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Monetary Policy at the Zero Lower Bound: Revelations from the FOMC's Summary of Economic Projections

By George A. Kahn and Andrew Palmer

In 2012, the Federal Open Market Committee (FOMC) added the federal funds rate to its quarterly Summary of Economic Projections (SEP). Since then, FOMC participants have repeatedly projected the funds rate would rise in conjunction with projected increases in inflation and declines in unemployment. However, the federal funds rate remained at its effective lower bound until December 2015.

Kahn and Palmer use the SEP to assess the relationship between projections for the target federal funds rate and projections for inflation and unemployment. They find a systematic relationship that is generally consistent with the FOMC's actual policy responses before the zero lower bound period. They also find that the repeated projections of liftoff from the effective lower bound were not realized due largely to unexpectedly low inflation.

The Lasting Damage from the Financial Crisis to U.S. Productivity

By Michael Redmond and Willem Van Zandweghe

The financial crisis and recession of 2007–09 left deep scars on the U.S. economy. Total factor productivity, a key source of long-run output growth, declined sharply during the crisis and has remained below its precrisis level. Tight credit conditions may have contributed to productivity's decline. During the crisis, widespread fear and uncertainty drove lenders to raise interest rates and lend more cautiously. As a result, firms faced reduced access to credit, potentially preventing them from investing in innovation.

Redmond and Van Zandweghe examine the relationship between credit conditions and total factor productivity and find the financial crisis altered their usual relationship. During normal times, productivity growth fluctuates over the business cycle largely unaffected by credit conditions. But during the crisis, distressed credit markets significantly dampened productivity growth, leaving total factor productivity on a lower trajectory as the economy began to recover.

Data Breach Notification Laws

By Richard J. Sullivan and Jesse Leigh Maniff

Data breaches have recently worsened in the United States, prompting concerns about a rise in identity theft. To help protect consumers, 47 states have enacted laws requiring breached organizations to both disclose breaches to the public and notify consumers whose data were exposed. In theory, these notification laws serve two purposes important to public policy: they incentivize organizations to protect sensitive data, and they allow individuals whose records were exposed to react quickly to mitigate or prevent damage.

Prior research suggests these laws do lead to an overall decline in identity theft. However, the specific provisions within notification laws differ significantly across states, and some may be more effective than others in deterring identity theft. Sullivan and Maniff study these provisions over time to determine their potential effects on identity theft. They find five provisions in state laws associated with less identity theft and three provisions associated with more identity theft.

Monetary Policy at the Zero Lower Bound: Revelations from the FOMC's Summary of Economic Projections

George A. Kahn and Andrew Palmer

In 2012, the Federal Open Market Committee (FOMC) added the federal funds rate to its quarterly Summary of Economic Projections (SEP). As a result, in addition to providing their individual projections of inflation, unemployment, and real GDP growth up to three years into the future, participants in FOMC meetings—including Federal Reserve Board governors and Bank presidents—also began providing their projections of the associated path for the target federal funds rate. These funds rate projections are not unconditional forecasts but rather reflect each participant's view of "appropriate" monetary policy. Thus, the projections reveal how participants expect the economy to evolve conditioned on their preferred future paths of the federal funds rate. While the federal funds rate remained at its effective lower bound from 2012 to 2015, FOMC participants repeatedly projected the funds rate would rise in conjunction with projected increases in inflation and declines in unemployment.

Although the SEP's various projections of liftoff from the zero lower bound did not materialize, the SEP still provides financial markets and the public valuable information about policymakers' outlook for the economy and their views about appropriate policy. In particular, the SEP can reveal information about Committee participants' policy

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reaction function. In this article, we use the SEP to evaluate the projected response of monetary policy to expected economic developments, compare this response to past policy actions, and assess why the actual policy path persistently differed from the projected path. We find that the relationship since 2012 between the FOMC's projections of the target funds rate and its projections of inflation and unemployment is data dependent and systematic, meaning the funds rate projections were not on a preset path. Moreover, we find that the relationship is generally consistent with the FOMC's actual policy responses prior to the onset of the zero lower bound. That the funds rate remained stuck at the effective lower bound after 2012 mainly reflects unexpectedly low inflation which was offset to some extent by a faster-than-expected decline in the unemployment rate.

Section I describes the SEP and shows how the projections of real GDP growth, unemployment, inflation, and the federal funds rate evolved over time. Section II estimates a policy reaction function relating FOMC participants' projections of the federal funds rate to their projections of inflation and unemployment and compares it to the Committee's actions before the onset of the zero lower bound. Section III decomposes the deviation of the projected funds rate from its realized level at the zero lower bound into three parts—projection "misses" for inflation and unemployment and an unexplained component.

I. Getting to Know the SEP

The SEP has its roots in the FOMC's semiannual economic reports to Congress that started in July 1979 after the Full Employment and Balanced Growth Act (commonly referred to as the Humphrey-Hawkins Act) took effect. These reports included projections of inflation, economic growth, and unemployment over various horizons, although many features of the projections—including the indicators used to measure inflation and growth—have evolved over time.[1]

The FOMC released the first SEP in the minutes of its October 2007 meeting and has since provided participants' economic projections in conjunction with four of the eight regularly scheduled FOMC meetings each year. A compilation and summary of these projections (without attribution) is circulated to participants of FOMC meetings, and a detailed summary of the economic projections is included as an addendum to the minutes released three weeks after each meeting. The summary includes the range of participants' projections of each variable and its central tendency—defined by excluding the top and bottom three projections. Since April 2011, an advance version of the SEP table presenting the range and central tendency of the participants' projections has been released in conjunction with the Federal Reserve Chair's post-meeting press conference.

The SEP reports participants' projections of real GDP growth, headline and core inflation, and unemployment. Inflation is measured by the personal consumption expenditure (PCE) price index. Growth rates for real GDP and the price indexes are computed on a fourth-quarter-to-fourth-quarter basis. Unemployment is the fourth-quarter average civilian unemployment rate. The forecast horizon is the current and subsequent two to three years.[2]

In addition, in April 2009, the FOMC began reporting the range and central tendency of the longer-run rates of real GDP growth, headline PCE inflation, and unemployment in the SEP.[3] These longer-run projections represent "each participant's assessment of the rate to which each variable would be expected to converge … in the absence of further shocks to the economy" (Board of Governors of the Federal Reserve System). Individual participants base their projections on their own view of appropriate monetary policy.

The FOMC further enhanced the SEP in January 2012, when it began reporting projections of the federal funds rate for the end of the current year, the next two to three years, and over the longer run. These projections are presented in the so-called "dot plot," which identifies without attribution each individual participant's judgment of the appropriate level of the target federal funds rate.[4] The dot plot can provide information about how Committee members view the appropriate stance of monetary policy as it relates to the outlook for inflation, unemployment, and growth. For example, since 2012, Committee participants have consistently projected a rising path for the funds rate based on projections that inflation would rise toward the FOMC's objective and unemployment would fall. Despite these projections, the FOMC ultimately continued to target the funds rate at the range of 0 to 25 basis points it established in December 2008 and maintained until December 2015.

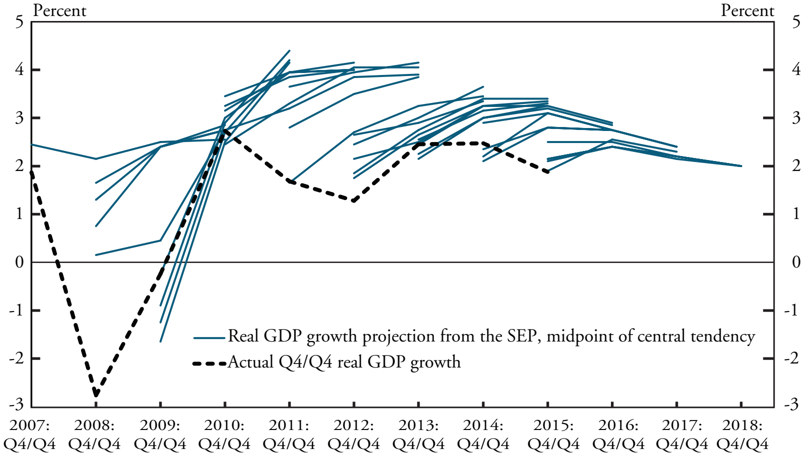
Examining the projections from the SEP shows how Committee members' outlook for growth, inflation, and unemployment led to overly optimistic projections that policy would lift off from the effective lower bound. Projections of real GDP growth, for example, have been too optimistic since the beginning of the SEP in 2007. Chart 1 shows the midpoint of the central tendency of the projections of real GDP growth over three- to four-year horizons made at FOMC meetings from 2007 to 2016.[5] Each solid line in the chart shows the projections made at a specific FOMC meeting, and the dashed line shows the actual real GDP growth rate as measured by current vintage data. For most of the period, the midpoints of the central tendencies projected faster real GDP growth than actually occurred. In general, the Committee participants missed the onset of the recession, underestimated its severity, and overestimated the speed of recovery. As the true depth of the recession was revealed in real time, many FOMC participants may have expected GDP growth to bounce back sharply as it had following previous deep recessions. Unfortunately, such a bounce back did not occur, and the Committee's optimistic projections were not realized.

With growth projected to be faster than its realization, the projections of unemployment were also too optimistic throughout the recession and early stages of recovery. As shown in Chart 2, projections of the unemployment rate made from 2007 to 2010 (solid lines) were consistently below the actual unemployment rate (dashed line). For example, in the January 2008 SEP, the midpoint of the central tendency of the unemployment rate projected for the fourth quarters of 2008, 2009, and 2010 was 5.25 percent, 5.15 percent, and 5 percent, respectively. The actual unemployment rate in those years turned out to be 6.9 percent, 9.9 percent, and 9.5 percent.

In contrast, as the recovery gained momentum, Committee participants' projections of unemployment became too pessimistic. From 2011 to 2015, the central tendencies of SEP unemployment projections were consistently above the actual realized unemployment rate (Chart 2). This divergence between the SEP's overly pessimistic outlook for unemployment and overly optimistic outlook for real GDP growth has been an ongoing conundrum for the FOMC, possibly reflecting low productivity growth, a sluggish cyclical rebound in labor force participation rates, and ongoing structural changes such as a decline in trend labor force participation.[6]

Chart 1

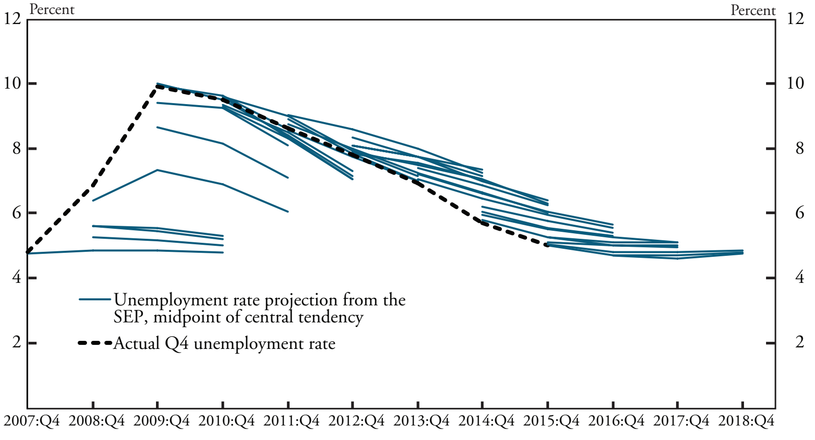
FOMC Projections of Real GDP Growth versus Actual



Sources: BEA, Federal Reserve Board, FRED, SEP, and Haver Analytics.

Chart 2

FOMC Projections of the Unemployment Rate versus Actual



Sources: BLS, Federal Reserve Board, FRED, SEP, and Haver Analytics.

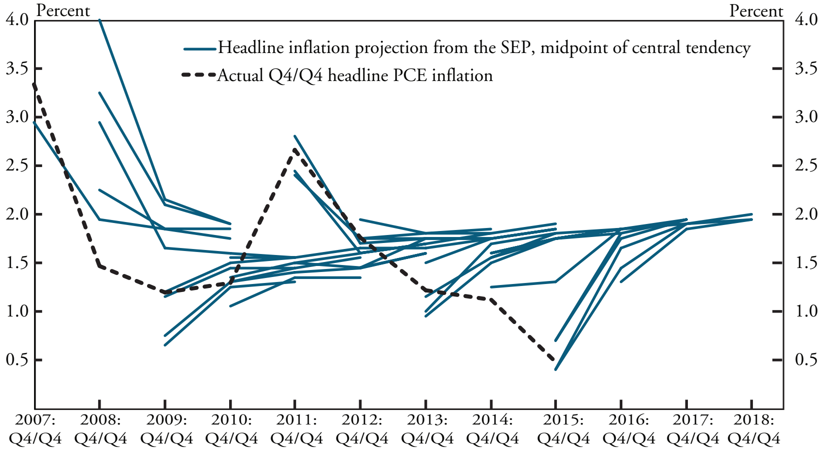
Projections of inflation have also consistently missed the mark, most likely due to unexpected fluctuations in energy prices. Chart 3 shows the midpoints of the central tendency of projected inflation, as measured by the headline PCE price index, were above the actual inflation rate in 2008 and 2009 as oil prices fell from $96 per barrel (for West Texas Intermediate) at the end of 2007 to $45 per barrel at the end of 2008. If the decline in oil prices was unexpected, it would not have been built into projections of headline inflation made in 2007 and 2008. In contrast, projected inflation was below actual inflation from 2010 to 2012 as oil prices rose from $45 per barrel at the end of 2008 to $99 per barrel at the end of 2011. Finally, projected inflation again rose above actual inflation from 2013 to 2015 as oil prices fell sharply from $99 per barrel at the end of 2011 to $37 per barrel at the end of 2015.

Projections of core PCE price inflation—which strips volatile food and energy prices from the headline measure—show a similar albeit more muted pattern. With the direct effects of oil price fluctuations removed from the headline price index, projected core inflation deviated from actual core inflation by less than the headline measures diverged (Chart 4). Nevertheless, because oil price increases to some extent pass through to the prices of other goods and services, the dramatic swings in oil prices over this period also likely contributed to the projection errors for core inflation. In addition, persistent movements in core import prices and an unusually muted response of core inflation to falling unemployment may have contributed to the overprediction of inflation.[7]

Since they were first reported in the SEP in 2012, the Committee's projections of the target federal funds rate appear to have reflected participants' projections of real GDP growth, inflation, and unemployment. Over this period, projections of real GDP growth suggested a stronger economic recovery than actually materialized. Projections of inflation generally suggested a relatively steady return to the FOMC's inflation objective of 2 percent. And while unemployment was not projected to fall as rapidly as actually occurred, the projections suggested a steady downward trajectory. As Committee participants expected inflation and labor market conditions to steadily converge on the FOMC's dual objectives of price stability and maximum employment, it is not surprising they would expect to lift the federal funds rate off its effective lower bound and move it toward its projected longer-run level. Indeed, Chart 5 shows FOMC participants repeatedly projected an upward trajectory for the funds rate

Chart 3

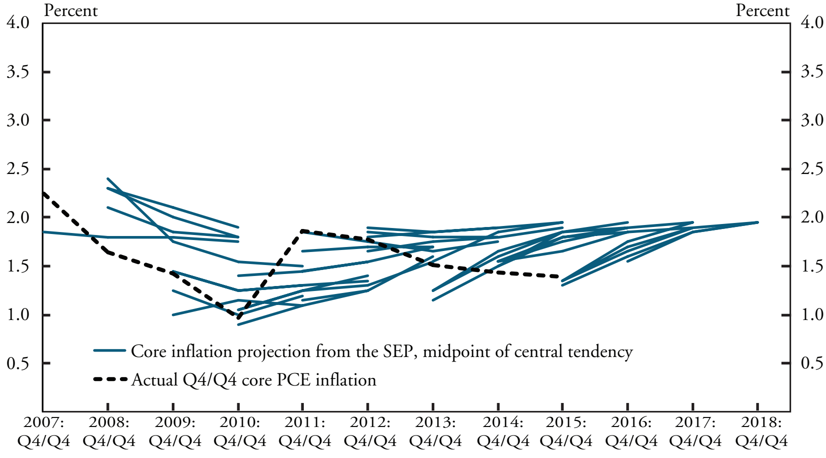
FOMC Projections of Headline PCE Inflation versus Actual



Sources: BEA, Federal Reserve Board, FRED, SEP, and Haver Analytics.

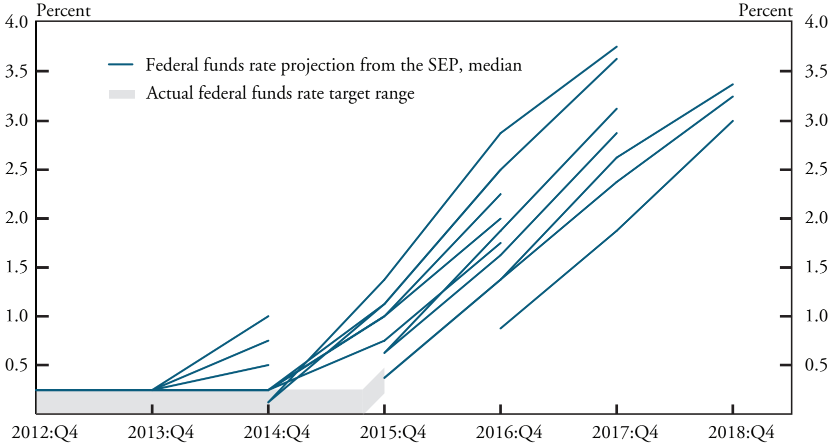
Chart 4

FOMC Projections of Core PCE Inflation versus Actual



Sources: BEA, Federal Reserve Board, FRED, SEP, and Haver Analytics.

Chart 5
FOMC Projections of Federal Funds Rate versus Actual



Sources: Federal Reserve Board, FRED, SEP, and Haver Analytics.

target (solid lines), while the actual funds rate remained in the 0 to 25 basis point range established in December 2008 and maintained until December 2015.

FOMC participants were not alone in projecting an upward sloping path for the funds rate. Private sector forecasts were also overly optimistic. For example, Bundick provides evidence from the federal funds futures market and the Blue Chip Economic Indicators showing that market participants and professional forecasters both expected short-term interest rates to rise after 2012. These projections, much like the Committee's, were associated with overly optimistic projections of growth and inflation.

II. Estimating the Policy Reaction Function Implied by the SEP

One way to more systematically determine the relationship between the FOMC participants' funds rate projections and their projections of inflation and unemployment is to estimate their implied policy reaction function. A reaction function provides a simple description of how policymakers generally move their policy instrument—in this case, the federal funds rate—in response to economic conditions. Although it is impossible to estimate such a reaction function from actual data over the period after 2012, as the funds rate target remained fixed at its effective lower bound until December 2015, it is possible to estimate a reaction function based on FOMC participants' *projections* of the funds rate (which were not consistently fixed at the lower bound) and their associated projections of inflation and unemployment.[8]

Predicting the funds rate path projected in the SEP

We assume the reaction function is based on simple rules economists have proposed for setting the federal funds rate as a function of contemporaneous indicators of inflation and economic slack. However, in contrast to normative rules that spell out a prescription for monetary policy that theory would suggest best stabilizes macroeconomic activity, the reaction function used here is *estimated* and designed to describe how policymakers actually behaved. While the specification is similar to normative rules such as the Taylor rule, we estimate the parameters from projections policymakers provided in the SEP rather than deriving them from theory.[9]

We estimate the reaction function by regressing projections from the SEP of the median federal funds rate on the deviation of projected inflation from its projected long-run target and the deviation of the projected unemployment rate from its projected long-run rate (the unemployment gap).[10] The projected long-run inflation rate is a constant 2 percent, reflecting that all FOMC participants expected that, under appropriate policy, the Committee would over time achieve its stated longer-run 2 percent objective for inflation.[11] In contrast, the long-run projection for the unemployment rate fluctuated over time as the Committee reassessed the level of unemployment that would be associated with full employment and therefore consistent with its employment mandate.

The observations used in the analysis are the projections made at FOMC meetings associated with SEP reports of the median federal funds rate and the midpoints of the central tendencies of inflation and unemployment. In a number of these observations, the median projected funds rate is at or below 0.25 percent, which is taken to be the effective lower bound on nominal interest rates and a binding constraint on policymakers' ability to further reduce short-term rates.

The estimated reaction function takes the following form:

$$FFR_t^{t-i} = a + b(p_t^{t-i} - 2) + c(u_t^{t-i} - u_t^{LRt-i}) + \varepsilon_t,$$

where FFR_t^{t-i} is the projection from the SEP for the median federal funds rate in period t made in period $t-i$, p_t^{t-i} is the projected headline or core PCE price inflation in period t made in period $t-i$, u_t^{t-i} is the projected unemployment rate in period t made in period $t-i$, and u_t^{LRt-i} is the projected long-run unemployment rate made in period $t-i$.[12] Period t refers to the projection of the end-of-year funds rate, the Q4/Q4 inflation rate, and the fourth quarter unemployment rate. Period $t-i$ refers to the quarter in which the projection was made. For example, for projection horizon t = 2015:Q4, $t-i$ indexes quarterly SEP reports from the third quarter of 2012 to the fourth quarter of 2015.[13]

The coefficients, a, b, and c, are estimated using a statistical model that accounts for the censoring of observations at the effective lower bound.[14] The constant, a, represents the equilibrium nominal funds rate—that is, the funds rate projected to be consistent with inflation at its longer-run target and the economy at full employment. The coefficients on the other variables represent the projected response of the target federal funds rate to projected changes in inflation and the unemployment gap. The residual term, ε_t, captures all other influences on the projected funds rate and is assumed to have zero mean and finite variance.[15]

The estimated coefficients indicate that the median of federal funds rate projections responded strongly to projected increases in inflation and declines in unemployment. In Table 1, column 1 provides coefficient estimates for a reaction function with headline inflation as the measure of inflation, and column 2 provides estimates with core inflation. These coefficients are both statistically significant and above one, indicating that, other things equal, an increase in projected inflation—either headline or core—is associated with a greater than one-for-one increase in the projected nominal federal funds rate.[16] In most macroeconomic models, this property is critical for the stabilization of inflation around its longer-run target.

In addition, the coefficient on headline inflation is smaller than the coefficient on core inflation. This is not surprising. Policymakers likely projected a more subdued response to fluctuations in headline inflation because headline inflation is subject to more volatility from temporary energy price shocks than core inflation. Policymakers would likely have looked through this short-run volatility as they planned a trajectory for the federal funds rate.

Table 1

Estimated Policy Reaction Functions Using Projections from the SEP

	Baseline federal funds rate projection		"Dovish" federal funds rate projection		"Hawkish" federal funds rate projection	
	(1)	(2)	(3)	(4)	(5)	(6)
Reaction function with:	Headline inflation	Core inflation	Headline inflation	Core inflation	Headline inflation	Core inflation
Inflation gap projection	1.589***	3.829***	1.552***	3.723***	1.991***	4.516***
	(0.231)	(0.419)	(0.285)	(0.441)	(0.557)	(0.883)
Unemployment gap projection	-1.551***	-1.459***	-2.090***	-2.184***	-1.153***	-1.090***
	(0.162)	(0.138)	(0.393)	(0.219)	(0.181)	(0.0935)
Constant	2.376***	2.710***	2.142***	2.649***	2.886***	3.041***
	(0.130)	(0.128)	(0.112)	(0.136)	(0.120)	(0.135)
Regression standard error	0.600***	0.502***	0.468***	0.375***	0.771***	0.593***
	(0.0700)	(0.0574)	(0.0466)	(0.0264)	(0.103)	(0.0656)
Pseudo-R^2	0.5394	0.6393	0.6844	0.7971	0.3894	0.5340
Left-censored observations	24	24	28	28	16	16
Uncensored observations	38	38	34	34	46	46

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

Notes: Standard errors are in parentheses. Estimates are from a Tobit regression using projections from the January 2012 to March 2016 SEPs, censoring observations for which the federal funds rate projection was at or below 0.25 percent. The baseline regressions use the median of the federal funds rate projection with the midpoints of the central tendency of projections of inflation, unemployment, and longer-run unemployment. The "dovish" regressions use the minimum of the central tendency of projections of the federal funds rate and inflation with the maximum of the central tendency of projections of unemployment and longer-run unemployment. The "hawkish" regressions use the maximum of the central tendency of projections of the federal funds rate and inflation with the minimum of the central tendency of projections of unemployment and longer-run unemployment.

Not only do the projections show a strong response of the funds rate to inflation, they also show a strong response to unemployment. The estimated coefficient on the projected unemployment gap is negative and significant, indicating the funds rate was projected to increase as the unemployment rate was projected to fall.[17]

Finally, the magnitude of the constant term—an estimate of the projected equilibrium federal funds rate—is consistent with the FOMC's policy statements indicating "the federal funds rate is likely to remain, for some time, below levels that are expected to prevail in the longer run." The constant is estimated at 2.4 percent for the specification with headline inflation and 2.7 percent for the specification with core inflation. In contrast, the median of the longer-run federal funds rate was projected to be 3.25 percent in the March 2016 SEP, down from 4.25 percent in the first two SEP reports in 2012. If FOMC participants lowered their estimates of longer-run productivity growth, their estimates of the longer-run federal funds rate may also have fallen (Laubach and Williams). Moreover, persistent headwinds—including ongoing adjustments from the financial crisis—may have kept the projected funds rate below its longer-run projection even when unemployment and inflation projections reached their mandate-consistent levels.

As a robustness check, Table 1 also provides estimates of the policy reaction function using the minimum (Columns 3 and 4) and maximum (Columns 5 and 6) of the central tendencies of the SEP projections of the federal funds rate instead of the midpoint. Specifically, we regress the maximum federal funds rate projection on the maximum inflation projection and the minimum unemployment projection under the assumption that the tightest policy projection—a "hawkish" policy—would be associated with the highest projected inflation and lowest unemployment. Similarly, we regress the minimum federal funds rate projection on the minimum inflation and maximum unemployment projection under the assumption that the most accommodative policy path—a "dovish" policy—would be associated with the lowest projected inflation and highest unemployment.

As the table shows, the coefficients in the policy reaction function are somewhat sensitive to whether the regression is based on the median, minimum, or maximum funds rate projections. For example, the coefficients on core and headline inflation are somewhat higher for the hawkish projection relative to the baseline or dovish projections. In contrast, the coefficients on the unemployment rate are more negative in the regression for the dovish projection relative to the baseline or hawkish projection. This may suggest FOMC participants who are more dovish in the sense of preferring a lower projected path for the funds rate place more weight on unemployment in making their projections, whereas participants who are more hawkish in the sense of preferring a higher projected path for the fund rate place a greater weight on inflation.

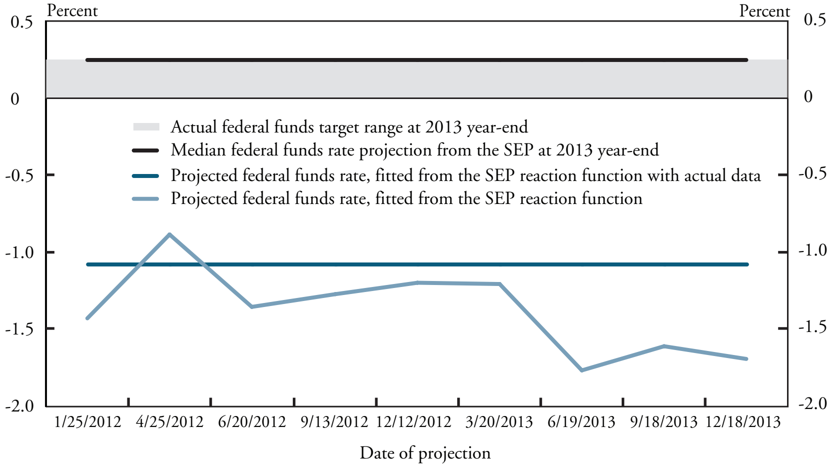
Comparing the projected funds rate path to prescriptions from the SEP reaction function

Comparing the median of the funds rate projected by FOMC participants to the federal funds rate predicted by the baseline SEP reaction function sheds additional light on how systematically the funds rate projection responded to economic conditions. Charts 6, 7, and 8 make this comparison using the reaction function with headline inflation. The black lines represent the median of the federal funds rate projected at various FOMC meetings for the end of 2013 (Chart 6), 2014 (Chart 7), and 2015 (Chart 8).[18] The light blue lines represent the predicted value of the funds rate at the end of the same years based on prescriptions from the SEP reaction function associated with each SEP meeting. For completeness, the gray bands show the range for the funds rate the FOMC actually targeted (which remained constrained by the effective lower bound until December 2015), and the dark blue lines show the end-of-year funds rate predicted by the SEP reaction function with the actual fourth-quarter inflation and unemployment rates substituted for their projected rates.

Chart 6 shows that the predictions from the SEP reaction function for the federal funds rate at the end of 2013 made at FOMC meetings in 2012 and 2013 (light blue line) were consistently negative. Moreover, as the outlook for inflation was revised down in 2013 and projections of unemployment indicated only gradual improvement, the SEP reaction function began predicting increasingly negative target funds rates. Based on the actual fourth-quarter inflation and unemployment rates, the SEP reaction function would have called for a somewhat higher funds rate target of about negative 1.1 percent (dark blue line). However, with the nominal funds rate constrained by the zero lower

Chart 6

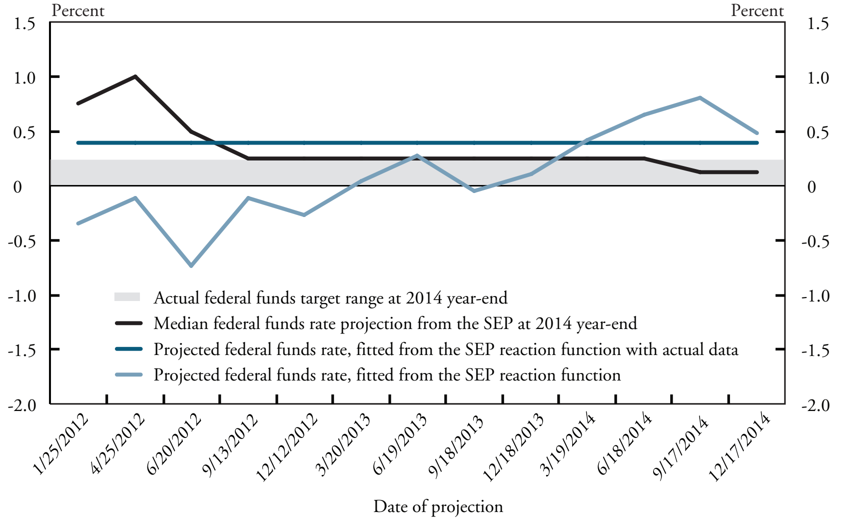
Projected, Fitted, and Actual Federal Funds Rate at the End of 2013



Notes: The light blue line shows the predicted federal funds rate from the estimated SEP reaction function using specification (1) from Table 1. The dark blue line shows the predicted federal funds rate from the same specification fitted with the actual Q4 unemployment rate and Q4/Q4 headline inflation for the projection year.
Sources: BEA, BLS, Federal Reserve Board, FRED, SEP, Haver Anaytics, and authors' calculations.

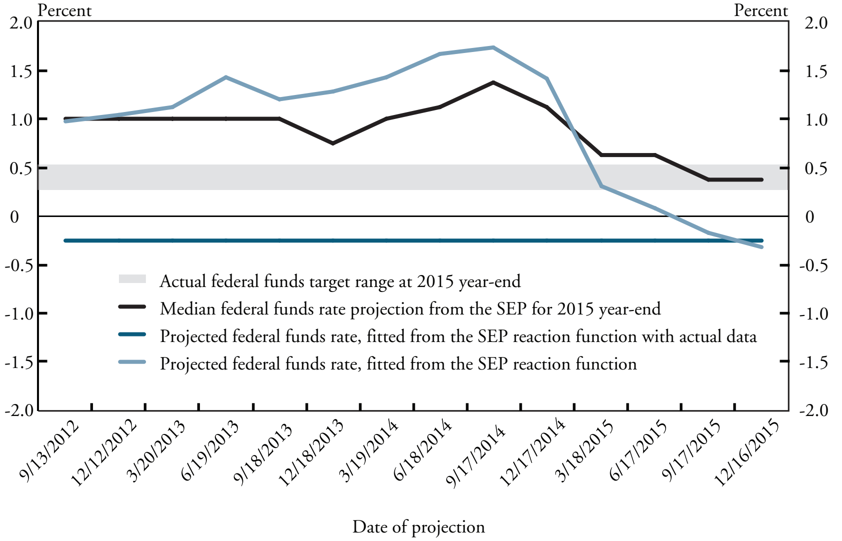
Chart 7

Projected, Fitted, and Actual Federal Funds Rate at the End of 2014



Notes: The light blue line shows the predicted federal funds rate from the estimated SEP reaction function using specification (1) from Table 1. The dark blue line shows the predicted federal funds rate from the same specification fitted with the actual Q4 unemployment rate and Q4/Q4 headline inflation for the projection year.
Sources: BEA, BLS, Federal Reserve Board, FRED, SEP, Haver Anaytics, and authors' calculations.

Chart 8
Projected, Fitted, and Actual Federal Funds Rate at the End of 2015



Notes: The light blue line shows the predicted federal funds rate from the estimated SEP reaction function using specification (1) from Table 1. The dark blue line shows the predicted federal funds rate from the same specification fitted with the actual Q4 unemployment rate and Q4/Q4 headline inflation for the projection year.
Sources: BEA, BLS, Federal Reserve Board, FRED, SEP, Haver Anaytics, and authors' calculations.

bound, the median projection of the funds rate remained fixed at 0.25 percent (black line). The same pattern (not shown) is observed if the funds rate is predicted on the basis of the SEP reaction function using core inflation rather than headline inflation, although the prescription for the funds rate falls much further to almost –3 percent.

Chart 7 shows that projections of the median funds rate at the end of 2014 differed significantly from what the SEP reaction function predicts. The median of the SEP federal funds rate projections (black line) rose from 75 basis points at the January 2012 FOMC meeting to 100 basis points at the April 2012 meeting. The median projection then fell in June and fell again in September 2012 as the funds rate hit its effective lower bound. It remained there through December 2014. In contrast, the SEP reaction function (light blue line) prescribes a gradual increase in the median funds rate from a low of –75 basis points at the June 2012 meeting to a high of +81 basis points at the September 2014 meeting before declining to 49 basis points at the end of 2014. Based on actual fourth-quarter data for inflation and unemployment, the SEP reaction function would have called for a funds rate of 43 basis points at the end of the year. The version of the reaction function with core inflation (not shown) more closely captures the downward movement in the prescribed funds rate through December 2013 but then diverges. By the December 2014 meeting, the reaction function calls for a funds rate of roughly 1 percent compared with the SEP projection of 13 basis points.

Chart 8 shows the prescriptions from the SEP reaction function for the funds rate at the end of 2015 more closely match the midpoint of the SEP federal funds rate projections made at FOMC meetings from 2012 to 2015. While the SEP reaction function called for a somewhat higher funds rate than the SEP projections through September 2014, neither measure showed much movement. But in December 2014, both measures began to decline back toward the effective lower bound, with the prescriptions from the SEP reaction function falling faster than the median funds rate projection. Based on actual fourth-quarter inflation and unemployment, the SEP reaction function prescribed a funds rate of –0.25 percent. A similar pattern is apparent for the SEP reaction function based on core PCE inflation (not shown).

Comparing the SEP reaction function to a historical reaction function

A key question is whether the SEP reaction function represents a shift in the Committee's thinking about how it should respond to changes in the economic outlook as it contemplated liftoff from the effective lower bound. Perhaps surprisingly, the answer appears to be no. The estimated coefficients from the SEP reaction function are similar to coefficients from a reaction function estimated over the period before the constraint of the zero lower bound. Table 2 shows results from a regression of the target federal funds rate on real-time estimates of the inflation gap and the unemployment gap from 1987:Q1 to 2007:Q4. The inflation gap is measured as the difference between real-time estimates of headline inflation as measured by the PCE price index and an implicit 2 percent target. The unemployment gap is measured as the difference between the real-time unemployment rate and an estimate of its natural rate. Real-time estimates of the natural rate come from the Federal Reserve Board staff estimates of the natural rate published in the Greenbook—the briefing document Board staff used at the time to describe its macroeconomic forecast to the FOMC. Because these real-time estimates are only available starting in 1989:Q1, the natural

Table 2
Estimated Policy Reaction Function Using Real-Time Historical Data

Variables	Actual federal funds rate target 1987:Q1–2007:Q4
Real-time headline inflation gap	1.349*** (0.120)
Real-time unemployment gap	-1.728*** (0.277)
Constant	4.031*** (0.235)
R^2	0.7814
Observations	84

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

Notes: Standard errors are in parentheses. The estimation uses Newey-West standard errors with a lag of 4. The federal funds rate is regressed on a constant, the deviation of real-time data on headline inflation—measured by the personal consumption expenditure price (PCE) index—from 2 percent and the deviation of the real-time unemployment rate from real-time estimates of the natural rate. Real-time estimates of the natural rate come from Federal Reserve Board staff estimates in the Greenbook. For the period before 1989, in which similar real-time estimates are not available, the natural rate is held at a constant 5.75 percent, the same as the estimate for 1989:Q1.
Sources: BEA, BLS, Federal Reserve Board, FRED, Philadelphia Fed, Haver Analytics, and authors' calculations.

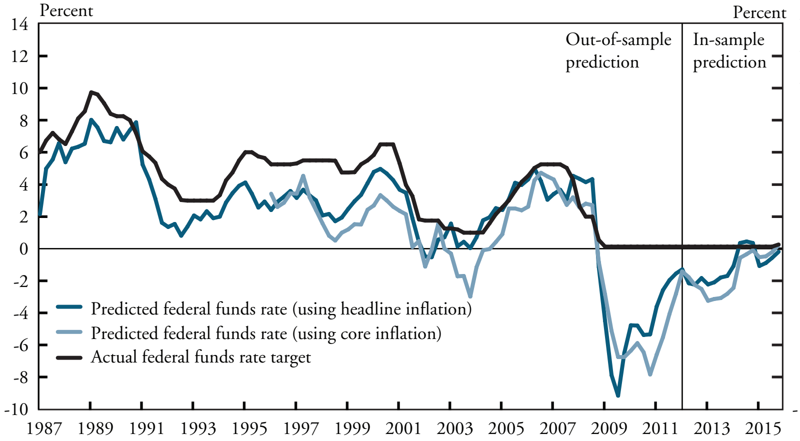
rate from 1987:Q1 to 1988:Q4 is assumed constant at its 1989:Q1 estimate of 5.75 percent.

Comparing the baseline SEP reaction function with the real-time historical reaction function shows that FOMC participants projected a trajectory for the federal funds rate in a manner not unlike their actual responses before the zero lower bound became a binding constraint. Table 2 shows the coefficient on the inflation gap in the historical policy reaction function (1.3) is close to the coefficient on inflation in the SEP reaction function (1.6). In addition, the coefficient on the unemployment gap is slightly more negative in the historical reaction function than in the SEP reaction function. Finally, the constant term of roughly 4 percent indicates a higher estimate of the historical equilibrium federal funds rate equal to the one John Taylor proposed in his original specification of the Taylor rule.[19]

One way to visualize the difference between the historical actions of the FOMC and the policy reaction function implied by the SEP is to consider a counterfactual scenario. In the counterfactual, we use the SEP reaction functions (using headline and core inflation) to "predict" the federal funds rate over the 1987 to 2008 period before the zero lower bound on interest rates became a constraint on policy. We can then compare the predicted funds rate with the actual funds rate. Chart

Chart 9

Federal Funds Rate Target: Actual versus Projections from the SEP



Notes: We generate the predicted federal funds rate paths using the reaction function coefficients estimated in specifications (1) and (2) from Table 1. These estimations use the median SEP projection for the federal funds rate and the midpoint of the central tendency for the unemployment rate, long-term unemployment rate, and both headline (dark blue line) and core (light blue line) inflation. The estimated regression is then fitted to the real-time historical data on unemployment and inflation. We piece together real-time estimates of the natural rate of unemployment from two sources. From 1989:Q1 to 2008:Q4, we use Federal Reserve Board staff estimates of the natural rate from the Greenbook; from 2009:Q1 to 2016:Q1, we use projections of the longer-term unemployment rate from the SEP. For the period before 1989, in which real-time estimates are not available from the Greenbook, the natural rate is held at a constant 5.75 percent, the same as the estimate for 1989:Q1. Predictions using core inflation begin in 1996, the first year for which real-time estimates of core inflation are available.
Sources: BEA, BLS, Federal Reserve Board, FRED, Philadelphia Fed, SEP, Haver Analytics, and authors' calculations.

9 shows the prediction from the SEP reaction function over the entire period using the same actual, real-time data for inflation and the unemployment gap used in Table 2. The dark blue line shows predictions based on the SEP reaction function with headline inflation, the light blue line shows predictions based on core inflation, and the black line shows the actual federal funds rate target. (The predictions based on core inflation begin in 1996, as that is the first year for which real-time estimates of the core PCE inflation rate are available.)

The SEP reaction function closely mirrors the actual federal funds rate target from roughly 2001 through 2015. Not surprisingly, for most of the in-sample period from 2012 to 2015, the SEP reaction function calls for a zero or negative funds rate. But the SEP reaction function also closely matches the actual funds rate in the out-of-sample period, at least from 2001 to 2012. During this period, the SEP reaction function prescribes a positive funds rate similar to the actual rate when the actual rate is above the effective lower bound and prescribes a negative funds rate when the actual funds rate is at the effective lower bound. Of greater interest is the period from 2001 to 2007, when the SEP reaction function also traces the actual path of the funds rate (especially in the specification with headline inflation). This is a period in which the actual funds rate fell to 1 percent, well below the rate normative policy rules, such as the Taylor 1993 rule, prescribed. Some commentators have argued that monetary policy was overly accommodative during this period, especially from 2003 to 2006, and thereby contributed to the financial crisis and Great Recession.[20] If policy was indeed overly accommodative in this period, then it would be cause for concern that policy since 2012 as described by the SEP reaction function could also be too accommodative.

Over the period from 1985 to 2001, the projections from the SEP reaction function diverge from the actual target federal funds rate. For most of this period, the SEP reaction functions prescribe a lower federal funds rate than was realized. Given that this period—the so-called Great Moderation—is considered a period of good macroeconomic performance, it may again be cause for concern that the implied SEP reaction function does not more closely mimic the earlier response of policymakers to inflation and unemployment.[21]

III. Decomposing the Projection Errors in the SEP

Why did the FOMC repeatedly project a liftoff from the zero lower bound that failed to materialize? Using the estimated SEP reaction function, we decompose the missed projections into three components. The first component is the projection error for inflation times the coefficient on inflation in the estimated SEP reaction function. The second component is the projection error for the unemployment gap times the coefficient on the unemployment gap in the SEP reaction function. And the third component is the unexplained difference between the actual federal funds rate and the prescription from the SEP reaction function.

In determining the first two components, we compute the difference between the funds rate prescriptions from the reaction function based on "perfect foresight" of the future paths of inflation and unemployment and the funds rate prescriptions from the reaction function based on the SEP projections of inflation and unemployment. More technically, the perfect foresight prescription is defined under the assumption that the SEP reaction function represents the Committee's systematic response to inflation and unemployment. It prescribes the funds rate the Committee might have chosen had it known the actual paths of future inflation and the unemployment gap. The resulting estimate of the perfect foresight funds rate target is determined as follows:

$$FFR_t^{PF} = \hat{a} + \hat{b}(p_t - 2) + \hat{c}(u_t - u_t^{LRt}) + \varepsilon_t,$$

where FFR_t^{PF} is the perfect foresight prescription for federal funds rate in period t, p_t and u_t are the actual inflation and unemployment rates in period t, ε_t is the residual term from the policy reaction function, and $\hat{a}$, $\hat{b}$, and $\hat{c}$ are the estimated coefficients from Table 1. The difference between the perfect foresight federal funds rate prescription and the projected federal funds rate is as follows:

$$FFR_t^{PF} - FFR_t^{t-i} = \hat{b}(p_t - p_t^{t-i}) + \hat{c}(u_t - u_t^{t-i} - u_t^{LRt} + u_t^{LRt-i}).$$

In addition, the difference between the actual funds rate and the perfect foresight funds rate is the component unexplained by the estimated policy reaction function. Thus, the difference between the actual federal funds rate target at time t, FFR_t, and the projected funds rate target at time $t–i$ can be decomposed as follows:

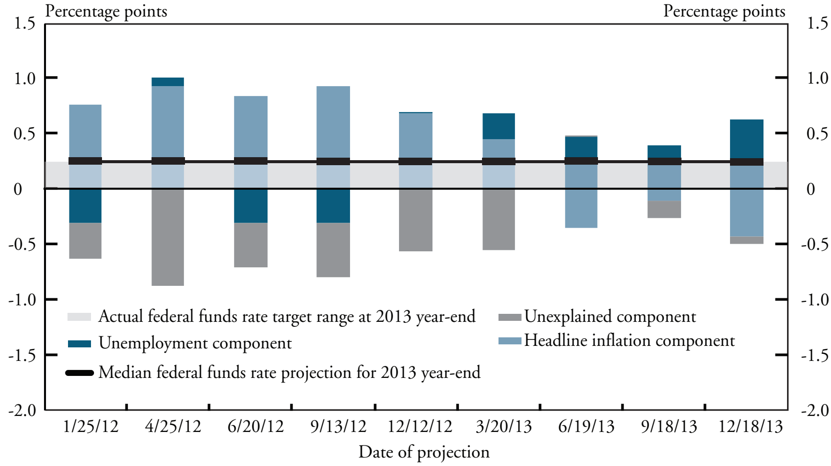
$$FFR_t - FFR_t^{t-i} = \hat{b}(p_t - p_t^{t-i}) + \hat{c}(u_t - u_t^{t-i} - u_t^{LR} + u_t^{LRt-i}) + \mu_t,$$

where μ_t is the unexplained component.

The decomposition shows that the repeated overestimation of inflation in the SEP was the primary contributor to projections that the federal funds rate would move off its effective lower bound. Missed projections of unemployment and unexplained deviations from the SEP reaction function played a smaller role. Charts 10, 11, and 12 show the decomposition of projection errors for the federal funds rate for 2013, 2014, and 2015, respectively. The decomposition is based on the SEP reaction function using headline inflation, but the results are qualitatively similar to those with the reaction function using core inflation. The light blue bars represent the inflation component of the projection error, the dark blue bars represent the unemployment gap component, and the gray bars represent the unexplained component. Together, these three components add up to the difference between the projected federal funds rate in the SEP—shown by the black lines—and the midpoint of the actual federal funds rate target range (13 basis points)—shown by the gray band.

Chart 10

Decomposition of 2013 Federal Funds Rate Projection Errors from the SEP



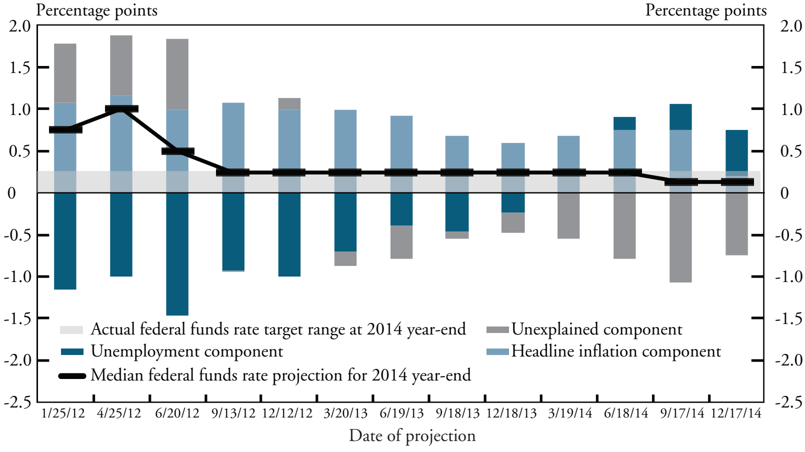
Note: We construct inflation and unemployment components as the difference between their projected and actual values multiplied by their respective coefficients in the estimated SEP reaction function (Table 1). The unexplained component is the difference between the actual federal funds rate and prescriptions from the estimated SEP reaction function with actual data (perfect foresight prescription).
Sources: BEA, BLS, CBO, Federal Reserve Board, FRED, SEP, Haver Analytics, and authors' calculations.

Chart 10 shows projections of the federal funds rate at the end of 2013 made at FOMC meetings from January 2012 to December 2013 at which the Committee issued a SEP report. At all of these meetings, the median funds rate projected in the SEP turned out to equal the upper end of the target range rate actually set by the FOMC at the end of 2013. Throughout 2012, overestimates of the inflation component were offset by underestimates of the unemployment component and a negative unexplained component. In contrast, in 2013, overestimates of the unemployment component were offset by underestimates of the inflation component and a negative unexplained component.

Chart 11 shows projections of the federal funds rate at the end of 2014 made at FOMC meetings from January 2012 to December 2014. For all of these projections, inflation was overestimated, tending to make the projected federal funds rate higher than otherwise would be the case. To a varying extent, these inflation projection errors were offset by projections of unemployment that proved to be too pessimistic from January 2012 to December 2013. These projection errors combined to lead to projected funds rates of 50 to 100 basis points

Chart 11

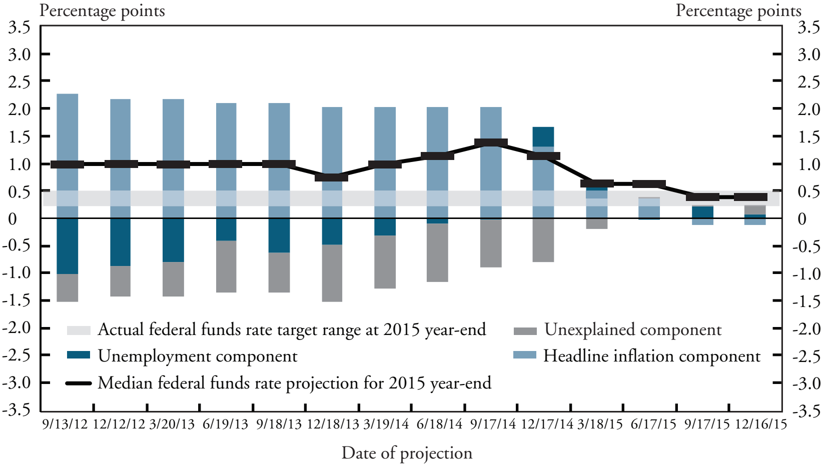
Decomposition of 2014 Federal Funds Rate Projection Errors from the SEP



Note: We construct inflation and unemployment components as the difference between their projected and actual values multiplied by their respective coefficients in the estimated SEP reaction function (Table 1). The unexplained component is the difference between the actual federal funds rate and prescriptions from the estimated SEP reaction function with actual data (perfect foresight prescription).
Sources: BEA, BLS, CBO, Federal Reserve Board, FRED, SEP, Haver Analytics, and authors' calculations.

Chart 12

Decomposition of 2015 Federal Funds Rate Projection Errors from the SEP



Note: We construct inflation and unemployment components as the difference between their projected and actual values multiplied by their respective coefficients in the estimated SEP reaction function (Table 1). The unexplained component is the difference between the actual federal funds rate and prescriptions from the estimated SEP reaction function with actual data (perfect foresight prescription).
Sources: BEA, BLS, CBO, Federal Reserve Board, FRED, SEP, Haver Analytics, and authors' calculations.

at FOMC meetings in January, April, and June 2012. However, by the September 2012 FOMC meeting, participants were correctly projecting the federal funds rate target within the range they ultimately targeted, with the various components of the projection error roughly offsetting each other.

Finally, Chart 12 shows projections of the federal funds rate at the end of 2015 made at FOMC meetings from September 2012 to December 2015. Again, for almost all of the projections, inflation was overestimated, contributing to the overestimate of the projected federal funds rate. The unemployment gap component played a relatively small role, while the unexplained component pushed the projected federal funds rate down over most of the period.

IV. Conclusions

The Summary of Economic Projections provides insights into FOMC participants' views on how the federal funds rate target should respond to inflation and unemployment. Although the projections in the SEP have proved to be consistently wrong—as have most projections of the future—they do provide information about the FOMC's implicit reaction function. For example, they show a systematic, planned response of the federal funds rate target to projected increases in inflation and projected declines in unemployment. Moreover, the estimated response function is similar to how policy responded to inflation and unemployment from 2001 to December 2008, when policy became constrained by the zero lower bound.

The estimated policy reaction function can also help explain why the SEP repeatedly got both the date of liftoff and the trajectory of the federal funds rate wrong. Taking into account not only projection errors for inflation and unemployment but also the SEP reaction function's estimate of the Committee's systematic response to inflation and unemployment, it is clear that the Committee's anticipated response to projected increases in inflation was the primary factor responsible for the missed projections.

Looking ahead, it will be interesting to see if the estimated SEP reaction function continues to describe the relationship between projections of the federal funds rate and projections of inflation and unemployment in future SEP reports. In any event, additional SEP reports will be useful in understanding how the Committee thinks about adjusting policy to achieve its dual mandate.

Appendix

Table A-1

Estimated Policy Reaction Functions Using Projections from the SEP by Forecast Horizon (OLS)

	One-year-ahead projections		Two-year-ahead projections		Three-year-ahead projections	
	(1)	(2)	(3)	(4)	(5)	(6)
Reaction function with:	Headline inflation	Core inflation	Headline inflation	Core inflation	Headline inflation	Core inflation
Inflation gap projection	1.177**	1.874	6.685***	4.516	6.216*	6.592
	(0.324)	(1.105)	(1.968)	(2.827)	(2.813)	(6.698)
Unemployment gap projection	-1.173***	-1.360**	-0.820***	-1.053***	-2.141***	-2.543***
	(0.272)	(0.463)	(0.191)	(0.215)	(0.378)	(0.414)
Constant	1.763***	1.871***	3.173***	2.816***	3.292***	3.208***
	(0.117)	(0.297)	(0.280)	(0.350)	(0.274)	(0.485)
R^2	0.810	0.590	0.850	0.763	0.934	0.890
Observations	9	9	16	16	8	8

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

Notes: Standard errors are in parentheses. The estimation uses projections from the January 2012 SEP to the March 2016 SEP with Newey-West standard errors with a lag of 4 and excludes projections for which the median federal funds rate is at or below 0.25 percent. There is no regression for same-year projections, since there are not sufficient observations with the median federal funds rate projection above 0.25 percent. The estimation uses the midpoint of the central tendency of SEP projections for inflation, unemployment, and long-run unemployment, and the median projections for the federal funds rate.

Sources: The Federal Reserve Board, FRED, and authors' calculations.

Table A-2

Estimated Policy Reaction Functions Using Projections from the SEP by Forecast Horizon (Tobit)

	One-year-ahead projections		Two-year-ahead projections		Three-year-ahead projections	
	(1)	(2)	(3)	(4)	(5)	(6)
Reaction function with:	Headline inflation	Core inflation	Headline inflation	Core inflation	Headline inflation	Core inflation
Inflation gap projection	1.204***	1.922**	6.764***	3.697	6.216**	6.592
	(0.256)	(0.853)	(1.852)	(2.578)	(2.224)	(5.295)
Unemployment gap projection	-1.264***	-1.404***	-0.929***	-1.235***	-2.141***	-2.543***
	(0.151)	(0.299)	(0.173)	(0.187)	(0.299)	(0.327)
Constant	1.766***	1.881***	3.177***	2.715***	3.292***	3.208***
	(0.0944)	(0.233)	(0.264)	(0.322)	(0.217)	(0.384)
Regression standard error	0.130***	0.191***	0.382***	0.487***	0.280***	0.360***
	(0.0303)	(0.0446)	(0.0684)	(0.0872)	(0.0700)	(0.0901)
Pseudo-R^2	1.2587	1.0988	0.6708	0.5250	0.9026	0.7348
Left-censored observations	9	9	2	2	0	0
Uncensored observations	9	9	16	16	8	8

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

Notes: Standard errors are in parentheses. The estimation uses a Tobit regression model, censoring projections for which the median federal funds rate forecast was at or below 0.25 percent. The estimation uses the midpoint of the central tendency of SEP projections for inflation, unemployment, and long-run unemployment, and the median projection for the federal funds rate.

Sources: The Federal Reserve Board, FRED, and authors' calculations.

Table A-3

Estimated Policy Reaction Functions Using Projections from the SEP by Forecast Horizon with Fixed Effects

	Baseline projection		"Dovish" projection		"Hawkish" projection	
	(1)	(2)	(3)	(4)	(5)	(6)
Reaction function with:	Headline inflation	Core inflation	Headline inflation	Core inflation	Headline inflation	Core inflation
Inflation gap (two-year horizon)	6.726*** (1.397)	3.724* (1.956)	2.873*** (0.659)	3.886*** (1.058)	2.664*** (0.898)	-4.591 (4.254)
d0*inflation gap	-6.637*** (1.437)	-4.066 (2.622)	-2.522*** (0.749)	-3.928 (2.465)	-2.554** (1.011)	4.751 (4.508)
d1*inflation gap	-5.450*** (1.505)	-1.514 (2.463)	-1.485* (0.761)	-2.140 (1.767)	-- --	8.272* (4.355)
d3*inflation gap	-0.510 (2.683)	2.868 (5.774)	0.789 (1.153)	1.184 (2.488)	-- --	-- --
Unemployment gap (two-year horizon)	-0.914*** (0.130)	-1.213*** (0.141)	-1.681*** (0.335)	-2.137*** (0.360)	-0.860*** (0.140)	-0.847*** (0.132)
d0*unemployment gap	-0.732 (0.731)	-0.686 (1.074)	-0.0395 (0.751)	0.505 (0.994)	-1.877 (1.195)	-1.870 (1.325)
d1*unemployment gap	-0.553* (0.318)	-0.408 (0.467)	0.162 (0.509)	0.533 (0.603)	0.0490 (0.185)	0.0578 (0.170)
d3*unemployment gap	-1.227*** (0.334)	-1.330*** (0.364)	-0.388 (0.435)	-0.403 (0.471)	0.0553 (0.387)	0.0420 (0.362)
Constant (two-year horizon)	3.172*** (0.199)	2.719*** (0.244)	2.507*** (0.191)	2.649*** (0.264)	3.118*** (0.126)	3.137*** (0.120)
d0*constant	-2.466*** (0.483)	-2.331** (1.097)	-1.633*** (0.523)	-2.292 (1.509)	-1.906*** (0.557)	-1.962** (0.804)

Table A-3 continued

d1*constant	-1.397*** (0.288)	-0.773 (0.485)	-0.871*** (0.287)	-1.006 (0.652)	-0.836*** (0.232)	-0.744*** (0.219)
d3*constant	0.120 (0.299)	0.489 (0.463)	0.490* (0.268)	0.412 (0.422)	0.332 (0.204)	0.313 (0.192)
Regression standard error	0.289*** (0.0333)	0.370*** (0.0427)	0.249*** (0.0303)	0.308*** (0.0374)	0.440*** (0.0464)	0.412*** (0.0432)
Pseudo-R^2	0.8988	0.7971	0.9673	0.8804	0.7042	0.7421
Left-censored observations	24	24	28	28	16	16
Uncensored observations	38	38	34	34	46	46

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

Notes: Standard errors are in parentheses. Estimation uses projections from the January 2012 SEP to the March 2016 SEP in a Tobit regression model, censoring projections for which the median federal funds rate forecast was at or below 0.25 percent. The baseline projection uses the midpoint of the central tendency of projections of inflation, unemployment, and long-run unemployment, and the median of the federal funds rate projections. The "dovish" projection uses the minimum of the central tendency of the federal funds rate and inflation, as well as the maximum of the central tendency for unemployment and long-run unemployment. The "hawkish" projection uses the maximum of the central tendency of the federal funds rate and inflation, as well as the minimum of the central tendency for unemployment and long-run unemployment. Missing coefficients in the table were omitted by the model due to collinearity. The dummy variables d0, d1, and d3 correspond to the horizon of the SEP projections made for zero-years ahead (same year), one-year ahead, and three-years ahead. The "baseline" case is for projections made for two-years ahead. The regression specification takes the form:

$$FFR_t^{t-i} = a_2 + \sum_{(i=0,1,3)}(d_i a_i) + b_2(p_2^{t-2} - 2) + \sum_{(i=0,1,3)} d_i b_i (p_t^{t-i} - 2) + c_2(u_2^{t-2} - u_2^{LRt-2}) + \sum_{(i=0,1,3)} d_i c_i (u_i^{t-i} - u_i^{LRt-i}),$$

where

$$d_i = \begin{cases} \textit{1 if projection was made for i=0,1, or 3 years ahead} \\ \textit{0 otherwise} \end{cases}$$

Sources: The Federal Reserve Board, FRED, and authors' calculations.

Endnotes

[1]In its first reports, the FOMC provided ranges of projections from only the Federal Reserve Board Governors (Reserve Bank presidents were not included). The projections were for the four-quarter growth rates for nominal and real gross national product, the rate of GNP inflation, and the fourth-quarter unemployment rate, all for the current year (in the February and July reports) and the following year (in the July reports). In July 1980, all voting members of the FOMC (the Reserve Board Governors and the five voting Reserve Bank presidents) began providing projections. In February 1981, the FOMC adopted the current practice of including all FOMC participants' projections in the reported ranges. In 1983, the FOMC began reporting central tendencies of the projections along with their ranges. The central tendencies omitted high and low outliers, which were specified in 1987 as the top and bottom three projections. Projections for economic growth released through July 1991 were based on GNP. Starting the following year, projections for growth were for GDP. The consumer price index (CPI) replaced the GNP deflator as the measure of inflation starting in February 1989. The personal consumption expenditure (PCE) price index replaced the CPI in February 2000. The core PCE price index replaced the headline PCE price index from July 2004 to July 2007. In November 2007, the Committee began reporting projections for inflation as measured by both the headline and core PCE price indexes.

[2]The forecast horizon is the current and three subsequent years in the third and fourth-quarter SEP reports and the current and two subsequent years in the other two quarterly reports.

[3]No longer-run projection is provided for core PCE inflation because core and headline inflation are expected to converge over the longer run and the FOMC's longer-run inflation objective is broadly defined as price stability.

[4]The median federal funds rate projection, as well as the range and central tendencies of the projections, can be readily determined from the dot plot.

[5]Starting in September 2015, the FOMC began reporting the median of FOMC participants' projections as well as the central tendency and range. For consistency, we focus on the midpoint of the central tendencies for all meetings, including those for September and December 2015 and March 2016. In addition for robustness, we examine the maximum and minimum of the central tendencies.

[6]See, for example, Van Zandweghe (2012) on the labor force participation rate and Van Zandweghe (2010) on productivity growth.

[7]In particular, some FOMC participants may have overestimated the slope of the Phillips curve.

[8]Taking an alternative approach, Berriel, Carvalho, and Machado calibrate standard New Keynesian models subject to the zero lower bound under different assumptions about the degree of policy commitment. They then assess which specification best fits the SEP dot plots. By simulating policy responses to economic developments, they construct uncertainty bands around interest rate forecasts using

the best-fitting specification. They conclude that "the degree of Fed commitment to low rates for an extended period of time decreased in recent years."

[9]The Taylor rule (1993) recommends that the funds rate should be set equal to 1 plus 1.5 times inflation plus 0.5 times the output gap. For a discussion of the Taylor rule and its use in monetary policy, see Kahn (2012a). Carlstrom and Lindner examine how prescriptions from the Taylor rule describe the distribution of FOMC participants' views in 2012 about the appropriate timing of policy tightening. They find that such a rule "roughly captures many Committee participants' views of appropriate monetary policy."

[10]An important caveat is that the estimated reaction function is not necessarily that of the median FOMC participant since the median federal funds rate and the midpoints of the central tendencies of the explanatory variables likely reflect the views of different participants. Carlstrom and Jacobson explore this issue in the context of private sector forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.

[11]In January 2012, the Committee adopted a numerical objective for the longer-run inflation rate of 2 percent as measured by the annual change in the PCE price index. Before that, the midpoints of the central tendency of longer-run projections of inflation from the SEP were slightly below 2 percent, varying from 1.8 to 1.85 percent. The SEP began including projections for the federal funds rate in January 2012. Thus, for the entire sample used in this analysis, the longer-run inflation projection is 2 percent.

[12]Theoretical and estimated policy reaction functions in the literature often also include a lagged federal funds rate on the right-hand side to reflect inertia or interest rate smoothing in the setting of monetary policy. Such smoothing is omitted here because of the end-of-year projection horizons. All projections are made for the end of the year based on projected Q4/Q4 inflation and Q4 unemployment. See Rudebusch for a discussion of interest rate smoothing and monetary policy inertia.

[13]The FOMC released five SEPs in 2012. After 2012, it released one SEP each quarter.

[14]Specifically, the estimation is by Tobit regression (Tobin).

[15]Because of the panel structure of the data set and the Tobit estimation procedure, correcting for possible serial correlation in the error term is problematic, at best. As a robustness check, we reestimate the reaction function separately for each forecast horizon from one to three years ahead using ordinary least squares (OLS) with Newey-West standard errors, omitting observations where the funds rate projection was at the effective lower bound. Hypothesis tests on the significance of regression coefficients are generally not affected. Appendix Table A-1 shows the OLS regression results. Appendix Table A-2 shows the comparable results from the Tobit regression for each forecast horizon.

In addition, to more fully exploit the panel structure of the data, we estimate a Tobit regression with fixed effects for each forecast horizon from the current year to three-years ahead, allowing the constant and slope coefficients to vary across forecast horizon. As shown in Appendix Table A-3, we find that the response of the projected federal funds rate to inflation in the model with headline inflation is strongest at the two- and three-year forecast horizons, while the response to unemployment gets increasingly strong as the forecast horizon is extended from the current year to three-years ahead. For the model with core inflation, we find no statistically different response of the projected funds rate to inflation across forecast horizons but an increased response to unemployment at the three-year horizon (in the baseline regressions).

Feroli, Greenlaw, Hooper, Mishkin, and Sufi estimate a policy reaction function from the SEP similar to the baseline regression reported here in Table 1, omitting observations at the effective lower bound. They present results for four specifications, using alternative measures of economic slack. The first measure is an estimate of the output gap based on Board staff estimates of the gap at the end of each calendar year and the subsequent deviation of projected real GDP growth from its long-run projected growth rate. The second measure is the projected change in the real GDP gap. The third measure is the projected unemployment gap. And the fourth measure is the change in the unemployment gap. Their results using the unemployment gap measure of slack are similar to those we report in this article.

[16]At 1.6, the estimated coefficient on headline inflation (as measured by the PCE price index) is very close to the coefficient on headline inflation (the GDP price deflator) in the 1993 Taylor rule.

[17]In addition to the specification of the policy reaction function given in the text, we estimate an alternative model that includes the deviation of projected real GDP growth from its longer-run level as an additional explanatory variable. Coefficients on this variable are not significantly different from zero except in the regressions using the core measure of inflation. However, the sign on the projected GDP growth variable is negative rather than the expected positive, suggesting a decrease in projected real GDP growth is associated with an increase in the projected federal funds rate. In retrospect, this result is not too surprising, as the SEP projected that growth would exceed potential in the near term as slack was gradually eliminated, then slow back to its long-run trend as policy was gradually tightened. Over this period of substantial economic slack, the FOMC would have been unlikely to lean against above-trend real GDP growth by raising the projected federal funds rate. See Coibion and Gorodnichenko (2011 and 2012) and Orphanides for a discussion of the role of real GDP growth in policy reaction functions estimated during the pre-zero lower bound period.

[18]Until June 2014, FOMC participants reported projections for the federal funds rate target at the upper end of the FOMC's prospective target range.

Starting in September 2014, they began reporting their projections as the midpoint of the target range. Thus for some of the sample, the effective lower bound is reported as 25 basis points while for the remainder, it is reported as 13 basis points.

[19]Bundick estimates the policy reaction function that private forecasters perceived the FOMC to have followed in the pre- and post-zero lower bound periods using a similar specification to ours and data from the Blue Chip Economic Indicators. He finds the coefficients on inflation and unemployment are similar across the two periods. In addition, for the zero lower bound period, he estimates a coefficient of 1.6 on inflation (the same as our estimate from the policy reaction function with headline inflation) and a coefficient of –6.8 on unemployment (somewhat larger than our estimate of –1.6).

[20]See Taylor (2007) for the view that monetary policy was overly accommodative and Bernanke for an opposing view.

[21]Kahn (2010, 2012b) discusses monetary policy during the Great Moderation in the context of normative and estimated policy rules.

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The Lasting Damage from the Financial Crisis to U.S. Productivity

Michael Redmond and Willem Van Zandweghe

The financial crisis and recession of 2007–09 left deep scars on the U.S. economy. Output of goods and services declined sharply during the crisis, and while output began to grow afterward, its level has not caught up to its pre-crisis trend. Likewise, total factor productivity, a key source of output growth in the long run, declined and has remained on a lower trajectory than before the crisis.

Tighter credit conditions may have contributed to these declines. Obtaining credit was more difficult and expensive for firms during the crisis, as widespread fear and uncertainty drove lenders to raise interest rates and lend more cautiously. The reduced credit supply may have prevented firms from investing in innovation and creating new jobs and prevented new firms from entering the market. In this way, tighter credit conditions may have lowered total factor productivity—and, consequently, real activity.

We examine the empirical relationship between credit conditions and total factor productivity growth during the financial crisis. Our empirical analysis shows the crisis indeed altered this relationship. During normal times, total factor productivity growth fluctuates over the business cycle along with changes in the intensity with which available labor and capital are used; credit conditions are unimportant.

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During the crisis, however, distressed credit markets and tighter lending conditions were significant drags on total factor productivity growth. Because productivity's sensitivity to credit conditions once again diminished after the crisis, the post-crisis easing of credit conditions did not boost productivity growth. As a result, the financial crisis left productivity, and therefore output, on a lower trajectory. Adverse credit conditions appear to have dampened total factor productivity growth by curtailing productivity-boosting innovation during the crisis rather than by hampering the efficient allocation of the economy's productive resources through reduced creation and destruction of firms and jobs.

Section I describes the behavior of credit conditions and productivity during the financial crisis. Section II provides empirical evidence of the relationship between productivity and credit conditions. Section III examines the relationships between credit conditions and two factors that affect productivity: innovation or resource reallocation.

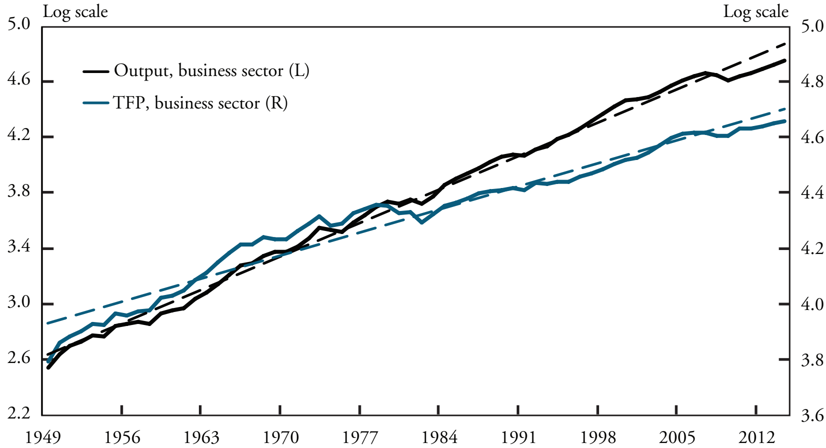
I. Total Factor Productivity in the Financial Crisis

The financial crisis and associated recession triggered a persistent drop in output below its long-run trend, due in part to a drop in total factor productivity (TFP). TFP declined as credit conditions tightened during most of the crisis; when credit conditions subsequently eased, TFP partially rebounded, though it remains below its long-run trend.

Chart 1 displays output in the business sector (solid black line) along with its long-run trend (dashed black line). In 2008 and 2009, output fell below the trend line; after the crisis subsided, output began to rise but remained well below the trend line. Indeed, by 2014, the gap between output and its long-run trend had widened somewhat further. Gross domestic product, which includes the government sector, declined less than business sector output from 2008 to 2009, but was slower to recover after the crisis. Many studies find output frequently does not rebound to its pre-crisis trend (Ball; Blanchard, Cerutti and Summers; Hall; and Reifschneider, Wascher, and Wilcox), perhaps because financial crises have long-lasting effects (Cerra and Saxena; Reinhart and Rogoff; Queralto; Martin, Munyan, and Wilson).[1]

Similar to the path of output, TFP fell below its trend line during the financial crisis and has remained there since. Chart 1 shows the historical trajectory of TFP (solid blue line) along with its long-run

Chart 1
Output and Productivity



Note: Dashed lines represent long-run trends and are estimated as linear regression lines.
Sources: Bureau of Labor Statistics and Haver Analytics.

trend line (dashed blue line). TFP declined in 2008 and 2009 before resuming modest growth from 2010 to 2014, thus leaving the level of TFP on a trajectory below its long-run trend.

The similar paths of output and TFP suggest the decline in TFP may have played a substantial role in the decline in output. As a matter of accounting, output growth can be attributed to growth in labor, capital, or TFP. The latter consists of productivity gains that allow more output to be produced without increasing the labor and capital used to produce it. These productivity gains can occur for several reasons, such as technological innovation, better resource allocation, a more intense use of available production factors, or changes in regulation, tax policies, and competitiveness.

Productivity and credit conditions in the financial crisis

Declining TFP appears to have weighed on output during the financial crisis—but what led to the decline in TFP? We home in on credit conditions as the primary suspect. Economists have cited theoretical arguments in relating the persistent decline in TFP to the sharp tightening of credit conditions during the financial crisis. Theoretical models predict a clear relationship between financial conditions and innovation, and recent analyses apply these theories to shed light on the macroeconomic effects of the recent financial crisis (Ikeda and Kurozumi; Guerron-Quintana and Jinnai; Anzoategui, Comin, Gertler, and Martinez; and Garcia-Macia). Other theoretical work highlights a connection between financial conditions and resource reallocation (Petrosky-Nadeau). Both innovation and resource reallocation are key determinants of TFP.

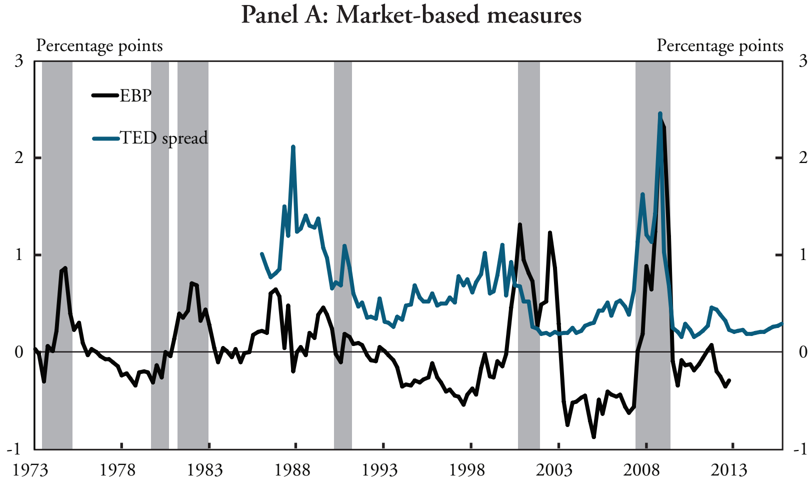
Chart 2 shows three measures of credit supply conditions, two market-based and one survey-based. The first market-based measure is the excess bond premium (EBP) of Gilchrist and Zakrajšek, which measures credit supply conditions as deviations in the pricing of corporate bonds relative to the issuer's measured default risk (Panel A, black line). The authors use firm-level data to account for firms' default risk in corporate bond credit spreads, so the remaining portion (the EBP) captures the compensation investors demand for bearing exposure to corporate credit risk. The second market-based measure is the spread between three-month eurodollar deposits and Treasury bills, or the TED spread (Panel A, blue line). The TED spread captures the cost of interbank borrowing measured as the difference between the rates at which banks can borrow from other banks and the risk-free rate.[2] A rising EBP or TED spread suggests lenders have reduced the supply of credit (thus raising its cost) because they perceive increased credit risk. A sudden sharp rise in the cost of credit can effectively limit access to credit for many firms.

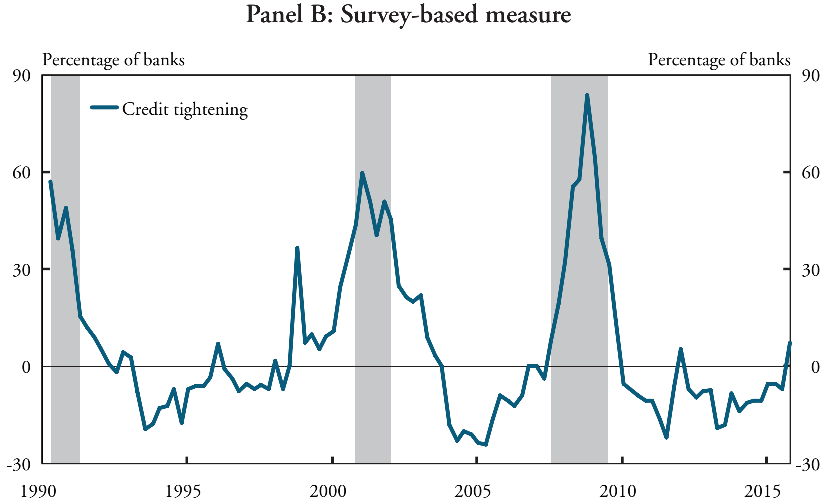
A third, survey-based measure displays the net percentage of banks tightening conditions for commercial and industrial loans to large firms, as captured by the Federal Reserve's Senior Loan Officers Opinion Survey (Panel B). This measure is a diffusion index, and thus provides a more qualitative reading on changes in credit conditions than the previous two. All three measures of credit conditions rose sharply during the financial crisis, as the distress in credit markets pushed credit conditions and bank lending standards to historically tight levels.

Credit supply conditions had a close relationship with TFP during the last recession. Panels A and B of Chart 3 display the market-based and survey-based measures of credit conditions, respectively, from the first quarter of the recession, 2007:Q4, to the last quarter of the recession, 2009:Q2.[3] The panels also show quarterly TFP, available from Fernald, as a blue line. Both panels show a negative relationship

Chart 2

Measures of Credit Conditions



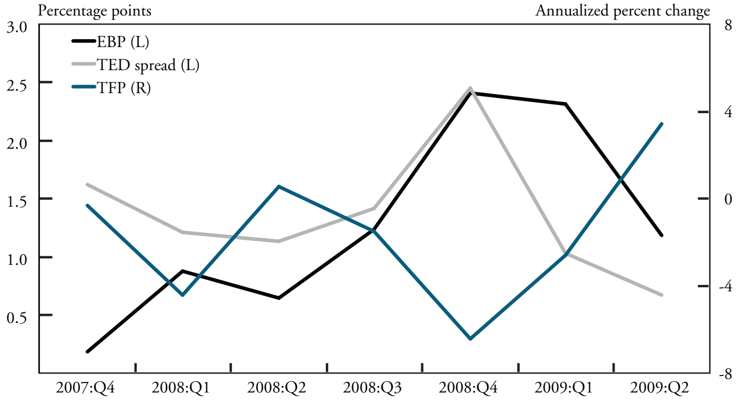


Note: Gray bars denote NBER-defined recessions.
Sources: Federal Reserve, Federal Reserve Bank of St. Louis FRED, Gilchrist and Zakrajšek, and Haver Analytics.

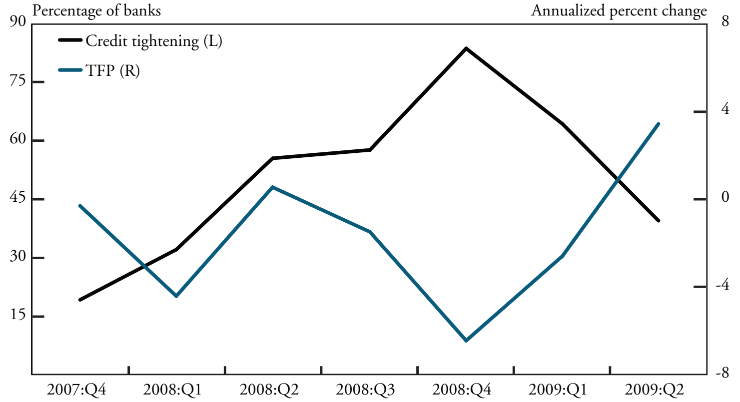
Chart 3

Credit Conditions and Productivity in the Great Recession

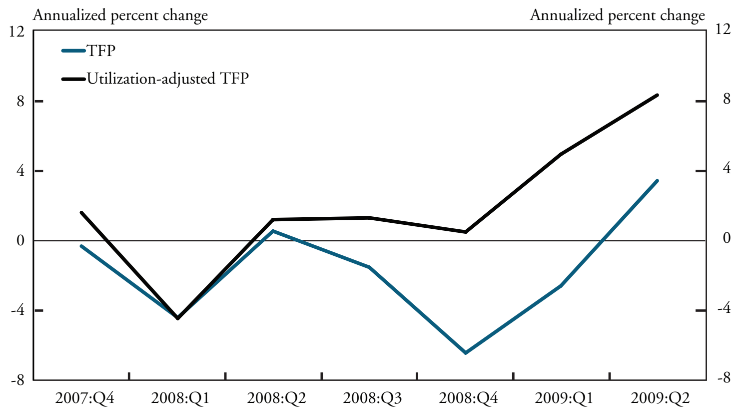
Panel A: Market-based measures of credit conditions



Panel B: Survey-based measure of credit conditions



Panel C: Utilization-adjusted productivity



Sources: Federal Reserve, Fernald, Federal Reserve Bank of St. Louis FRED, Gilchrist and Zakrajšek, and Haver Analytics.

between credit conditions and TFP during the recession. During the first year of the recession, TFP slowed as credit conditions worsened. But in the last six months of the recession, TFP growth resumed as access to credit began to ease.[4]

But could the decline in TFP during the recession merely reflect a less intense use of labor and capital? After all, indicators of the intensity with which firms use their production factors, such as the Federal Reserve Board's industrial capacity utilization, declined sharply over the same period, suggesting firms idled machinery and required less effort from workers. These responses to the economic downturn, commonly referred to as declines in factor utilization, would result in lower TFP, as they reduce output but do not change labor and capital. To gauge the structural component of TFP, Fernald and Matoba remove the fluctuations in factor utilization from TFP growth and find that utilization-adjusted TFP actually rose during the recession. Panel C of Chart 3 shows Fernald's measure of utilization-adjusted TFP (gray line) diverged sharply from the unadjusted measure during the height of the recession, as factor utilization fell sharply. A decline in unobserved worker effort and capital utilization during downturns is consistent with the idea that firms adjust labor on all margins—paid hours as well as unobserved effort and capital utilization—and helps explain the procyclical pattern of labor productivity that characterized recessions until the early 1980s (Biddle).

However, the last recession differed from past recessions in that it was associated with a severe financial crisis. The collapse of product demand and the lack of access to credit forced firms to cut paid hours sharply in a bid to survive. Keeping nonessential workers on the payroll while sharply reducing their labor effort was likely not viable for many firms. Indeed, Lazear, Shaw, and Stanton find evidence that worker effort actually increased during the last recession. Thus, measures of factor utilization that assume the relationship between paid hours and unobserved effort was unchanged in the last recession—such as Fernald's measure—could exaggerate factor utilization's influence on TFP growth.[5]

Similarly, the Federal Reserve Board's measure of capacity utilization may also exaggerate the decline in worker effort during the last recession. The Board's measure largely reflects capital utilization, which is expected to decline as firms idle factories and machinery, even if workers in the remaining shifts raise their labor effort. For the economy as a whole, labor effort, not capital utilization, should dominate factor utilization, as the income share of labor exceeds that of capital. Therefore, the preceding measures of factor utilization and capacity utilization arguably exaggerate the decline in worker effort during the last recession. For these reasons, we follow Hall in viewing the unadjusted measure of TFP as more relevant.

Innovation and resource reallocation

If credit conditions are responsible for the decline in TFP during the financial crisis, through which channels could this have happened? Two channels are consistent with the theoretical literature: a reduction in credit availability could have hurt TFP by curbing innovation or by hampering resource reallocation, two key contributors to productivity growth.

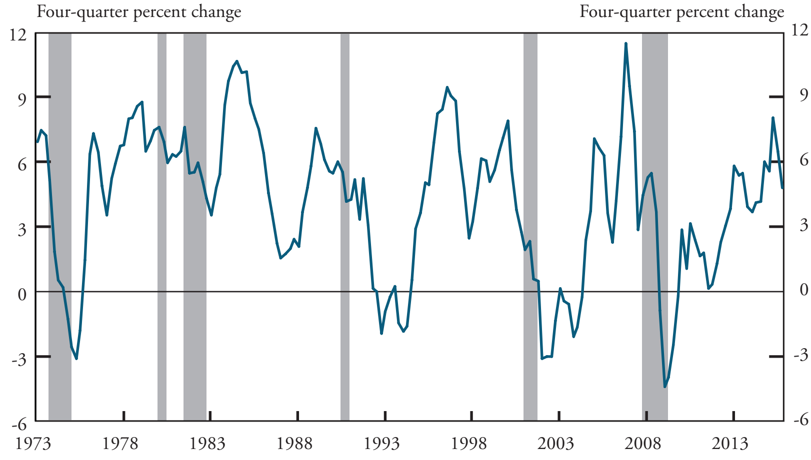
First, a lack of access to credit could have curbed innovation if it caused firms to cancel or postpone research and development (R&D) projects. Chart 4 shows real R&D growth in the private sector collapsed during the recession from a rate of more than 4 percent in the fourth quarter of 2007 to a rate of –4 percent in the second quarter of 2009. R&D growth started slowing in the beginning of 2007; including that period, the reversal in R&D growth from the beginning of 2007 to the beginning of 2009 was the largest since the 1960s.

Lower R&D spending likely reduced innovation and its productivity-enhancing effects on the economy. A large body of empirical literature suggests R&D spending has a significant positive effect on productivity growth (see Congressional Budget Office for a review). Moreover, TFP could have responded quickly to the decline in R&D spending during the crisis. While basic research may not be commercialized for many years, much of private R&D spending consists of product development such as model-year updates of manufactured goods. In addition, TFP could have responded quickly to a downturn in R&D to the extent such investments were correlated with intangible investments that went unmeasured.

Second, a lack of access to credit could have hampered resource reallocation by preventing the creation of new firms and jobs. Business startups and the jobs they generate are often highly productive, as such firms bring new ideas to market and implement advanced production processes. For instance, Haltiwanger, Faberman, and Jarmin find new

Chart 4

Private Investment in R&D



Note: Gray bars denote NBER-defined recessions.
Sources: Bureau of Economic Analysis and Haver Analytics.

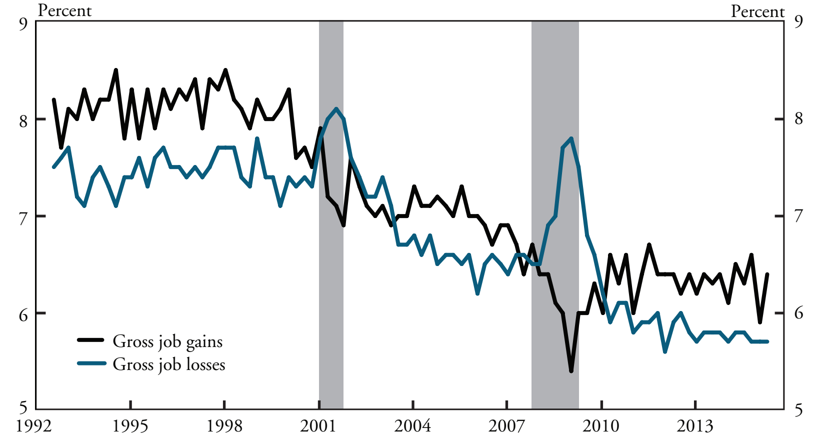
firms make a substantial contribution to job creation. By stunting this type of reallocation, reduced access to credit could lower productivity. Chart 5 shows the rate of gross job gains in the private sector (expressed as a percent of employment) dropped steeply during the recession, reaching a trough of 5.4 percent in the first quarter of 2009. Although the rate of job gains subsequently recovered, its average since the end of the recession (6.3 percent) has remained well below its average during the expansion in the 2000s (7.1 percent).

However, reduced access to credit may not always have a negative effect on productivity. Indeed, a tightening of credit conditions could have a positive effect on aggregate productivity by leading firms to eliminate the least productive jobs and forcing the least productive firms out of business. The blue line in Chart 5 shows the rate of gross job losses surged during the recession, peaked at 7.8 percent in the first quarter of 2009, and stabilized at a low level after the recession ended. Consequently, the rate of gross job losses has been lower on average during the current expansion (5.9 percent) than during the previous one (6.8 percent).[6]

On balance, reallocation remained relatively stable during the recession, as the negative effects of fewer new jobs and firm entries offset the positive effects of more job losses and firm exits. Chart 6 shows the rate of job reallocation, which is the sum of the rates of gross job gains

Chart 5

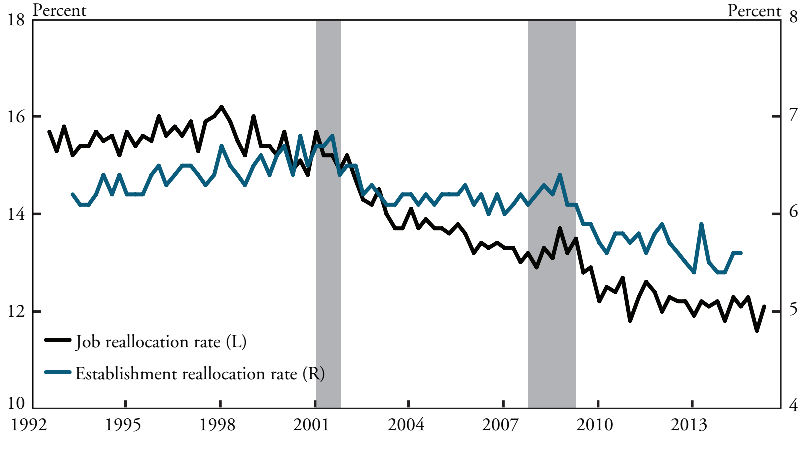
Job Gains and Losses



Note: Gray bars denote NBER-defined recessions.
Sources: Bureau of Labor Statistics and Haver Analytics.

Chart 6

Job and Establishment Reallocation



Note: Gray bars denote NBER-defined recessions.
Sources: Bureau of Labor Statistics and Haver Analytics.

and losses, and the rate of establishment reallocation, which is the sum of the rates of births of and deaths of business establishments. The rate of job reallocation ticked up from 13.2 percent in the fourth quarter of 2007 to 13.5 percent in the second quarter of 2009, as the increase in the rate of gross job losses more than offset the decline in the rate of gross job gains. The rate of establishment reallocation stood at 6.1 percent in the first and last quarters of the recession, though both reallocation rates continued to slip in the recession's aftermath.

In sum, the severe tightening in credit conditions during the financial crisis may have lowered TFP by impeding innovation and resource reallocation. The next two sections investigate these hypotheses more formally—first, by establishing a relationship between credit conditions and TFP growth, and second, by examining the role of credit conditions in innovation and resource reallocation.

II. Empirical Analysis of Credit Conditions and TFP

To examine whether tight credit supply impeded productivity growth during the financial crisis, we estimate a regression model that quantifies the relationship between TFP growth and credit conditions. The results suggest a tight credit supply during the crisis temporarily restrained the growth rate of TFP, leaving a lasting mark on the level of productivity.

The regression model relates TFP growth in a quarter t (y_t) to three explanatory variables. The first two variables, a measure of credit conditions in the current quarter (x_t) and the previous quarter (x_{t-1}), allow us to account for the immediate and lagged influence of credit conditions on TFP growth. The third variable, a measure of factor utilization (u_t), allows us to control for utilization-driven fluctuations in TFP growth, as the series of TFP growth we use in the estimation is not utilization-adjusted. In addition, the model contains a constant term and an error term (ε_t) that captures unexplained variation in TFP growth.

One challenge in constructing such a model is that the financial crisis may have affected the usual economic relationships between the variables. For example, the propagation of shocks to the economy could have changed because the economy was highly leveraged, allowing small shocks to have large effects on the real economy; Ng and Wright emphasize this balance sheet effect.[7] Furthermore, policy responses may have been weaker than usual relative to the magnitude of the shock, as monetary policy was constrained by the zero lower bound on interest rates. To account for these possibilities, we allow the coefficients on each variable and the constant term to differ during the crisis. Specifically, the regression model is as follows:

$$y_t = a_f + a_n d_{n,t} + b_{f,0}\left(x_t d_{f,t}\right) + b_{f,1}\left(x_{t-1} d_{f,t}\right) + b_{n,0}\left(x_t d_{n,t}\right) + b_{n,1}\left(x_{t-1} d_{n,t}\right) + c_f\left(u_t d_{f,t}\right) + c_n\left(u_t d_{n,t}\right) + \varepsilon_t$$

where $d_{f,t}$ is a dummy variable that takes a value of 1 in the quarters of the financial crisis and recession (from the fourth quarter of 2007 to the second quarter of 2009) and 0 in other quarters, and $d_{n,t}$ is its complement (that is, $d_{n,t} = 1 - d_{f,t}$).[8] The coefficients with the subscript f (that is, a_f, $b_{f,0}$, $b_{f,1}$, and c_f) predict TFP growth based on credit conditions and factor utilization during the financial crisis. The coefficients with the subscript n (that is, $b_{n,0}$, $b_{n,1}$, and c_n) predict TFP growth during normal times (except for the constant term that is the sum of the coefficients with subscripts f and n—that is, $a_f + a_n$). We omit lags of TFP growth from the list of regressors because they were not statistically significant.

To gauge the robustness of the estimation results, we use the various measures of credit conditions and factor utilization introduced in the previous section. Specifically, for credit conditions, we use the EBP, the TED spread, and the survey-based measure of bank lending conditions. For utilization, we use Fernald's measure of factor utilization and the Federal Reserve Board's measure of capacity utilization. The quarterly series of TFP growth is also obtained from Fernald. We estimate the model using ordinary least squares; regressor endogeneity tests indicate that the exogeneity assumption for ordinary least squares is satisfied, as an instrumental variables estimation yields similar results.[9] Because the financial crisis was a period of high volatility, inference relies on heteroscedasticity and autocorrelation consistent (HAC) standard errors.

The regression analysis indicates that during the financial crisis, the sharp deterioration in credit conditions is associated with a significant slowing of TFP growth; during normal times, there is no significant association. Table 1 summarizes the estimation results.

Table 1
Regression Results for Productivity Growth

Dependent variable: TFP growth						
	(1)	(2)	(3)	(4)	(5)	(6)
Measures (x,u)	(ebp, facutil)	(ebp, caputil)	(ted, facutil)	(ted, caputil)	(sloos, facutil)	(sloos, caputil)
x*df	-5.3872***	-6.8266***	-4.9578***	-4.6824***	-0.1293***	-0.0679**
x(-1)*df	3.3696***	2.8203***	-4.4154***	-4.2118***	0.1167***	0.2609***
x*dn	-1.8757*	-1.7675*	-0.3306	-0.6082	-0.0172	-0.0037
x(-1)*dn	1.5902*	2.1118**	0.2239	0.2966	0.0247	0.0207
u*df	-0.2349***	-1.0622***	-0.3234***	-0.3023**	0.5013*	2.8877***
u*dn	0.4367***	1.0443***	0.2848**	0.7159***	0.2998**	0.8219***
Sample	1973:Q2–2012:Q4	1973:Q2–2012:Q4	1986:Q2–2015:Q4	1986:Q2–2015:Q4	1990:Q3–2015:Q4	1990:Q3–2015:Q4
Observations	159	159	119	119	102	102
R^2	0.2925	0.3268	0.1876	0.2014	0.1784	0.2042
x*df+x(-1)*df	-2.0176***	-4.0062***	-9.3733***	-8.8942***	-0.0126	0.1930*
x*dn+x(-1)*dn	-0.2856	0.3443	-0.1066	-0.3116	0.0075	0.0170

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

Notes: Regressions include constant terms for the financial crisis and normal times (not reported). Inference is based on HAC standard errors.

Columns 1 and 2 show that a rise in the EBP may have a persistent dampening effect on TFP. During both the financial crisis and normal times, a rise in the EBP is associated with an immediate decline in TFP growth; however, some of the decline is offset in the following quarter, as indicated by the positive estimated coefficient on the lagged EBP (denoted *x*(-1)**df* and *x*(-1)**dn* in the table). The cumulative effect of a 1 percentage point rise in the EBP can be gauged by the sum of the estimated coefficients on the current and the lagged credit variable, which is shown in the last two rows. During the financial crisis, the sum is negative and statistically significant, indicating the rise in the EBP during the crisis dampened TFP growth. In contrast, during normal times, the sum is not significantly different from zero, indicating changes in credit conditions did not affect TFP growth outside of the financial crisis.

Columns 3 and 4 show the TED spread has an even stronger negative association with TFP growth. The rising TED spread during the financial crisis is associated with slower TFP growth, both contemporaneously and in the next quarter. These estimation results suggest tightening credit conditions exerted strong downward pressure on productivity growth. Once again, this conclusion holds only for the financial crisis, as the sum of the estimated coefficients on the current and lagged TED spread is not significantly different from zero during normal times.

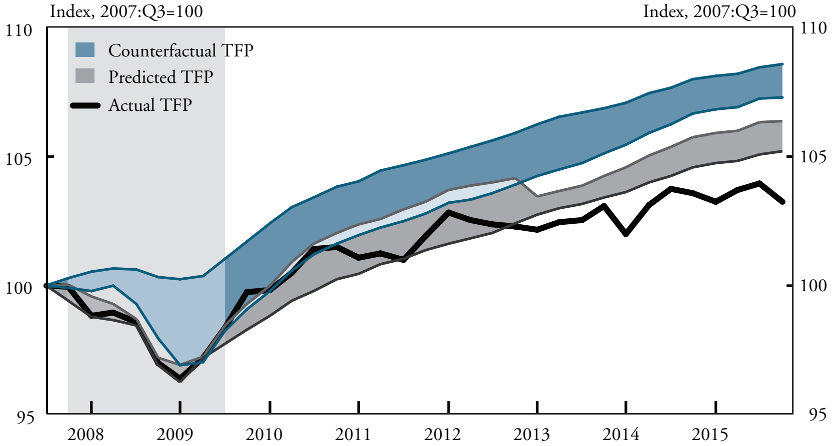
Columns 5 and 6 report the results for the survey-based measure of credit conditions, denoted *sloos*. The estimated coefficients on the current and lagged credit measure largely offset one another, so their sum is barely significantly different from zero if at all. This suggests that tightening conditions for bank loans did *not* restrain TFP growth even during the financial crisis. This finding conflicts with that of the market-based measures; however, it seems reasonable to place less weight on the survey-based measure because of its qualitative characteristics.

The joint results obtained with the three measures of credit conditions support the conclusion that the financial crisis acted as a brake on TFP growth due to the distress in credit markets and the heightened sensitivity of TFP growth to credit conditions. That is, both a large shock and an altered propagation of that shock to the economy likely played crucial roles for the path of productivity. The temporary decline in the growth rate of TFP during the crisis permanently reduced the level of TFP, as TFP growth did not receive a subsequent boost when credit conditions and productivity's sensitivity to those conditions normalized. As a result, TFP remained on a lower trajectory during the economic recovery.

The estimation results for the utilization variables indicate factor or capacity utilization did not dampen TFP growth during the financial crisis as it did during past recessions. The regressions show a positive association during normal times, indicating that a less intense use of available labor and capital lowered productivity in downturns—the usual "labor hoarding" effect of recessions on productivity. During the financial crisis, however, the estimated coefficients on factor utilization and capacity utilization—denoted *facutil* and *caputil*, respectively—turn negative, with the exception of the regressions using the survey-based measure of credit conditions. Taken literally, the negative estimated coefficients suggest that lower utilization boosted TFP growth during the crisis. More realistically, however, the boost to TFP growth

Chart 7

Counterfactual Path of Productivity



Notes: The gray shaded area denotes the range of TFP paths predicted by the regressions in Table 1, and the blue shaded area denotes the counterfactual range of TFP paths predicted by the regressions in Table 1 assuming the estimated coefficients during the financial crisis are the same as the estimated coefficients during normal times. Gray bar denotes NBER-defined recession.
Sources: Fernald and authors' calculations.

from the utilization factor likely resulted from the increase in worker effort during the crisis documented by Lazear, Shaw, and Stanton. In sum, the results suggest TFP growth did not slow because of declining utilization during the crisis.

To assess how TFP would have evolved had the financial crisis not affected it, we perform a counterfactual exercise. Chart 7 shows the historical path of TFP (black line) along with a range of predictions of TFP from the onset of the financial crisis onward (gray shaded region) generated by the six regressions summarized in Table 1. The regressions effectively capture the drop and rebound in TFP through 2012, but they fail to account for the shallower path of TFP since then. The blue shaded band shows the range of counterfactual paths TFP might have followed had its relationship with credit conditions and utilization during the financial crisis remained the same as in normal times. The counterfactual suggests TFP would have declined in the recession due to the observed drop in utilization even though the distress in credit markets would not have had a visible effect. However, as utilization normalized, the effect on TFP would have dissipated, leaving the level of TFP noticeably higher by the end of 2015. This exercise indicates that by cutting firms' access to credit and upending the usual macroeconomic relationships, the financial crisis had a lasting effect on productivity.

III. Channels from Credit Conditions to TFP

As credit conditions likely had an adverse effect on TFP growth during the crisis, a natural question is through which channel—innovation or resource reallocation—this apparent effect was transmitted. We find empirical evidence of an adverse effect of tight credit conditions on R&D, suggesting that the innovation channel contributed to the decline in TFP. The evidence does not point to job reallocation as an important channel.

The innovation channel

The sharp rise in credit risk and tightening in bank lending conditions likely impaired innovation during the financial crisis. Table 2 presents estimation results of regressions of R&D growth on its own first four lags and on credit conditions.[10] As before, the model allows the association of the dependent variable with the measures of credit conditions during the financial crisis to differ from the association during normal times.[11] The regression results in columns 1 through 3 reveal a negative association between credit conditions and R&D growth which is statistically significant for two of the three credit measures—the EBP and bank lending conditions. For those two measures, the estimated relationship becomes more negative during the financial crisis. The shift is statistically significant at the 1 percent level, suggesting fluctuations in credit availability are a less important consideration for R&D in normal times. Therefore, by temporarily dampening R&D growth, the lack of access to credit during the financial crisis may have temporarily restrained TFP growth. Easing credit conditions during the economic recovery provided only a relatively small boost to R&D, leaving the level of R&D persistently lower. Moreover, the estimated coefficients on the lags of R&D growth are significant, reflecting inertia in R&D growth. These results imply that deteriorating credit conditions during the crisis persistently lowered the growth rate of R&D.

Although firms appear to have cut R&D due to a lack of access to credit, they may also have cut R&D spending in response to a perceived lack of demand for their innovations. To address the concern that the

Table 2
Regression Results for R&D Growth

Dependent variable: r&d						
	(1)	(2)	(3)	(4)	(5)	(6)
ebp*df	-1.6343***			-2.9236**		
ebp*dn	-0.5136***			-0.5449**		
ted*df		-0.1548			0.7167	
ted*dn		0.2524			0.0276	
sloos*df			-0.0693***			-0.0737*
sloos*dn			-0.0094**			-0.0126**
spf*df				-1.4944	1.9478***	-0.1543
spf*dn				0.0899	-0.4187*	-0.5120**
r&d(-1)	0.3302**	0.2881***	0.2342**	0.3447***	0.2718***	0.1962*
r&d(-2)	0.1876**	0.2593***	0.2629***	0.1754**	0.2037***	0.2479***
r&d(-3)	-0.2742***	-0.3402***	-0.2925***	-0.2644***	-0.3377***	-0.3239***
r&d(-4)	0.2741***	0.1966**	0.2322**	0.2956***	0.2642***	0.2038**
Sample	1974:Q1–2012:Q4	1986:Q1–2015:Q4	1990:Q2–2015:Q4	1974:Q4–2012:Q4	1986:Q1–2015:Q4	1990:Q2–2015:Q4
Observations	156	120	103	153	120	103
R^2	0.3567	0.2439	0.3387	0.3672	0.3187	0.3705

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

Notes: Regressions include constant terms for the financial crisis and normal times (not reported). Inference is based on HAC standard errors.

regressions may pick up voluntary declines in R&D due to weak anticipated demand for new and better products, columns 4 through 6 add the median one-year-ahead forecast of real GDP growth from the Survey of Professional Forecasters, denoted *spf*, as an explanatory variable. The estimation results show no clear relationship between such forecasts and R&D spending. More importantly, the relationship between the measures of credit conditions and R&D spending remains qualitatively unchanged.[12]

The cuts in R&D during the financial crisis by credit-starved firms may have affected TFP fairly quickly. While it can take years for basic research to be commercialized and even longer for the benefits of new technologies to spill over to the wider economy, a significant part of R&D pertains to product development. Development spending accounted for an average of 71 percent of private R&D spending from 1953 to 2001, while applied research accounted for another 23 percent

(Congressional Budget Office). Spending on basic research averaged just 5 percent of total private R&D spending over this period. Product and process developments can raise productivity in a short time, since such developments are typically well beyond the idea stage and close to market-ready. Moreover, R&D investment is likely correlated with other intangible investments absorbed in TFP, such that cutbacks in R&D investment could be closely associated with declines in productivity. Corrado and Hulten review the research on intangible investment and conclude that the innovation that powers economic growth does not result from R&D alone but is rather linked to "a complex process of investments in technological expertise, product design, market development, and organizational capability." They estimate these investments account for a significant share of productivity-enhancing, intangible capital accumulation. A tightening of credit conditions may therefore interfere with the entire product development process as tight credit squeezes investment spending broadly defined.

The reallocation channel

If the distress in credit markets and the tightening of bank lending conditions caused resource reallocation to drop during the financial crisis, this factor, too, could have restrained TFP growth temporarily. Indeed, empirical studies such as Foster, Haltiwanger, and Krizan show that such reallocation is closely linked to productivity growth. Did the adverse effects of tight credit conditions on job creation outweigh the positive effects on job destruction, or were the two effects largely offsetting? To answer this question, we consider four measures of resource reallocation in the private sector: the rates of gross job gains and losses and the rates of establishment births and deaths.

The regression results in Table 3 suggest tight credit conditions were associated with lower gross job gains during the financial crisis. The estimated coefficients are significantly different from zero except for the TED spread during the financial crisis. Thus, by reducing job creation, the lack of access to credit may have dampened TFP growth during the crisis. The remaining regression coefficients for credit conditions during normal times and for lagged job gains imply that the rate of gross job gains was pulled in opposite directions after the crisis. On the one hand, the estimated coefficients on credit conditions during normal

Table 3
Regression Results for the Rate of Gross Job Gains

Dependent variable: jobgains			
	(1)	(2)	(3)
ebp*df	-0.2719***		
ebp*dn	-0.1494***		
ted*df		-0.0801	
ted*dn		-0.2661*	
sloos*df			-0.0088***
sloos*dn			-0.0041***
jobgains(-1)	0.2890***	0.3209***	0.2521***
jobgains(-2)	0.3249***	0.3784***	0.3051***
jobgains(-3)	-0.1218	-0.1367	-0.1313
jobgains(-4)	0.4547***	0.4444***	0.5447***
Sample	1993:Q3–2012:Q4	1993:Q3–2015:Q2	1993:Q3–2015:Q2
Observations	78	88	88
R^2	0.9353	0.9324	0.9401

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

Notes: Regressions include constant terms for the financial crisis and normal times (not reported). Inference is based on HAC standard errors.

times (that is, *ebp*dn*, *ted*dn*, and *sloos*dn*) are significant, indicating the normalization of credit conditions after the crisis had a positive effect on job creation. On the other hand, the estimated coefficients for past job gains are also significant, suggesting the adverse effects of the financial crisis persisted even in the recovery. That gross job gains failed to rebound to pre-recession levels suggests the persistent effects of the financial crisis dominated in its aftermath. Consistently, regressions of the rate of establishment births on its own lags and on credit conditions in and outside the financial crisis yielded similar results (not shown), except that the estimated coefficients on credit conditions during normal times were not significantly different from zero. Thus, the reduced reallocation may have had a persistent adverse effect on the level of TFP.

Job reallocation can be due to the destruction of obsolete jobs as well as the creation of new ones. Table 4 presents regressions of the rate of gross job losses on its own lags and on credit conditions. Each of the credit measures has a positive, statistically significant association with the rate of gross job losses during the financial crisis, indicating the tight

Table 4
Regression Results for the Rate of Gross Job Losses

Dependent variable: joblosses			
	(1)	(2)	(3)
ebp*df	0.2538***		
ebp*dn	0.0579		
ted*df		0.3833***	
ted*dn		0.2565**	
sloos*df			0.0132***
sloos*dn			0.0005
joblosses(-1)	0.8477***	0.8643***	0.8503***
joblosses(-2)	0.0366	0.0127	0.0383
joblosses(-3)	-0.0836	-0.0697	-0.0772
joblosses(-4)	0.1501	0.1377	0.1514
Sample	1993:Q3–2012:Q4	1993:Q3–2015:Q2	1993:Q3–2015:Q2
Observations	78	88	88
R^2	0.8675	0.9129	0.9118

*** Significant at the 1 percent level
** Significant at the 5 percent level
* Significant at the 10 percent level
Notes: Regressions include constant terms for the financial crisis and normal times (not reported). Inference is based on HAC standard errors.

credit conditions contributed to the surge in job losses during the recession. While job losses characterize a major cost of recessions for workers, research on productivity associates higher reallocation with higher productivity growth. When the least productive jobs are destroyed, the economy becomes more productive, and workers are freed up to ultimately move into more productive jobs. Thus, by encouraging the destruction of unproductive jobs, the tight credit supply may have boosted TFP growth during the financial crisis.[13] Moreover, the estimated coefficients on lagged job losses suggest the effect of the crisis on job losses may have lingered in the crisis's aftermath. However, the regression on the TED spread also yields a significant coefficient during normal times, suggesting the normalization of credit conditions may have contributed to the decline in job losses after the crisis by allowing less productive jobs to once again survive. Regressions of the rate of establishment deaths on its own lags and on credit conditions during the financial crisis and during normal times yielded similar results (not shown).

Table 5
Regression Results for the Rate of Job Reallocation

Dependent variable: jobrlc

	(1)	(2)	(3)
ebp*df	0.1523**		
ebp*dn	-0.1326		
ted*df		0.2283***	
ted*dn		0.0796	
sloos*df			0.0081***
sloos*dn			-0.0034
jobrlc(-1)	0.3745***	0.3924***	0.3599***
jobrlc(-2)	0.2570***	0.2803***	0.2807***
jobrlc(-3)	-0.1224	-0.1843*	-0.1435
jobrlc(-4)	0.5427***	0.5212***	0.5389***
Sample	1993:Q3–2012:Q4	1993:Q3–2015:Q2	1993:Q3–2015:Q2
Observations	78	88	88
R^2	0.9602	0.9663	0.9683

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

Notes: Regressions include constant terms for the financial crisis and normal times (not reported). Inference is based on HAC standard errors.

As tightening credit conditions pulled job gains and job losses in opposite directions, the net effect of credit conditions on job reallocation was likely small during the financial crisis. Table 5 presents estimation results for the rate of job reallocation. The estimated coefficient on credit conditions is positive and significant during the financial crisis, suggesting tightening credit availability raised job reallocation. In other words, the positive effect of the credit squeeze on the rate of gross job losses may have outweighed its negative effect on the rate of gross job gains; however, the net effect is likely small, since the rate of job reallocation only ticked up slightly during the crisis. Moreover, the estimation result is not robust using the rate of establishment reallocation, which yields a significant estimated coefficient on only one of the three measures of credit conditions. Taken together, the evidence suggests the financial crisis had largely offsetting effects on resource reallocation; reduced innovation thus seems a more likely explanation for the link between credit conditions and TFP growth.

IV. Conclusion

A decline in TFP contributed to a persistent drop in output during the financial crisis and recession of 2007–09. To unpack the sources of these declines, this article investigates the effects of the distress in credit markets and the tightening of bank lending conditions on total factor productivity during the financial crisis and recession. The analysis suggests productivity declined persistently as a result of the crisis. We find empirical evidence suggesting a lack of access to credit likely curtailed R&D, one channel through which financial stress can affect productivity. However, we find little empirical evidence of a reduction in resource reallocation, another channel through which credit conditions can affect productivity.

Our analysis does not explain the slow pace of productivity growth since the crisis, which has been a source of great concern among economists and policymakers. From 2010 to 2014, TFP growth averaged just 0.6 percent per year, well below its average growth rate of 1 percent from 1970 to 2010. If the slowdown persists, it may affect future standards of living. However, while the financial crisis seems to have persistently reduced the level of TFP, we have not found persistent effects on the growth rate of TFP.

Endnotes

[1]A few of these studies examine the role of labor and capital inputs for the persistent decline in output (Blanchard, Cerutti, and Summers; Hall; Reifschneider, Wascher, and Wilcox).

[2]Eichengreen, Park, and Shin find that a higher TED spread is associated with the incidence of TFP slumps prior to the global financial crisis in a sample of advanced economies.

[3] The start date and end date of the financial crisis are assumed to coincide with the peak and trough of the recession, as determined by the National Bureau of Economic Research, to facilitate comparisons with previous business cycles. The onset of the financial crisis is often traced back a quarter earlier, to August 2007, when the French bank BNP Paribas suspended redemptions from three of its investment funds (see, for example, Bernanke).

[4]Davig and Hakkio perform an empirical analysis of the relationship between financial stress and broad economic activity and find that financial stress has a stronger effect on economic activity when the economy is in a distressed state.

[5]Bils, Chang, and Kim provide a rigorous framework in which paid work and unobserved effort do not move in tandem. Their search and matching model predicts a decline in employment and a rise in worker effort in recessions when wages are slow to adjust.

[6] The rates of gross job gains and losses have been trending down since well before the last recession, as noted by others (see, for example, Davis and Haltiwanger). Clearly, this secular decline is unrelated to the financial crisis.

[7]More broadly, Ng and Wright survey business cycle facts, emphasizing the last recession, and document how recessions with financial market origins are distinct from those in which financial markets play a passive role.

[8]Distinguishing between expansions and recessions prior to the last one did not affect the qualitative results regarding the association of TFP growth with credit conditions and factor utilization during the financial crisis.

[9]We perform a Durbin-Wu-Hausman test for regressor endogeneity to address the concern that ordinary least squares may yield inconsistent estimates if some of the right-hand-side variables are endogenous. Specifically, the test uses two-stage least squares with the first eight lags of the 10-year Treasury yield as instruments. The null hypothesis that x and u are exogenous cannot be rejected for any of the combinations of measures of x and u (we obtain similar results using the first four lags of x and u as instruments instead). Because estimation by ordinary least squares yields more efficient estimators than instrumental variables estimation, we adopt the former method.

[10]R&D growth is measured by the quarterly growth rate of real private fixed investment in research and development (NIPA Table 5.3.3). Using the growth rate of total real research and development (NIPA Table 1.2.3) as an alternative

measure of R&D yields qualitatively similar regression results, though the drop in the growth rate from a year earlier during the recession is less dramatic.

[11]We estimate the models in Tables 2–5 using ordinary least squares. The regressor endogeneity test using lags of the 10-year Treasury yield as instruments cannot reject the null hypothesis of exogeneity of the measures of credit conditions for any of the regressions.

[12] In the same spirit, we also add four lags of GDP growth in the regressions reported in Tables 2–5 to account for aggregate demand effects on the variable of interest. This addition has only a minor effect on the magnitude and significance of the estimated coefficients on credit conditions.

[13]Petrosky-Nadeau highlights a related effect of credit conditions on resource reallocation: as reduced access to credit has a more adverse influence on less productive firms, the financial crisis may have raised aggregate productivity by shifting the mix of firms toward more productive ones.

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Data Breach Notification Laws

By Richard J. Sullivan and Jesse Leigh Maniff

Data breaches, which expose sensitive data often used for payment fraud and identity theft, have recently worsened in the United States. Exposed records provide essential data for identity thieves, who in 2014 victimized 17.6 million people in the United States (Harrell). As a consequence, policymakers are placing greater emphasis on procedures to protect consumers from harm.

Breach notification laws are one such approach. Forty-seven state laws and some sector-specific federal laws already require organizations suffering a breach to disclose the incident and notify consumers if their data were exposed. In theory, breach notification laws serve two purposes important to public policy. First, they provide an incentive for organizations to protect sensitive data, as publicly disclosed security failures may harm their reputation and trigger costly remediation activities. Second, they inform individuals whose records were exposed, allowing them to react quickly to mitigate potential damages.

Research has shown that identity theft declines after a state adopts a data breach notification law (Romanosky and others). Research is less conclusive regarding how specific provisions in these laws might affect identity theft. In this article, we study recent identity theft complaints to investigate how provisions of state data breach notification laws affect identity theft. We find five provisions in notification laws associated with less identity theft. We also find three provisions associated

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with more identity theft. These results may help guide public policy concerning breach notifications to protect the public after a breach and encourage organizations to improve data security.

Section I discusses organizations' legal duty to protect data and reviews prior research on whether notification laws incentivize organizations to protect data and inform customers in the event of a breach. Section II describes the various provisions in states' data breach notification laws. Section III presents a statistical analysis of the effect of 10 breach notification law provisions on identity theft.

I. The Case for Data Breach Notification Laws

An increase in the number of data breaches in the United States has led to public concern about protection against identity theft. In 2014, 1,343 breaches in the United States exposed more than 512 million records (Risk Based Security 2015). Policymakers have responded by enacting state and federal laws that require organizations to notify customers whose data are exposed in a security breach to allow them to take actions to reduce the potential harm from exposed data.

Although a few large, well-publicized breaches have drawn attention to data security recently, publicly disclosed data breaches have been increasing in the United States since 2009.[1] More than 600 breaches occurred in 2009, 1,054 in 2013, and 1,343 in 2014 (Risk Based Security 2015, 2014a; Sullivan 2012). The number of records exposed has also increased in recent years, largely due to a rise in the number of megabreaches—breaches exposing more than 10 million records (Sullivan 2014). As personally identifiable information is the most common type of information exposed during breaches, the increase in breaches is likely to result in greater instances of identity theft.

Over the past few years, the types of fraud committed using victims' information have evolved, particularly in the financial services sector. According to the Federal Trade Commission, the share of identity theft due to bank fraud and credit card fraud has steadily increased (Consumer Sentinel Network). The share of identity theft due to credit card fraud increased from 13.6 percent in 2012 to 16.9 percent in 2013 to 17.4 percent in 2014. Similarly, the share of identity theft due to

Table 1
States with Data Breach Notification Laws, 2003–14

Year	Number	Year	Number
2003	1	2009	45
2004	1	2010	45
2005	10	2011	46
2006	25	2012	46
2007	38	2013	46
2008	41	2014	47

Notes: Year is determined by the time the law took effect.
Sources: Perkins Coie and authors' calculations.

bank fraud rose from 6.4 percent in 2012 to 7.7 percent in 2013 to 8.2 percent in 2014.

Legal duty to protect data and notify consumers

In 2002, concerns over consumer privacy and data security on the Internet led lawmakers in California to enact a law requiring breached organizations to inform consumers whose personal data were exposed. Since California's law took effect in 2003, an additional 46 states have enacted data breach notification laws (Table 1).

An organization's legal duty to secure personal information can arise from tort law or legislation (Johnson). In tort law, an organization may have a duty to protect its customers if the organization increases the foreseeable risk of harm from third-party criminals (Bishop). If customers cannot prove this duty exists, they will be unable to satisfy a negligence claim against a breached organization. Even if customers prove this duty exists, they must then prove that the organization breached its duty, that the breach caused the harm, and that damages ensued. In previous cases, customers have had difficulty proving how they were harmed by the breach (Tabuchi).

To fill the gap, many state legislatures have enacted statutes affirming organizations' legal duty to secure personal information and codifying potential consequences of their failure to do so.[2] The most common way states have created this legal duty is by enacting data breach notification laws that require organizations to notify customers if a breach occurs. These laws have their foundation in environmental law's "community right to know" (CRTK) provisions (Winn).[3]

The CRTK model, when applied to security breaches, would alert consumers when a breach occurs and allow them to take the necessary steps to protect themselves against identity theft. The model would also encourage organizations to improve their security and prepare for potential breaches.[4] Critics of CRTK laws, however, claim incentives are misaligned—for example, organizations may be reluctant to disclose information that could ultimately be used against them. Furthermore, organizations with weak security features may not be able to detect that a breach has even occurred. Still, 47 states currently have breach notification laws in place.

Research on data breach notification laws

Research on breach notification laws is at an early stage but has nevertheless shed some light on the mechanisms and effects of disclosure. For example, some research has shown that notification laws can reduce the rate of identity theft, but oversight might be needed to encourage compliance. What information organizations disclose to consumers after a breach may also be important to consumer protection.

Empirical evidence suggests data breach notification laws reduce identity theft. Romanosky and others investigate the relationship between notification laws and the rate of identity theft in the United States from 2002 to 2009. Consistent with the mechanism of a CRTK law, they hypothesize that after a law is passed, more consumers will be notified of breaches and in turn will take steps to protect themselves. The authors find that adopting a notification law reduced identity theft during the period of study by an estimated average of 6.1 percent, resulting in a mean reduction in the cost of identity theft of $93 million.

However, certain aspects of notification laws can strongly influence their effectiveness. Organizations that suffer a breach have some incentive *not* to notify customers to avoid the costs and consequences of disclosure. Stefan and Böhme investigate this incentive in a theoretical model and show that including a periodic audit requirement for security systems can greatly enhance the effectiveness of notification laws.

The language used to notify consumers can also influence these laws' effectiveness. Breach notification laws provide organizations some latitude in how they inform customers about a breach, which can lead to suboptimal outcomes for affected consumers. Bisogni studies a sample of notification letters sent in 2014 to consumers whose data were exposed and finds that while these letters comply with notification laws, some organizations sending them understated the seriousness of the breach to reduce their reputational damage.

Furthermore, a notification law's efficacy can depend on how quickly it requires organizations to act in the event of a breach. In the organizations Bisogni studies, consumers were at risk for a considerable time prior to notification: the average time between an organization discovering a breach and notifying consumers was 35 days. More troubling, the average time between when a breach actually occurred and notification was 117 days. In other words, organizations are often unaware of the breach for an extended period in which potential harm could occur.

II. Provisions in State Data Breach Notification Laws

While research has shown that the presence of a data breach notification law reduces identity theft, few studies have examined the effects of variations in these laws on reported rates of identity theft.[5] To examine these differences, we review state notification laws from 2006 to 2014 to determine if a state's law includes one or more of 10 provisions. We begin our review in 2006 because it is the first year for which consistent state-level data on identity theft are available. The provisions are as follows:

State Enforcement provisions allow the attorney general or another designated state entity to enforce organizations' failure to comply with the statute.

Risk of Harm provisions require a breached organization to notify customers only if the organization determines that the breach constitutes a reasonable likelihood of harm to the customer.

Baseline Encryption Exemption provisions exempt an organization from notifying consumers if the data stolen in the breach were redacted or encrypted.[6]

Notification Policy Exemption provisions allow an organization that maintains its own notification procedures to be deemed in compliance with the state notification law so long as the organization does, in fact, disclose breaches.

Notify AG/Credit Agencies provisions require organizations to notify one or more parties, such as the attorney general or a credit reporting agency, when a breach occurs.

Cap on Civil Penalty provisions limit the financial civil penalty imposed on organizations found in violation of the statute.

Doing Business in State provisions specify that the notification law only covers organizations that conduct business in the state. In states without this provision, organizations that do not conduct business in the state are still required to notify if a customer whose personal information is breached is a resident of the state.

Expanded Definition of Personal Information provisions indicate whether the notification law covers more information than meets the standard definition of personal information (PI). States typically define PI as a first name or initial in combination with a last name and a Social Security number, driver's license number, state ID card number, or financial account number. An expanded definition of PI includes other personal data, most often health and medical information.

Private Right of Action provisions allow customers whose data were exposed to sue organizations for failure to comply with the data breach notification statute.

Explicit Time Limit to Notify provisions specify that organizations must notify affected customers within a given number of days (usually 30 or 45). Notification laws without a specific time limit require notification as quickly as possible and without unreasonable delay.

Notification laws are present in 84.7 percent of our sample observations, but the prevalance of provisions within the laws varies across state and time (Table 2). The most common provision is State Enforcement, which is present in 76.2 percent of the 450 state and year observations in our data. Other common provisions are Risk of Harm (65.3 percent), Baseline Encryption Exemption (57.8 percent), and Notification Policy Exemption (57.3 percent); the least common provisions are Explicit Time Limit to Notify (6.8 percent), Private Right of Action (23.1 percent), Expanded Definition of PI (36.2 percent), and Doing Business in State (50 percent).

Table 2
Implementation of Data Breach Notification Laws Across States

Provision	Share of observations with the provision (percent)
State Enforcement	76.2
Risk of Harm	65.3
Baseline Encryption Exemption	57.8
Notification Policy Exemption	57.3
Notify AG/Credit Agencies	55.8
Cap on Civil Penalty	55.1
Doing Business in State	50.0
Expanded Definition of PI	36.2
Private Right of Action	23.1
Explicit Time Limit to Notify	6.7

Note: The sample contains 450 state and year observations.
Sources: Steptoe & Johnson, Schar and Gibbins, and authors' tabulation.

The share of states with the various provisions varies by year. One reason for this variation is that 22 states implemented notification laws during our sample period. A second reason is that four states amended existing notification laws during this period and added provisions we examine in this study. For our purposes, the variation is valuable in the statistical analysis we conduct.

III. Examining the Effects of Notification Law Provisions on Identity Theft

The CRTK effect of data breach notification laws enables victims to take actions to protect against identity theft. But provisions within notification laws may vary in how quickly and effectively they provide this opportunity. To examine whether certain provisions are more or less effective in reducing identity theft, we first rank individual states by their records on identity theft over the 2006–14 period. We then compare these rankings with the use of specific provisions in the notification laws of each state.

State records on identity theft

Ranking states' records on identity theft presents two challenges. First, more populous states will inherently have more identity theft than

Table 3
Sample Summary Statistics: Notification Law Provisions

	State identity theft per million persons				Deviation from the state average rate		
Record	Number of states	Average, 2006–09	Average, 2011–14	Change, 2011–14 minus 2006–09	Average, 2006–09 (percent)	Average, 2011–14 (percent)	Change, 2011–14 minus 2006–09 (percent)
Better	16	867	774	-93.4	23.8	3.8	-20.0
Mixed	19	592	628	35.2	-15.6	-16.0	-0.5
Worse	15	662	873	210.8	-5.7	16.2	22.0
All states	50	701	748	46.7			

Sources: Steptoe & Johnson, Schar and Gibbins, and authors' calculations.

smaller states, making direct comparisons unfair. To adjust for this difference, we consider identity theft per million persons. Second, forces may contribute to a rise or fall in identity theft that affects multiple states. Perpetrators of data breaches look for vulnerable databases in any location, but the data they obtain may be from customers in multiple states. Consequently, a rise in breaches nationwide can lead to a rise in identity theft in any of the states. To adjust for national fluctuations, we compute the difference of a particular state's identity theft per million persons from the average of identity theft per million persons for all states.

We evaluate the performance of states in deterring identity theft by first calculating the identity theft complaints per million persons for each of two periods: 2006–09 and 2011–2014.[7] States perform better if there is a reduction in identity theft over the two periods. Identity theft nationwide averaged 701 incidents per million persons in 2006–09 and 748 incidents per million persons in 2011–14 (Table 3).

We then calculate the annual percent deviation of identity theft per million persons for each state from the average rate nationwide. We then average the annual deviations over the 2006–09 and 2011–14 periods. The change in the percent deviation of identity theft per million persons is our basic measure of each state's record on identity theft. If the change is negative, then the state's identity theft per million persons has fallen relative to the national average, indicating a better record on identity theft. If the change is positive, then the state's identity theft per million persons has risen relative to the national average, indicating a worse record on identity theft.

We then sort states by the change in the difference of identity theft complaints per million persons relative to the national average and split them into three groups. States with a notable improvement over the 2006–09 and 2011–14 periods are labeled "Better," states with a notable decline are labeled "Worse," and states with little change from one period to the next are labeled "Mixed."[8] Details on how we group states and assess provisions' effects on identity theft are available in the Appendix.

While the overall rate of identity theft per million persons rose from 2006–09 to 2011–14, individual state records of identity theft varied considerably. In the Better group, 16 states had an average decline of 93.4 identity theft complaints per million persons from the 2006–09 period to the 2011–14 period (Table 3). By contrast, 19 states in the Mixed group had an average increase of 35.2 identity theft complaints per million persons over the same period. In the Worse group, the increase was much more dramatic: 15 states saw an average increase of 210.8 identity theft complaints per million persons. Relative to the national average rate, the change in identity theft per million persons was -20 percent for the Better group, -0.5 percent for the Mixed group, and 22 percent for the Worse group.

Provisions in data breach notification laws and the record of state identity theft

To assess how provisions in state data breach notification laws might affect identity theft, we examine the prevalence of various provisions in the Better, Mixed, and Worse groups of states. We consider a provision to be associated with less identity theft if it is common in the Better states, uncommon in the Worse states, and neither common nor uncommon in Mixed states. For example, in the 2006–09 period, 81.3 percent of states in the Better group had the State Enforcement provision compared with 67.1 percent of states in the Mixed group and 51.7 percent of states in the Worse group, suggesting the State Enforcement provision is associated with lower identity theft (Table 4).

Conversely, we consider a provision to be associated with increased identity theft if it is uncommon in Better states, common in Worse states, and neither common nor uncommon in Mixed states. For example, in the 2006-09 period, 43.8 percent of states in the Better group

Table 4

Identity Theft and Provisions in U.S. Notification Laws, 2006–14

Panel A: 2006–09

Identity theft record	Percent of states with provision									
	State Enforcement	Risk of Harm	Baseline Encryption Exemption	Notification Policy Exemption	Notify AG/Credit Agencies	Cap on Civil Penalty	Doing Business in State	Expanded Definition of PI	Private Right of Action	Explicit Time Limit to Notify
Better	81.3	43.8	40.6	59.4	57.8	68.8	43.8	37.5	26.6	0.0
Mixed	67.1	67.1	63.2	59.2	46.1	48.7	59.2	26.3	22.4	5.3
Worse	51.7	58.3	51.7	33.3	33.3	21.7	28.3	28.3	8.3	13.3
P-value	0.002**	0.020**	0.029**	0.003**	0.024**	0.000**	0.002**	0.326	0.027**	0.007**

Panel B: 2011–14

Identity theft record	Percent of states with provision									
	State Enforcement	Risk of Harm	Baseline Encryption Exemption	Notification Policy Exemption	Notify AG/Credit Agencies	Cap on Civil Penalty	Doing Business in State	Expanded Definition of PI	Private Right of Action	Explicit Time Limit to Notify
Better	93.8	50.0	43.8	68.8	68.8	81.3	50.0	50.0	31.3	0.0
Mixed	78.9	78.9	68.4	63.2	67.1	57.9	63.2	34.2	31.6	5.3
Worse	80.0	86.7	73.3	53.3	53.3	46.7	46.7	40.0	13.3	18.3
P-value	0.044**	0.000**	0.001**	0.194	0.129	0.000**	0.094*	0.182	0.026**	0.000**

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

Notes: The Better, Mixed, and Worse groups include 16, 19, and 15 states, respectively. We study four years in each period, which yields 64, 76, and 60 observations for the performance groups. The p-values are for chi-square statistics that test whether the percentage of states with the breach law notification provisions are different from one another across the Better, Mixed, and Worse groups. Asterisks indicate the significance level at which a null hypothesis of equal adoption of the provisions across performance groups is rejected.

Table 5
Associations between Notification Law Provisions and State Identity Theft

Provisions associated with lower identity theft	Strength of evidence
State Enforcement	Medium
Notify AG/Credit Agencies	Medium
Cap on Civil Penalty	High
Private Right of Action	Medium
Notification Policy Exemption	Low
Provisions associated with higher identity theft	**Strength of evidence**
Risk of Harm	Medium
Baseline Encryption Exemption	Low
Explicit Time Limit to Notify	High

Notes: The Doing Business in State and Expanded Definition of PI provisions have mixed or no association with identity theft. The strength of evidence designation is based on a statistical test of whether records of identity theft across the Better, Mixed, and Worse groups of states are equal; the pattern of use of a provision across the groups; and the extent to which the pattern is consistent across time periods.

had the Risk of Harm provision compared with 67.1 percent of states in the Mixed group and 58.3 percent of states in the Worse group, suggesting the Risk of Harm provision may be associated with higher identity theft.

The statistical analysis does not always point to a clear association between variables. Accordingly, we also assess the strength of evidence for a particular relationship. The evidence for an association is stronger if the pattern of use across the states is clear, rising or falling across all three groups. The evidence is also stronger if the pattern is consistent over both the 2006–09 and 2011–14 periods. Finally, we conduct a statistical test for whether provisions are equally prevalent across the three groups of states. If a provision is equally common in the Better, Mixed, and Worse groups of states, the provision is unlikely to have a strong association with identity theft.[9]

We apply this method to the results from Table 4 and find five provisions associated with lower identity theft (Table 5). Two of these, State Enforcement and Notify AG/Credit Agencies, signify formal involvement of state government in enforcing or managing responses to data breaches. These provisions may signal the commitment of state resources to fighting identity theft, which may, in turn, encourage organizations to comply with notification requirements when they suffer a data breach.

Two other provisions associated with lower identity theft, Cap on Civil Penalty and Private Right of Action, manage the options that victims of data breaches have when their personal information is exposed. Both provisions may also encourage organizations to comply with notification requirements and thus reduce identity theft. A cap on civil penalties may provide greater certainty to organizations regarding the costs and consequences of disclosing a data breach. A private right of action, on the other hand, allows victims to pursue recourse when their data are exposed, an option that an organization can preclude by disclosing a breach.

Finally, the Notification Policy Exemption is also associated with lower identity theft. To secure an exemption, organizations must have data security policies that may be part of a comprehensive security strategy. To the extent the provision signals how seriously an organization attempts to protect electronic data, it may both reduce a state's actual data breaches and enable breach victims to protect themselves against identity theft.

We find three provisions associated with higher identity theft. Two of these provisions, Risk of Harm and Baseline Encryption Exemption, may make it easier for organizations to legally avoid disclosing a data breach. If an organization misinterprets the risk of harm from a breach and chooses not to notify victims, then preventable identity theft may occur. Likewise, if an organization with a weak encryption system does not notify victims, then the breach's perpetrators may be able to decrypt the stolen data and consequently steal identities.

A third provision, Explicit Time Limit to Notify, is also associated with higher identity theft. While this provision requires timely notifications, the short timeframe may result in organizations deciding to notify consumers when they would not have otherwise. Without this provision, a business may have more time to weigh the costs and benefits of disclosure, and, in some cases, decide not to disclose. Thus, Explicit Time Limit to Notify may lead to consumers being oversaturated with notifications, some of which are not necessary, and subsequently choosing to ignore them after a certain point.[10]

IV. Summary and Conclusion

In this article, we present evidence of data breach notification laws' "right to know" effect through which increased disclosure of breaches is associated with reduced identity theft. We find states with provisions that signal active state enforcement have lower rates of identity theft. Likewise, states with provisions that provide incentives to organizations to comply with notification requirements have lower identity theft. Finally, states with a provision that exempts organizations from notification laws if they have internal policies to notify customers also have lower identity theft.

Some provisions are associated with higher identity theft. In some cases, these provisions give an organization control regarding notification, such as exempting the organization from notification if it determines there is little potential harm to an exposed consumer or if it adopts a relatively weak method of encrypting sensitive data. In both cases, the provision may block the "right to know" mechanism after serious breaches and thus lead to greater identity theft.

Although policymakers are rightly concerned about data theft, fraudulent use of the data is the real danger. Thieves can use payment data to replicate credit cards and make fraudulent purchases, and they can use medical insurance data to perpetrate fraud for medical services. They can use nonpayment data to receive tax refunds and open new accounts to draw on lines of credit. Further progress is needed to ward off fraud, particularly as attacks shift to industries with weaker security practices.

Appendix

Methodology

The method we use to rank how states perform in deterring identity theft accounts for both the size of each state and the nationwide average of identity theft.

The ranking is based on the record of identity theft in each state for the 2011–14 period compared with the 2006–09 period. We exclude 2010 for two reasons. First, it allows us to compare periods with the same number of years. Second, starting the later period in 2011 provides a one-year lag that allows the laws of the four states that adopted notification laws in 2009 to have a more observable effect on identity theft as state enforcement is established and news of notification requirements spreads among eligible organizations.

Including 2010 in either the first or the second period does not change our results. None of the patterns of provision prevalence across the groups of states is affected. In one case (Doing Business in State), the p-value falls to 0.04, a smaller value than the 0.094 reported in Table 4. However, the prevalence pattern for Doing Business in State is not consistent with either a worse or better record on identity theft, and thus we would not include the provision in Table 5 even with a lower p-value.

The states of Oklahoma, Kansas, and Missouri provide examples of states classified, respectively, as Better, Mixed, and Worse performers. The three states' records of identity theft per million persons are similar in the 2006–09 period, ranging from 648 to 681. In the 2011–14 period, identity theft per million persons declined to 630 in Oklahoma, a change of -51.1; rose to 663 in Kansas, a change of 15.1; and rose to 829 in Missouri, a change of 154.8 (Table A-1). Thus, identity theft declined in Oklahoma, increased somewhat in Kansas, and increased more dramatically in Missouri.

To adjust for national trends, we subtract each state's annual identity theft per million persons from the 50 state average, then divide that number by the 50 state average and multiply it by 100. The result is the annual percent difference of the state's identity theft per million persons from the national average. The annual percent differences are then averaged over 2006–09 and 2011–14.

Table A-1
State Records of Identity Theft

State	Identity theft per million persons		
	2006–09	2011–14	Change, 2006–09 to 2011–14
Oklahoma	681	630	-51.1
Kansas	648	663	15.1
Missouri	674	829	154.8

Table A-2
State Versus Nationwide Identity Theft

State	Difference from national average		
	2006–09 (percent)	2011–14 (percent)	Change, 2006–09 to 2011–14 (percent)
Oklahoma	-2.7	-15.6	-12.9
Kansas	-7.5	-10.7	-3.2
Missouri	-3.6	10.9	14.6

In Oklahoma, identity theft per million persons averaged 2.7 percent less than the national average in 2006–09, and 15.6 percent less than the national average for 2011–14, a net change of -12.9 percent (Table A-2). In Kansas, identity theft per million persons was below the national average in both 2006–09 and 2011–14, at -7.5 percent and -10.7 percent, respectively, for a net change of -3.2 percent. Missouri's identity theft per million persons was below the states' average by 3.6 percent for 2006–09, but above the states' average by 10.9 percent for 2011–14, a net gain of 14.6 percent.

To determine the cutoff point for the Better, Mixed, and Worse performance levels, we estimate trend lines for each state's identity theft per million persons as a percentage of the states' average.[11] The model is

$$y_{it} = \alpha + \beta \, year_{it} + \varepsilon_{it},$$

where y_{it} is identity theft per million persons as a percent of the states' average, and β is the trend coefficient. The trend coefficients in the estimated equations are significantly different from zero for half of the states (both positive and negative). The cutoff point for the Better performing states is determined by the state with a significant and negative trend coefficient and the smallest percent reduction of identity theft per million persons. The cutoff point for the Worse performing states is determined by the state with a significant and positive trend coefficient and the smallest percent increase of identity theft per million persons. State performance groups are as follows:

Better: AZ, CA, CO, HI, IL, IN, MN, MA, NC, OK, NM, NV, NY, TX, UT, VA

Mixed: AK, CT, NE, ID, KS, KY, LA, MD, ME, MT, ND, NH, NJ, OH, OR, PA, RI, SD, TN

Worse: AR, AL, DE, FL, GA, IA, SC, MI, MO, MS, WA, WI, WV, WY

To assess the strength of evidence for relationships between certain provisions in state notification laws and state performance with identity theft, we use three criteria. First, we use statistical analysis to test a hypothesis that a provision is equally common across all three groups of states. The test generates a probability value (p-value) that, if sufficiently small (0.05 or less), rejects the hypothesis. If the test rejects the hypothesis, then we have more confidence that differences in the effect of notification law provisions in states are unlikely to be a result of random sample variation.

The other two criteria consider a provision's pattern of use across the groups of states and whether the pattern is similar across the 2006–09 and 2011–14 periods. If a provision is more common in states in the Better group, then the provision may be effective at deterring identity theft. Conversely, if a provision is more common in states in the Worse group, then the provision may not be effective at deterring identity theft. The evidence for these associations is stronger if the patterns are similar across the two periods.

When we apply these criteria to the State Enforcement provision, the most common provision in our sample, we find the groups of states have low p-values for both periods, suggesting the variation in use is not due to random sample variation (see Table 4). In the 2006–09 period, the Better, Mixed, and Worse groups of states had this provision in place in 81.3 percent, 67.1 percent, and 51.7 percent of observations, respectively. This finding suggests the provision is associated with lower identity theft. In the 2011–14 period, the Better, Mixed, and Worse groups of states had the provision in 93.8 percent, 78.9 percent, and 80 percent of observations, respectively. The statistical pattern suggests the State Enforcement provision helps reduce identity theft; however, because the pattern of use is not consistent across the two time periods, we assign a medium score to the strength of evidence.

The second most common provision, Risk of Harm, has similarly low p-values in both periods. In the 2011–14 period, the Better group had the provision in 50 percent of observations, the Mixed group in 78.9 percent of observations, and the Worse group in 86.7 percent of observations, suggesting that a Risk of Harm provision is associated with increased identity theft. The pattern is muddier in the 2006–09 period: the Mixed group had the provision in 67.1 percent of observations, slightly more than the Worse group (58.3 percent). The Better group had the provision in only 43.8 percent of observations in the 2006–09 period, consistent with the pattern in the 2011–14 period. We again assign a medium score to the strength of evidence.

Table 5 shows the results from this method. Five provisions are associated with lower identity theft, and three are associated with higher identity theft. The strength of evidence varies for each provision.

Endnotes

[1]The breaches at Target in 2013 and Home Depot in 2014, which exposed 110 million and 109 million records, respectively, are possibly best known among recent breaches (Risk Based Security 2015). Other recent breaches include 152 million records exposed at Adobe Systems in 2013, 173 million records exposed at the New York City Taxi & Limousine Commission in 2014, and 145 million records exposed at eBay in 2014.

[2]Federal statues regarding security breaches are fragmentary. Statutes include the Federal Fair Credit Reporting Act, the Health Insurance Portability and Accountability Act, and the Gramm-Leach-Bliley Act. In addition, the Federal Trade Commission has used its authority under Section 5 of the FTC Act, which prohibits unfair or deceptive acts or practices, to challenge unfair data security practices.

[3]CRTK notifications provide the public with information about potential hazards, allowing those in the community to protect themselves. Additionally, notifications encourage improvements that prevent hazards by exposing the risk within an organization.

[4]In a 2007 study, chief security officers stated breach notification obligations led to new access controls, auditing measures, and encryption (Samuelson).

[5]Romanosky and others do not find any significant relationship between simple measures of notification law features that influence strictness and identity theft. However, our approach digs deeper by studying a more complete characterization of data breach disclosure laws.

[6]Some states with this provision add requirements such as a strong encryption standard or an uncompromised encryption key. Because these states require more than baseline encryption, we do not count them as having this provision.

[7]We exclude 2010 to compare periods of equal length and because starting the later period in 2011 provides a one-year lag allowing the laws of four states that adopted notification laws in 2009 to have an effect on identity theft. Including 2010 in either the early or late period does not affect our results (see Appendix).

[8]The term “notable” is based on a statistically significant trend in percent deviation of identity theft per million persons for each state from the nationwide average rate (see Appendix).

[9]More specifically, the statistics do not allow rejection of equal prevalence of the provision across the three groups of states. A hypothesis of equal prevalence of the provisions across the three groups of states could not be rejected in the case of Expanded Definition of PI for both the 2006–09 and 2011–14 time periods. The hypothesis is rejected in the case of Doing Business in State for the 2006–09 period and marginally rejected for the 2011–14 period, but there is no clear pattern of how the provision affects identity theft. As a consequence, we find no association of these provisions with state records on identity theft.

[10]Note that only 6.7 percent of observations have this provision.

[11]We also estimate a similar model that accounts for the years in which states implemented a data breach notification law and find results consistent with the simpler model.

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