.g., Crawford, Menand, and Ricks, 2021). Others seem less enthusiastic (e.g., White, 2020; Selgin, 2021; and Waller, 2021). In principle, a private, public, or private-public arrangement could be made to work well.

Like most central banks, the Federal Reserve is designed to facilitate payments at the wholesale level. It performs a vital function and overall performs it well. Traditionally, servicing the needs of a large and demanding retail sector in the United States is left to the private sector. A CBDC could be designed to respect this division of labor in one of two ways:

1. Permit free entry into the business of “narrow banking.” This would entail granting Fed master accounts to qualified firms with the requirement that they hold only reserves (and possibly U.S. Treasury bills) as assets. In this arrangement, digital currency remains a private liability (though fully backed by reserves).
2. Grant households and firms direct access to CBDC and delegate the responsibility of processing payments at the retail level to private firms. This latter arrangement is the one described in the aforementioned BOG (2022) report on CBDC.

## CONCLUSION

The ability to write history is a tremendous power. Who should be entrusted with such power? And how should privileges be restricted to ensure honesty, accuracy, and (where needed) privacy?

All sorts of individual and group histories play an important role in coordinating economic activity, including credit histories, work histories, performance histories, educational attainment histories, and regulatory compliance histories. In this article, we have focused primarily on payment histories in the context of cryptocurrency—including the fact that histories can be fabricated and that individuals and organizations may be tempted to misrepresent their own histories for private gain at the expense of the broader community. Even relatively well-functioning societies must devote considerable resources to reconciling conflicting claims of past behavior, given the absence of reliable databases that contain those histories.<sup>17</sup>

Much of our everyday economic activity occurs outside any formal record-keeping, and societies have relied on *informal* communal record-keeping to incentivize individual and organizational behavior. Paper and electronic receipts issued for most commercial exchanges are more formal but are often incomplete and easily fabricated. More important records—for physical property, bank accounts, financial assets, licenses, certificates of education, etc.—are managed by trusted authorities.

These traditional forms of record-keeping are likely to be challenged by blockchain technology, which provides a very different model of information management and communication. Competitive pressures compel organizations and institutional arrangements to evolve in response to technological advances in data storage and communications. Consider, for example, how the telegraph, telephone, computer, and internet have transformed the way people interact and organize themselves. Advances in blockchain technology are likely to generate even more dramatic changes, though what these may be remains highly uncertain. ■

## NOTES

- <sup>1</sup> See Federal Reserve Bank of St. Louis (2014) for a video and presentation from the event.
- <sup>2</sup> See, for example, the Federal Reserve Bank of St. Louis “Cryptocurrencies and Fintech” theme page: <https://research.stlouisfed.org/publications/cryptocurrencies-and-fintech/>.
- <sup>3</sup> See also Andolfatto (2018), “Block, Cryptocurrencies and Central Bank,” the keynote presentation from a later St. Louis Fed lecture series.
- <sup>4</sup> For an accessible introduction to the technology, see Schär and Berentsen (2020).
- <sup>5</sup> See Kocherlakota (1998).
- <sup>6</sup> Relatively minor patches to the code to fix bugs or otherwise improve performance have been implemented. But certain key parameters, like the one that governs the cap on the supply of bitcoin, are likely impervious to change.
- <sup>7</sup> Beyond viewing the balances, one can also view the transaction histories of every monetary unit in the account (i.e., its movement from account to account over time since it was created).
- <sup>8</sup> It is important to note that many cryptocurrency users hold their funds via third parties to whom they relinquish control of their private keys. If an intermediary is hacked and burgled, one’s cryptocurrency holdings may be stolen. This has nothing to do with security flaws in the cryptocurrency itself—but with the security flaws of the intermediary.
- <sup>9</sup> Andolfatto and Spewak (2019).
- <sup>10</sup> Legal tender is an object that creditors cannot legally refuse as payment for debt. While deposits are claims to legal tender (they can be converted into cash on demand), they also constitute claims against all bank assets in the event of bankruptcy.
- <sup>11</sup> For a more extensive review, see Schär (2021); also see an analysis by Feenan et al. (2021).
- <sup>12</sup> See Szabo (1994 and 1997). The key idea is that contractual terms, once agreed upon, are not renegotiable and are therefore automatically executed in the future. In economic theory, so-called Arrow-Debreu securities have the same property.
- <sup>13</sup> For example, Hyperledger allows for confidential transactions, whereas Ethereum, a public network, does not. Bitcoin is also able to handle a variety of smart contracts.
- <sup>14</sup> Some stablecoins stabilize their value by pegging to the U.S. dollar, backed with non-U.S. dollar assets; Dai, for example, pegs its value to a senior tranche of other cryptoassets. See Feist (2021).
- <sup>15</sup> The opacity of financial structures is not necessary to explain bank runs. For example, the canonical model of bank runs assumes the existence of transparent balance sheets. See Diamond and Dybvig (1983).
- <sup>16</sup> See <https://www.theclearinghouse.org/payment-systems/rtp>.
- <sup>17</sup> The U.S. Chamber of Commerce [Institute for Legal Reform](#) (2018) found the cost of litigation in the United States amounted to \$429 billion, or 2.3 percent of U.S. gross domestic product, in 2016. Over 40 percent of this cost was used to pay legal, insurance, and administrative costs. These costs constitute a lower bound, as most disputes are reconciled outside the legal system.

## REFERENCES

- Andolfatto, David. “Blockchain, Cryptocurrencies and Central Banks.” Keynote presentation at the Federal Reserve Bank of St. Louis Dialog with the Fed (lecture series), August 28, 2018; <https://www.stlouisfed.org/dialogue-with-the-fed/blockchain>.
- Andolfatto, David and Martin, Fernando M. 2022 Annual Report: *The Blockchain Revolution: Decoding Digital Currencies*. Federal Reserve Bank of St. Louis, 2021; <https://www.stlouisfed.org/annual-report/2021/essay>.
- Andolfatto, David and Spewak, Andrew. “Whither the Price of Bitcoin?” Federal Reserve Bank of St. Louis, *Economic Synopses*, 2019, No. 1; <https://doi.org/10.20955/es.2019.1>.
- Board of Governors of the Federal Reserve System. “FedNOW<sup>SM</sup> Service.” Last update: April 28, 2021; [https://www.federalreserve.gov/paymentsystems/fednow\\_about.htm](https://www.federalreserve.gov/paymentsystems/fednow_about.htm).

- Board of Governors of the Federal Reserve System. "Money and Payments: The U.S. Dollar in the Age of Digital Transformation." January 2022; <https://www.federalreserve.gov/publications/files/money-and-payments-20220120.pdf>.
- Crawford, John; Menand, Lev and Ricks, Morgan. "FedAccounts: Digital Dollars." *George Washington Law Review*, January 2021, 89(1), pp. 113-172; [https://scholarship.law.columbia.edu/faculty\\_scholarship/3118/](https://scholarship.law.columbia.edu/faculty_scholarship/3118/).
- Diamond, Douglas and Dybvig, Philip. "Bank Runs, Deposit Insurance, and Liquidity." *Journal of Political Economy*, June 1983, 91(3), pp. 401-19; <http://links.jstor.org/sici?doi=0022-3808%28198306%2991%3A3%3C401%3ABRDIAL%3E2.0.CO%3B2-Z>.
- Federal Reserve Bank of St. Louis. "Bitcoin and Beyond: The Possibilities and the Pitfalls of Virtual Currencies." Dialog with the Fed (lecture series), March 30, 2014; <https://www.stlouisfed.org/dialogue-with-the-fed/the-possibilities-and-the-pitfalls-of-virtual-currencies>.
- Feenan, Sara; Heller, Daniel; Lipton, Alexander; Morini, Massimo; Ram, Rhomaios; Sams, Robert; Swanson, Tim; Yong, Stanley and Barrero Zalles, Diana. "Decentralized Financial Market Infrastructures: Evolution from Intermediated Structures to Decentralized Structures for Financial Agreements." *Journal of FinTech*, 2021, 1(2); <https://doi.org/10.1142/S2705109921500024>.
- Feist, Dankrad. "On Supply and Demand for Stablecoins." September 27, 2021; <https://dankradfeist.de/ethereum/2021/09/27/stablecoins-supply-demand.html>.
- Goodwin, Keith. "Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010." Federal Reserve History, July 21, 2010; <https://www.federalreservehistory.org/essays/dodd-frank-act>.
- Kocherlakota, Narayana. "The Technological Role of Fiat Money." Federal Reserve Bank of Minneapolis *Quarterly Review*, Summer 1998; <https://doi.org/10.21034/qr.2231>.
- Schär, Fabian. "Decentralized Finance: On Blockchain- and Smart Contract-Based Financial Markets." Federal Reserve Bank of St. Louis *Review*, Second Quarter 2021, 103(2), pp. 153-74; <https://doi.org/10.20955/r.103.153-74>.
- Schär, Fabian and Berentsen, Aleksander. *Bitcoin, Blockchain, and Cryptoassets: A Comprehensive Introduction*. MIT Press, 2020; <https://mitpress.mit.edu/books/bitcoin-blockchain-and-cryptoassets>.
- Selgin, George. "Central Bank Digital Currency as a Potential Source of Financial Instability." Cato Institute *Cato Journal*, Spring/Summer 2021; <https://www.cato.org/cato-journal/spring/summer-2021/central-bank-digital-currency-potential-source-financial-instability>.
- Steelman, Aaron. "Full Employment and Balanced Growth Act of 1978 (Humphrey-Hawkins)." Federal Reserve History, October 1978; <https://www.federalreservehistory.org/essays/humphrey-hawkins-act>.
- Szabo, Nick. "Smart Contracts." 1994; <https://www.fon.hum.uva.nl/rob/Courses/InformationInSpeech/CDROM/Literature/LOTwinterschool2006/szabo.best.vwh.net/smарт.contracts.html>.
- Szabo, Nick. "The Idea of Smart Contracts." Satoshi Nakamoto Institute, 1997; <https://nakamotoinstitute.org/the-idea-of-smart-contracts/>.
- U.S. Chamber of Commerce Institute for Legal Reform. "Cost and Compensation of the U.S. Tort System." October 24, 2018; <https://instituteforlegalreform.com/research/costs-and-compensation-of-the-u-s-tort-system/>.
- Waller, Christopher. "A CBDC: A Solution in Search of Problem." Presented at the American Enterprise Institute, Washington, DC (via webcast), August 2, 2021; [https://www.federalreserve.gov/news\\_events/speech/waller20210805a.htm](https://www.federalreserve.gov/news_events/speech/waller20210805a.htm).
- White, Larry. "Should the U.S. Government Create a Token-Based Digital Dollar?" Alt-M.org, June 19, 2020; <https://www.alt-m.org/2020/06/19/should-the-u-s-government-create-a-token-based-digital-dollar/>.

# Increasing Employment by Halting Pandemic Unemployment Benefits

Iris Arbogast and [Bill Dupor](#)

In mid-2021, 26 states halted participation in all or some federal emergency unemployment benefits (EUB) programs before those programs' federal funding lapsed. This article uses this asynchronous EUB cessation between early- and late-halting states to estimate the causal impact of benefit cessation on employment. We find that cessation increased employment by 29 persons for every 100 (pre-halt) EUB recipients. Expressed as a number of jobs, if all states had halted EUB in June, September employment would have been 3.4 million persons higher relative to a no-halt counterfactual. Late-halting states could have significantly accelerated their states' jobs recoveries in the second half of 2021 through early program cessation. (JEL J65, E24)

Federal Reserve Bank of St. Louis *Review*, Third Quarter 2022, 104(3), pp. 166-77.  
<https://doi.org/10.20955/r.104.166-77>

**A**s part of the 2020 CARES Act, the federal government augmented regular state unemployment insurance (UI) programs with several temporary measures: a \$600 weekly add-on for UI recipients, extended eligibility to persons who otherwise would not have been covered by their state programs (e.g., gig and contractor workers), and the extension of benefits beyond the duration of those provided by regular state programs. These emergency unemployment benefits (EUB) were renewed in later legislation, with the only major change being a reduction in the add-on from \$600 to \$300 per week.

In late winter and spring 2021, job vacancies in the United States soared to near historic highs while employment growth slowed. This pattern for vacancies and employment was observed across regions and sectors. The Federal Reserve Beige Books from those months provide accounts of business owners lamenting difficulty in filling job vacancies. Moreover, business owners nationwide linked this difficulty with the historic generosity of unemployment benefits.

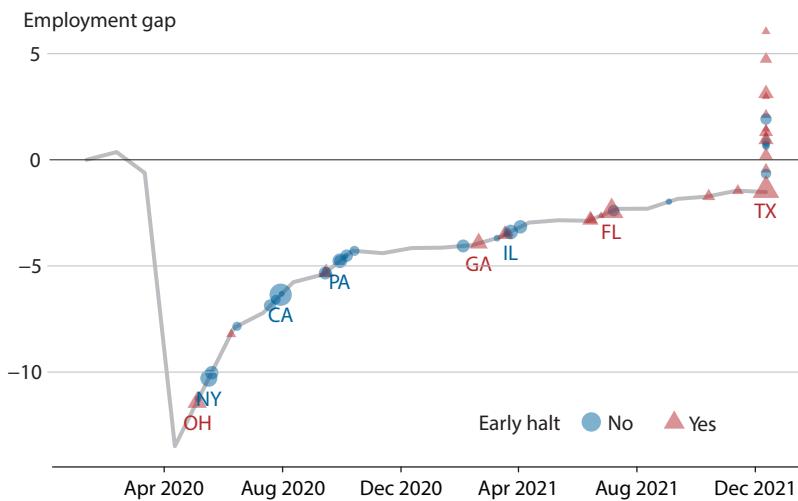
Over a period of several weeks, 26 governors announced that their states would halt participation in these EUB programs either partially or fully.<sup>1</sup> Twenty states halted program participation between June 19 and July 3. Four states did so on June 12 as did two states later in July. After September 9, the remaining states ended participation because the programs' federal funding lapsed.

Iris Arbogast is a research associate and Bill Dupor is vice president and economist at the Federal Reserve Bank of St. Louis.

© 2022, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

**Figure 1**

**Aggregate Employment Gap Path, January 2020–December 2021, and State-Level May 2021  
Employment Gaps Placed Along the Aggregate Gap Path**



NOTE: The employment gap equals the deviation of employment at a point in time from employment in January 2020. The four largest early-halting and late-halting states are labeled with postal abbreviations. The sizes of the circles and triangles represent the relative pre-pandemic employment levels.

While both Republican- and Democrat-led states saw high job openings and slowed employment growth,<sup>2</sup> with one exception, only Republican governors implemented the policy change before funding lapsed. This politically driven policy variation provides a source of identification to assess the jobs effect of terminating EUB. Our outcome variable is the four-month change in employment, scaled by the lagged number of EUB recipients. We run a panel least-squares regression of the outcome on a dummy indicator for the halt month and include several alternative sets of control variables. The model is identified by our assumption that, conditional on our control variables, the regression error term is orthogonal to the halt-month indicator.

We find that, as a result of cessation, employment increased by 29 persons for each 100 individuals receiving these benefits pre-cessation. We show this effect is statistically significant and robust to controlling for a battery of additional covariates. Expressed as an aggregate jobs effect, our estimate implies that had all states terminated benefits in June 2021, employment would have been 3.4 million persons higher in September 2021 relative to a no-halt counterfactual.

## 1 STATE-LEVEL EMPLOYMENT DYNAMICS BEFORE HALTING BEGINS

In this section, we document an important difference between early- and late-halting states: pre-cessation employment dynamics. Figure 1 demonstrates that early halters were further along in their employment recoveries than late halters in the period immediately preceding the first set of states halting benefits. First, the solid gray path plots the log of the ratio of national employment in each month to national employment in January 2020 multiplied by 100. Thus, a value of -10

implies that, in the respective month, national employment was 10 percent below its pre-pandemic level. The line gives a sense of the “average employment trajectory” along the recovery path. The figure indicates that in the first few months following the employment trough, national employment recovered very quickly, after which the pace of the recovery slowed as the nation moved closer and closer to closing its employment gap.

On the same figure, we also plot the corresponding variable for each state in May 2021. For each state, we locate its point on the national path to give a sense of how far the state had progressed in its recovery up to that date. States that are off the national path had recovered further by May 2021 than the corresponding national value for December 2021. The sizes of the blue circles (late halters) and the red triangles (early halters) indicate the relative pre-pandemic employment levels across states. We label the four largest states of each type with their postal codes.

The figure starkly shows that, immediately prior to the first wave of benefit terminations, early halters were much closer to their pre-pandemic employment levels on average than late halters. The early halters had much smaller employment gaps even before the policy interventions began than the late halters did.

The immediate takeaway from the figure is that one should not interpret states’ asynchronous cessation timing as a pure natural experiment. In this article, we take the view that some conditioning is required to infer a causal treatment effect from a cross-state comparison of employment for this episode. Our analysis will address systematic differences across states in two ways we describe below.

Our outcome variable will be the scaled four-month change in employment. We use the four-month change because many continued to receive benefits several months past cessation (due to delayed filing and administrative delays) and also because a share of recipients may have built up a few months of savings to finance not working following their final benefit payment. Also, we will include several one-month employment changes to control for the pattern observed in Figure 1: Along the transition path, employment growth slows as states close their remaining employment gaps.

Next, another implication of Figure 1 is that—since early halters had smaller employment gaps—the early halters also had smaller per capita shares of the population collecting benefits. In fact, EUB recipients per capita in May 2021 in late-halting states were nearly double those in early-halting states. To adjust for this difference across states, we use a novel form of scaling of the outcome variable. We scale the change in employment in a state by the lagged number of EUB recipients in that state, as described in the next section.

## 2 DATA, MODEL, AND RESULTS

The sample consists of 46 U.S. states and Washington, D.C. The underlying data are monthly and cover December 2020 through December 2021. First, let  $Y_{i,t}$  equal the number of employed persons 16 years of age and older in state  $i$  at month  $t$ . These non-seasonally adjusted data are from Current Population Survey (CPS) microdata, which we sum to the corresponding state levels. We discuss alternative employment measures after presenting our benchmark findings. We exclude Alabama, Georgia, South Carolina, and Vermont because the U.S. Bureau of Labor Statistics (BLS) does not provide complete EUB data for these states.

To construct our outcome variable, we divide the change in employment by the number of EUB recipients. To construct our recipient measure, we first calculate for each state the sum of weeks paid on regular state programs, Pandemic Unemployment Assistance (PUA), and Pandemic Emergency Unemployment Compensation (PEUC), which are available from the Employment and Training Administration (ETA) 5159 reports.<sup>3</sup> To map the number of weeks paid to the number of recipients, we divide the number of weeks by four. Next, we multiply this raw recipient number by 0.8 to construct our recipient number. This adjustment is necessary because, according to Census Pulse Surveys from the time, about 20 percent of surveyed UI recipients reported engaging in some work while collecting UI. If an individual losing benefits had already been working some hours pre-cessation, then their survey response would be “employed” both before and after the state terminated benefits. Throughout the article, “recipients” refers to non-working recipients.

Our outcome variable is then

$$(1) \quad y_{i,t+\delta} = 100 \times \left( \frac{Y_{i,t+\delta} - Y_{i,t-1}}{\text{Recipients}_{i,t-5}} \right).$$

Importantly, we use the fifth lag of the number of beneficiaries in the denominator of the dependent variable. For the response horizon of interest, the denominator is (in every period) predetermined with respect to the halt month. Thus, the response to the halt shock arises from the dependent variable’s numerator, that is, the change in employment.

The independent variable of interest,  $h_{i,t}$ , equals 1 if state  $i$  ended participation in all or some of the EUB programs in month  $t$  and zero otherwise. The CPS survey occurs during the calendar week containing the 12th day of the respective month. With this in mind, for each state we choose the halt month as the month in which the 12th day is closest to the date the state ended benefits. For example, 24 states and Washington, D.C., terminated benefits on September 9; therefore, we set September as the halt month in these cases.

Our use of lagged recipients in the denominator of the dependent variable is motivated by the following overarching question in public discourse during the episode: When a state halts benefits, how many recipients losing benefits will become employed? The outcome variable we choose is an “employment yield” for those losing benefits, which squarely addresses this question. If instead of the change in employment per beneficiary we were to use employment growth as the outcome variable, we would be answering a *different* question than the one posed above.

To further see the usefulness of our construct, consider the following extreme example. If a state had zero beneficiaries when it announced a halt to benefits, then that state’s “return to work” channel would be absent.

Our regression equation is

$$(2) \quad y_{i,t+3} = \gamma_i + \psi_t + \phi h_{i,t} + \beta' X_{i,t-1} + \eta_{i,t+3}.$$

As explained in the previous section, following the employment trough in spring 2020, states generally followed a similar dynamic path for employment, although their initial gaps and transition rates differed substantially; therefore, we condition on these dynamics in our estimation.

The coefficient  $\phi$  is the causal impact of halting benefits on the employment change per 100 EUB recipients between  $t - 1$  and  $t + 3$ .  $\gamma_i$  and  $\psi_t$  are state and time fixed effects, respectively. In our

**Table 1****Jobs Effect of Benefit Termination: Four-Month Employment Change Per 100 Emergency Benefit Recipients**

|                         | (1)<br>Benchmark   | (2)<br>Drop lags  | (3)<br>Drop FE     | (4)<br>Placebo     |
|-------------------------|--------------------|-------------------|--------------------|--------------------|
| Termination             | 28.82**<br>(11.19) | 22.03*<br>(11.30) | 29.02***<br>(9.37) | 5.13<br>(7.00)     |
| Emp change, 1-month lag | -0.69***<br>(0.08) |                   | -0.54***<br>(0.08) | -0.68***<br>(0.08) |
| Emp change, 2-month lag | -0.55***<br>(0.11) |                   | -0.44***<br>(0.12) | -0.54***<br>(0.11) |
| Emp change, 3-month lag | -0.52***<br>(0.15) |                   | -0.38***<br>(0.14) | -0.52***<br>(0.15) |
| Number of observations  | 470                | 470               | 470                | 470                |

NOTE: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . FE, fixed effects; emp, employment. Regressions include state and time fixed effects (not reported) and are weighted by the pre-pandemic (1/2020) employment level. Standard errors are computed using state-level clustering. Sample covers 12/2020 to 12/2021. Sample excludes Alabama, Georgia, South Carolina, and Vermont because of unavailability of EUB recipient data.

benchmark specification,  $X_{i,t-1}$  contains three lags of the one-month change in employment scaled by the lagged number of recipients. We estimate equation (2) using least squares in which we weight each observation by its pre-pandemic (January 2020) employment level. We compute standard errors using state-level clustering.<sup>4</sup>

Table 1 reports estimates of equation (2). Column 1, our benchmark specification, indicates that halting EUB increased employment by 28.8 persons for each 100 (pre-halt) recipients. The estimate is statistically different from zero at the 5 percent level. Thus, halting benefits provided a substantial boost to state employment. By delaying the end of EUB, late-halting states delayed part of their states' employment recoveries dramatically.

To express this effect as the number of jobs created, note that in January 2021, five months prior to the treatment, the total number of EUB recipients was about 11.8 million. Thus, had all 47 states in our sample halted EUB in June, national employment in September would have been 3.4 million persons higher relative to a “no early halt” counterfactual.<sup>5</sup> In actuality, the 23 early-halting states for which we have data had about 3.3 million EUB recipients five months prior to their halt dates. Thus, the jobs effect of the 23 early-halter initiatives was to increase those states’ combined employment by 950,000 persons.

Column 2 of Table 1 modifies the benchmark by dropping the lagged employment changes as controls. This modification reduces the employment effect from 28.8 jobs to 22.0 jobs. This occurs because being an early-halting state is correlated with having a smaller remaining employment gap, and having a smaller remaining employment gap implies that future employment growth tends to be low. Thus, failing to condition on pre-cessation state employment dynamics downwardly biases the jobs effect estimate.

In our benchmark specification, we follow the common practice of adding fixed effects to the panel regression. For example, state fixed effects would control for different trend behavior in

**Table 2****Jobs Effect of Benefit Termination: Four-Month Employment Change Per 100 Emergency Benefit Recipients, Impact of Changing Beginning Month of Sample**

|                        | (1)<br>Start 12/2020<br>(benchmark) | (2)<br>9/2020      | (3)<br>10/2020     | (4)<br>11/2020     | (5)<br>1/2021      |
|------------------------|-------------------------------------|--------------------|--------------------|--------------------|--------------------|
| Termination            | 28.82**<br>(11.19)                  | 28.20**<br>(10.88) | 28.30**<br>(10.97) | 28.60**<br>(11.04) | 29.00**<br>(11.31) |
| Number of observations | 470                                 | 610                | 564                | 517                | 423                |

NOTE: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . Regressions include state and time fixed effects as well as three lags of the one-month change in employment (not reported) and are weighted by the pre-pandemic (1/2020) employment level. Standard errors (in parentheses) are computed using state-level clustering. Each sample ends in 12/2021. Sample excludes Alabama, Georgia, South Carolina, and Vermont because of unavailability of EUB recipient data.

employment growth. Strict exogeneity of the halt-month variable would mean that removing state fixed effects should have little effect on our results. In Column 3 we report results without month and state fixed effects and find little change in the employment effect.

Next, as a placebo exercise, we randomly reassign halt months across states, with a uniform distribution from June to September, to create a new termination month variable. Column 4 reports the benchmark results except we replace the actual halt variable with this placebo variable, suggesting that our instrument is not estimating a spurious jobs effect.

The starting month of the sample is dictated by our intent to capture employment dynamics using a sufficiently long sample as well as to build a model for the pandemic period. The latter concern limits how far back our period of estimation can reasonably extend. Recall that we include as controls three lags of the one-month change in employment scaled by the number of recipients. We lag the recipients variable in the denominator such that, for every state in every month, the variable is measured in a pre-treatment month. To accomplish this, the variable is lagged by five periods. As such, we cannot start a sample before September 2020, as data for EUB start in May 2020 in many states.

We start our sample in December for the benchmark results in order to avoid using recipient data from the early months of the pandemic, before recipient numbers had stabilized. For example, California's number of recipients more than doubled between May and August 2020. Table 2 shows that our results are robust to changes in the start dates of the sample used. Estimates from samples starting in September, October, and November 2020 and January 2021 compared with the December 2020 results vary by less than one job per 100 benefit recipients.

Next, Table 3 shows that recognizing cross-state differences in the number of EUB recipients is important in understanding our results; ignoring them biases the jobs effect downward. First, Column 1 restates the benchmark estimates. In Column 2, our dependent variable's definition deviates from the benchmark model. Instead of scaling employment changes by the lagged number of recipients, Column 2 scales by lagged state employment multiplied by the national recipients-to-population ratio.<sup>6</sup> As such, we treat each state as if it had the same number of recipients (after controlling for state population). In this case, the jobs coefficient is 14.43, falling roughly one-half from the benchmark specification.

**Table 3****Jobs Effect of Benefit Termination: Four-Month Employment Change Per 100 Emergency Benefit Recipients, Effect of Changing Variable Used to Scale Employment Changes**

|                        | (1)<br>Scale by claims<br>(benchmark) | (2)<br>Scale by<br>average claims | (3)<br>Scale by<br>PP emp |
|------------------------|---------------------------------------|-----------------------------------|---------------------------|
| Termination            | 28.82**<br>(11.19)                    | 14.43**<br>(6.41)                 | 1.17**<br>(0.50)          |
| Number of observations | 470                                   | 470                               | 470                       |

NOTE: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . PP emp, pre-pandemic employment. Regressions include state and time fixed effects as well as three lags of the one-month change in employment (not reported) and are weighted by pre-pandemic (1/2020) employment level. Standard errors (in parentheses) are computed using state-level clustering. Sample covers 12/2020 to 12/2021. Sample excludes Alabama, Georgia, South Carolina, and Vermont because of unavailability of EUB recipient data. See text for dependent variable construction in columns 2 and 3.

**Table 4****Jobs Effect of Benefit Termination: Four-Month Employment Change Per 100 Emergency Benefit Recipients, Effect of Using Alternative Employment Measures**

|                        | (1)<br>CPS non-SA<br>(benchmark) | (2)<br>CPS SA     | (3)<br>CES non-SA | (4)<br>CES SA  |
|------------------------|----------------------------------|-------------------|-------------------|----------------|
| Termination            | 28.82**<br>(11.19)               | 25.73*<br>(10.78) | 3.17<br>(3.90)    | 0.98<br>(1.35) |
| Number of observations | 470                              | 470               | 470               | 470            |

NOTE: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . CPS, Current Population Survey; CES, Current Employment Statistics; SA, seasonally adjusted. Regressions include state and time fixed effects as well as three lags of the one-month change in employment (not reported) and are weighted by the pre-pandemic (1/2020) employment level. Standard errors (in parentheses) are computed using state-level clustering. Sample covers 12/2020 to 12/2021. Sample excludes Alabama, Georgia, South Carolina, and Vermont because of unavailability of EUB recipient data.

In Column 3, we scale employment changes by pre-pandemic employment, instead of the number of recipients, to construct the dependent variable. This is a second way, beyond the Column 2 specification, to ignore cross-state differences in the number of recipients. The jobs coefficient falls to 1.17. In this case, the coefficient is interpreted, roughly, as a growth rate response rather than a per 100 persons response. The total jobs effect implied by Column 3 is 1.73 million ( $= 0.0117 \times 148$  million: January 2020 employment for the 47 states in our sample). This is roughly one-half the corresponding impact from our benchmark specification.

Table 4 reports the effect of changing the employment measure used. The benchmark specification uses non-seasonally adjusted data because we do not want to exclude seasonal hires from the jobs effect of terminating benefits. Column 2 of Table 3 uses the benchmark specification's employment series, except we seasonally adjust using the U.S. Census Bureau's X-13 procedure; the seasonal adjustment has minimal impact on the coefficient of interest. Two alternatives to the state-aggregated CPS microdata are employment from the Current Establishment Survey (CES) and the Local Area Unemployment Statistics (LAUS) datasets.

**Table 5****Jobs Effect of Benefit Termination: Four-Month Employment Change Per 100 Emergency Benefit Recipients, Effect of Adding Additional Controls**

|                        | (1)<br>(Benchmark) | (2)                | (3)                | (4)                | (5)                | (6)                | (7)                |
|------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| Termination            | 28.82**<br>(11.19) | 28.95**<br>(11.09) | 27.39**<br>(10.63) | 28.29**<br>(11.36) | 28.82**<br>(11.17) | 27.75**<br>(10.56) | 27.67**<br>(10.45) |
| Mask use               |                    | 1.13<br>(16.88)    |                    |                    |                    | 3.75<br>(16.93)    | 11.42<br>(16.55)   |
| Stringency index       |                    |                    | -6.10<br>(5.94)    |                    |                    | -6.36<br>(5.91)    | -6.94<br>(5.88)    |
| COVID-19 cases         |                    |                    |                    | -9.80<br>(17.49)   |                    |                    | -14.80<br>(18.23)  |
| COVID-19 deaths        |                    |                    |                    |                    | -0.16<br>(22.08)   |                    |                    |
| Number of observations | 470                | 470                | 470                | 470                | 470                | 470                | 470                |

NOTE: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.1$ . Regressions include state and time fixed effects as well as three lags of the one-month change in employment (not reported) and are weighted by the pre-pandemic employment level (in January 2020). Standard errors (in parentheses) are computed using state-level clustering. Sample covers December 2020 to December 2021. Sample excludes Alabama, Georgia, South Carolina, and Vermont because of unavailability of EUB recipient data.

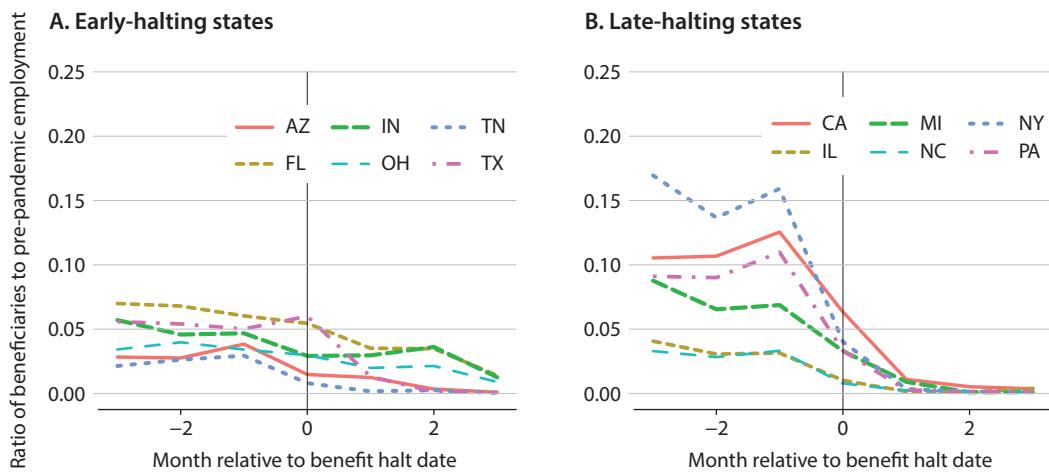
We use the household-based CPS data rather than the firm-based CES data because the latter excludes contractors and gig workers. More than one-half of EUB recipients in May 2021 were collecting PUA benefits, a program for contractors and gig workers. Using the establishment-based data would likely bias our results downward substantially if pre-recession unemployed contractors and gig workers tended to return to the same work upon taking jobs. Results using non-seasonally adjusted CES data are reported in Column 3 of Table 4, and results for seasonally adjusted data are reported in Column 4.

We use aggregated micro-level data from the CPS instead of the model-based LAUS data from the BLS. The LAUS uses data from the CPS as well as from the CES and state UI systems as inputs to time-series models. The BLS noted that the COVID-19 pandemic created an unprecedented challenge to the BLS's LAUS model estimation due to the magnitude and scope of outliers. According to the BLS (2021), in a BLS FAQ section for the LAUS, the model estimates were biased by the influence of pre-pandemic data during the pandemic.<sup>7</sup>

Table 5 adds a series of alternative control variables that might potentially explain the different outcomes between early and late halters: the mask-usage rate, a lockdown intensity index, COVID-19 cases, and COVID-19 deaths. We introduce scaled versions of each variable expressed as four-month changes between months  $t - 4$  and  $t$ . We measure lockdown intensity using an index from the Oxford COVID-19 Government Response Tracker that averages over indicator variables for containment policies, closure policies, and public information campaigns. Mask-usage data are from the Institute of Health Metrics and Evaluation and indicate the percent of the population reporting always wearing a mask when leaving home. Case and death data are from the *New York Times*, based on reports from state and local health agencies.

**Figure 2**

**Ratio of Beneficiaries to Pre-pandemic Employment for 12 States in the Month of and Months Surrounding Benefit Cessation**



NOTE: Panel A reports the recipient ratio for the six early-halting states with the largest populations, and Panel B reports the recipient ratio for the six late-halting states with the largest populations. States are labeled with postal abbreviations.

We standardize each regressor to have mean zero and unit variance. Thus, the reported coefficient on a given control variable should be interpreted as the four-month change in employment per 100 EUB pre-halt recipients in response to a one-standard-deviation increase in that control variable. For both levels (results available on request) and changes, the benchmark results do not change by more than two persons per 100 emergency benefit recipients. This likely occurs because the covariates at the state level vary only slightly over time and state-level differences are controlled for with fixed effects.

### 3 BENEFITS PAID AFTER PROGRAM TERMINATION

In this section, we document that many states, even after halting EUB, continued to pay out benefits for several months. For example, Alaska paid about 21,400 weeks of PUA benefits to recipients in May (the month before halting) and roughly 12,200 weeks in August. This persistence was possible because federal law permitted individuals to submit claims if a past unemployment spell occurred when the PUA program was in effect. Also, backlogs in some states may have played a role in payment delays.

Figure 2 plots the ratio of the sum of PUA and PEUC recipients relative to pre-pandemic employment for six early- and six late-halting states. The figure indicates that many states experienced only a gradual decline in EUB payouts following the termination of their program participation.

Even if an individual received benefits from a state for a past unemployment spell, program termination meant that—going forward—a potential disincentive for supplying labor had been lifted. The termination channel should lead to increased employment in the months after the termination date. However, some individuals continued to receive benefits. Liquidity constrained

consumers may have been able to finance consumption and use those benefits to shift their time away from work and toward non-market activities.

In another article (Arbogast and Dupor, 2022), we take a different approach. Using the same underlying data as in this article, we regress changes in employment on the reduction in the number of beneficiaries, using the timing of benefit termination as an instrument. In that article, we find that employment increases by 37 persons for every 100 persons who, on net, stop receiving EUB. As such, the approach taken in the current article may underestimate the stimulative jobs effect of EUB cessation.

## 4 RELATED RESEARCH

There is a large body of empirical research examining the incentive effects of unemployment on the labor supply going back at least 50 years. A long literature review is beyond the scope of a short article such as this one. Instead, we describe a few particularly relevant articles on UI benefit termination and extension during the two most recent recessions.

During the 2007-09 recession, unemployment benefits were extended through two temporary federal programs. One extended benefits up to 53 weeks depending on the state and expired in 2013. The other extended benefits for between 13 and 20 weeks in states with high unemployment rates. Farber, Rothstein, and Valletta (2015) study changes in benefit lengths resulting from each program's end, using individual-level CPS data. They estimate that availability of UI to an unemployed worker reduced the probability of exiting unemployment by 3.5 percentage points from 2008 to 2011 and 2.7 percentage points from 2012 to 2014 but do not find significant impacts on the likelihood of transitioning from unemployment to employment. They conclude that the primary effect of phasing out the benefits programs was on labor force attachment.

Coombs et al. (2021) study the impact of EUB early termination during the same time period as this article. They use individual-level data on bank transactions from a sample of low-income and credit-constrained workers to examine the impact of the policy change. They use a difference-in-difference approach comparing UI recipients in early-halting and non-early-halting states and reweight this sample for people in non-early-halting states to match the unemployment duration in the early-halting sample. They find a 4.4-percentage-point relative increase in the probability of job finding through the first week of August 2020 in states where EUB were halted early.

Several authors look at how CPS unemployment-to-employment transition rates differ between halting and non-halting states and use these rates as a measure of the treatment effect of early benefit termination (e.g., Holzer, Hubbard, and Strain, 2021). However, there were nearly twice as many EUB recipients measured by the 5159 data as there were unemployed measured by the CPS. This difference is due, at least in part, to the fact that many EUB recipients had no work-search requirements during much of the early pandemic period. Our observation motivates us to use the number of EUB recipients as the denominator in our treatment variable.

In contrast to the above articles that use individual-level data, we use data aggregated to the state level. Using state-level data brings us closer to identifying a macroeconomic employment effect, which is our primary interest, than one would find using individual-level data in the presence of cross-individual spillovers. Using individual-level data may miss important spillovers that could be either positive or negative. For example, if a person increases consumption upon losing emergency

benefits and taking a job (e.g., from spending on clothes and fuel and car maintenance for traveling to and from work), then this increase in consumption may drive up demand for goods in the local economy. This increase may in turn stimulate employment in the state indirectly. This indirect positive effect would be missed in an individual-level regression. Thus, the estimate from that regression would provide a downwardly biased estimate of the macro jobs effect of halting UI benefits.

Indeed, the results that we find are larger than those in the individual-level articles we discuss above. Farber, Rothstein, and Valletta (2015) find no increase in the probability of job finding in the 2007–09 recession. Coombs et al. (2021) find only a small effect; however, it is not directly comparable to our results, because they use job-finding probabilities as an outcome.

One could envision negative spillovers, on the other hand, that would reverse the direction of the bias. By working with data aggregated to the state level, we are at least partially immunized against this concern. This is because within-state spillovers are subsumed by aggregating the outcome variable to the state level.<sup>8</sup>

This article estimates that employment increased by 29 persons for each 100 pre-halt recipients in a state. We note, however, that this does not necessarily mean that 71 persons stopped receiving benefits and/or were no longer making claims for past unemployment spells. Our use of state-level employment data implies that we cannot track individuals receiving EUB before cessation to see whether these persons were the ones that boosted employment or alternatively whether employment increased through a more indirect channel. Rather, our outcome variable is the net change in total state employment. Parsing the extent to which the employment increase comes from the pre-treatment number of EUB recipients, the unemployed not collecting EUB, or those out of the labor force is not possible using our methodology.

## 5 CONCLUSION

The exogenous variation resulting from the decisions of about one-half of state governors to cease providing EUB in June and July 2021 provides a valuable opportunity to identify EUB programs' short-term causal effect on state-level employment. Our estimate indicates a 29-person increase in state employment—within a few months—for every 100 (pre-halt) EUB recipients. The jobs effect is statistically significant and robust to allowing for a number of controls. There remains a great deal of work to be done on this episode. Useful research might examine the effect of halting benefits on, for example, the employment response of older individuals, labor force participation, job openings, quits, and hires. ■

## NOTES

- <sup>1</sup> Montana Governor Greg Gianforte announced his state's plan on May 4, 2021. On May 6, South Carolina Governor Henry McMaster set forth a similar plan. By May 17, 21 total states had laid out plans to halt benefits.
- <sup>2</sup> Beige Book reports discussing worker shortages and linking them to unemployment benefits span both Federal Reserve Bank regions with primarily non-halting states (e.g., the New York Fed) and those with primarily halting states (e.g., the Atlanta Fed).
- <sup>3</sup> We include regular state programs in this measure because a regular program recipient also received the \$300 add-on from the EUB program in halting states before those states ended participation.
- <sup>4</sup> Given our panel's short time dimension, we do not attempt to adjust standard errors for potential serial correlation in our reported results. In results available upon request, we compute standard errors—applying a Newey-West correction—and find the adjustment has little effect.
- <sup>5</sup> Recall from equation (1) that recipients are lagged by five months in the outcome variable; thus, we use January recipient data for our June halting counterfactual.
- <sup>6</sup> Specifically, the denominator becomes  $P_{i,t-5} / \left( \sum_i Recipients_{i,t-5} / \sum_i P_{i,t-5} \right)$ . Here,  $P$  is state population.
- <sup>7</sup> The FAQ section states that "the regression coefficients showed some flexibility in real time between the CPS and covariate inputs, but not enough to prevent bias due to the influence of past data."
- <sup>8</sup> Note that our approach does not account for potential cross-state spillovers. These spillovers imply our state-level estimates would provide a biased estimate of the national effects of halting EUB. Thus, using state-level data is not sufficient to completely overcome the spillover issue. For a methodology to conduct causal inference regarding aggregate, spillover, and local effects in a unified framework, see Conley et al. (2021).

## REFERENCES

- Arbogast, I. and Dupor, B. "The Jobs Effect of Ending Pandemic Unemployment Benefits: A State-Level Analysis." Working Paper 2022-10A, Federal Reserve Bank of St. Louis, 2022; <https://doi.org/10.20955/wp.2022.010>.
- Conley, T.; Dupor, B.; Ebsim, M.; Li, J.C. and McCrory, P. "The Local-Spillover Decomposition of an Aggregate Causal Effect." Working Paper 2021-006A, Federal Reserve Bank of St. Louis, 2021; <https://doi.org/10.20955/wp.2021.006>.
- Coombs, K.; Dube, A.; Jahnke, C.; Kluender, R.; Naidu, S. and Stepner, M. "Early Withdrawal of Pandemic Unemployment Insurance: Effects on Earnings, Employment and Consumption." Working paper, University of Toronto, August 2021.
- Farber, H.; Rothstein, J. and Valletta, R. "The Effect of Extended Unemployment Insurance Benefits: Evidence from the 2012-2013 Phase-Out." *American Economic Review*, 2015, 105(5), pp. 171-76; <https://doi.org/10.1257/aer.p20151088>.
- Holzer, H.; Hubbard, R. and Strain, M. "Did Pandemic Unemployment Benefits Reduce Employment? Evidence from Early State-Level Expirations in June 2021." NBER Working Paper 29575, National Bureau of Economic Research, 2021; <https://doi.org/10.3386/w29575>.
- U.S. Bureau of Labor Statistics. "Questions and Answers on Changes to Model-Based Estimation in the Local Area Unemployment Statistics (LAUS) Program." 2021; <https://www.bls.gov/lau/gen-5-changes-in-2021.htm>.

# The Murky Future of Monetary Policy

Mickey D. Levy and Charles Plosser

In August 2020, the Federal Reserve unveiled its new strategic framework. One major objective of the Fed was to address its concerns over the potential consequences for the conduct of monetary policy when the policy rate was constrained by its effective lower bound. This article concludes that there are significant flaws in the new strategy and that it encourages a more discretionary approach to monetary policy and increases the risks of policy errors. The new framework is an overly complex and asymmetric flexible average inflation targeting scheme that introduces a significant inflationary bias into policy and expands the scope for discretion by broadening the Fed's employment mandate to "maximum inclusive employment." In a postscript, the article describes how quickly the flaws have been revealed and urges a reset toward a more systematic and coherent strategy that is transparent and broadly understood by the public. (JEL E52)

Federal Reserve Bank of St. Louis *Review*, Third Quarter 2022, 104(3), pp. 178-88.

<https://doi.org/10.20955/r.104.178-88>

---

## INTRODUCTION

The Federal Reserve first published a "Statement on Longer-run Goals and Monetary Policy Strategy" in January 2012.<sup>1</sup> The purpose was to enhance transparency and accountability by clarifying its interpretation of the statutory mandates established by Congress. The two key elements of that effort were to formally establish a 2 percent longer-run inflation target as being consistent with its price stability mandate and to stress that it was not appropriate to establish a quantitative target for maximum employment, as such a target was not directly observable and was influenced by many factors unrelated to monetary policy. This document was frequently referred to by the Fed as the "consensus statement."

During the ensuing eight years, the economy continued its recovery from the 2007-09 recession. The unemployment rate fell to a 50-year low of 3.5 percent prior to the pandemic and government shutdowns of 2020. The inflation rate remained modestly below the Fed's adopted inflation target, averaging about 1.4 percent over the 2012-19 period. In response to concerns about low inflation

Mickey D. Levy is senior economist at Berenberg Capital Markets. Charles Plosser is a visiting fellow at the Hoover Institution at Stanford University and former president and CEO of the Federal Reserve Bank of Philadelphia. Both authors are members of the [Shadow Open Market Committee](#).

© 2022, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

and the challenges facing monetary policy as interest rates approached zero, referred to the effective lower bound (ELB), the Fed announced in November 2018 its intention to review the “strategies, tools, and communication practices it uses to pursue its congressionally-assigned mandate.”<sup>2</sup>

The main result of this “strategic” review was revealed in a revised “Statement on Longer-Run Goals and Monetary Policy Strategy” released in August 2020.<sup>3</sup> A description and rationale was provided by Fed Chair Jerome Powell at the Federal Reserve Bank of Kansas City’s annual Jackson Hole symposium.<sup>4</sup> The revised policy document significantly changed the Fed’s interpretation of its dual mandate. The interpretation of the maximum employment mandate was broadened by the Fed to maximum “inclusive” employment, adding for the first time a distributional dimension to its objectives for monetary policy. The interpretation of the price stability mandate became more complex, but also more vague. This was done by replacing the existing inflation target (IT) with an average inflation target (AIT) that was flexible over time and included built-in asymmetries.

We prepared this critique of the Fed’s new strategic plan in September 2020 as a response to the revised framework announced in August 2020.<sup>5</sup> Our view, both then and now, is that the strategy and its implementation is misguided: The attempt to include distributional objectives for the employment mandate expands the Fed’s scope and rationale for policy action. This leads to a more discretionary and uncertain path of policy, increases the risks of policy errors, and makes it more difficult to hold the Fed accountable. It is ironic that while the Fed expands the scope of its employment goals, it acknowledges, as it did in the original consensus statement, and correctly in our view, that such goals may lie beyond the scope of monetary policy.

Thus, these more-expansive (and likely unachievable) ambitions could undermine the Fed’s credibility and invite greater political involvement in monetary policy decisionmaking, further eroding the Fed’s independence. The new flexible and asymmetric average inflation targeting framework is confusing and lacks an explanation of how the Fed will use its tools to achieve its inflation objectives. We anticipated that this would lead to confusion in financial market and consumer assessments of the future path of monetary policy, challenging the Fed’s communications and its transparency along with its credibility. We indicated that these problems meant that the new strategy was unlikely to serve monetary policy or the economy well over the longer term.

These themes are developed below. At the end of the article, we provide a postscript that puts our critique in the light of the events in 2020-21. What is so striking is how quickly our concerns about the Fed’s new strategic plan have become realities. The surge in inflation beginning in late 2020, prior to the Fed achieving its view of maximum inclusive employment, came as a surprise to the Fed, and its new strategy was not designed or equipped to confront such an occurrence. The confusion and uncertainty on the part of the public and markets in assessing the Fed’s implementation of its new strategy highlighted the troubles with the underlying plan and its communication. It now seems readily apparent that the Fed needs to reassess its new strategy and address its shortcomings.

## THE NEW PERSPECTIVE ON PRICE STABILITY

The January 2012 consensus statement was important because it established a specific quantitative target for inflation. The Fed was explicit in saying that an inflation rate of 2 percent was most consistent with its statutory mandates. Moreover, it was symmetric in that the Fed was clear that it would seek to return inflation to 2 percent to maintain long-run expectations firmly at the target

regardless of whether inflation was running below or above 2 percent. The Fed chose this single numeric mandate because it had the advantage of being a simple, clear, and precise long-term commitment. It was easily communicated and widely understood. Beginning with the 2012 consensus statement and up to the start of the pandemic in 2020, inflation remained modestly below 2 percent, but most measures of inflationary expectations remained well anchored near 2 percent.

In June 2019, the Fed held a conference as part of its strategic review. Powell (2019) spoke to some of the challenges facing the Fed. He touted the sustained economic expansion and strong labor markets but expressed concerns that persistent inflation modestly below 2 percent raised the risks of a downward spiral in inflation expectations and in actual inflation.<sup>6</sup> Such an event, he argued, could lower the nominal interest rate such that encounters with the ELB would become more frequent, complicating the task of monetary policy. Fed Vice Chair Richard Clarida (2020) subsequently spelled out these concerns in detail, arguing that based on Fed models and specific assumptions, if inflation persisted below 2 percent it would likely harm future economic performance. The Fed's aversion to adopting a negative policy rate and its concern that quantitative easing may be less effective than it had previously thought underline its concerns and its search for an alternative approach.

In response to these concerns, the Fed's new policy framework seeks to establish an AIT but one that is flexible and asymmetric around its target of 2 percent. The messaging retains the view that 2 percent inflation is consistent with its price stability mandate and stresses that it seeks an "average" inflation rate of 2 percent rather than a target. But the Fed complicates its inflation objective and the task at hand in several ways that leave the strategy risky and potential counterproductive.

The new framework modifies the Fed's inflation objective from an IT to an AIT. This may seem a small change, but it has important ramifications for the conduct of monetary policy. AIT is similar to price-level targeting (PLT) except for the initial conditions. The key difference between an AIT and IT framework is that, to achieve an average inflation rate target, policy seeks to offset below-target inflation outcomes and above-target inflation outcomes to maintain the average at the target. An IT framework simply seeks to keep inflation on target, not making up for past deviations. The theoretical attraction of this approach is that the public will expect that periods of below-target inflation will be followed by periods of above-target inflation and vice versa. The theory suggests this can be particularly attractive in the context of the ELB. Above-target inflation expectations help at the ELB because temporarily higher expectations can reduce the real interest rate even when the Fed can no longer lower the nominal federal funds target.<sup>7</sup> But as discussed below, the Fed's credibility and its commitment to manage inflation and inflation expectations over time are central to countering the limitations that may occur when operating at the ELB.<sup>8</sup> The ability of the Fed to do so is taken as given in the rationale for the new framework. Such high regard for the Fed's credibility seems somewhat out of place given the Fed's own aforementioned concern that its previous commitment to 2 percent inflation might not have been sufficiently credible to prevent the decline in inflation and inflation expectations arising from the ELB. Why should the Fed think the public will find its new commitments any more credible than its old commitments? Nevertheless, a straightforward AIT framework does have appeal.

A challenge with the AIT is that making it credible requires more quantitative guidance regarding how it will be implemented. For example, over what horizon (2 years, 5 years, 10 years) does the Fed expect to achieve its target? How much undershooting or overshooting will be tolerated

and for how long before monetary policy is likely to adjust? Put differently, how quickly and how aggressively will monetary policy respond?<sup>9</sup> Without clearer quantitative guidelines for its strategy, the Fed provides insufficient information about its intermediate-term goals and when it will react to movements in inflation. This lack of understanding by the public of the Fed's intentions may undercut the Fed's ability to manage inflationary expectations. The quantitative details become more important with an AIT framework. The simple IT framework requires a numeric target and understanding that the Fed is always trying to get inflation back to target. In the AIT framework, the market's understanding or assessment of the time-varying paths of inflation are critical to its success.

The Fed's new framework, however, is even more complex and confusing. The Fed complicates the new strategy further by stating that it intends to offset episodes when the inflation rate falls short of target but makes no mention of its response to inflation rates above target. One can infer from Powell's remarks that this framing was intentional and is to be interpreted as an asymmetric policy. This is troubling, as it is hard to see how such an asymmetric approach can result in an average inflation rate of 2 percent over the longer term. The approach would likely result in average inflation and inflation expectations above 2 percent, especially if there were shocks that drove inflation higher than anticipated for a period of time. If such movements were not offset by a monetary policy response to achieve lower-than-target inflation, average inflation would drift above 2 percent. For this reason, Powell (2020) stresses in his Jackson Hole speech that the "average" inflation goal is "flexible" and not to be construed in terms of some "mathematical formula that defines the average"; and Clarida (2020) subsequently stated "'inflation that averages 2 percent over time' represents an ex ante aspiration."

The asymmetry of the framework suggests that the Fed is unconcerned about the possibility that elevated inflation in the intermediate term might lead to an unexpected increase in longer-term expectations. This is especially relevant if the Fed's commitment to 2 percent is not fully credible. Will the Fed be able or willing to bring inflation and expectations back down in a timely way even if its makeup strategy is incomplete? The behavior of the Federal Open Market Committee (FOMC) when, and if, inflation rises above 2 percent will be a real test for the policy, particularly if inflation comes sooner rather than later and lasts longer than anticipated. This strategy of fine-tuning or managing a varying IT and varying inflation expectations in such a controlled manner seems overly complex and difficult to execute with any confidence.

Without clearer guidance from the Fed, the asymmetry of the framework risks inflation expectations rising above its 2 percent target and inflicting a serious blow to the Fed's credibility. Historically, rising inflation expectations frequently contribute to higher and more persistent inflationary episodes. The Fed acknowledges this risk but dismisses it in the design of its strategy. The asymmetry of the new strategy as outlined suggests the 2 percent average inflation rate is more likely to act as a floor than a target, which illustrates the clear inflationary bias of the new asymmetric approach to inflation. A symmetric AIT strategy could similarly address the ELB, with less inflationary bias, less complexity, and more transparency. Why make policy more complex when credibility and commitment are so important to the Fed's success?<sup>10</sup>

An alternative, but similar approach has been proposed by Bernanke (2017). He suggests a regime-switching framework where the Fed conducts policy using a standard IT regime in normal times, not the AIT adopted by the Fed, but switches to a PLT regime if and when the Fed is actually

confronted with the ELB. But this is not what the Fed's new strategy describes. If the Fed had this in mind, it should be more forthcoming and describe its approach. The communication and implementation challenges for the regime-switching model would be formidable and much the same as have been highlighted. In it, the Fed would be seeking to raise expectations above 2 percent for some period of time to offset the shortfalls of inflation that it thinks occur during the binding constraint of the ELB. Because the Fed's objective would be to credibly manage inflationary expectations, it would need to develop guidelines that would signal under what circumstances and how policy would respond. Communicating this time-varying approach to inflation and inflation expectations and securing the credibility and commitment to make it successful seem quite difficult.

The Fed's rationale underlying its new framework for inflation rests largely on addressing the ELB while largely ignoring other factors that may have influenced the monetary transmission channels and aggregate demand. More specifically, the Fed made major changes to its operating framework beginning in 2008. It started paying interest on reserves, and its large-scale asset purchases decimated the traditional federal funds market and ballooned the Fed's balance sheet. The regulatory environment for banks also changed, including capital requirements, leverage ratios, and liquidity requirements, to name just a few. These and other elements may help explain why the Fed's zero interest rates and asset purchases did not stimulate aggregate demand, and thus inflation, as much as anticipated. The full array of the Fed's monetary policy framework and its tools deserve close attention alongside the Fed's focus on the ELB, expectations, and credibility.

## BROADENING THE EMPLOYMENT MANDATE

The Fed's January 2012 consensus statement emphasized that the maximum employment objective cannot be defined by a numeric target, noting that employment is affected by an array of non-monetary factors. The Fed's view on this has not changed: Powell emphasized the important roles of education and skills training, health care, and fiscal policy on employment. We would add the impact of taxes and regulations on businesses and labor as important determinants of employment. The unobservable aspect of a maximum employment mandate has always made the Fed's task difficult. Yet the Fed's new framework involves two important changes that broaden its own objectives on employment that it has acknowledged may be beyond the reach of its policy tools.

First, the Fed's new strategy emphasizes that it will assess the employment mandate in terms of the "shortfall" from maximum employment, rather than "deviations." Second, the Fed broadened its mandate to "maximum inclusive employment," and Chair Powell and other Fed policymakers have emphasized the importance of adding the term "inclusive." In practice, the Fed most often communicated its assessment of the labor market in terms of the unemployment rate relative to some perspective on the unobservable normal or "natural" rate,  $U^*$ , and the trend in wages. This approach, for better or worse, has a long history and meshed with the Fed's reliance on the Phillips curve as the central link between monetary policy, the labor market, and inflation.

"Shortfall" introduces asymmetry into the Fed's employment mandate. The focus on employment shortfalls suggests that the Fed places a higher priority on employment that is shy of some unmeasurable maximum, which suggests a tilt toward monetary ease. The problem is that it will always be easy to argue, and some surely will, that employment could be higher. The Fed has not offered much guidance as to how it will assess labor markets as they pertain to monetary policy

actions. Maximum employment, as discussed, is determined by a myriad of factors including demographics, productivity, and labor regulations that influence the supply and demand for labor. How will the Fed interpret trends in employment-to-population ratios, participation rates, and demographics? What is the mechanism by which monetary policy can shape the desired outcomes? These issues raise both strategic and communication challenges for the Fed, as they have in the past.

Second, the revised policy framework interprets the maximum employment mandate to mean maximum inclusive employment. An inclusive labor market for all citizens is an important and desirable feature of an efficient market economy. Lifting employment of underprivileged and minority citizens would enhance economic performance and lift potential growth. Yet monetary policy is not an appropriate or effective policy tool for achieving such an objective. The Fed acknowledges its limited scope in maximizing inclusive employment. For these reasons, the maximum employment mandate has long been problematic for the Fed. The problem is aggravated by the addition of a distributional dimension to its list of policy objectives. Such an addition gives the impression that monetary policy can effectively address these laudable objectives. The explicit expansion of the Fed's monetary objectives in this manner seems unwise, as it elevates the expectations for what monetary policy is capable of achieving.

By highlighting and elaborating on the seemingly nuanced word changes in numerous presentations—the replacement of “deviations” with “shortfalls” and adding “inclusive” to maximum employment—Powell, Clarida, and other Fed members emphasize the material shift in the Fed's interpretation of its mandate.

The result of the Fed broadening and elevating the employment mandate is to deepen the quagmire that the dual mandate imposes on the Fed. It invites the public and politicians to hold the Fed accountable for goals it cannot achieve, which risks undermining the Fed's credibility and invites greater political interference into monetary policy decisionmaking, further eroding the Fed's independence. The Fed should provide more guidance to Congress on the capabilities and limitations of monetary policy and the important role of other policy tools. The Fed's new policy statement further blurs the lines of responsibility and accountability.

## ABANDONING THE PHILLIPS CURVE?

For years following the financial crisis, the unemployment rate receded but was not accompanied by upward pressure on inflation. The Fed's standard response was that the Phillips curve was flatter than had been presumed—an ex post rationale for why inflation stayed low—but did not provide any insight into its view of the underlying sources of inflation or the inflation process. The Phillips curve was an empirical finding that described certain periods in the data, but it is flawed analytically and has not been a reliable or quantitatively important predictor of inflation in the past 50 years. In recent decades, the Fed has grudgingly acknowledged the unreliability the Phillips curve as a guide to inflation or the mechanism it uses to implement stabilization policy. Yet, its only response has been to heighten the role of inflationary expectations in the inflation process.

It is wise that Fed Chair Powell, Vice Chair Clarida, and other members have acknowledged that the reliance on the Phillips curve framework is deeply problematic. But while taking this step, the Fed has not replaced the Phillips curve with any alternative framework or model for predicting inflation. Specifically, Vice Chair Clarida (2020) discussed the unreliability of the Phillips curve

and the inaccuracy of macro models based on it, but he did not offer any new line of thought about what causes inflation or how to predict it. The Fed emphasizes the important role of expectations but does not mention nominal gross domestic product or excess aggregate demand as sources of inflation and does not mention the money supply. Moreover, it has not explained how its tools can be used to manage inflation and achieve its goals. This is a fundamental challenge to macroeconomics, and it is critical for the Fed. The Fed should focus more on transmission channels that link policies to aggregate demand and inflation. Doing so is important for forecasting and sorting out the causes and dynamics of inflation as well as achieving its mandates.

The Fed's view that the Phillips curve is flat contributes to the change in its new strategy statement (BOG, 2020a) that now emphasizes "shortfalls of employment from the Committee's assessment of its maximum level" rather than "deviations," with important implications for monetary policy. Clarida (2020) stated that a robust jobs market and low unemployment "in the absence of evidence that price inflation is running or is likely to run persistently above mandate-consistent levels...will not, under our new framework, be a sufficient trigger for policy action." According to Clarida (2020), "This is a robust evolution in the Federal Reserve's policy framework."

These remarks clearly imply and were widely interpreted in financial markets as meaning that the Fed has significantly raised the hurdle for preemptive monetary tightening and that employment had become the Fed's primary objective. This interpretation was reinforced in the September 2020 FOMC statement that suggested the Fed would not raise the federal funds target "until labor market conditions have reached levels consistent with the Committee's assessments of maximum employment and inflation has risen to 2 percent."<sup>11</sup> This statement indicates a definite inflationary bias in the policy framework and an elevation of employment to the Fed's primary objective. It replaces a decades-long framework of "leaning against the wind" and seemingly runs counter to the emphasis on managing inflationary expectations. But the missing link is the absence of any clear framework or model for forecasting inflation. It also would seem to ignore the Fed's recognition that monetary policy works with lags and the evidence that, once established, inflation can be costly to bring down. Downgrading the relevance of preemptive monetary tightening without a clear understanding of the inflation process and lags between monetary policy tools and inflation seems risky.

## COMMUNICATIONS

The Fed's new strategy seeks to make some fundamental changes in the Fed's reaction function as it has come to be understood by the public and the markets. The lack of clarity in the Fed's new policy framework, with asymmetric and undefined goals for both employment and inflation, has and will continue to generate communications problems. Conveying the Fed's assessment of inflationary expectations, which play a heightened role, will be difficult. The Fed will be looking to markets for indicators of expectations, while the markets will be seeking advice from the Fed. This new strategy further heightens the Fed's unhealthy relationship with financial markets.<sup>12</sup>

Some of the difficulties in communications arose quickly. While the FOMC voted unanimously in support of the new statement on strategy and longer-term goals, two members dissented at the September 2020 meeting, both expressing different interpretations of the Fed's forward guidance and flexibility under the new strategy. During the post-meeting press conference, Chair Powell's responses to journalists' questions about inflation, the economy, and labor market conditions

echoed the Fed's old Phillips curve framework. In the absence of an alternative explanation of the inflation process, the Fed's communications have led to more confusion than clarity.

The new strategy also adds complications and uncertainties to the Fed's quarterly Summary of Economic Projections (SEP). The Fed states clearly that its projections are not forecasts, rather compilations of projections of FOMC members based on each member's assumption that "appropriate" monetary policies will be followed. But markets and the public widely view them as forecasts. In any case, these quarterly updates are widely viewed as important communication tools. The Fed has emphasized that while interest rates are its primary monetary policy instrument, it sees massive asset purchases as an important tool. Yet nowhere in the new, or old, strategic framework does the Fed address the use of the balance sheet or how it fits into its overall long-term strategy of monetary policy decisionmaking. Although the Fed sometimes offers observations as to how it hopes to shrink or exit from large asset purchases and even reduce the balance sheet, there should be a more coherent strategy articulated to improve transparency and clarity around the conduct of monetary policy.

## POSTSCRIPT

The flaws in the Fed's new framework have become readily apparent even faster than we had earlier anticipated. The primary impetus of the new strategy—the Fed's fears of the downward bias in inflation imposed by the constraint of the ELB and worries that it would harm employment—have been superseded by rising inflation that is harming economic performance. Under the new framework, the Fed's delayed responses to rising inflation now risk the sustainability of the economic expansion that is critical to achieving the Fed's maximum inclusive employment mandate.

The Fed's discretionary approach that places a high priority on the employment mandate has led to bad judgments that have resulted in misguided policies. As labor markets recovered rapidly and inflation rose sharply in 2021, the Fed either ignored or misinterpreted the data. It attributed the inflation to supply shortages even though measures of aggregate demand were accelerating sharply. It failed to acknowledge that aggressive monetary easing had contributed to strong nominal demand, and it downplayed the sharp rise in inflation and inflationary expectations. The Fed stated that it would not consider tapering its asset purchases until "significant progress" had been made toward achieving its maximum employment mandate and continued to indicate it would not raise its federal funds target until maximum employment was reached. The Fed's subjective interpretation of progress toward its poorly defined employment objective was difficult to follow and seemingly inconsistent with economic data. Following its new strategic plan, the Fed eschewed preemptive monetary tightening, even after inflation and inflationary expectations had risen and there was mounting evidence of unprecedented labor market tightness.

It is important to note that the Fed has always been reluctant to adopt quantitative rules in its conduct of policy, but it does acknowledge there is value in conducting monetary policy in a systematic manner. Over the years, the public and the markets had come to a general understanding of the Fed's reaction function. The new framework publicly discarded that acquired knowledge and attempted to replace it with a new reaction function that was quite different and not well understood. Some of that confusion could have been eliminated had the Fed offered more quantitative guidance regarding how the new framework would be implemented. But without such information, the public and the markets have been left wondering how the Fed will respond to the evolving economy.

Yet our view is that the framework's flaws go beyond communication and include some of its fundamental premises. The new strategy was based on the idea that all recoveries going forward would be similar to the one that followed the financial crises: that is, exhibiting low inflation that was unresponsive to monetary stimulus and inflation that would only arise after the economy reached full employment. The new framework ruled out the possibility that inflation could arise without achieving maximum employment. The premise basically concluded that the 1970s was a unique period that would never occur again. The Fed learned the wrong lessons from history (Bordo and Levy, 2022, and Plosser, 2021). The new framework offered no guidance for monetary policy should inflation rise sharply. Of course, that is what became reality beginning in late 2020, throughout 2021, and continuing into 2022. Trying to stick to its new playbook, the Fed's response was that this was all driven by exogenous supply-side constraints and monetary policy had nothing to do with it. This strategy is gradually looking to prove a significant policy error that was a result of the flawed framework.

These weaknesses have been highlighted in the quarterly updates of the Fed's SEP. In December 2020, the Fed's SEP forecasted that PCE (personal consumption expenditures) inflation would rise to 1.8 percent in 2021 (Q4/Q4) and 2 percent in 2022, while the FOMC members estimated that it would be appropriate to keep the federal funds rate at zero in those years. In each succeeding SEP in 2021, as inflation rose dramatically and the unemployment rate fell (and FOMC members forecasted that the unemployment rate would fall below their estimates of the longer-run natural rate of unemployment), FOMC members arithmetically raised their forecasts of inflation in 2021 but continued to forecast that inflation would recede toward its 2 percent longer-run object in 2022 and 2023. While these forecasts presumably reflected the Fed's assertion that inflation was due entirely to supply shortages that it expected would dissipate, it is striking that the inflation forecasts were invariant to changes in monetary policy—the expanding balance sheet and the increasingly negative real federal funds rate—and the massive amounts of fiscal stimulus that were enacted.

The Fed's new flexible average inflation targeting and the lack of numeric guidelines for inflation raised more uncertainties. Powell has announced that the dramatic rise in inflation has met the Fed's "makeup strategy." However, it is unclear how the Fed will react if inflation remains materially above its stated 2 percent longer-run average target. As a result, the Fed's interpretation of its inflation and employment mandates and how it will adjust monetary policy to achieve them remain murky. These weaknesses pose a significant challenge for the Fed's communications and threaten its credibility. Now that the economy has recovered from the impacts of the pandemic, the Fed does not seem to have a coherent strategy. It is now appropriate for the Fed to reassess its strategic plan and address the flaws in its new framework. ■

## NOTES

- <sup>1</sup> Board of Governors of the Federal Reserve System (BOG; 2012).
- <sup>2</sup> BOG (2018).
- <sup>3</sup> BOG (2020a).
- <sup>4</sup> Powell (2020).
- <sup>5</sup> The earlier version of this paper was presented to the Shadow Open Market Committee on September 29, 2020, and to the Hoover Institution's Economic Policy Working Group on October 1, 2020. See Levy and Plosser (2020).
- <sup>6</sup> Of course, the risks of such downward spirals have been talked about for decades, but empirical evidence is hard to find. Most recently, Japan has experienced near zero nominal short-term interest rates and near-zero inflation for nearly three decades, but there has not been evidence of any "downward spiral" in prices or real economic activity. The Fed seems most concerned that a near-zero nominal rate is bad because it would limit its ability to implement stabilization policy in response to negative shocks in the short run. The net loss in long-term welfare for the economy in this case depends critically on the model used and its parameterization.
- <sup>7</sup> Eggertsson and Woodford (2003) present a theoretical discussion of monetary policy at the ELB. They note that PLT, which is closely related to AIT, though unlikely to be optimal, can improve performance relative to rules that are not history dependent. See Plosser (2019) for a brief discussion of the pros and cons of implementing PLT.
- <sup>8</sup> Similarly, the theory suggests an AIT can also have benefits when inflation is above target as well. The commitment, if credible, to offset above-target outcomes with below-target inflation strengthens the commitment to the longer-run target and can help prevent inflation expectations from undesirable upward shifts.
- <sup>9</sup> For example, if the Fed measures the shortfall in inflation since January 2012, four years of 3 percent inflation would gradually lift average inflation to 2 percent during 2012-24. Of course, it would take longer if the inflation rate rose to only 2.5 percent. The desired path of inflation in a makeup strategy would be different if the Fed used a rolling window of say two years or five years. Would the Fed allow 2.5 percent or 3 percent inflation for several years? Financial markets can only guess, as the Fed gives the public little clue as to how it expects to proceed. During the higher inflation makeup period, would inflationary expectations remain anchored to 2 percent?
- <sup>10</sup> See Plosser (2019) for further discussion.
- <sup>11</sup> BOG (2020b).
- <sup>12</sup> See Levy (2019).

## REFERENCES

- Board of Governors of the Federal Reserve System. "Statement on Longer-Run Goals and Monetary Policy Strategy." January 24, 2012; [https://www.federalreserve.gov/monetarypolicy/files/FOMC\\_LongerRunGoals\\_201201.pdf](https://www.federalreserve.gov/monetarypolicy/files/FOMC_LongerRunGoals_201201.pdf).
- Board of Governors of the Federal Reserve System. "Federal Reserve to Review Strategies, Tools, and Communication Practices It Uses to Pursue Its Mandate of Maximum Employment and Price Stability." Press Release, November 15, 2018; <https://www.federalreserve.gov/newsevents/pressreleases/monetary20181115a.htm>.
- Board of Governors of the Federal Reserve System. "Statement on Longer-Run Goals and Monetary Policy Strategy." Amended August 27, 2020a; <https://www.federalreserve.gov/monetarypolicy/review-of-monetary-policy-strategy-tools-and-communications-statement-on-longer-run-goals-monetary-policy-strategy.htm>.
- Board of Governors of the Federal Reserve System. "FOMC Statement." Press Release, September 16, 2020b; <https://www.federalreserve.gov/newsevents/pressreleases/monetary20200916a.htm>.
- Bernanke, Ben S. "Monetary Policy in a New Era." Prepared for the Peterson Institute for International Economics conference *Rethinking Macroeconomic Policy*, October 12-13, 2017; [https://www.brookings.edu/wp-content/uploads/2017/10/bernanke\\_rethinking\\_macro\\_final.pdf](https://www.brookings.edu/wp-content/uploads/2017/10/bernanke_rethinking_macro_final.pdf).
- Bordo, Michael D. and Levy, Mickey D. "The Fed's Delayed Exits from Monetary Ease: The Fed Rarely Learns from History." Shadow Open Market Committee, February 11, 2022; <https://www.shadowfed.org/wp-content/uploads/2022/02/Bordo-Levy-SOMC-February2022.pdf>.

Clarida, Richard H. "The Federal Reserve's New Monetary Policy Framework: A Robust Evolution." Speech delivered at the Peterson Institute for International Economics, August 31, 2020;  
<https://www.federalreserve.gov/newsevents/speech/clarida20200831a.htm>.

Eggertsson, Gauti B. and Woodford, Michael. "The Zero Bound on Interest Rates and Optimal Monetary Policy." *Brookings Papers on Economic Activity*, 2003, 1, pp. 139-211;  
[https://www.brookings.edu/wp-content/uploads/2003/01/2003a\\_bpea\\_eggertsson.pdf](https://www.brookings.edu/wp-content/uploads/2003/01/2003a_bpea_eggertsson.pdf).

Levy, Mickey D. "The Fed and Financial Markets: Suggestions to Improve an Unhealthy Relationship." Presented at the Hoover Institution, Stanford University conference *Strategies for Monetary Policy*, May 3, 2019;  
[https://www.hoover.org/sites/default/files/levy-monetary\\_policy\\_and\\_financial\\_markets\\_hoover\\_may\\_2019-v2.pdf](https://www.hoover.org/sites/default/files/levy-monetary_policy_and_financial_markets_hoover_may_2019-v2.pdf).

Levy, Mickey D. and Plosser, Charles. "The Murky Future of Monetary Policy." Economics Working Paper 20119, Hoover Institution, Stanford University, October 1, 2020;  
[https://www.hoover.org/sites/default/files/research/docs/20119-levy-plosser\\_1.pdf](https://www.hoover.org/sites/default/files/research/docs/20119-levy-plosser_1.pdf).

Plosser, Charles. "A Cautionary Note on Price-Level Targeting." Hoover Institution, Stanford University *Defining Ideas*, May 1, 2019; <https://www.hoover.org/research/cautionary-note-price-level-targeting>.

Plosser, Charles. "The Fed's Risky Experiment." Economics Working Paper 21116, Hoover Institution, Stanford University, June 18, 2021; [https://www.hoover.org/sites/default/files/research/docs/21116-plosser\\_1.pdf](https://www.hoover.org/sites/default/files/research/docs/21116-plosser_1.pdf).

Powell, Jerome H. "Opening Remarks." Presented at the Federal Reserve Bank of Chicago conference *Monetary Policy Strategy, Tools, and Communications Practice*, June 4, 2019;  
<https://www.federalreserve.gov/newsevents/speech/powell20190604a.htm>.

Powell, Jerome H. "New Economic Challenges and the Fed's Monetary Policy Review." Presented at the Federal Reserve Bank of Kansas City symposium *Navigating the Decade Ahead: Implications for Monetary Policy*, Jackson Hole, WY, August 27, 2020; <https://www.federalreserve.gov/newsevents/speech/powell20200827a.htm>.

# Turbulent Years for U.S. Banks: 2000-20

Paul W. Wilson

The first 20 years of the twenty-first century have presented U.S. banks with three recessions, long periods of very low interest rates, and increased regulation. The number of commercial banks operating in the United States declined by 51 percent during this period. This article examines the performance of U.S. commercial banks from 2000 through 2020. An overall picture is provided by examining the evolution of assets, deposits, loans, and other financial characteristics over the period. In addition, new estimates of technical inefficiency are provided, offering additional insight into banks' performance during the recent difficult years. (JEL C14, G01, G21)

Federal Reserve Bank of St. Louis *Review*, Third Quarter 2022, 104(3), pp. 189-209.

<https://doi.org/10.20955/r.104.189-209>

---

## 1 INTRODUCTION

The first two decades of the twenty-first century have been turbulent for U.S. commercial banks. Banks have confronted recessions in 2001, 2007-09, and 2020, increased regulation, unprecedented periods of low interest rates, and other disruptions. The number of Federal Deposit Insurance Corporation (FDIC) insured commercial banks and savings institutions fell from 10,222 at the end of the fourth quarter of 1999 to 5,002 at the end of the fourth quarter of 2020. During the same period, among the 5,220 banks that disappeared, 571 exited the industry because of failures or assisted mergers,<sup>1</sup> while the creation of new banks slowed. From 2000 through 2007, 1,153 new bank charters were issued, and in 2008 and 2009, 90 and 24 new charters were issued, respectively. But from 2010 through 2020, only 48 new commercial bank charters were issued. The decline in the number of institutions since 2000 continues a long-term reduction in the number of banks operating in the United States since the mid-1980s.

Banks are a critical part of the U.S. economy and, among other roles, serve as financial intermediaries for all types of businesses. Banks in effect arbitrage financial capital by renting funds from depositors and renting funds to borrowers. The rents received on either side depend on prevailing interest rates and in particular on the spread between rates on deposits and loans. This role also

Paul W. Wilson is the J. Wilson Newman Professor of Economics at Clemson University and a research fellow at the Federal Reserve Bank of St. Louis.

© 2022, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

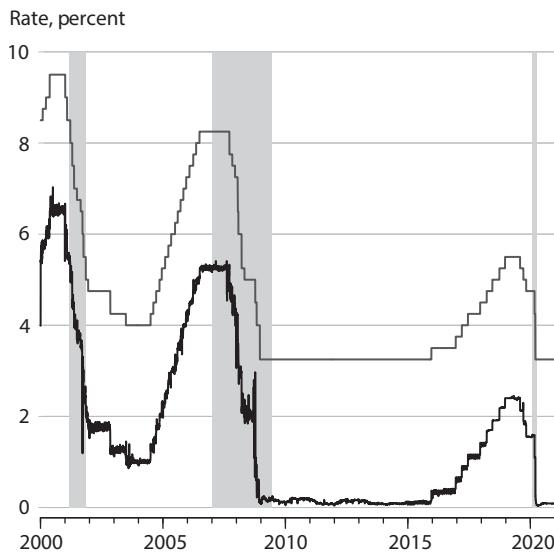
requires that banks manage risk to avoid becoming insolvent. Diamond and Rajan (2001) note that banks perform valuable functions on both sides of their balance sheets. Banks provide liquidity on demand to depositors while at the same time making loans to illiquid borrowers, thereby enhancing the flow of credit in the economy. Despite the unusually low interest rates experienced during 2009-16 and 2020, banks remain an important and substantial part of the U.S. economy. As shown below, financial sector profits accounted for approximately 24.5 percent of corporate profits at the beginning of 2000. The share of corporate profits accruing to the financial sector fluctuated widely during 2000-20, but at the end of 2020 still accounted for approximately 23.2 percent of corporate profits, down only slightly from the beginning of 2020.

This article examines the performance of commercial banks over 2000-20. The next section provides a look at the “big picture” by examining the U.S. banking industry as a whole and how the industry has evolved during the turbulent period from 2000 to 2020. Section 3 presents a model of how individual banks convert inputs (i.e., labor, financial capital, and physical capital) into outputs (i.e., loans, securities, and off-balance-sheet activities) while allowing for risk. The specified model is fully nonparametric, thereby allowing more flexibility and fewer assumptions than more traditional parametric models. Section 4 discusses estimation of the model. The estimation method is almost fully nonparametric; a local assumption on the distribution of efficiency is needed for identification of expected efficiency, but the parameters of the distribution are functional and are estimated locally. The noise term in the model is assumed to have a symmetric density, but no functional form assumptions (even local ones) are needed. The data used for estimation and specification of variables are described in Section 5. Section 6 presents the estimation results, which are discussed in view of the big picture shown in Section 2. Summary and conclusions are given in Section 7.

## 2 AN OVERALL VIEW OF THE U.S. BANKING INDUSTRY

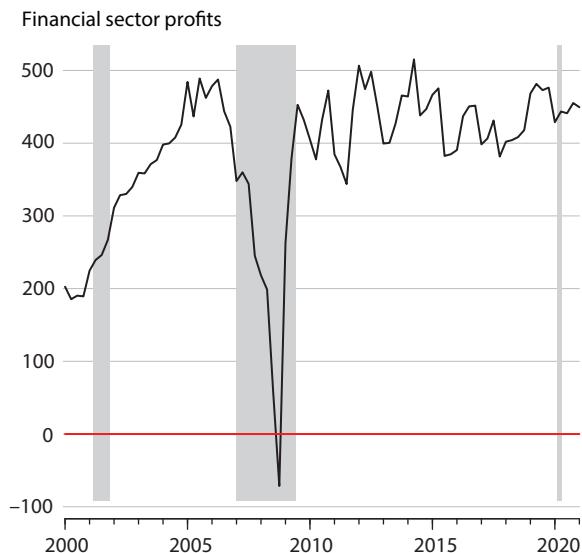
The National Bureau of Economic Research (NBER) dates U.S. recessions starting at the peak and ending at the next trough of a business cycle. The NBER indicates that from 2000 to 2020, recessions occurred from March to December 2001, December 2007 to June 2009, and February to April 2020.<sup>2</sup> The first of these three recessions was slight and brief, with real gross domestic product (GDP) declining by 0.11 percent from its peak at the end of the third quarter of 2000 to the trough at the end of the second quarter of 2001 and then surpassing the previous peak level in the third quarter of 2001. The second recession—the Great Recession—was more severe. Real GDP declined by 3.84 percent between the end of the third quarter of 2007 and the end of first quarter of 2009 and did not reach the previous peak level until the third quarter of 2010. The third recession saw the largest decline in real GDP—13.12 percent from the end of the third quarter of 2019 to the end of the second quarter of 2020—but by the end of 2020, real GDP had recovered to 99.24 percent of the previous peak level. To the extent that banks serve as financial intermediaries in the economy by smoothing the flow of capital from lenders to borrowers, one might expect that both the Great Recession and the recession of 2020 had significant impacts on banks’ operations.

The federal funds rate is one of the Federal Reserve System’s primary policy levers, and it is well known that the Fed used this tool intensively in recent years. The federal funds rate heavily influences the bank prime loan rate, that is, the interest rate that banks charge their most credit worthy customers. Figure 1 plots both the effective federal funds rate and the prime rate as functions

**Figure 1****Prime and Effective Federal Funds Rates**

NOTE: The bank prime loan rate (lighter-colored line) is the rate posted by a majority of top 25 (by assets in domestic offices) insured U.S.-chartered commercial banks. The effective federal funds rate (darker, more variable line) is the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight. The federal funds rate influences the higher prime rate. Gray bars indicate recessions as determined by the NBER.

SOURCE: Board of Governors of the Federal Reserve System (2021a,b).

**Figure 2****Financial Sector Profits**

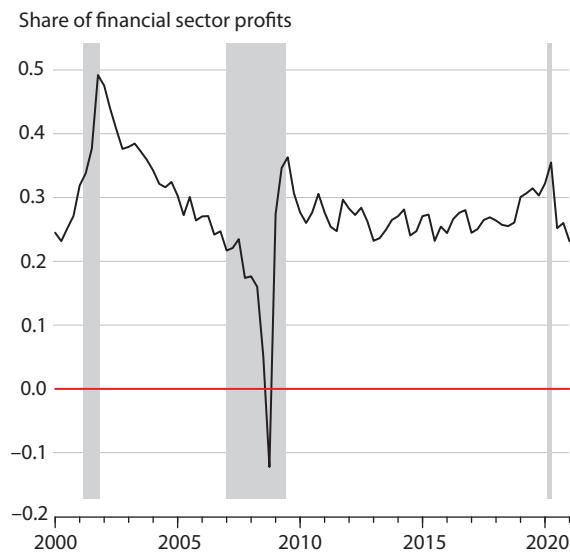
NOTE: Financial sector profits are measured in billions of constant 2012 dollars, seasonally adjusted annual rate. Financial sector profits are computed by subtracting nonfinancial corporate profits before tax from corporate profits before tax. In both cases, profits are not adjusted for inventory valuation nor for capital consumption. Gray bars indicate recessions as determined by the NBER.

SOURCE: U.S. Bureau of Economic Analysis (2021a,d).

of time. The effective federal funds rate fluctuates somewhat in the short run, and Figure 1 shows the effects of Federal Reserve policy on interest rates. The federal funds rate remained below 0.5 percent from October 29, 2008, until December 15, 2016. During much of this period, the rate was below 0.1 percent. The federal funds rate was allowed to rise beginning in 2016, reaching a high of 2.41 percent in July 2019. By March 1, 2020, the federal funds rate stood at 1.58 percent, then plunged to 0.08 percent by the end of March. Recall that in the United States, March 2020 saw the beginning of lockdowns and other restrictions caused by the COVID-19 pandemic. From the beginning of the pandemic until mid-September 2021, the federal funds rate remained at or below 0.1 percent. Figure 1 also illustrates how the prime rate moves in lockstep with the federal funds rate.

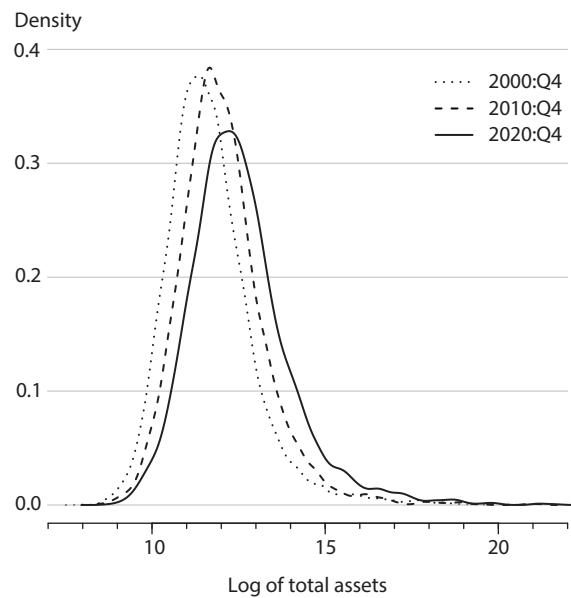
In principle, low interest rates on loans constrain the spread between rates on loans and deposits, and consequently, low interest rates tend to limit banks' ability to earn profits. But as noted in Section 1, financial sector profits rose from 2000 to 2020. Figure 2 plots financial sector profits as a function of time. It shows that financial sector profits increased prior to the Great Recession but then plunged deeply, becoming negative in the third quarter of 2008 and then recovering over the next three quarters. Financial sector profits then oscillated up and down, reaching \$452.8 billion in the second quarter of 2009, ending at \$449.5 billion at the end of 2020.<sup>3</sup>

A somewhat different picture is provided by Figure 3, which shows the ratio of financial sector profits to total corporate profits. Figure 3 reveals that the financial sector took an increasing share of

**Figure 3****Ratio of Financial Sector Profits to Total Corporate Profits**

**NOTE:** Financial sector profits are computed by subtracting nonfinancial corporate profits before tax from corporate profits before tax. In both cases, profits are not adjusted for inventory valuation nor for capital consumption; data are seasonally adjusted at an annual rate. Gray bars indicate recessions as determined by the NBER.

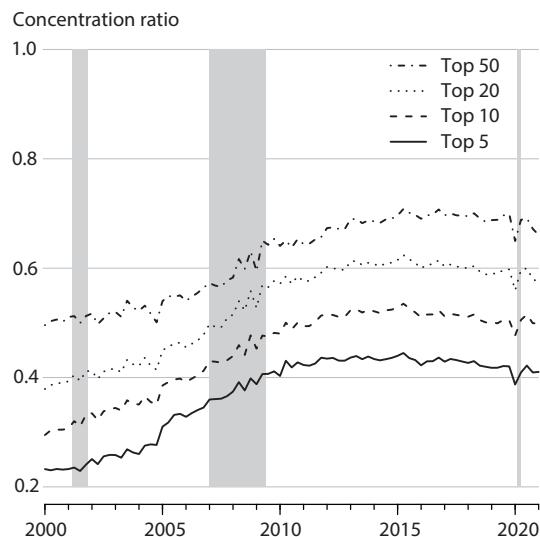
**SOURCE:** U.S. Bureau of Economic Analysis (2021a,d).

**Figure 4****Density of (Log) Total Assets of U.S. Commercial Banks in the Fourth Quarters of 2000, 2010, and 2020**

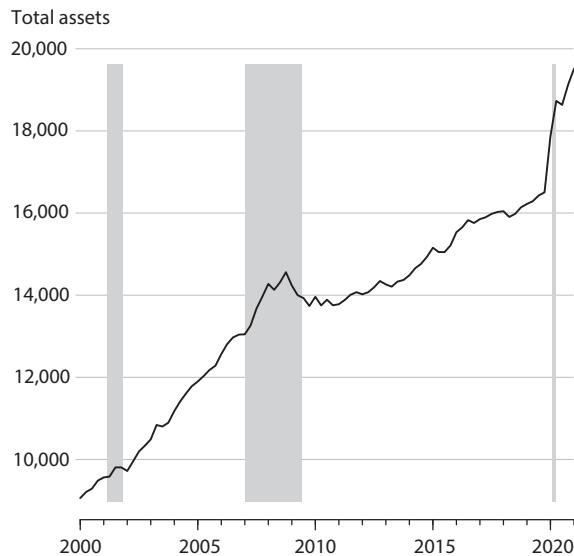
**NOTE:** Total assets are measured in billions of constant 2012 U.S. dollars.

total corporate profits up to the third quarter of 2009. But starting in the fourth quarter of 2009, the financial sector's share of corporate profits declined, becoming negative (due to the negative profits mentioned above) in the third quarter of 2008. As a share of total corporate profits, financial sector profits recovered after 2008 but did not reach the levels of 2001-03. Nonetheless, the financial sector remains an important part of the U.S. economy, accounting for a quarter or more of corporate profits.

As mentioned in Section 1, there has been a great deal of consolidation among U.S. banks. Wheelock (2011) discusses the effects of the Great Recession on bank consolidation through 2010, and the Bank for International Settlements (2018) discusses bank concentration after the Great Recession. Others, such as Janicki and Prescott (2006) and Goddard, McKillop, and Wilson (2014), examine changes in the size distribution of U.S. banks. It is well known that since the 1980s, banks have become fewer in number and larger in size. Figure 4 shows kernel density estimates of the log of total assets of U.S. banks in the fourth quarters of 2000, 2010, and 2020. Even after taking logarithms, the distribution of total assets remains skewed to the right. Figure 4 illustrates how the density of total assets has shifted rightward over time. In addition, the density for 2020 reaches a maximum that is lower than the maxima in 2000 or 2010, reflecting the fact that the variance of log total assets changed little from 2000 to 2010 (the corresponding variances are 1.643 and 1.625, respectively) but increased by more than 30 percent (to 2.140) in 2020. In addition, the right tail of the density of log total assets is thicker in 2020 than in either 2000 or 2010.

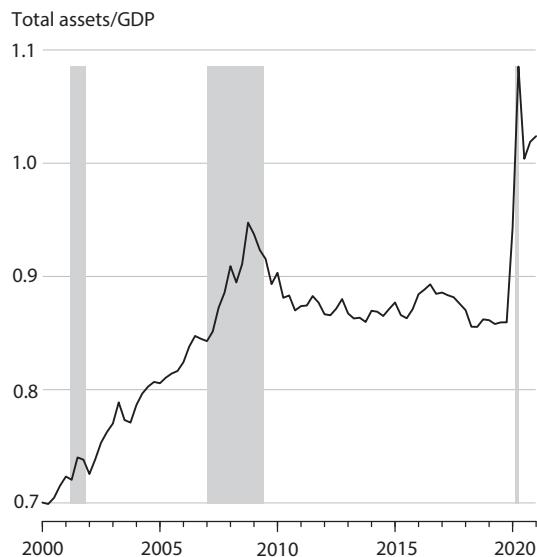
**Figure 5****Concentration Ratios in Terms of Total Assets of U.S. Commercial Banks**

NOTE: Concentration ratios are computed by dividing the sum of total assets of the largest commercial banks by the sum of total assets of all commercial banks in a given period, where  $m \in \{5, 10, 20, 50\}$ . Gray bars indicate recessions as determined by the NBER.

**Figure 6****Total Assets of U.S. Commercial Banks**

NOTE: Total assets are measured in billions of constant 2012 U.S. dollars, not seasonally adjusted. Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021d) and U.S. Bureau of Economic Analysis (2021c).

**Figure 7****Ratio of Total Assets of U.S. Commercial Banks to GDP**

NOTE: Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021d) and U.S. Bureau of Economic Analysis (2021b).

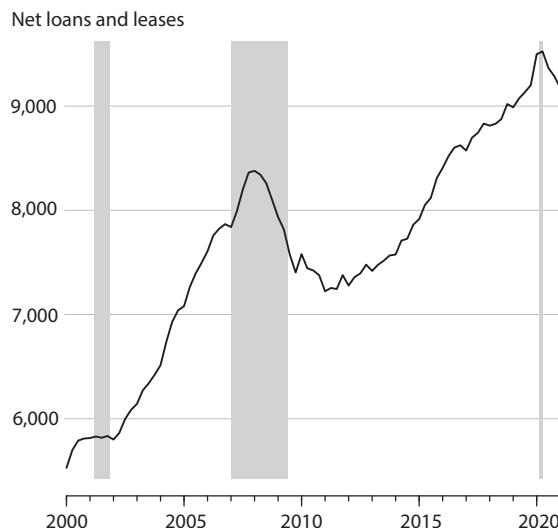
Figure 5 shows concentration ratios for large U.S. banks as functions of time. For a given point in time, the concentration ratio is computed as the sum of total assets of the  $m$  largest banks divided by the sum of total assets of all banks. Figure 5 shows concentration ratios for the top 5, 10, 20, and 50 banks in each quarter. The concentration ratios show an upward trend through 2010 or 2011, but become flat or even decrease slightly from 2011 to 2020. Nonetheless, the five largest banks at the beginning of 2000 controlled 23 percent of bank assets, while the five largest at the end of 2020 controlled 41 percent of bank assets. The largest banks became much larger from 2000 to 2020.

Additional evidence on the increasing size of banks is provided by Figures 6 and 7. Figure 6 shows that total assets of all commercial banks trended upward from 2000 to 2020, especially just before the pandemic-induced recession in 2020. Overall, assets held by commercial banks increased from \$9.2 trillion at the end of the fourth quarter of 1999 to \$19.5 trillion at the end of the fourth quarter of 2020. Of course, GDP also increased over the same period. Figure 7 shows the ratio of total bank assets to GDP as a function of time. The ratio of assets to GDP peaked at 0.9475 in the third quarter of 2008 and did not reach this level again until the first quarter of 2020 before peaking at 1.0853 at the end of the first quarter of 2020.

In order to provide some insight into what drove the increase in total bank assets in Figure 6, Figures 8, 9, and 10 show net loans and leases, total securities, and cash assets as functions of time. Figure 8 shows that net loans and leases peaked at \$8.378 trillion in the fourth quarter of 2007, then fell to \$7.223 trillion in the fourth quarter of 2010. Net loans and leases reached the previous peak level in the fourth quarter of 2015 and climbed to \$9.525 trillion in the first quarter of 2020 before falling again.

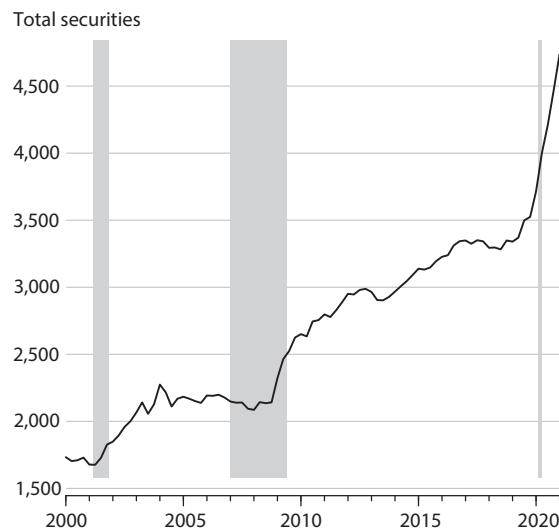
Figures 9 and 10 show different trajectories for total securities and for cash assets, respectively. Whereas net loans and leases experienced a sharp decline during and after the Great Recession, banks increased their holdings of securities and cash assets during and after the recession. In addition, whereas net loans and leases declined after the first quarter of 2020, total securities held by banks increased from \$3.524 trillion at the end of the third quarter of 2019 to \$4.738 trillion at the end of the fourth quarter of 2020. Cash assets held by banks increased from \$1.476 trillion to \$3.138 trillion over the same period.

Figure 11 shows the composition of total assets. The solid curve indicates the proportion of total assets consisting of net loans and leases, and the dashed curve indicates the part of total assets made up of net loans and leases plus securities; hence, the distance between the solid and dashed curves indicates the proportion of total assets consisting of securities. The dotted line represents net loans and leases plus securities plus cash assets divided by total assets; the distance between the dotted and dashed curves indicates the proportion of total assets consisting of cash assets. The distance between 1.0 and the dotted curve indicates the proportion of other assets, including premises and fixed assets, other real estate owned, investments in unconsolidated subsidiaries and associated companies, and intangible assets. As the figure shows, net loans and leases as a proportion of total assets declined from 61.02 percent at the beginning of 2000 to 47.02 percent at the end of 2020. Net loans and leases plus securities declined from 80.02 percent to 71.31 percent of total assets over the same period, with securities increasing from 19.13 percent to 24.28 percent of total assets. At the beginning of 2020, the sum of net loans and leases securities, and cash assets accounted for 85.06 percent of total assets and at the end of 2020 accounted for 87.39 percent of total assets, implying that other assets as a percentage of total assets also changed little from 2000 to 2020. However, cash

**Figure 8****Net Loans and Leases of U.S. Commercial Banks**

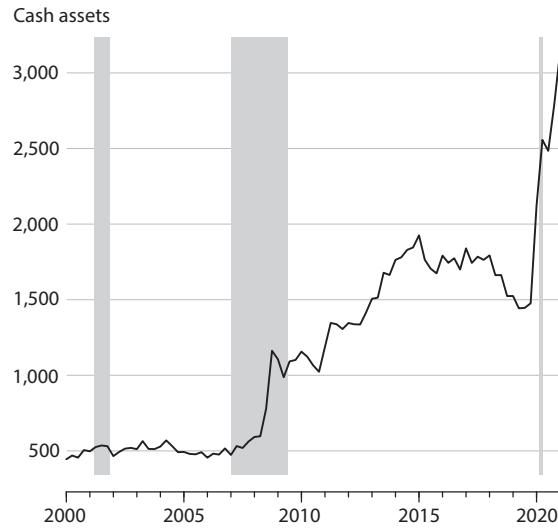
NOTE: Net loans and leases include gross loans and leases less unearned income and reserve for losses, and are measured in billions of constant 2012 U.S. dollars, not seasonally adjusted. Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021c) and U.S. Bureau of Economic Analysis (2021c).

**Figure 9****Total Securities Held by U.S. Commerical Banks**

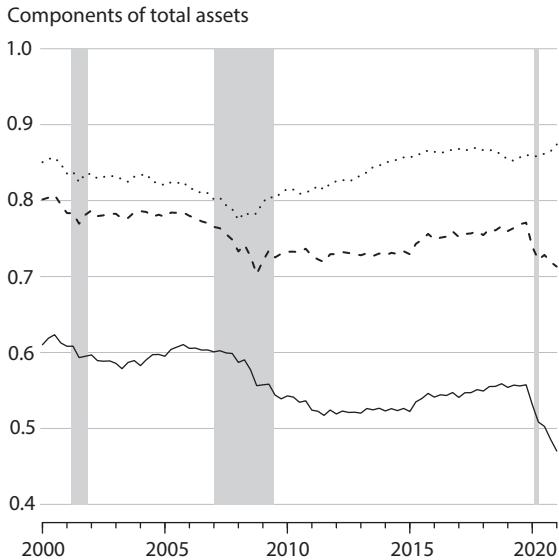
NOTE: Total securities include securities available for sale (fair value), securities held to maturity (amortized cost), U.S. Treasury securities, mortgage-backed securities, state and municipal securities, and equity securities and are measured in billions of constant 2012 U.S. dollars, not seasonally adjusted. Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021e) and U.S. Bureau of Economic Analysis (2021c).

**Figure 10****Cash Assets from Depository Institutions, U.S. Commercial Banks**

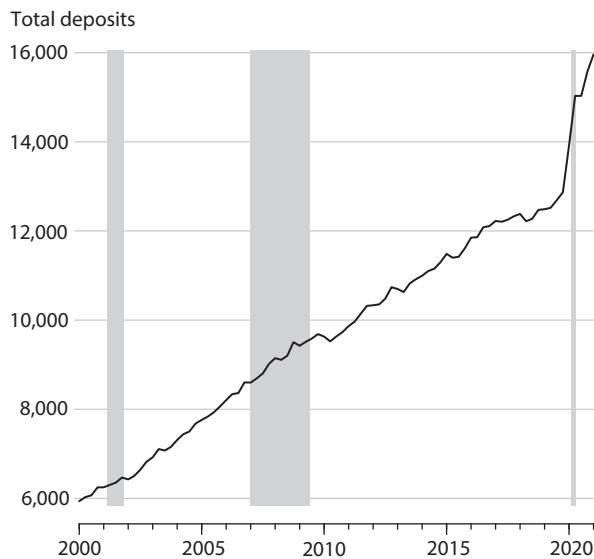
NOTE: Cash assets include cash and due from depository institutions. Cash assets are measured in billions of constant 2012 U.S. dollars, not seasonally adjusted. Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021b) and U.S. Bureau of Economic Analysis (2021c).

**Figure 11****Components of Total Assets of U.S. Commercial Banks**

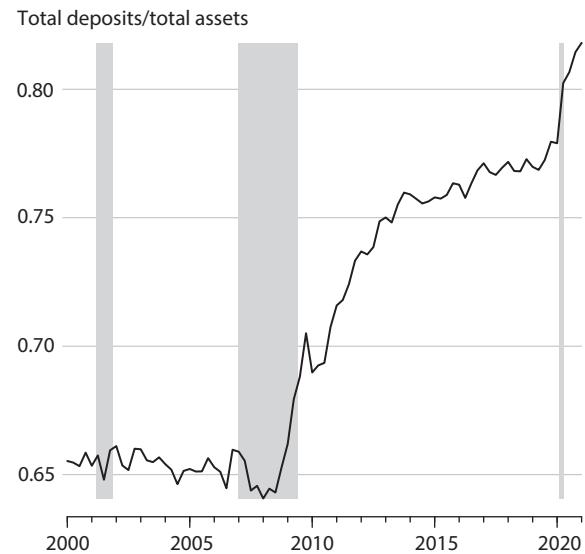
NOTE: The solid curve shows the ratio of net loans and leases to total assets. The dashed curve shows the ratio of net loans and leases plus securities to total assets. The dotted curve shows the ratio of net loans and leases plus securities plus cash assets to total assets. Data are not seasonally adjusted. Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021b,c,d,e).

**Figure 12****Total Deposits of U.S. Commercial Banks**

NOTE: Deposits are measured in billions of constant 2012 dollars, not seasonally adjusted. Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021f).

**Figure 13****Ratio of Total Deposits to Total Assets, U.S. Commercial Banks**

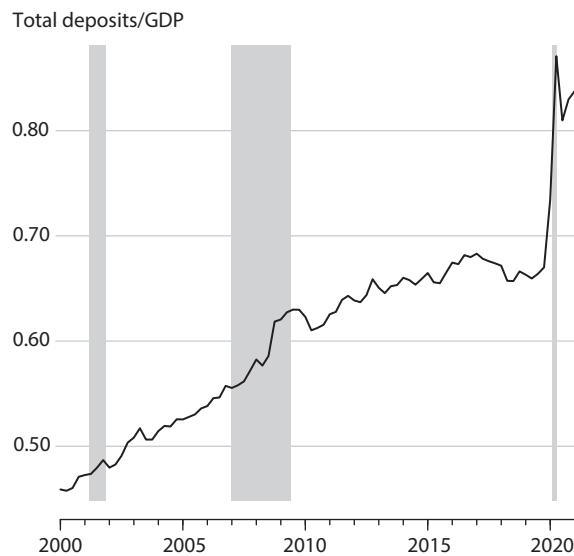
NOTE: Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021f).

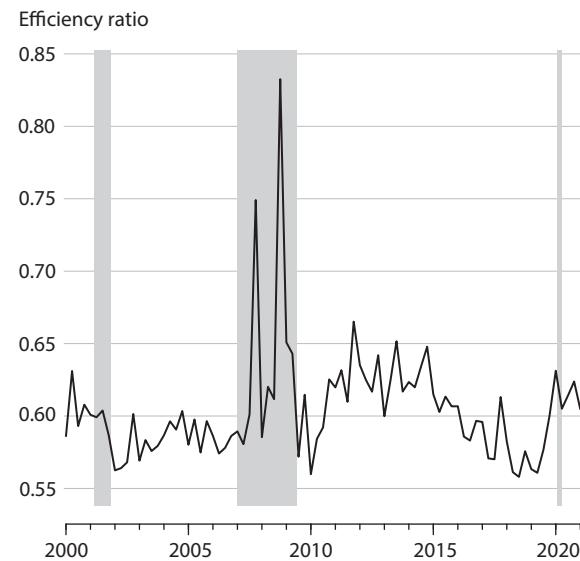
assets increased from 4.91 percent to 16.08 percent of total assets over the same period. The *Wall Street Journal* reported in January 2021 that “big banks have a tantalizing amount of cash on their books, but there is still a ways [sic] to go before that money can make its way into shareholders’ pockets” (Demos, 2021). The decline in net loans and leases and the increases in securities and cash assets held by banks during 2008–10 correspond loosely with periods of ultra-low interest rates discussed above. The fact that banks held more cash and lent less suggests that although the Federal Reserve can affect the supply of loans, it is more difficult for it to affect the demand for loans. Nonetheless, GDP has increased from 2000 to 2020.

Coincident with declining loans was an increase in bank deposits, as shown in Figure 12. Figure 12 shows that the quantity of deposits held by banks increased steadily after 2000 but began increasing at a much faster rate in the fourth quarter of 2019. The ratio of total deposits to total assets fluctuated around a flat trend until mid-2008, then increased sharply afterward, with large jumps in 2008–09 and in 2020, as shown in Figure 13. Perhaps even more dramatic is the increase in the ratio of total deposits to GDP shown in Figure 14. The ratio trended upward after 2000 but began to increase rapidly in the fourth quarter of 2019. The ratio of deposits to GDP increased by 0.9 percent in the third quarter of 2019, by 9.6 percent in the fourth quarter of 2019, and then by 18.6 percent in the first quarter of 2020 before falling by 7.0 percent in the second quarter of 2020 before increasing again in the second half of 2020.

A simple measure of banks’ performance is the ratio of non-interest expense to net interest income plus non-interest income, sometimes called “the efficiency ratio.” The ratio provides a

**Figure 14****Ratio of Total Deposits Held by U.S. Commercial Banks to GDP**

NOTE: Gray bars indicate recessions as determined by the NBER.  
SOURCE: FDIC (2021f) and U.S. Bureau of Economic Analysis (2021b).

**Figure 15****Efficiency Ratio**

NOTE: The efficiency ratio is computed as non-interest expense divided by the sum of net interest income and non-interest income. Data are not seasonally adjusted. Gray bars indicate recessions as determined by the NBER.

SOURCE: FDIC (2021i,j,k).

measure of how well banks control their operating expenses; higher values imply more overhead in the form of labor, physical capital, and other expenses (apart from interest expense) relative to revenue. Seay and Tofiq (2020) report (in mid-December 2020) that U.S. banks' efficiency ratios are worsening, causing banks to focus on cost-cutting efforts. Figure 15 shows the efficiency ratio for the banking industry as a function of time. While there is some fluctuation from quarter to quarter, as Seay and Tofiq (2020) observe, the efficiency ratio has increased during the ongoing COVID-19 pandemic but has not reached the levels of the Great Recession. In fact, the efficiency ratio was higher at various points during 2011–14 than during recent quarters. Obviously, the efficiency ratio can increase if either non-interest expense increases or net interest income declines. Given the unusually low interest rates during 2011–14 and 2020, it seems that these low rates have caused the efficiency ratio to rise above levels experienced in other periods by reducing banks' net interest income.

As noted at the beginning of this section, the analysis here has focused on aggregate measures of banks' performance. The next section develops a model of bank production and employs statistical methods to estimate technical efficiency, providing further insight into how well banks convert financial and physical capital and labor into loans, securities, and off-balance sheet activities.

### 3 A MODEL OF BANKING PRODUCTION

The model described here is the model used by Simar and Wilson (2021) to develop nonparametric methods for estimating directional distance functions while avoiding endogeneity issues. Only a brief presentation is given here; for more discussion and details, see Simar and Wilson (2021). To establish notation, let  $X \in \mathbb{R}_+^p$  and  $Y \in \mathbb{R}_+^q$  denote stochastic vectors of input and output quantities, respectively, and let  $x \in \mathbb{R}_+^p$  and  $y \in \mathbb{R}_+^q$  denote fixed, nonstochastic vectors of input and output quantities, respectively. Let  $f(x,y)$  denote the joint density of  $(X,Y)$  with support on a strict subset of  $\mathbb{R}_+^{p+q}$  and consider the production set

$$(3.1) \quad \Psi := \{(x,y) \mid x \text{ can produce } y\}$$

containing all feasible combinations of inputs and outputs. In the absence of any stochastic noise, the support of the joint density  $f(x,y)$  is a subset of  $\Psi$  and  $\Pr((X,Y) \in \Psi) = 1$ . But if stochastic noise is present, then the support of  $f(x,y)$  may extend outside  $\Psi$  and hence  $\Pr((X,Y) \in \Psi) < 1$ .

Assume that  $\Psi$  is a closed set, to ensure the existence of an efficient frontier, or technology, given by

$$(3.2) \quad \Psi^\delta := \left\{ (x,y) \mid (\alpha^{-1}x, \alpha y) \notin \Psi \text{ for } \alpha > 1 \right\}.$$

Now define  $r := p + q$  and define a fixed, nonstochastic  $(r \times 1)$  direction vector  $d = (-d'_x, d'_y)'$ , where  $d_x \in \mathbb{R}_+^p$  and  $d_y \in \mathbb{R}_+^q$ . Then for a fixed point  $(x,y) \in \mathbb{R}_+^r$ , distance to the frontier  $\Psi^\delta$  in the direction  $d$  is given by the directional distance function

$$(3.3) \quad \delta(x,y|d) := \sup \left\{ \delta \mid (x - \delta d_x, y + \delta d_y) \in \Psi \right\}$$

whenever  $\delta(x,y|d)$  exists.<sup>4</sup>

The model of Simar and Wilson (2021) assumes that a set of  $n$  independent, identically distributed (iid) optimal but latent points  $W_i^\delta := (X_i^\delta, Y_i^\delta)$  on the efficient frontier  $\Psi^\delta$  are generated by a well-defined probability mechanism. These optimal points are unobserved due to inefficiency and statistical noise. Let  $W_i := (X_i, Y_i)$  denote observed input-output combinations for  $i = 1, \dots, n$  and assume that the random sample of observations  $S_n = \{W_i\}_{i=1}^n$  is generated by the statistical generating process  $W_i = W_i^\delta + \xi_i d$  so that

$$(3.4) \quad \begin{bmatrix} X_i \\ Y_i \end{bmatrix} = \begin{bmatrix} X_i^\delta \\ Y_i^\delta \end{bmatrix} + \xi_i d,$$

where, conditional on  $W_i^\delta$ , the  $\xi_i$  are independent scalar random variables whose characteristics may depend on  $W_i^\delta$ .

Next, the stochastic term  $\xi_i$  is assumed to consist of both noise and inefficiency. Specifically, assume that  $\xi_i$  includes both an inefficiency component  $\eta_i \in \mathbb{R}_+$  and a noise component  $\epsilon_i \in \mathbb{R}$  such that

$$(3.5) \quad \xi_i := \epsilon_i - \eta_i,$$

where conditional on  $W_i^\delta$ ,  $\epsilon_i$  and  $\eta_i$  are independent, with

$$(3.6) \quad \epsilon_i | W_i^\delta \sim \text{Sym} \left( 0, \tilde{\sigma}_\epsilon \left( W_i^\delta \right) \right)$$

and

$$(3.7) \quad \eta_i | W_i^\delta \sim D_+ \left( \tilde{\sigma}_\eta \left( W_i^\delta \right) \right),$$

where  $\text{Sym}(0, a)$  denotes a symmetric (around zero) two-sided distribution on  $\mathbb{R}$  with standard deviation  $a \geq 0$ , and  $D_+(b)$  denotes a one-sided distribution on  $\mathbb{R}_+$  belonging to some one-parameter scale family with parameter  $b \geq 0$ .<sup>5</sup>

As discussed by Simar and Wilson (2021), direct estimation of the proposed model involves significant complications related to endogeneity issues. Simar and Wilson (2021) propose transforming the model to a new space to avoid these difficulties. Let  $V_d[v_1 \dots v_{r-1}]$  denote an orthonormal basis for the direction vector  $d$  (see, e.g., Noble and Daniel, 1977, for discussion and details). As noted by Simar and Wilson (2021),  $V_d$  is not unique, but this is not a problem as long as it is treated as fixed by using only one such matrix. Note that  $V_d$  is an  $r \times (r-1)$  matrix and depends only on the given direction vector  $d$ . Now define the  $(r \times r)$  rotation matrix

$$(3.8) \quad R_d = \begin{bmatrix} V_d' \\ d'/\|d\| \end{bmatrix},$$

where  $\|\cdot\|$  denotes the  $L_2$  norm.<sup>6</sup>

To transform the model, define

$$(3.9) \quad \begin{bmatrix} Z_i \\ U_i \end{bmatrix} := R_d W_i = R_d \begin{bmatrix} X_i \\ Y_i \end{bmatrix},$$

where  $Z_i \in \mathbb{R}^{r-1}$  and  $U_i \in \mathbb{R}^1$  for each  $i = 1, \dots, n$ , thereby transforming the iid sample  $S_n$  to an iid sample  $S_n(d) = \{(Z_i, U_i)\}_{i=1}^n$ . Clearly,  $U_i = d' W_i / \|d\|$  and hence is invariant to the ordering of the inputs and outputs since the ordering of the elements of the direction vector  $d$  necessarily corresponds to whatever order is chosen for elements of the input and output vectors  $X_i$  and  $Y_i$ .

Note that the transformation from  $(x, y)$ -space to  $(z, u)$ -space is linear; it is also one to one and therefore can be inverted. The production set in  $(x, y)$ -space is transformed to the set

$$(3.10) \quad \Gamma_d = \left\{ (z, u) \in \mathbb{R}^r \mid R_d' [z' \ u]' \in \Psi \right\}$$

in  $(z, u)$ -space, and the density  $f(x, y)$  in  $(x, y)$ -space is transformed to a density  $g(z, u) = g(u|z)g(z)$  in  $(z, u)$ -space. More importantly, the frontier  $\Psi^\delta$ —an  $(r-1)$ -dimensional manifold in  $(x, y)$ -space—is transformed to the scalar-valued function  $\phi(z) : \mathbb{R}_+^{r-1} \mapsto \mathbb{R}^1$  in  $(z, u)$ -space such that

$$(3.11) \quad \phi(z) = \sup \{u \mid (z, u) \in \Gamma_d\}.$$

Pre-multiplying both sides of the model in (3.4) by the rotation matrix  $R_d$  yields the transformed model

$$(3.12) \quad \begin{bmatrix} Z_i \\ U_i \end{bmatrix} = \begin{bmatrix} Z_i^\delta \\ U_i^\delta \end{bmatrix} + \xi_i \begin{bmatrix} 0_{r-1} \\ \|d\| \end{bmatrix}.$$

Note that both  $U_i$  and  $Z_i = Z_i^\partial$  are observed, given the direction vector  $d$ . Moreover, since  $Z_i = Z_i^\partial$  is observed, the frontier points in  $(z, u)$ -space can be expressed as  $(Z_i, U^\partial(Z_i)) = (Z_i, \phi(Z_i))$ . Then by conditioning on  $Z_i$ ,

$$(3.13) \quad U_i = \phi(Z_i) + \|d\| \epsilon_i - \|d\| \eta_i,$$

where the scale functions  $\tilde{\sigma}_\epsilon(W_i^\partial)$  and  $\tilde{\sigma}_\eta(W_i^\partial)$  in (3.6) and (3.7) can be written as functions of  $Z_i$  due to the fact that  $W_i^\partial$  can be expressed as a function of  $Z_i$  only. Hence (3.6) and (3.7) can be rewritten as

$$(3.14) \quad \epsilon_i | Z_i \sim \text{Sym}\left(0, \sigma_\epsilon(Z_i)\right)$$

and

$$(3.15) \quad \eta_i | Z_i \sim D_+\left(\sigma_\eta(Z_i)\right).$$

As shown by Simar and Wilson (2021), only  $U_i$  is endogenous in (3.12), making estimation much easier than working in the original  $(x, y)$ -space where all the elements of  $X_i$  and  $Y_i$  are potentially endogenous.

In order to identify the frontier function  $\phi(Z_i)$  in (3.11), a functional form for the distribution  $D_+$  in (3.15) must be specified, but no additional assumptions on the distribution of  $\epsilon_i$  are needed. Assume that the distribution of  $\eta_i$ , conditional on  $Z_i$ , is half normal with scale parameter  $\sigma_\eta(Z_i)$ ; that is,

$$(3.16) \quad \eta_i | Z_i \sim N^+(0, \sigma_\eta^+(Z_i)).$$

The scale parameter is functional and will be estimated locally as explained below. Consequently, the half-normal specification used here is rather flexible. Simar and Wilson (2021) present Monte Carlo results showing the effects of an incorrect specification for  $\eta$ , and while there is a price to pay for misspecification, it appears to be small since the estimation is local. Some additional mild technical assumptions regarding the smoothness of the frontier function  $\phi(Z)$  and existence of moments of  $U_i$  are needed for consistency of the nonparametric estimators described in the next section; see Simar and Wilson (2021) for details. Such assumptions are far less restrictive than those imposed for parametric estimation.

## 4 ESTIMATION METHOD

Estimation of the transformed model is straightforward using the method proposed by Simar, Van Keilegom, and Zelenyuk (2017) and used by Simar and Wilson (2021). The goal is to obtain estimates of

$$(4.1) \quad \mu_\eta(Z_i) := E(\eta_i | Z_i) = k_1 \sigma_\eta(Z_i),$$

where  $k_1 = 2^{1/2} \pi^{-1/2}$  due to the assumption of a local half-normal distribution for  $\eta$ .<sup>2</sup>

Note that  $\mu_\eta(Z_i)$  defined in (4.1) must be nonnegative for all  $i = 1, \dots, n$ . In order to simplify notation, assume that the direction vector  $d$  is normalized so that  $\|d\| = 1$  (this has no effect on the results that follow). Define  $\varepsilon_i := \xi_i + \mu_\eta(Z_i)$  and  $r_1(Z_i) := \phi(Z_i) - \mu_\eta(Z_i)$ . Clearly,  $E(\varepsilon_i | Z_i) = 0$ , and it follows that

$$(4.2) \quad U_i = r_1(Z_i) + \varepsilon_i$$

and  $E(U_i | Z_i) = r_1(Z_i) + \phi(Z_i) - \mu_\eta(Z_i)$ . The function  $r_1(Z_i)$  is an ordinary conditional mean function that can be estimated using standard nonparametric regression estimators (e.g., the local-linear estimator; see Wheelock and Wilson, 2001, 2018a, for examples).

By the assumption of symmetry for  $\varepsilon_i | Z_i$ ,

$$(4.3) \quad E(\varepsilon | Z_i) = 0,$$

and

$$(4.4) \quad E(\varepsilon^3 | Z_i) = -E\left[\left(\eta - \mu_\eta(Z_i)\right)^3 | Z_i\right].$$

Let  $r_3(Z_i) := E(\varepsilon^3 | Z_i)$ . Using the assumptions of the model, it is easy to show that

$$(4.5) \quad \mu_\eta(Z_i) = E(\eta | Z_i) = \sqrt{\frac{2}{\pi}}\sigma_\eta(Z_i)$$

and

$$(4.6) \quad r_3(Z_i) = \sqrt{\frac{2}{\pi}}\frac{\pi-4}{\pi}\sigma_\eta^3(Z_i) \leq 0.$$

Due to (4.6), the scale function  $\sigma_\eta(Z_i)$  is identified by the third (local) moment  $r_3(Z_i)$ , providing identification of  $\mu_\eta(Z_i)$ .

To estimate  $\mu_\eta(Z_i)$ , (4.2) is first estimated by local-linear least squares, yielding estimates  $\hat{r}_1(Z_i)$  of  $r_1(Z_i)$ .<sup>8</sup> Next, residuals  $\hat{\varepsilon}_i = U_i - \hat{r}_1(Z_i)$  are computed for  $i = 1, \dots, n$ , and local-linear regression is used again to regress  $\hat{\varepsilon}_i^3$  on  $Z_i$  to obtain estimates  $\hat{r}_3(Z_i)$  of  $r_3(Z_i)$ .<sup>9</sup>

Substituting  $\hat{r}_3(Z_i)$  into (4.6) yields (after some algebra) the estimator

$$(4.7) \quad \hat{\sigma}_\eta(Z_i) = \max\left\{0, \left[\sqrt{\frac{\pi}{2}}\frac{\pi}{\pi-4}\hat{r}_3(Z_i)\right]^{1/3}\right\} \geq 0$$

of the scale function  $\sigma_\eta(Z_i)$ . Then substituting  $\hat{\sigma}_\eta(Z_i)$  into (4.5) yields an estimator of mean conditional inefficiency  $\mu_\eta(Z_i)$ ; that is,

$$(4.8) \quad \hat{\mu}_\eta(Z_i) = \sqrt{\frac{2}{\pi}}\hat{\sigma}_\eta(Z_i).$$

The only remaining issues surround specification of specific inputs and outputs, and this is discussed in the next section.

## 5 DATA AND VARIABLE SPECIFICATION

As noted in Section 1, there is a large literature on estimation of efficiency among banks. The specification of inputs and outputs used here is rather standard and similar to the variable specifications used by Wheelock and Wilson (2012, 2018a). Five inputs are specified, including purchased funds ( $X_1$ ), consisting of deposits, federal funds purchased and securities sold under agreements to repurchase, trading liabilities, other borrowed money, and subordinated notes and debentures; labor ( $X_2$ ), measured in full-time equivalents; physical capital ( $X_3$ ), measured as the book value of premises and fixed assets, including capitalized leases; equity ( $X_4$ ); and nonperforming loans ( $X_5$ ), including loans past due 30–89 days and still accruing, loans past due 90 days or more and still accruing, loans not accruing, and other real estate owned. Both purchased funds and equity are sources of financial capital. Nonperforming loans are included to provide a measure of risk-taking, which is otherwise difficult to measure. Other real estate owned is included in this measure to reflect foreclosed loans. In the analysis that follows, both  $X_4$  and  $X_5$  are held constant when estimating technical efficiency.<sup>10</sup> Three outputs are specified: (i) total loans and leases held for investment and held for sale ( $Y_1$ ); (ii) securities ( $Y_2$ ), including held-to-maturity securities, available-for-sale debt securities, equity securities with readily determinable fair values not held for trading, and federal funds sold and securities purchased under agreements to resell; and (iii) off-balance-sheet activities ( $Y_3$ ). Securities represent a type of lending other than loans. Off-balance sheet activities are measured here by non-interest income and include loan commitments, letters of credit, revolving underwriting facilities, and other activities that potentially generate revenue.<sup>11</sup> All dollar amounts are in thousands of constant 2012 dollars, and labor is measured in terms of full-time equivalents.

Data on commercial banks are taken from the quarterly Federal Financial Institutions Examination Council call reports for commercial banks for the first quarter of 2000 through the fourth quarter of 2020. After deleting outliers and observations with missing or obviously invalid values, 518,165 observations remain, covering the 84 quarters from the first quarter of 2000 through the fourth quarter of 2020. The numbers of observations in each quarter range from 8,236 in the first quarter of 2000 to 4,152 in the fourth quarter of 2020, reflecting the decreasing numbers of U.S. banks, as discussed earlier in Section 2. The first eight rows of Table 1 present summary statistics on the input and output variables. The values shown for the first, second, and third quartiles, as well as for comparison of the median and mean values, reveal considerable right-skewness in the marginal distributions, reflecting similar skewness in the size distribution of U.S. banks.

With  $p = 5$  inputs and  $q = 3$  outputs, there are potentially seven right-hand-side variables in the nonparametric regressions that must be estimated in order to obtain estimates of technical efficiency. Moreover, it is well known that nonparametric estimators such as local-linear least squares are subject to the “curse of dimensionality,” which means that their convergence rates become slower with increasing dimensionality. This translates into increasing estimation error as the number of right-hand-side variables increases in nonparametric regressions. However, both the input variables and the output variables are highly collinear, allowing the dimensionality of the problem to be reduced using the methods examined by Wilson (2018).

To employ dimension reduction, each of the input and output variables defined above are first divided by their standard deviations. Next, let  $X_1$  denote the  $(n \times 3)$  matrix whose columns contain observations on  $X_1$ ,  $X_2$ , and  $X_3$ . Similarly, let  $X_2$  denote the  $(n \times 2)$  matrix whose columns contain observations on  $X_4$  and  $X_5$ , and let  $Y$  represent the  $(n \times 3)$  matrix whose columns contain observa-

**Table 1****Summary Statistics for Inputs and Outputs**

|         | Min        | Quartile 1 | Median      | Mean       | Quartile 3  | Max       |
|---------|------------|------------|-------------|------------|-------------|-----------|
| $X_1$   | 2.7183(2)  | 5.9195(4)  | 1.2189(5)   | 8.2012(5)  | 2.7449(5)   | 1.6834(9) |
| $X_2$   | 1.0000     | 1.8500(1)  | 3.6000(1)   | 1.7132(2)  | 7.8500(1)   | 2.3482(5) |
| $X_3$   | 8.6466(-1) | 7.5831(2)  | 2.2583(3)   | 1.1090(4)  | 5.7194(3)   | 1.1321(7) |
| $X_4$   | 0.0000     | 1.2866(4)  | 2.8746(4)   | 2.2939(5)  | 6.6601(4)   | 9.5467(8) |
| $X_5$   | 0.0000     | 2.8400(2)  | 7.5600(2)   | 1.3913(4)  | 2.2120(3)   | 4.1728(7) |
| $Y_1$   | 1.6680(2)  | 7.3079(3)  | 1.4484(4)   | 9.9085(4)  | 3.1371(4)   | 1.9245(8) |
| $Y_2$   | 0.0000     | 3.4929(1)  | 5.4878(2)   | 1.0017(4)  | 2.4543(3)   | 6.6467(7) |
| $Y_3$   | 4.0000     | 3.5380(4)  | 8.0414(4)   | 5.4528(5)  | 1.9270(5)   | 9.3292(8) |
| $X_1^*$ | 6.5958(-5) | 4.0802(-3) | 8.3114(-3)  | 6.0068(-2) | 1.8684(-2)  | 1.9145(2) |
| $X_2^*$ | 4.5063(-4) | 8.1962(-3) | 1.7908(-2)  | 8.9313(-2) | 4.0639(-2)  | 1.1473(2) |
| $Y^*$   | 3.5902(-5) | 3.5545(-3) | 7.5067(-3)  | 6.0806(-2) | 1.7562(-2)  | 1.4207(2) |
| $Z_1$   | -7.3519    | -4.2017    | -3.6583     | -3.5481    | -3.0396     | 4.0130    |
| $Z_2$   | -3.9117    | 2.6067     | 3.2320      | 3.1371     | 3.7934      | 6.1151    |
| $U$     | -2.9426(3) | -1.5689    | -6.8551(-1) | -3.0313    | -3.0085(-1) | 9.8881(1) |

NOTE: All monetary values are in thousands of constant 2012 dollars. Values are represented in scientific notation with the number  $a \times 10^b$  denoted as  $a(b)$ ; for example, the number  $1.1824 \times 10^2$  is denoted as 1.1824(2).

tions on the three output variables. Then an eigensystem decomposition is performed to obtain eigenvalues and eigenvectors of the moment matrices  $X_1'X_1$ ,  $X_2'X_2$ , and  $Y'Y$ . For each moment matrix, the ratio of the largest eigenvalue to the sum of eigenvalues for the moment matrix gives a measure of the portion of the independent linear information contained in the first principal component (e.g., for  $X_1$ , the first principal component is the  $(n \times 1)$  vector  $X_1^* = X_1\Lambda_{X_1}$ , where  $\Lambda_{X_1}$  is the  $(3 \times 1)$  eigenvector corresponding to the largest eigenvalue of  $X_1'X_1$ ). Computing this ratio for each moment matrix yields values 0.9523, 0.8091, and 0.9118 for  $X_1'X_1$ ,  $X_2'X_2$ , and  $Y'Y$ , respectively. These values indicate that most of the information in  $X_1$ ,  $X_2$ , and  $Y$  is contained in their first principal components, and hence the principal components are used for estimation. Summary statistics for the principal components  $X_1^*$ ,  $X_2^*$ , and  $Y^*$  are shown in rows 9 to 11 of Table 7.<sup>12</sup>

Using the principal components  $X_1^*$ ,  $X_2^*$ , and  $Y^*$  results in  $p = 2$ ,  $q = 1$ , and hence  $r = 3$  in terms of the notation of Sections 3 and 4. Thus the direction vector  $d$  contains three elements. The first element is set equal to the negative of the median of  $X_1^*$ , the second element (corresponding to  $X_2^*$ ) is set to zero, and the third element is set equal to the median of  $Y^*$ . Setting the second element of the direction vector equal to zero ensures that distance to the frontier is measured while holding constant both equity and the risk measure given by nonperforming loans. The chosen direction vector completely determines the rotation matrix  $R_d$ , as explained in Section 3. Applying the rotation matrix to  $X_1^*$ ,  $X_2^*$ , and  $Y^*$  yields the transformed variables  $Z_1$ ,  $Z_2$ , and  $U$ , as described in Section 3. Summary statistics for these transformed variables appear in the last three rows of Table 1.

## 6 ESTIMATION RESULTS

The data used for estimation form an unbalanced panel covering 84 quarters. Consequently, both (fixed) time and firm effects are included in the regression of  $U$  on  $Z$  and the regression of cubed residuals from this regression on  $Z$ . For estimation of  $r_1(\cdot)$  in (4.2),  $U_i$  is regressed on  $(Z_i, T_i, L_i)$ ,  $i = 1, \dots, n$ , where  $T_i \in \{1, 2, \dots, 84\}$  (corresponding to the 84 quarters represented in the sample), and  $L_i$  is a unique numeric label for the firm represented by observation  $i$ . Local-linear least-squares regression amounts to feasible generalized least squares with the  $(n \times n)$  weighting matrix consisting of a diagonal matrix of kernel weights. A Gaussian product kernel is used for the two continuous elements of  $Z_i$ . For estimation of  $r_\ell(Z_i, T_i, L_i)$ ,  $\ell \in \{1, 3\}$ , at observation  $i$  the  $j$ th diagonal element of the weighting matrix is given by

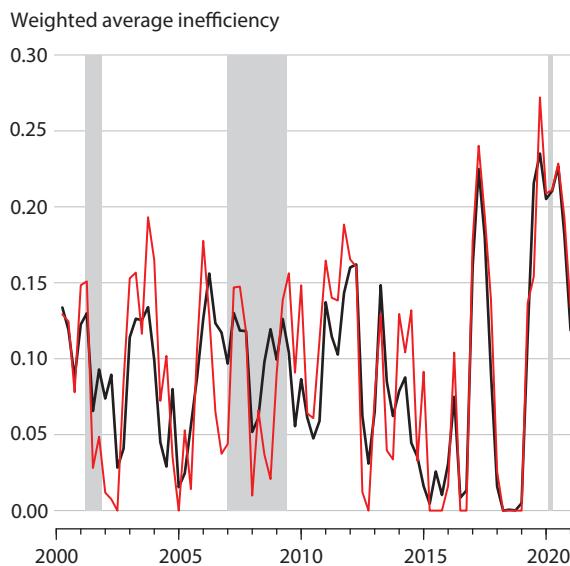
$$(6.1) \quad \omega_j^{(\ell)} = \left[ \prod_{k=1}^2 \left( h_k^{(\ell)} \right)^{-1} K \left( \frac{Z_{jk} - Z_{ik}}{h_k^{(\ell)}} \right) \right] \left( h_3^{(\ell)} \right)^{|T_j - T_i|} \left( h_4^{(\ell)} \right)^{I(L_j \neq L_i)},$$

where  $Z_{ik}$  denotes the  $k$ th element of  $Z_i$ ,  $K(\cdot)$  denotes a kernel function (i.e., the standard normal density function),  $I(\cdot)$  denotes the indicator function, and  $h_k^{(\ell)}$ ,  $k \in \{1, \dots, 4\}$  are bandwidths with  $h_k^{(\ell)} \in [0, 1]$  for  $k \in \{3, 4\}$ . The rate of convergence in the nonparametric regressions depends on the number of continuous right-hand-side variables (two in our case) and is not affected by the discrete time and firm effects (see Li and Racine, 2007, or Henderson and Parmeter, 2015, for discussion). Smaller (larger) values of the bandwidths result in less (more) smoothing or more (less) localization. Bandwidths are optimized via leave-one-out, least-squares cross validation, which amounts to choosing values for bandwidths to minimize a least-squares estimate of the integrated mean-square error. See Simar and Wilson (2021) for details and additional discussion.

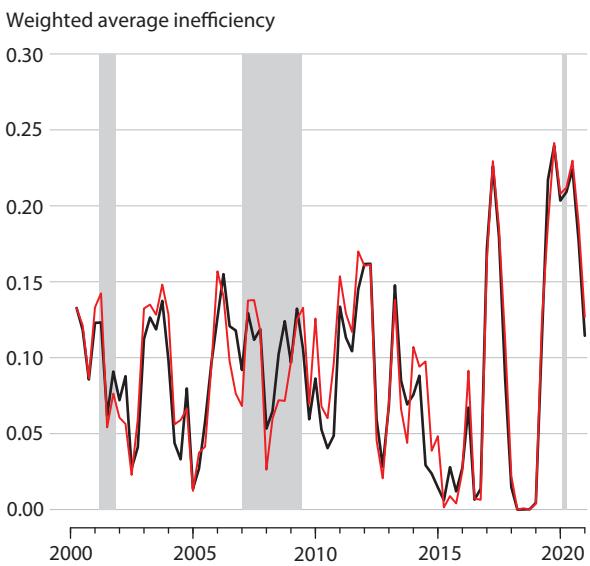
For each observation in the sample, estimates  $\sigma_\eta(Z_i)$  are computed using (4.7), and these are used to compute estimates  $\hat{\mu}_\eta(Z_i)$  using (4.8). The estimates  $\hat{\mu}_\eta(Z_i)$  give the *expected* inefficiency for observation  $i$  facing  $Z_i$ . Then for each quarter, weighted averages of the  $\hat{\mu}_\eta(Z_i)$  are computed for (i) the five largest banks in each quarter and (ii) all other banks in each quarter, with the weight for bank  $i$  given by its total assets in the given quarter. These weighted averages are plotted in Figure 16, where the red curve corresponds to the five largest banks (i.e., the top 5), and the black curve corresponds to all other banks, with larger (smaller) values indicating greater (less) technical *inefficiency*. Figure 17 shows similar information for the top 50 and non-top 50 banks in each quarter.

It is evident that the two curves in Figure 16 and in Figure 17 follow a similar pattern. However, where peaks occur in Figure 16, the top 5 banks are typically more inefficient on average than banks outside the top 5. The same is true for the top 50 versus non-top 50 banks in Figure 17, but the differences are smaller than in Figure 16. At the same time, when average inefficiency is low, the top 5 (and top 50) banks are often less inefficient than the non-top 5 (and non-top 50) banks. Consistent with the discussion in Section 2, the 2001 recession seems to have had little adverse impact on banks' technical inefficiency. Average inefficiency peaked at the beginning of the brief 2001 recession but was lower at the end of the recession.

The estimates in both figures reveal fluctuations in technical efficiency, as does the efficiency ratio in Figure 15, with the fluctuations in technical efficiency becoming larger beginning in 2017. Both Figures 16 and 17 show technical efficiency initially improving during the Great Recession but then worsening again at the end of the recession.

**Figure 16****Weighted-Average Technical Efficiency Estimates,  
Top 5 Banks Versus All Others**

NOTE: The red curve shows averages of technical efficiency estimates for the five largest (top 5) banks weighted by total assets in each period. The black curve shows similar values for non-top 5 banks. Smaller (larger) values correspond to greater (less) efficiency. Gray bars indicate recessions as determined by the NBER.

**Figure 17****Weighted-Average Technical Efficiency Estimates,  
Top 50 Banks Versus All Others**

NOTE: The red curve shows averages of technical efficiency estimates for the 50 largest (top 50) banks weighted by total assets in each period. The black curve shows similar values for non-top 50 banks. Smaller (larger) values correspond to greater (less) efficiency. Gray bars indicate recessions as determined by the NBER.

While Figure 15 shows the efficiency ratio increasing during the Great Recession, Figures 16 and 17 show technical efficiency improving during the Great Recession but then worsening again at the end of the recession. This contrasts with the efficiency ratio depicted in Figure 15, where large peaks occur during the Great Recession. The efficiency ratio gives a rough measure of profit efficiency, whereas technical inefficiency estimates do not consider cost nor revenue, but instead consider resource usage and output production. The two measures are not unrelated but can (and sometimes do) deviate.

Both Figures 16 and 17 show technical inefficiency peaking prior to the 2020 pandemic-induced recession but then falling rapidly after reaching the peak. A large peak in technical inefficiency also occurs in the third quarter of 2017 as interest rates were climbing, but in both cases, the estimates suggest that banks quickly recovered. The efficiency ratio plotted in Figure 15 shows a similar, though less pronounced, pattern.

The large peaks in technical inefficiency during 2017 and 2019-20 shown in Figures 16 and 17 are consistent with the data on deposits and net loans and leases discussed in Section 2. As discussed earlier and shown in Figure 12 and as reported in the financial press (e.g., *Financial Review*, 2020, and Son, 2020), an unusually rapid and large increase in deposits occurred beginning in the fourth quarter of 2019, while loans increased much less. The model developed in Section 3 treats deposits as an input and loans as an output, and consequently technical inefficiency is found to increase to high levels in 2019 and 2020. The efficiency ratio plotted in Figure 15 includes only interest income

and non-interest income and expense, and so was less affected than technical inefficiency by the rapid increase in deposits.

## 7 CONCLUSIONS

The technical efficiency estimates discussed in Section 6 provide an additional measure of banks' performance, beyond examination of specific items such as loans and deposits from banks' balance sheets. The estimates of technical efficiency indicate, among other things, that while banks experience periods of high technical inefficiency, these episodes are typically short-lived; that is, while banks may experience periods of inefficiency, they typically recover quickly, at least on average. The efficiency ratio shown in Figure 15 reached higher levels in the Great Recession of 2007-09 than in the short recession of 2020, but technical inefficiency estimates are found to be higher on average in 2019-20 than in 2007-09. Periods of high technical inefficiency imply that financial resources are being wasted, but the cost of this waste depends not only on the quantities involved, but also on prices, that is, interest rates.

Of course, the recession of 2007-09 was much longer than the recession of 2020, making comparisons problematic. However, 25 commercial banks failed in 2008, followed by 140 in 2009 and then 157, 92, and 51 in 2010, 2011, and 2012, respectively. By contrast, only four banks failed in 2019, another four in 2020, and none in 2021.<sup>13</sup> Wheelock and Wilson (2000) find evidence that cost and technical inefficiency contribute to the probability of bank failure. However, extrapolating from the experience of the Great Recession, it may be that while technical inefficiency reached high levels in 2019 and 2020, the episode was of short duration and did not have time to lead to another wave of insolvencies among banks. To the extent that the Fed's stimulus policy during the pandemic period limited the duration of the 2020 recession, it is likely that a number of banks remained solvent that might otherwise have failed. ■

## NOTES

<sup>1</sup> Data on the number of institutions are from the Federal Deposit Insurance Corporation (FDIC, 2021a). Data on failures and assisted mergers are also from the FDIC (2021h). The FDIC resolves bank failures by arranging mergers of failed institutions with other banks; such mergers are referred to as "assisted mergers."

<sup>2</sup> NBER recession data are available at <https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions>, and the recession dates determined by the NBER are used in the figures. Dating recessions in the economy necessarily involves some subjectivity. See the *FRED® Blog* (2021) for additional discussion.

<sup>3</sup> Throughout, dollar values are expressed in constant 2012 U.S. dollars.

<sup>4</sup> Directional distance functions were first proposed by Chamber, Chung, and Färe (1996, 1998). It is possible that the path  $(x,y) + \delta d$  does not pass through  $\Psi$  for any real-valued  $\delta$ , in which case  $\delta(x,y|d)$  does not exist.

<sup>5</sup> A density  $f(\cdot)$  belongs to a one-parameter scale family if it can be written as  $f(\cdot) = (1/\sigma)\tilde{f}(\cdot/\sigma)$  for some  $\sigma > 0$ , where  $\tilde{f}(\cdot)$  is any density on  $\mathbb{R}_+$ . Examples include the half-normal and exponential distributions and the gamma and Weibull distributions with fixed-shape parameters.

<sup>6</sup> See Noble and Daniel (1977) or Goldstein (1980) for discussion and explanation of rotation matrices.

<sup>7</sup> Using a different distributional assumption would change the value of  $k_1$ .

<sup>8</sup> See Fan and Gijbels (1996) for details. The properties of this estimator are well known; see Fan and Gijbels (1996) or Li and Racine (2007) for discussion.

- <sup>9</sup> Simar, Van Keilegom, and Zelenyuk (2017) show that the usual asymptotic properties (i.e., consistency, rates of convergence, and asymptotic normality) for  $\hat{r}_3(Z_i)$  hold under mild regularity conditions. See Simar and Wilson (2021) for additional discussion.
- <sup>10</sup> Equity is difficult to adjust in the short run. Risk is held constant in order to evaluate banks' performance at observed levels of risk-taking.
- <sup>11</sup> See FDIC (2021I, Section 3.8) for discussion and additional details.
- <sup>12</sup> The extensive simulation results reported by Wilson (2018) suggest that when efficiency is estimated using nonparametric free-disposal hull or data envelopment analysis estimators, estimation based on the first principal components of  $X_1$ ,  $X_2$ , and  $Y$  (denoted by  $X_1^*$ ,  $X_2^*$ , and  $Y^*$ ) is likely to result in less estimation error than would arise using the original eight variables. To my knowledge, no comprehensive Monte Carlo experiments have been done to provide guidelines for when dimension reduction should be used with local-linear estimation, but the results of Wilson (2018) are suggestive. More work is needed.
- <sup>13</sup> Data on bank failures are from the FDIC (2021g).

## REFERENCES

- Bank for International Settlements. "Structural Changes in Banking after the Crisis." CGFS Papers, 2018, No. 60; <https://www.bis.org/publ/cgfs60.htm>.
- Board of Governors of the Federal Reserve System. Bank Prime Loan Rate (DPRIME). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/DPRIME>, accessed August 31, 2021a.
- Board of Governors of the Federal Reserve System. Effective Federal Funds Rate (DFF). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/DFF>, accessed September 2, 2021b.
- Chambers, R.G., Chung, Y. and Färe, R. "Benefit and Distance Functions." *Journal of Economic Theory*, 1996, 70, pp. 407-19; <https://doi.org/10.1006/jeth.1996.0096>.
- Chambers, R.G., Chung, Y. and Färe, R. "Profit, Directional Distance Functions, and Nerlovian Efficiency." *Journal of Optimization Theory and Applications*, 1998, 98, pp. 351-64; <https://doi.org/10.1023/A:1022637501082>.
- Demos, T. "Banks Are Not Ready to Show You the Money." *Wall Street Journal*, January 16, 2021, pp. B.14.
- Diamond, D.W. and Rajan, R.G. "Risk, Liquidity Creation, and Financial Fragility: A Theory of Banking." *Journal of Political Economy*, 2001, 109, pp. 287-327; <https://doi.org/10.1086/319552>.
- Fan, J. and Gijbels, I. *Local Polynomial Modelling and Its Applications*. Chapman and Hall, 1996.
- Federal Deposit Insurance Corporation. Balance Sheet: Number of Institutions Reporting (QBPBNSUMINST). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QBPBNSUMINST>, accessed September 13, 2021a.
- Federal Deposit Insurance Corporation. Balance Sheet: Total Assets: Cash and Due from Depository Institutions (QBPB-STASCSDHP). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QPBSTASCSDHP>, accessed September 8, 2021b.
- Federal Deposit Insurance Corporation. Balance Sheet: Total Assets: Net Loans and Leases (QBPBTSNTLN). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QPBTSNTLN>, accessed September 8, 2021c.
- Federal Deposit Insurance Corporation. Balance Sheet: Total Assets (QBPBSTAS). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QPBSTAS>, accessed September 8, 2021d.
- Federal Deposit Insurance Corporation. Balance Sheet: Total Assets: Securities (QBPBSTALLSC). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QPBSTALLSC>, accessed September 8, 2021e.
- Federal Deposit Insurance Corporation. Balance Sheet: Total Liabilities and Capital: Deposits (QBPBTLKDP). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QPBTLKDP>, accessed September 8, 2021f.
- Federal Deposit Insurance Corporation. "Bank Failures in Brief—Summary 2001 through 2021." <https://www.fdic.gov/bank/historical/bank/>, accessed September 27, 2021g.

Federal Deposit Insurance Corporation. Failures And Assistance Transactions of All Institutions for the United States and Other Areas (BNKTTLA641N). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/BNKTTLA641N>, accessed September 13, 2021h.

Federal Deposit Insurance Corporation. Income and Expense: Net Interest Income (QBPQYNTIY). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QBPQYNTIY>, accessed September 2, 2021i.

Federal Deposit Insurance Corporation. Income and Expense: Total Noninterest Expense (QBPQYTNIEX). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QBPQYTNIEX>, accessed September 2, 2021j.

Federal Deposit Insurance Corporation. Income and Expense: Total Noninterest Income (QBPQYTNIIY). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/QBPQYTNIIY>, accessed September 2, 2021k.

Federal Deposit Insurance Corporation. "Off-Balance Sheet Activities," in *Risk Management Manual of Examination Policies*; <https://www.fdic.gov/regulations/safety/manual/section3-8.pdf>, accessed September 22, 2021l.

*Financial Review*. "US Banks Are Awash With Deposits, But That's Not All Good." August 12, 2020; <https://www.afr.com/companies/financial-services/us-banks-are-awash-with-deposits-but-that-s-not-all-good-20200812-p55111>.

FRED® Blog. "Discrepancies in Dating Recessions." Federal Reserve Bank of St. Louis, August 26, 2021; <https://fredblog.stlouisfed.org/2021/08/discrepancies-in-dating-recessions/>.

Goddard, J.A.; McKillop, D.G. and Wilson, J.O.S. "The Size Distribution of U.S. Banks and Credit Unions." *International Journal of the Economics of Business*, 2014, 21, pp. 139-56; <https://doi.org/10.1080/13571516.2013.835970>.

Goldstein, H. *Classical Mechanics*. Addison-Wesley Publishing Co., 1980.

Henderson, D. J. and Parmeter, C.F. *Applied Nonparametric Econometrics*. Cambridge University Press, 2015; <https://doi.org/10.1017/CBO9780511845765>.

Janicki, H.P. and Prescott, E.S. "Changes in the Size Distribution of U.S. Banks: 1960-2005." *Federal Reserve Bank of Richmond Economic Quarterly*, 2006, 92, pp. 291-316.

Li, Q and Racine, J. *Nonparametric Econometrics*. Princeton University Press, 2007; <https://doi.org/10.1561/0800000009>.

Noble, B. and Daniel, J.W. *Applied Linear Algebra*. 2nd Edition. Prentice-Hall, Inc., 1977.

Seay, L. and Tofiq, M. "US Banks Focused on Cost-Cutting Efforts as Efficiency Ratios Deteriorate." *S&P Global Market Intelligence*, December 16, 2020; <https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/us-banks-focused-on-cost-cutting-efforts-as-efficiency-ratios-deteriorate-61577158>.

Simar, L.; Van Keilegom, I. and Zelenyuk, V. "Nonparametric Least Squares Methods For Stochastic Frontier Models." *Journal of Productivity Analysis*, 2017, 47, pp. 189-204; <https://doi.org/10.1007/s11123-016-0474-2>.

Simar, L. and Wilson, P.W. "Nonparametric, Stochastic Frontier Models with Multiple Inputs and Outputs." Unpublished working paper, Institut de Statistique Biostatistique et Sciences Actuarielles, Université Catholique de Louvain, Louvain-la-Neuve, Belgium, 2021.

Son, H. "U.S. Banks Are 'Swimming In Money' as Deposits Increase by \$2 Trillion Amid the Coronavirus." CNBC Finance, June 21, 2020; <https://www.cnbc.com/2020/06/21/banks-have-grown-by-2-trillion-in-deposits-since-coronavirus-first-hit.html>.

U.S. Bureau of Economic Analysis. Corporate Business: Profits Before Tax (Without IVA and CCAdj) (A446RC1Q027SBEA). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/A446RC1Q027SBEA>, accessed September 15, 2021a.

U.S. Bureau of Economic Analysis. Gross Domestic Product (GDP). Retrieved from FRED®, Federal Reserve Bank of St. Louis, <https://fred.stlouisfed.org/series/GDP>, accessed September 2, 2021b.

U.S. Bureau of Economic Analysis. Gross Domestic Product: Implicit Price Deflator (GDPDEF). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/GDPDEF>, September 2, 2021c.

U.S. Bureau of Economic Analysis. Nonfinancial Corporate Business: Profits Before Tax (Without IVA and CCAdj) (A446RC1Q027SBEA). Retrieved from FRED®, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/A446RC1Q027SBEA>, September 15, 2021d.

U.S. Bureau of Economic Analysis. Real Gross Domestic Product (GDPC1). Retrieved from FRED®, Federal Reserve Bank of St. Louis, <https://fred.stlouisfed.org/series/GDPC1>, September 2, 2021e.

Wheelock, D.C. "Banking Industry Consolidation and Market Structure: Impact of the Financial Crisis and Recession." *Federal Reserve Bank of St. Louis Review*, November/December 2011, 93(6), pp. 419-38; <https://doi.org/10.20955/r.93.419-438>.

Wheelock, D.C. and Wilson, P.W. "Why Do Banks Disappear? The Determinants of U.S. Bank Failures and Acquisitions." *Review of Economics and Statistics*, 2000, 82, pp. 127-38; <https://doi.org/10.1162/003465300558560>.

Wheelock, D.C. and Wilson, P.W. "New Evidence on Returns to Scale and Product Mix Among U.S. Commercial Banks." *Journal of Monetary Economics*, 2001, 47, pp. 653-74; [https://doi.org/10.1016/S0304-3932\(01\)00059-9](https://doi.org/10.1016/S0304-3932(01)00059-9).

Wheelock, D.C. and Wilson, P.W. "Do Large Banks Have Lower Costs? New Estimates of Returns to Scale for U.S. Banks." *Journal of Money, Credit, and Banking*, 2012, 44, pp. 171-99; <https://doi.org/10.1111/j.1538-4616.2011.00472.x>.

Wheelock, D.C. and Wilson, P.W. "The Evolution of Scale-Economies in U.S. Banking." *Journal of Applied Econometrics*, 2018, 33, pp. 16-28; <https://doi.org/10.1002/jae.2579>.

Wilson, P. W. "Dimension Reduction in Nonparametric Models of Production." *European Journal of Operational Research*, 2018, 267, pp. 349-67; <https://doi.org/10.1016/j.ejor.2017.11.020>.

# Subjective Assessment of Managerial Performance and Decisionmaking in Banking

Drew Dahl and Daniel C. Coster

We examine subjective supervisory assessments of managerial performance in the banking industry. Results of empirical tests show that better assessments are (i) positively associated with decisions made by examiners to upgrade relatively objective bank performance ratings; (ii) negatively associated with decisions made by examiners to downgrade relatively objective bank performance ratings; and (iii) positively associated with decisions made by bank holding company managers to distribute resources among subsidiary banks. These results are consistent with the finding that soft information generated in the supervisory process is validated by subsequent decisionmaking both internally (by bankers) and externally (by examiners). (JEL G28, G21, L14)

Federal Reserve Bank of St. Louis *Review*, Third Quarter 2022, 104(3), pp. 210-23.

<https://doi.org/10.20955/r.104.210-23>

---

## 1 INTRODUCTION

Subjective assessments of managerial performance have been widely hypothesized to play an important role in contracting within firms and other organizations. Empirical support for this hypothesis, however, is limited by overlaps with objective metrics on which performance also depends.

We approach this issue from the perspective of information identified by bank examiners during their evaluations of managers of commercial banks. Examiners are well placed to observe the subtleties of managerial behavior (Baker, Gibbons, and Murphy, 1994) and are therefore able to assess contributions to firm value that are not objectively measurable. Their assessments rely on soft information that requires effort to obtain, judgment to assess, and knowledge that becomes less useful when separated from the environment in which it was collected (Eisenbach, Luca, and Townsend, 2016, and Liberti and Petersen, 2019).

Performance ratings are prominent in this process. These ratings are assigned by examiners following on-site inspections to measure capital (C), asset quality (A), earnings (E), management (M), liquidity (L), and market sensitivity (S). They range numerically from 1, for the best banks, to 5, for the worst. They collectively are rolled up into a composite (CAMELS) rating. All are non-public.

Drew Dahl is an economist at the Federal Reserve Bank of St. Louis. Daniel C. Coster is a professor of mathematics and statistics at Utah State University.

© 2022, Federal Reserve Bank of St. Louis. The views expressed in this article are those of the author(s) and do not necessarily reflect the views of the Federal Reserve System, the Board of Governors, or the regional Federal Reserve Banks. Articles may be reprinted, reproduced, published, distributed, displayed, and transmitted in their entirety if copyright notice, author name(s), and full citation are included. Abstracts, synopses, and other derivative works may be made only with prior written permission of the Federal Reserve Bank of St. Louis.

The management rating, the M component, encompasses a broad range of factors that are subjective in nature. They include community service, the nature and degree of working relationships, and the level and quality of oversight (Federal Deposit Insurance Corporation [FDIC], 2022; Board of Governors of the Federal Reserve System [BOG], 2021). They have been said to include those that are so intuitive as to reflect “a particular banker’s temperament” (Effinger, 2017).

Critics contend that the management rating is excessively subjective. They advocate an overhaul that emphasizes “clear, cogent and objective measures of financial condition over vague, arbitrary and subjective ones” (Baer and Newell, 2017). Supervisors appear sympathetic: The BOG, the Federal Financial Institutions Examination Council, and the FDIC are exploring how to ensure that the different agencies and different examiners within each agency are applying ratings consistently and uniformly (McWilliams, 2019a,b).

We contribute to this debate by determining whether soft information about a bank—embodied in its management rating—can be linked to decisionmaking. We use a proxy variable for soft information, derived from CAMELS components, that is statistically independent of information that is more quantitative in nature. Separate analyses consider decisions that are made externally, by examiners in establishing subsequent CAMELS component ratings, and internally, by bank holding company managers in allocating resources among affiliated banks.

With respect to decisions of examiners, results of tests using a sample of 27,484 commercial banks over the 2011 to 2017 period show that subjective assessments indicating better managerial performance are positively related to improvement and negatively related to deterioration in subsequent CAMELS component ratings. Base-case scenarios are confirmed in robustness tests that account for potential endogeneity in how examiners are assigned to specific banks.

With respect to decisions of bank managers, results of tests based on 21,259 observations on subsidiaries in multi-bank holding companies over the 1999 to 2017 period show that subjective assessments indicating better performance are positively related to the likelihood that a bank subsidiary receives more resources from its parent holding company. Base-case scenarios are confirmed in robustness tests that account for potential endogeneity in how examiners, or managers, are assigned to specific banks.

Results across the two analyses are consistent with a production of soft information whose usefulness is validated in decisions about banks that are made both internally (by bankers) and externally (by examiners). The former has theoretical roots in prior empirical analyses of qualitative factors in corporate decisionmaking (Jian and Lee, 2011; Duchin and Sosyura, 2013; McNeil and Smythe, 2009; Glaser, Lopez-De-Silanes, and Zautner, 2013; and Gaspar and Massa, 2011), while the latter can be understood in the context of earlier studies showing that CAMELS ratings predict regulatory outcomes (Cole and Gunther, 1998; Hirtle and Lopez, 1999; Berger and Davies, 1998; DeYoung et al., 2001; and Gopalan, 2018). Both are part of a larger theoretical literature on how information is used in contracting within organizations (Rajan and Reichelstein, 2006; Baker, Gibbons, and Murphy 1994; and MacLeod, 2003).

## 2 SOFT INFORMATION AND CAMELS RATINGS

The role of M as a measure of soft information may be attenuated by correlations with other CAMELS components. We address this issue with an approach used by Calomiris and Carlson

(2018) to extract soft information generated by bank examiners in the nineteenth century. They found that this information was useful in forecasting performance outcomes.

Our methodology uses the residual of a regression of the M rating on C, A, E, L, and S ratings as a proxy for soft information:

$$(1) \quad M_{i,(t-1)} = b_0 + b_1 C_{i,(t-1)} + b_2 A_{i,(t-1)} + b_3 E_{i,(t-1)} + b_4 L_{i,(t-1)} + b_5 S_{i,(t-1)} + e_{i,(t-1)}, \quad i=1,\dots,n,$$

where  $n$  denotes the number of banks for which ratings are observed. The residual,  $e_{i,(t-1)}$ , will be designated as  $\text{SOFT}_{i,(t-1)}$  in both studies. It is orthogonal to the more objectively assessed elements of performance embodied in  $C_{i,(t-1)}$ ,  $A_{i,(t-1)}$ ,  $E_{i,(t-1)}$ ,  $L_{i,(t-1)}$ , and  $S_{i,(t-1)}$ . More positive values of  $\text{SOFT}_{i,(t-1)}$  indicate that actual M ratings were worse (larger numerically) than what would be expected based on the more objective C, A, E, L, and S ratings; conversely, negative values are associated with actual M values that were better (lower numerically) than expected based on the objective assessments.<sup>1</sup>

### 3 THE FIRST ANALYSIS: SOFT INFORMATION AND CHANGES IN RATINGS

We use a sample of 27,484 observations on commercial banks over the 2011 to 2017 period to determine whether soft information that reveals better (worse) managerial performance is positively (negatively) related to improvement or negatively (positively) related to deterioration in subsequent performance ratings.<sup>2</sup> We derive  $\text{SOFT}_{i,(t-1)}$  at the point of bank  $i$ 's initial examination at  $t-1$  in the 2011 to 2015 period.<sup>3</sup> The time to the next examination at time  $t$  could vary from one quarter to eight quarters, at which point we truncate our analysis.<sup>4</sup> The fourth quarter of 2017, therefore, is the last quarter in which the succeeding (second) examination could have occurred.

#### 3.1 The Model

Over the interval from  $t-1$  to  $t$ , any given bank  $i$  could exhibit an upgrade, no change, or downgrade in rating for C, A, E, L, or S.<sup>5</sup> Conditional on our assessed measure of soft information, we fit a multinomial (generalized) logit model for response variable  $y$  to assess the impact of  $\text{SOFT}_{i,(t-1)}$  on the likelihood of an upgrade in rating ( $y = 1$ ) or downgrade in rating ( $y = 3$ ) relative to the reference category of no change in rating ( $y = 2$ ). For each of the relatively objective ratings C, A, E, L, and S, separately, we define  $P_j(t | \text{SOFT}_{i,(t-1)})$  as the probability that  $y = j$  for observed value  $\text{SOFT}_{i,(t-1)}$  at subsequent examination time  $t$ :

$$(2) \quad \log_e \left( \frac{P_j(i,t)}{P_2(i,t)} \right) = a_j + b_j \text{SOFT}_{i,(t-1)} \text{ for } j = 1, 3 \quad \text{and } i = 1, \dots, n$$

and thus  $e^{b_j}$  provides the multiplicative change in the odds of an upgrade ( $j = 1$ ) or downgrade ( $j = 3$ ) relative to no change in rating per unit change in  $\text{SOFT}_{i,(t-1)}$ .

We hypothesize a negative coefficient on  $\text{SOFT}_{i,(t-1)}$  in determining the odds of an upgrade (i.e.,  $b_1 < 0$ ) and a positive coefficient for the odds of a downgrade (i.e.,  $b_3 > 0$ ). Specifically, when  $b_1 < 0$  and observed M is better than what would be expected based on objective assessments C, A,

E, L, and S, in which case  $\text{SOFT}_{i,(t-1)} < 0$ , then our model predicts a (multiplicative) increase in the odds of an upgrade ( $j - 1$ ). The opposite holds if  $b_3 > 0$  and  $\text{SOFT}_{i,(t-1)} > 0$ , as this results in increased odds of a downgrade.

The distributions of ratings, upgrades, and downgrades are presented in Table 1. Mean ratings were highest (worst) for earnings and lowest (best) for liquidity. Variation in ratings was highest for capital and lowest for market sensitivity.

**Table 1****Descriptive Statistics, CAMELS Components**

|                          | $M_{(t-1)}$ | $C_{(t-1)}$ | $A_{(t-1)}$ | $E_{(t-1)}$ | $L_{(t-1)}$ | $S_{(t-1)}$ |
|--------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Mean                     | 2.41        | 2.24        | 2.47        | 2.54        | 1.89        | 2.13        |
| Standard deviation       | 1.03        | 1.13        | 1.21        | 1.22        | 0.92        | 0.87        |
| Coefficient of variation | 42.9        | 50.6        | 49.0        | 47.9        | 48.8        | 40.6        |
| Upgrades                 | 3,755       | 2,981       | 5,022       | 3,989       | 2,385       | 2,537       |
| Downgrades               | 1,814       | 1,150       | 1,535       | 1,756       | 1,499       | 1,429       |

Upgrades were more common than downgrades for every CAMELS component, which is unsurprising insofar as our sample period coincides with economic expansion. The number of upgrades was highest for asset quality and lowest for liquidity. Downgrades were most common for management.

**3.2 The Derivation of  $\text{SOFT}_{(t-1)}$** 

Results for equation (1) deriving  $\text{SOFT}_{(t-1)}$  are presented in Table 2. All of the independent variables have positive and statistically significant coefficients. The coefficients are largest for asset quality and lowest for liquidity.

**Table 2****Regression Results for Derivation of  $\text{SOFT}_{(t-1)}$** 

Dependent variable:  $M_{i(t-1)}$

| INT                | $C_{(t-1)}$         | $A_{(t-1)}$         | $E_{(t-1)}$         | $L_{(t-1)}$         | $S_{(t-1)}$         |
|--------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| 0.265***<br>(6.10) | 0.162***<br>(0.006) | 0.253***<br>(0.005) | 0.158***<br>(0.004) | 0.135***<br>(0.006) | 0.232***<br>(0.006) |
| <i>N</i> = 27,484  |                     |                     |                     |                     |                     |

NOTE: INT is intercept. \*\*\* indicates the coefficient is statistically significantly different from 0 at an  $\alpha$  level of 0.01. Standard errors are in parentheses.

**3.3 Multinomial Results**

Our base-case assessments using equation (2) are presented in Table 3. Each column has results for upgrade, no change, or downgrade in  $C_{(t)}$ ,  $A_{(t)}$ ,  $E_{(t)}$ ,  $L_{(t)}$ , and  $S_{(t)}$ . We designate  $b_3$  in equation

(2) as DOWNSOFT<sub>(t)</sub> and  $b_1$  in equation (2) as UPSOFT<sub>(t)</sub>, UPINT<sub>(t)</sub>, and DOWNINT<sub>(t)</sub> are intercept coefficients  $a_1$  and  $a_3$ , respectively.

Because the multinomial logit model in equation (2) computes standard errors for estimated coefficients based on the expected value of the second derivative of the conditional log-likelihood, and thus may underestimate unexplained variation and hence standard errors, we obtained robust parameter estimates and standard errors using 1,000 bootstrap samples taken with replacement from the original data for each C, A, E, L, and S. Means and standard deviations for UPSOFT<sub>(t-1)</sub> and DOWNSOFT<sub>(t-1)</sub> are shown in the lower panel of Table 3. The bootstrap standard deviations are consistent with the standard errors from the fit of equation (2) to the original dataset. We conclude that the multinomial logit model has adequately assessed the significance of coefficients.

**Table 3****Multinomial Logit Results for Likelihood of Change in Rating**

|                                | C <sub>(t)</sub>     | A <sub>(t)</sub>     | E <sub>(t)</sub>     | L <sub>(t)</sub>     | S <sub>(t)</sub>     |
|--------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| DOWNINT <sub>(t-1)</sub>       | -3.022***<br>(0.030) | -2.623***<br>(0.026) | -2.541***<br>(0.024) | -2.762***<br>(0.026) | -2.817***<br>(0.027) |
| DOWNSOFT <sub>(t-1)</sub>      | 0.318***<br>(0.061)  | 0.272***<br>(0.053)  | 0.447***<br>(0.049)  | 0.223***<br>(0.054)  | 0.375***<br>(0.054)  |
| UPINT <sub>(t-1)</sub>         | -2.059***<br>(0.019) | -1.438***<br>(0.015) | -1.708***<br>(0.017) | -2.291***<br>(0.021) | -2.237***<br>(0.024) |
| UPSOFT <sub>(t-1)</sub>        | -0.096**<br>(0.041)  | -0.384***<br>(0.035) | -0.376***<br>(0.038) | -0.208***<br>(0.046) | -0.319***<br>(0.054) |
| -2 Log L                       | 28,117               | 37,175               | 35,063               | 27,536               | 27,766               |
| Upgrades                       | 2,981                | 5,022                | 3,989                | 2,385                | 2,537                |
| Downgrades                     | 1,150                | 1,535                | 1,756                | 1,499                | 1,429                |
| No change                      | 23,335               | 20,927               | 21,739               | 23,600               | 23,518               |
| <b>Bootstrap averages</b>      |                      |                      |                      |                      |                      |
| Mean DOWNSOFT <sub>(t-1)</sub> | -0.098               | -0.384               | -0.376               | -0.207               | -0.319               |
| STD DOWNSOFT <sub>(t-1)</sub>  | 0.043                | 0.035                | 0.038                | 0.046                | 0.044                |
| Mean UPSOFT <sub>(t-1)</sub>   | 0.317                | 0.270                | 0.447                | 0.223                | 0.377                |
| STD UPSOFT <sub>(t-1)</sub>    | 0.060                | 0.053                | 0.050                | 0.052                | 0.052                |

NOTE: \*\*, \*\*\* indicate the coefficient is statistically significantly different from 0 at an  $\alpha$  level of 0.05 and 0.01, respectively. Standard errors are in parentheses. DOWNSOFT<sub>(t)</sub> is  $b_3$  in equation (2) and UPSOFT<sub>(t)</sub> is  $b_1$ . UPINT<sub>(t)</sub> and DOWNINT<sub>(t)</sub> are intercept coefficients  $a_1$  and  $a_3$ , respectively. Bootstrap averages were obtained from random samples of the original dataset. STD is standard deviation.

The coefficients on DOWNSOFT<sub>(t-1)</sub> are positive and statistically significant at the 1 percent level in all cases. This finding indicates that banks with more positive values for SOFT<sub>(t-1)</sub>, which represent worse performance than expected based on objective measures, are more likely to experience downgrades in subsequent performance evaluations. The coefficients on UPSOFT<sub>(t-1)</sub> are negative and statistically significant at the 1 percent level for each regression of A<sub>(t)</sub>, E<sub>(t)</sub>, L<sub>(t)</sub>, and S<sub>(t)</sub>, and at the 5 percent level for C<sub>(t)</sub>. These findings indicate that banks with more positive values for SOFT<sub>(t-1)</sub>, which represent worse performance than expected, are less likely to experience upgrades in objective performance outcomes.

Our results confirm the finding of Gilbert, Meyer, and Vaughn (2002) that supervisory decisions to downgrade CAMELS ratings are more likely when a bank's management rating (M) is worse than its composite rating (CAMELS)—and extend that research by considering decisions to upgrade as well. Our results contrast with Gaul and Jones (2021, p. 5), who found that management ratings “have little or no predictive power” for bank failures after controlling for CAMELS composite ratings. Interpretations of both studies are limited by large overlaps between management ratings and composite ratings (Gaul and Jones, 2021) that our methodology is intended to limit.

The focus of previous research on downgrades, including Gilbert, Meyer, and Vaughn (2002), is understandable from the perspective of assessing risks to financial system stability. But our inclusion of upgrades is important to the extent that subjective assessments of soft information by examiners are found to be symmetric—that is, examiner opinions are not limited by consideration of characteristics that only are useful in the prediction of underperformance. From this perspective, they are not necessarily arbitrary in terms of this aspect of potential bias (Baer and Newell, 2017).

### 3.4 Robustness

Examination intervals can vary in response to bank condition. This variation raises an issue of endogeneity that we address with supplemental tests that isolate banks in different ratings categories. It is a useful decomposition of our sample because the vast majority of banks within a given rating category are examined at fixed, scheduled intervals (BOG, 2021).

In Table 4, we present this analysis for  $E_{(t)}$  only (separate analyses for  $C_{(t)}$ ,  $A_{(t)}$ ,  $L_{(t)}$ , and  $S_{(t)}$  generated comparable results but are not shown, to conserve space). In these models, we employ a binary logit, rather than a multinomial logit, as movement from some categories to others are possible in one direction only.

**Table 4**  
**Logit Model Results at Varying Initial Levels of M**

| Panel A: Odds of downgrade in rating for $E_{(t)}$ |                      |                      |                      |                      |
|--|----------------------|----------------------|----------------------|----------------------|
|  | M = 1                | M = 2                | M = 3                | M = 4                |
| INT  | -1.844***<br>(0.177) | -2.364***<br>(0.206) | -2.617***<br>(0.376) | -3.399***<br>(0.740) |
| SOFT <sub>(t-1)</sub>                              | 0.237***<br>(0.087)  | 0.6160***<br>(0.092) | 0.645***<br>(0.118)  | 0.650***<br>(0.156)  |
| Downgrades   | 773                  | 576                  | 265                  | 142                  |
| Panel B: Odds of upgrade in rating for $E_{(t)}$   |                      |                      |                      |                      |
|  | M = 2                | M = 3                | M = 4                | M = 5                |
| INT  | -2.261***<br>(0.172) | -0.853***<br>(0.183) | -1.538***<br>(0.349) | -2.082***<br>(0.476) |
| SOFT <sub>(t-1)</sub>                              | -0.317***<br>(0.076) | -0.567***<br>(0.065) | -0.336***<br>(0.076) | -0.059<br>(0.112)    |
| Upgrades   | 1,163                | 1,581                | 880                  | 365                  |

NOTE: INT is intercept. \*\*\* indicates the coefficient is statistically significantly different from 0 at an  $\alpha$  level of 0.01. Standard errors are in parentheses. SOFT<sub>(t-1)</sub> is the residual of a regression of the  $M_{(t-1)}$  rating on  $C_{(t-1)}$ ,  $A_{(t-1)}$ ,  $E_{(t-1)}$ ,  $L_{(t-1)}$ , and  $S_{(t-1)}$ .

Coefficients on  $\text{SOFT}_{(t-1)}$  are positive and statistically significant in the determination of downgrades in each of the four possible initial management ratings (1, 2, 3, and 4). Coefficients on  $\text{SOFT}_{(t-1)}$  are negative in the determination of upgrades in each of the four possible initial management ratings (2, 3, 4, and 5) and statistically significant for all ratings except 5. These results are similar to those previously reported. We conclude that our findings in Table 3 are robust to varying levels of initial rating levels.

Another concern is that the error term in equation (2) may incorporate criteria that are not captured by the independent variables and intercept terms. Practical impacts of our parsimonious approach are limited, however, insofar as CAMELS ratings are assessed in a “comprehensive and uniform manner” (FDIC, 2022). We note, however, that alternative versions of equation (1) that include bank-specific and economic variables generated comparable results to those reported. The sign and significance of the coefficients on  $\text{SOFT}_{(t-1)}$  were unaffected in all equations.

Another potential criticism of our empirical approach concerns the possibility that the personal attributes or incentives of examiners in overseeing CAMELS ratings may not be randomly distributed across banks. For example, it is possible that an individual examiner may justify a high (low) subjective assessment with subsequent ratings upgrades (downgrades). To address this issue, we exploit the alternating examination program whereby most state-chartered banks are assigned to rotations between state and federal regulators. Specifically, we use alternate regressions to isolate banks that switched examination status (state to federal and federal to state). The results are comparable to those reported.

## 4 SECOND ANALYSIS: SOFT INFORMATION AND THE ALLOCATION OF INTERNAL CAPITAL

Bank holding companies are organizations with controlling interest in one or more subsidiary banks that operate as separate reporting entities for regulatory purposes. Managers at the holding company level typically do not run the day-to-day operations of these banks but rather exercise control over management and policies. They distribute resources on which the growth and sustainability of their subsidiaries depend.

We measure resource flows in terms of allocations of equity capital by holding companies to their subsidiary banks.<sup>6,7</sup> Our sample consists of 21,259 bank observations for the 1999 to 2017 period. Of these banks, 2,390 received allocations.

### 4.1 The Model

The likelihood of receiving capital allocation is modeled using a binary logit methodology to determine the probability of a bank experiencing, or not experiencing, a capital allocation during year  $t$  (see Dahl and Shrieves, 1990). Defining  $P_{i,(t)}$  to be the probability of a capital allocation to subsidiary bank  $i$  during year  $t$ , our logit equation to be tested is

$$(3) \quad \begin{aligned} \log_e \left( P_{i,(t)} / (1 - P_{i,(t)}) \right) = & b_0 + b_1 \text{SOFT}_{i,(t-1)} + b_2 \text{ECAP}_{i,(t-1)} \\ & + b_3 \text{CASH}_{i,(t-1)} + b_4 \text{GROW}_{i,(t-1)} + b_5 \text{BNKSIZE}_{i,(t-1)}. \end{aligned}$$

Among the independent variables is  $ECAP_{(t-1)}$ , the ratio of equity capital to assets, which controls for incentives for holding companies to allocate capital to undercapitalized subsidiary banks.  $BNKSIZE_{(t-1)}$  is the log of beginning-of-period bank assets.  $CASH_{(t-1)}$  is the sum of net income plus provisions for loan losses and is expressed relative to assets. To the extent that internally generated funds substitute for capital allocation, the sign of the coefficient for this variable will be negative. If, on the other hand, capital is allocated to banks in which cash flows are higher, the coefficient will be positive.  $GROW_{(t-1)}$  is the median growth rate of loans for all banks in the market in which a given bank operates.<sup>8</sup> Expected growth, all else equal, would require additional capital.

The key variable is  $SOFT_{(t-1)}$ . Since a positive value for  $SOFT_{(t-1)}$  corresponds to an observed  $M$  that is higher numerically (worse) than what would be anticipated on the basis of  $C_{(t-1)}$ ,  $A_{(t-1)}$ ,  $E_{(t-1)}$ ,  $L_{(t-1)}$ , and  $S_{(t-1)}$ , and a negative value corresponds to an observed  $M_{(t-1)}$  that is lower numerically (better) than what would be anticipated, we hypothesize that  $SOFT_{(t-1)}$  will have a negative coefficient, meaning that the odds of decisions by bank holding company managers to allocate capital to a subsidiary are lower when soft information is worse (higher numerically).<sup>9</sup>

#### 4.2 Derivation of $SOFT_{(t-1)}$

Table 5 presents results of equation (1) for deriving  $SOFT_{(t-1)}$ . (Note that the sample of banks used in this regression differs from that used in the previous analysis.) All independent variables, once again, have positive and statistically significant coefficients.

**Table 5**

**Logit Regression Results for  $SOFT_{(t-1)}$**

Dependent variable:  $M_{(t-1)}$

| INT                 | $C_{(t-1)}$         | $A_{(t-1)}$         | $E_{(t-1)}$         | $L_{(t-1)}$         | $S_{(t-1)}$         |
|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| 0.300***<br>(0.027) | 0.155***<br>(0.014) | 0.301***<br>(0.010) | 0.148***<br>(0.009) | 0.094***<br>(0.011) | 0.184***<br>(0.010) |

NOTE: INT is intercept. \*\*\* indicates the coefficient is statistically significantly different from 0 at an  $\alpha$  level of 0.01. Standard errors are in parentheses.

Descriptive statistics on the overall sample are presented in Table 6.<sup>10</sup> Panel A is for banks that received capital allocations, and Panel B is for banks that did not receive capital allocations. Comparisons between the panels indicate that banks receiving capital allocations had lower cash flow, less capital, and higher market growth potential. The mean  $SOFT_{i,(t-1)}$  is -0.013 in Panel A and -0.003 in Panel B. These findings indicate that the derived measure of soft information is, on average, lower numerically (better) for banks obtaining capital allocations versus those that do not.

**Table 6****Descriptive Statistics**

| Panel A: Banks receiving capital allocations ( $N = 2,390$ )      |        |       |         |         |
|---|--------|-------|---------|---------|
|   | Mean   | STD   | Minimum | Maximum |
| ECAP <sub>(t-1)</sub>   | 0.096  | 0.055 | 0.040   | 0.826   |
| CASH <sub>(t-1)</sub>   | 0.011  | 0.009 | -0.009  | 0.097   |
| GROW <sub>(t-1)</sub>   | 0.118  | 0.105 | -0.099  | 0.494   |
| BNKSIZE <sub>(t-1)</sub>  | 12.426 | 1.697 | 6.784   | 21.36   |
| SOFT <sub>(t-1)</sub>   | -0.013 | 0.436 | -1.208  | 1.967   |
| Panel B: Banks not receiving capital allocations ( $N = 18,869$ ) |        |       |         |         |
|   | Mean   | STD   | Minimum | Maximum |
| ECAP <sub>(t-1)</sub>   | 0.109  | 0.064 | 0.027   | 0.898   |
| CASH <sub>(t-1)</sub>   | 0.014  | 0.08  | -0.009  | 0.099   |
| GROW <sub>(t-1)</sub>   | 0.076  | 0.078 | -0.099  | 0.497   |
| BNKSIZE <sub>(t-1)</sub>  | 11.801 | 1.412 | 6.429   | 21.21   |
| SOFT <sub>(t-1)</sub>   | -0.003 | 0.433 | -1.280  | 2.699   |

NOTE: STD is standard deviation. ECAP<sub>(t-1)</sub> is equity/assets; CASH<sub>(t-1)</sub> is net income plus provisions for loan losses/assets; GROW<sub>(t-1)</sub> is the median market loan growth; BANKSIZE<sub>(t-1)</sub> is the log of bank assets; and SOFT<sub>(t-1)</sub> is the residual of a regression of the M<sub>(t-1)</sub> rating on C<sub>(t-1)</sub>, A<sub>(t-1)</sub>, E<sub>(t-1)</sub>, L<sub>(t-1)</sub>, and S<sub>(t-1)</sub>.

### 4.3 Results

Results using the logit model in equation (3) are presented for each of the four levels of M in Table 7.

In all columns of Table 7, the coefficients on GROW<sub>(t-1)</sub> are positive and statistically significant for all rating categories except 4 (lowest); banks in markets with greater growth in loans are more likely to obtain capital allocations. The coefficients on BANKSIZE<sub>(t-1)</sub> are positive and statistically significant. The coefficients on ECAP<sub>(t-1)</sub> are negative, as hypothesized, but are not always statistically significant. The coefficients on CASH<sub>(t-1)</sub> are negative, indicating that internally generated funds substitute for capital allocation, but, once again, have varying levels of statistical significance.

Our key findings concern the coefficients on SOFT<sub>(t-1)</sub>. In the first column, for the highest rated banks, the coefficient is -2.190 and statistically significant. The negative coefficient means that when the assessment of soft information is worse (higher numerically), or better (lower numerically), the odds of an allocation, respectively, decrease (increase). The effect is economically significant; for the subsample of M = 1, an increase of one-quarter of a point in SOFT<sub>(t-1)</sub> (slightly more than one standard deviation) implies a multiplicative decrease in the odds of an allocation of 42 percent ( $\exp[-2.190 \times 0.25] = 0.58$ ).

The coefficients on SOFT<sub>(t-1)</sub> remain negative and statistically significant, albeit at smaller magnitudes: -1.029, -1.058, and -0.775 in the second through fourth columns, respectively. Supplemental inferential tests among M levels indicate that these coefficients are statistically different at the 5 percent level only for M = 1 and not for M = 2, M = 3, or M = 4. We note that the odds of an allocation when M = 1 starts lower overall, before considering the effects of all predictors in equation (3), as is evident from its more negative intercept. Thus, a more negative coefficient for SOFT<sub>(t-1)</sub>

**Table 7****Logit Model Results, All Bank Sample**

|                          | M = 1                 | M = 2                 | M = 3                | M = 4                |
|--------------------------|-----------------------|-----------------------|----------------------|----------------------|
| INT                      | -8.532***<br>(0.886)  | -4.456***<br>(0.543)  | -4.780***<br>(1.181) | -4.031<br>(2.232)    |
| SOFT <sub>(t-1)</sub>    | -2.190***<br>(0.244)  | -1.029***<br>(0.123)  | -1.058***<br>(0.215) | -0.775*<br>(0.420)   |
| ECAP <sub>(t-1)</sub>    | 0.174<br>(1.848)      | -10.599***<br>(2.585) | -7.406<br>(2.672)    | -18.163**<br>(8.628) |
| CASH <sub>(t-1)</sub>    | -40.815***<br>(14.89) | -61.864***<br>(11.85) | -21.034<br>(13.32)   | -11.069<br>(14.37)   |
| GROW <sub>(t-1)</sub>    | 5.047***<br>(0.574)   | 6.125***<br>(0.396)   | 6.319***<br>(0.952)  | 5.537*<br>(2.580)    |
| BNKSIZE <sub>(t-1)</sub> | 0.258***<br>(0.034)   | 0.273***<br>(0.028)   | 0.301***<br>(0.059)  | 0.431**<br>(0.193)   |
| N                        | 8,548                 | 11,316                | 1,203                | 192                  |

NOTE: INT is intercept. \*, \*\*, \*\*\* indicate the coefficient is statistically significantly different from 0 at an  $\alpha$  level of 0.10, 0.05, and 0.01, respectively. Standard errors are in parentheses. The dependent variable indicates capital allocation (1 for allocation, zero otherwise). All estimated regression coefficients are on the logit scale. ECAP<sub>(t-1)</sub> is equity/assets; CASH<sub>(t-1)</sub> is net income plus provisions for loan losses/assets; GROW<sub>(t-1)</sub> is the median market loan growth; BANKSIZE<sub>(t-1)</sub> is the log of bank assets; and SOFT<sub>(t-1)</sub> is the residual of a regression of the M<sub>(t-1)</sub> rating on C<sub>(t-1)</sub>, A<sub>(t-1)</sub>, E<sub>(t-1)</sub>, L<sub>(t-1)</sub>, and S<sub>(t-1)</sub>.

when M = 1 adjusts the lower starting odds of allocation by increasing the odds more for the same improvement in subjective performance in comparison to the 2, 3, and 4 M levels.

#### 4.4 Robustness

In addition to the previous base case, we also create two subsamples for further tests of equation (3). The first subsample consists of banks that experience a change in M rating from year  $t-2$  to year  $t-1$ . This subsample mitigates concerns with a potentially endogenous assignment of managers in which subjective performance may be easier to achieve—or easier for examiners to identify—in certain banks or markets (which are now held constant as performance changes).

A second subsample exploits the alternating examination programs between state and federal regulators as previously described. This subsample allows us to identify a sample of banks that change “examiners-in-charge” from year  $t-2$  to year  $t-1$ .

Results of these tests are reported in Tables 8 and 9. The coefficients on SOFT<sub>(t-1)</sub> remain negative and statistically significant.

**Table 8****Logit Model Results, Banks That Change Management Rating**

|                          | M = 1                 | M = 2                 | M = 3                 | M = 4               |
|--------------------------|-----------------------|-----------------------|-----------------------|---------------------|
| INT                      | -4.580***<br>(1.101)  | -4.278***<br>(0.684)  | -4.017***<br>(1.038)  | -3.057<br>(2.420)   |
| SOFT <sub>(t-1)</sub>    | -1.464***<br>(0.544)  | -0.691***<br>(0.206)  | -1.165***<br>(0.232)  | -1.074**<br>(0.474) |
| ECAP <sub>(t-1)</sub>    | -1.718<br>(3.612)     | -10.588***<br>(2.874) | -16.469***<br>(5.741) | -12.609<br>(9.518)  |
| CASH <sub>(t-1)</sub>    | -84.900***<br>(25.94) | -73.161***<br>(17.62) | -11.309<br>(16.76)    | -19.677<br>(20.27)  |
| GROW <sub>(t-1)</sub>    | 5.972***<br>(0.574)   | 5.141***<br>(0.713)   | 7.985***<br>(1.288)   | 3.771<br>(2.431)    |
| BNKSIZE <sub>(t-1)</sub> | 0.258***<br>(1.019)   | 0.337***<br>(0.051)   | 0.369***<br>(0.075)   | 0.339*<br>(0.201)   |
| N                        | 1,243                 | 1,957                 | 670                   | 124                 |

NOTE: INT is intercept. \*, \*\*, \*\*\* indicate the coefficient is statistically significantly different from 0 at an  $\alpha$  level of 0.10, 0.05, and 0.01, respectively. Standard errors are in parentheses. The dependent variable indicates capital allocation (1 for allocation, zero otherwise). All estimated regression coefficients are on the logit scale. ECAP<sub>(t-1)</sub> is equity/assets; CASH<sub>(t-1)</sub> is net income plus provisions for loan losses/assets; GROW<sub>(t-1)</sub> is the median market loan growth; BANKSIZE<sub>(t-1)</sub> is the log of bank assets; and SOFT<sub>(t-1)</sub> is the residual of a regression of the M<sub>(t-1)</sub> rating on C<sub>(t-1)</sub>, A<sub>(t-1)</sub>, E<sub>(t-1)</sub>, L<sub>(t-1)</sub>, and S<sub>(t-1)</sub>

**Table 9****Logit Model Results, Banks That Change Examiner-in-Charge**

|                          | M = 1                 | M = 2                 | M = 3                | M = 4                 |
|--------------------------|-----------------------|-----------------------|----------------------|-----------------------|
| INT                      | -6.710***<br>(0.857)  | -5.103***<br>(0.598)  | -4.459***<br>(1.344) | -3.340<br>(3.432)     |
| SOFT <sub>(t-1)</sub>    | -2.854***<br>(0.349)  | -1.019***<br>(0.152)  | -0.966***<br>(0.280) | -1.083*<br>(0.628)    |
| ECAP <sub>(t-1)</sub>    | -11.050**<br>(1.848)  | -14.350***<br>(2.675) | -6.828<br>(5.468)    | -36.617**<br>(16.871) |
| CASH <sub>(t-1)</sub>    | -42.490***<br>(16.46) | -83.213***<br>(12.30) | -27.355<br>(22.02)   | 69.677**<br>(28.72)   |
| GROW <sub>(t-1)</sub>    | 6.808***<br>(0.769)   | 5.380***<br>(0.501)   | 7.582***<br>(1.241)  | 1.248<br>(3.113)      |
| BNKSIZE <sub>(t-1)</sub> | 0.323***<br>(0.052)   | 0.447***<br>(0.043)   | 0.344***<br>(0.103)  | 0.513**<br>(0.272)    |
| N                        | 4,548                 | 5,452                 | 662                  | 71                    |

NOTE: INT is intercept. \*, \*\*, \*\*\* indicate the coefficient is statistically significantly different from 0 at an  $\alpha$  level of 0.10, 0.05, and 0.01, respectively. Standard errors are in parentheses. The dependent variable indicates capital allocation (1 for allocation, zero otherwise). All estimated regression coefficients are on the logit scale. ECAP<sub>(t-1)</sub> is equity/assets; CASH<sub>(t-1)</sub> is net income plus provisions for loan losses/assets; GROW<sub>(t-1)</sub> is the median market loan growth; BANKSIZE<sub>(t-1)</sub> is the log of bank assets; and SOFT<sub>(t-1)</sub> is the residual of a regression of the M<sub>(t-1)</sub> rating on C<sub>(t-1)</sub>, A<sub>(t-1)</sub>, E<sub>(t-1)</sub>, L<sub>(t-1)</sub>, and S<sub>(t-1)</sub>

#### 4.5 Section Summary

Our results show that soft information revealed by examiners creates informational value given that it is validated by the decisions of bank holding company managers to allocate capital among their subsidiary banks: Subsidiaries with better subjective assessments of managerial ability are more likely to obtain capital infusions. This finding is consistent with an accumulation of soft information on personal attributes including experience, expertise, and competence (Hattori, Shintani, and Uchida, 2015). It also is consistent with an expansion of credit by banks in markets in which they have better local information or better relationships with local borrowers (Gilje, Loutskina, and Strahan, 2016).

Our results are relevant, more generally, to prior studies of subjective managerial characteristics and corporate decisionmaking. Jian and Lee (2011) study decisions within corporations that are motivated by reputations of divisional managers as imputed from performance outcomes. Duchin and Sosyura (2013) evaluate the “influence” of divisional managers as evident in factors such as manager salaries. The power of divisional managers in McNeil and Smythe (2009) and in Glaser, Lopez-De-Silanes, and Zautner (2013) is based, in part, on the number of years managers have worked at a firm. Gaspar and Massa (2011) consider a trust between CEOs and managers based on shared educational institutions, non-profit organizations, and other connections.

We extend these studies by showing that decisions based on soft information regarding managerial attributes are not necessarily limited to those correlated with data-dependent metrics or those that happen to coincide with the activities and backgrounds of CEOs. They are, rather, assessed subjectively by bank examiners that are independent of the bank and its management. Our research extends the “growing literatures on the role of manager-specific characteristics” (Gaspar and Massa, 2011, p. 845) on corporate decisionmaking.

### 5 CONCLUSIONS

Results of empirical tests show that soft information revealing better managerial performance is positively related to improvement and negatively related to deterioration in subsequent performance ratings that are relatively objective. Other test results show that subsidiaries in multi-bank holding companies with soft information that reveals better managerial performance are more likely to obtain resources that are allocated at the holding company level. Both serve as a counterpoint to criticisms that qualitative aspects of performance ratings are excessively arbitrary.

Our results also can be viewed, more generally, from the perspective of intra-organizational performance assessment. Our finding that soft information generated in the supervisory process is validated in subsequent decisionmaking by bankers and examiners provides evidence that subjectivity in performance evaluation, despite being difficult to specify or verify for contracting purposes (Rajan and Reichelstein, 2006), can serve as a useful complement to objective measures (Baker, Gibbons, and Murphy, 1994, and MacLeod, 2003). ■

## NOTES

- <sup>1</sup> The variables are expressed as lags to accommodate easier interpretation in later analyses.
- <sup>2</sup> Data are obtained from call reports published by the Federal Financial Institutions Examination Council.
- <sup>3</sup> Multiple observations on the same bank are possible.
- <sup>4</sup> Examination intervals longer than two years are extremely rare, less than 0.001, and may reflect aberrational circumstances.
- <sup>5</sup> Time points  $t - 1$  and  $t$  vary for each bank based on its individual examination schedule.
- <sup>6</sup> To focus on allocations that are relatively infrequent and comparatively large, we consider only those that constitute 5 percent or more of beginning equity capital. Supplementary tests considered thresholds of 1 percent and 10 percent of equity. The results are comparable to those reported.
- <sup>7</sup> We excluded from the sample banks with capital allocations greater than zero but less than 5 percent of equity, banks that changed holding company ownership in the year of allocation, and banks with other allocations in the previous three years.
- <sup>8</sup> A market is defined as a standard metropolitan statistical area (SMSA), if applicable, or a county. Some markets include only one bank. In these situations, market loan growth and bank loan growth are the same.
- <sup>9</sup> We used repeated measures to capture bank-to-bank variation in the form of a single variance term and fixed effects for years. Attempts to include the large number of fixed effects for banks created a highly collinear collection of bank and year effects with a non-positive definite variance-covariance matrix and unstable parameter estimation (see Belsley, Kuh, and Welsch, 1980). Fixed effects for years were excluded in some categories for the same reasons.
- <sup>10</sup> We excluded observations on banks exceeding the upper 1 percent level for  $CASH_{(t-1)}$ ,  $GROW_{(t-1)}$ , and  $ECAP_{(t-1)}$ . Inclusion of these outlying observations in alternate tests did not affect the coefficients on  $SOFT_{(t-1)}$  but did reduce the statistical significance of some other independent variables.

## REFERENCES

- Baer, G. and Newell, J. "How Bank Supervision Lost Its Way." *Bank Policy Institute Banking Perspectives*, May 25, 2017.
- Baker, G.; Gibbons R. and Murphy, K. "Subjective Performance Measures in Optimal Incentive Contracts." *Quarterly Journal of Economics*, 1994, pp. 1125-56; <https://doi.org/10.2307/2118358>.
- Belsley, D.; Kuh, E. and Welsch, R. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. Wiley, 1980; <https://doi.org/10.1002/0471725153>.
- Berger, A. and Davies, S. "The Information Content of Bank Examinations." *Journal of Financial Services Research*, October 1998, 14, pp. 117-44; <https://doi.org/10.1023/A:1008011312729>.
- Board of Governors of the Federal Reserve System. *Commercial Bank Examination Manual*. Last update June 15, 2021; [https://www.federalreserve.gov/publications/supervision\\_cbem.htm](https://www.federalreserve.gov/publications/supervision_cbem.htm).
- Calomiris, C. and Carlson, M. "Bank Examiners Information and Expertise and Their Role in Monitoring and Disciplining Banks Before and After the Panic of 1893." Working Paper, Office of the Comptroller of the Currency, 2018; <https://doi.org/10.3386/w24460>.
- Cole, R. and Gunther, J. "Predicting Bank Failures: A Comparison of On- and Off-Site Monitoring Systems." *Journal of Financial Services Research*, 1998, 13, pp. 103-17; <https://doi.org/10.1023/A:1007954718966>.
- Dahl, D. and Shrieves, R. "The Impact of Regulation on Bank Equity Infusions." *Journal of Banking and Finance*, 1990, 14, pp. 1209-28; [https://doi.org/10.1016/0378-4266\(90\)90010-Y](https://doi.org/10.1016/0378-4266(90)90010-Y).
- DeYoung, R.; Flannery, M.; Lang, W. and Sorescu, S. "The Information Content of Bank Exam Ratings and Subordinated Debt Prices." *Journal of Money, Credit, and Banking*, 2001, 33, pp. 900-25; <https://doi.org/10.2307/2673928>.
- Duchin, R. and Sosyura, D. "Divisional Managers and Internal Capital Markets." *Journal of Finance*, 2013, 68, pp. 387-439; <https://doi.org/10.1111/jofi.12003>.
- Effinger, C. "The CAMELS' Broken Back." *Bankstocks.com*, July 25, 2017.

- Eisenbach, T.; Luca, D. and Townsend, R. "The Economics of Bank Supervision: So Much to Do, So Little Time." Federal Reserve Bank of New York *Liberty Street Economics*, April 12, 2016; <https://libertystreeteconomics.newyorkfed.org/2016/04/the-economics-of-bank-supervision-so-much-to-do-so-little-time/>.
- Federal Deposit Insurance Corporation. "5000 - Statements of Policy: Uniform Financial Institution Rating System." 2022; <https://www.fdic.gov/regulations/laws/rules/5000-900.html#fdic5000uniformfi>.
- Gaul, L. and Jones, J. "CAMELS Ratings and Their Information Content." Working Paper, Office of the Comptroller of the Currency, 2021.
- Gaspar, J. and Massa, M. "The Role of Commonality Between CEO and Divisional Managers in Internal Capital Markets." *Journal of Financial and Quantitative Analysis*, 2011, 46, pp. 841-69; <https://doi.org/10.1017/S0022109011000111>.
- Gilbert, R.; Meyer, A. and Vaughn, M. "Could a CAMELS Downgrade Model Improve Off-Site Surveillance?" *Federal Reserve Bank of St. Louis Review*, January/February 2002, 84(1), pp. 47-63; <https://doi.org/10.20955/r.84.47-63>.
- Gilje, E.; Loutsikina, E. and Strahan, P. "Exporting Liquidity: Branch Banking and Financial Integration." *Journal of Finance*, 2016, 71, pp. 1159-84; <https://doi.org/10.1111/jofi.12387>.
- Glaser, M.; Lopez-De-Silanes, F. and Zautner, Z. "Opening the Black Box: Internal Capital Markets and Managerial Power." *Journal of Finance*, 2013, 68, pp. 1577-630; <https://doi.org/10.1111/jofi.12046>.
- Gopalan, Y. "The Effects of Ratings Disclosure by Bank Regulators." Working Paper, Indiana University, 2018; <https://doi.org/10.2139/ssrn.3164528>.
- Hattori, M.; Shintani, K. and Uchida, H. "The Repository of Soft Information Within Bank Organizations." *Journal of Money, Credit, and Banking*, 2015, 47, pp. 737-70; <https://doi.org/10.1111/jmcb.12226>.
- Hirtle, B. and Lopez, J. "Supervisory Information and the Frequency of Bank Examinations." *Federal Reserve Bank of New York Economic Policy Review*, 1999, 5, pp. 1-19; <https://www.newyorkfed.org/research/epr/99v05n1/9904hirt.html>.
- Jian, M. and Lee, K. "Does CEO Reputation Matter for Capital Investments?" *Journal of Corporate Finance*, 2011, 17, pp. 929-46; <https://doi.org/10.1016/j.jcorpfin.2011.04.004>.
- Liberti, J. and Petersen, M. "Information: Hard and Soft." *Review of Corporate Finance Studies*, 2019, 8, pp. 1-41; <https://doi.org/10.1093/rcfs/cfy009>.
- McNeil, C. and Smythe, T. "Division Manager Lobbying Power and the Allocation of Capital." *Financial Review*, 2009, 44, pp. 59-85; <https://doi.org/10.1111/j.1540-6288.2008.00210.x>.
- MacLeod, W.B. "Optimal Contracting with Subjective Evaluation." *American Economic Review*, 2003, 93, pp. 216-40; <https://doi.org/10.1257/000282803321455232>.
- McWilliams, J. Statement before the Committee on Banking, Housing and Urban Affairs, U.S. Senate, May 15, 2019a; <https://www.fdic.gov/news/speeches/2019/spmay1519.html>.
- McWilliams, J. Remarks at the American Bar Association Banking Law Committee Annual Meeting *Principles of Supervision*, January 11, 2019b; <https://www.fdic.gov/news/speeches/2019/spjan1119.html>.
- Rajan, M. and Reichelstein, S. "Subjective Performance Indicators and Discretionary Bonus Pools." *Journal of Accounting Research*, 2006, 44, pp. 585-618; <https://doi.org/10.1111/j.1475-679X.2006.00212.x>.