FEDERAL RESERVE BANK OF KANSAS CITY

ECONOMIC REVIEW

First Quarter 2017 *Volume 102, Number 1*

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By Craig S. Hakkio and A. Lee Smith

The natural real rate of interest—the level of the real federal funds rate most consistent with the Federal Reserve's statutory mandates of maximum sustainable employment and stable prices—is a key guidepost for monetary policy decisions. But most approaches used to estimate the natural rate, also known as r^*, have not kept pace with the Federal Open Market Committee's rapidly expanding set of monetary policy tools.

Craig S. Hakkio and A. Lee Smith introduce two approaches to estimating the natural real rate that account for the broad state of U.S. financial conditions as well as the additional accommodation that unconventional policies provide. Their results suggest bond premiums are an important determinant of the natural real rate of interest. Specifically, their estimates of r^* from both approaches suggest a reduction in bond premiums increases the natural real rate.

Crowdedness, Centralized Employment, and Multifamily Home Construction

By Jordan Rappaport

After the 2007–08 financial crisis, both multifamily and single-family home construction collapsed. But multifamily construction, unlike single-family construction, has since rebounded strongly. This recent aggregate strength has varied considerably across metropolitan areas: multifamily construction boomed in metros such as Austin, TX, and Charlotte, NC, but remained weak in others such as Pittsburgh, PA, and Chicago, IL.

Jordan Rappaport examines potential drivers behind the recent variation in multifamily construction and finds that factors related to population, population density, and centralized employment played important roles. More specifically, he finds multifamily construction was stronger in metropolitan areas with larger populations, lower average population density, and more concentrated employment in the city center. These relationships appear to largely capture differences in metros' productivity, urban amenities, and availability of land for development.

Identifying State-Level Recessions

By Jason P. Brown

Although the U.S. economy is in its eighth consecutive year of expansion since the Great Recession, some states are nevertheless in recession. The timing of states entering recession often differs from the nation as a whole. States with higher concentrations in specific sectors may enter downturns earlier than other states—and may remain in them longer. For example, energy-producing states in the Tenth Federal Reserve District entered a recession in 2015 and 2016 following a 70 percent decline in the price of oil. Most non-energy-producing states experienced steady growth over the same period.

Jason P. Brown tests two approaches to determining whether the seven states of the Tenth District are in a recession: one approach is well suited for identifying state recession in retrospect, while the other is more helpful for identifying state recessions in real time. Both approaches suggest Oklahoma and Wyoming entered downturns in early to mid-2015, while only the second approach suggests Kansas and New Mexico entered recessions in late summer 2016. His results indicate that on average, recessions in energy-producing states occur more frequently but are typically shorter than recessions in non-energy-producing states.

Bond Premiums and the Natural Real Rate of Interest

By Craig S. Hakkio and A. Lee Smith

The natural real rate of interest—the level of the real federal funds rate most consistent with the Federal Reserve's statutory mandates of maximum sustainable employment and stable prices—is a key guidepost for monetary policy decisions. But most approaches used to estimate the natural rate have not kept pace with the Federal Open Market Committee's (FOMC) rapidly expanding set of monetary policy tools. From 2008 to 2014, the FOMC purchased large amounts of Treasury and agency mortgage-backed securities to put downward pressure on longer-term interest rates and ease overall financial conditions. However, existing measures of the natural real rate, also known as r^*, do not explicitly account for the additional accommodation these unconventional policies may provide.

In this article, we provide two estimates of the natural real rate that account for the Fed's balance sheet and, more generally, the broad state of U.S. financial conditions. Since the goal of the 2008–14 asset purchases was to ease financial market conditions by reducing bond yields, we use bond premiums to gauge the ease or tightness of financial markets. More specifically, we derive our first estimate of r^* from a statistical model that explicitly incorporates term and risk premiums from bond markets. We then produce a second, purely data-driven estimate

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of r^* by looking for a common component across multiple variables that have been plausibly linked to the natural rate, including bond premiums. While we construct these two estimates of r^* quite differently, they yield similar results. Both estimates reveal that the natural rate reached historically low values during the 2007–09 financial crisis and recession but rebounded more recently as the economy improved and financial conditions eased.

Our results suggest bond premiums are an important determinant of the natural real rate and lead to highly cyclical estimates. In particular, our estimates from both approaches show that a reduction in bond premiums increases the natural real rate. All else equal, lower bond premiums can provide an additional source of policy accommodation by reducing financing costs for housing, consumer durables, and investment projects. Therefore, if the economy is operating at full employment and inflation rests at the FOMC's 2 percent longer-run objective, a change in bond premiums may require offsetting changes in the real federal funds rate to keep the economy on an even keel.

Section I motivates the inclusion of bond premiums in models of the natural real rate of interest and reviews the relationships between the Federal Reserve's balance sheet, bond premiums, and the natural rate. Section II presents a model-based estimate of r^* that augments the popular Laubach and Williams model with bond premiums. Section III presents a purely data-driven approach for estimating r^*. Section IV highlights how r^* is related not only to the Federal Reserve's balance sheet but also to other factors that shape global financial markets.

I. The Balance Sheet, Bond Premiums, and the Natural Real Rate

Assets held by the Federal Reserve increased from around $900 billion in 2007 to nearly $4.5 trillion in 2014. The balance sheet initially expanded during the financial crisis, when the Federal Reserve provided short-term liquidity to banks to fulfill its role as lender of last resort. However, the recession that followed proved too severe for conventional policy tools to address. To provide additional accommodation, the Fed began expanding its balance sheet further by purchasing substantial Treasury and agency mortgage-backed securities, a policy known as large-scale asset purchases or, more commonly, quantitative easing (QE). The last of three rounds of QE ended in October 2014, but the FOMC maintains a large portfolio of agency debt and Treasury securities by reinvesting proceeds of maturing securities. Consequently, the size and composition of the balance sheet continues to influence financial market conditions.

Some members of the FOMC have explicitly argued that changes to the balance sheet may influence the natural rate through their effects on bond premiums (Fischer). While multiple event studies have confirmed a relationship between the balance sheet and bond premiums, less is known about the empirical relationship between bond premiums and the natural real rate.

The link between the Federal Reserve's balance sheet and bond premiums

Since the goal of QE was to ease financial market conditions largely by reducing bond yields, most event studies have focused on how two bond premiums, the term premium and the risk premium, respond to announced changes in the asset purchase programs. The term premium measures the extra compensation investors require to hold a long-term government bond instead of buying a sequence of short-term government bonds. The risk premium measures the extra return investors require to hold a bond with some risk of default instead of holding a Treasury security of a similar maturity. The sum of the term and risk premium is therefore equal to the spread between corporate bond rates and the average of the expected future path of short-term interest rates.

Many event studies have concluded that the FOMC was successful in reducing the level of the term premium by expanding its balance sheet. Gagnon and others show that the cumulative effect of FOMC announcements regarding QE1, a round of asset purchases from November 2008 to March 2010, lowered the term premium on Treasury securities by about 50 basis points. Using a similar approach, Abrahams and others find that the cumulative effect of FOMC announcements for all three rounds of asset purchases plus the maturity extension program—which increased the average maturity of the FOMC's balance sheet without altering its size—decreased the term premium by about 110 basis points.

Evidence on the ability of large-scale asset purchases to reduce risk premiums is more mixed. Gagnon and others find that FOMC announcements during the QE1 program depressed risk premiums on corporate bonds by almost 20 basis points. In contrast, Krishnamurthy and Vissing-Jorgenson show that large-scale asset purchases actually raised risk premiums by lowering Treasury yields more than corporate bond yields. However, both event studies focus on changes in bond yields over a one- to two-day window, which may be too short to capture meaningful movements in risk premiums. A short window may be valid for highly liquid Treasury securities, but risky corporate debt changes hands less frequently. To check this possibility, Edgerton looks at how corporate bond yields reacted over a longer window around QE announcements and finds more meaningful reductions in risk premiums.[1]

The link between bond premiums and the natural real rate

Monetary policy makers have previously highlighted a relationship between bond premiums and the natural real rate of interest. For example, both former Federal Reserve Chair Bernanke (2006) and former Governor Stein expressed the view that monetary policy makers may need to monitor, and possibly offset, changes in bond premiums when the economy is operating near levels consistent with the Fed's dual mandate. However, there is little empirical evidence for the relationship between r^* and bond premiums, particularly for term premiums, which are the primary channel through which asset purchases operate.

Economic theory predicts that an increase in bond premiums lowers the natural real rate. The widely cited Smets and Wouters model of the U.S. economy features adverse "risk shocks" that, like increases in bond premiums, raise the return on bonds relative to the interest rate controlled by the central bank. Smets and Wouters' model predicts that increases in these bond premiums reduce the natural rate one for one: higher bond premiums in the model cause consumers to save more in the present and delay consumption for the future. Since postponed consumption decreases current demand, policymakers must lower real policy rates to prevent a slowdown in the economy.[2] Woodford and Curdia's model of credit frictions similarly shows that policymakers should offset shifts in risk spreads, but not necessarily one for one.[3]

Monetary policy makers have also advocated for adjusting short-term policy rates to counteract shifts in bond premiums. For example, Bernanke (2006) suggests "to the extent that the decline in forward rates can be traced to a decline in the term premium . . . the effect is financially stimulative and argues for greater monetary policy restraint, all else being equal. . . . thus, when the term premium declines, a higher short-term rate is required to obtain the long-term rate and the overall mix of financial conditions consistent with maximum sustainable employment and stable prices." Similarly, a joint paper by Taylor and Federal Reserve Bank of San Francisco President Williams suggests short-term policy rates may need to be lowered to offset increases in risk spreads following the recent financial crisis. And Stein argues from a financial stability perspective that "all else being equal, monetary policy should be less accommodative . . . when estimates of [term and credit] risk premiums in the bond market are abnormally low."

Despite these views, the empirical relationship between the natural real rate and term premiums is not well understood. While many economists and policymakers believe lower term premiums are stimulatory, Hamilton and Kim find that lower term premiums actually predict slower GDP growth.[4] But Rudebusch, Sack, and Swanson show that regression models such as Hamilton and Kim's can be sensitive to the empirical specification and the sample period.

Unlike the term premium, empirical evidence widely supports the idea that rising risk premiums dampen future economic activity. In the closest paper to ours, Kiley finds an inverse relationship between risk spreads and his estimate of the natural real rate. However, his model doesn't include term premiums, which are a primary channel through which asset purchases are thought to operate (Bernanke 2012b). Pescatori and Turunen take a related approach by positing that global savings, economic policy uncertainty, and the equity risk premium all affect the natural real rate. While these factors are likely to capture some elements that drive bond premiums, they may not fully capture how a central bank's asset purchases alter the relative demand for bonds or their yields.

II. A Model of Bond Premiums and the Natural Real Rate of Interest

The current mix of monetary policy tools employed by the FOMC warrants a fresh look at how bond premiums influence the natural rate. Since the natural real rate of interest is not observable, we use a semistructural model to explore the link between bond premiums and r^*. Our approach therefore follows Laubach and Williams, who developed a stylized model of the U.S. economy to estimate low-frequency movements in the natural rate. However, our model accounts for bond premiums. By doing so, our estimates take into account not only medium-term growth prospects and aggregate demand conditions but also current financial market conditions as measured by financing premiums implied by corporate and government bond yields.

An overview of the model

Laubach and Williams' model identifies the natural real rate of interest using an estimated investment-savings (IS) equation. The IS equation relates the output gap—the percent difference between the level of real GDP and its potential level—to the real interest rate gap—the difference between the real effective federal funds rate and the natural real rate. The IS equation posits a negative relationship between the real interest rate gap and the output gap. More specifically, the IS equation suggests that an increase in the real interest rate above the natural rate leads to a decline in real GDP below its potential level.

The relationship implied by the IS equation can be used to infer the natural real rate. Suppose, for example, that the economy is initially operating at potential with no real interest rate gap. If output falls persistently below its potential level, then the model would infer that the real interest rate has risen above the natural rate, thereby turning the real interest gap positive. Conversely, if output persists above potential, then the model would infer that the real interest rate has fallen below the natural rate, thereby turning the real interest rate gap negative. By setting the real federal funds rate equal to the natural real rate, monetary policy makers can keep the economy from slowing or overheating. In this sense, the natural real rate provides a guidepost for monetary policy.

If the output gap and the real effective federal funds rate were observable, we could directly extract a measure of the natural real rate from an estimated IS equation. However, the output gap is unobservable.[5] To infer whether GDP is above or below its potential level, Laubach and Williams use an accelerationist Phillips curve. This version of the Phillips curve relates the change in the inflation rate to the output gap. More specifically, the accelerationist curve implies that rising inflation is due to output exceeding its potential level, while falling inflation is due to output falling below potential.[6] In this way, data on output and inflation can be used to measure potential output—which, in turn, can be used to infer the natural real rate of interest.

Model specification

The IS equation and Phillips curve can be directly estimated in principle, but certain features of the data can make them challenging to model in practice. Laubach and Williams' IS equation, for instance, assumes that the output gap depends in part on lags of itself, reflecting that the U.S. economy has momentum when expanding or contracting. In addition, Laubach and Williams' IS equation assumes that the economy is slow to adjust to the real interest rate gap, reflecting the longstanding notion that monetary policy influences the economy with a lag of one to two quarters. Given these assumptions, the IS equation that enters the model is expressed mathematically as:

$$\tilde{y}_t = a_1\tilde{y}_{t-1} + a_2\tilde{y}_{t-2} + \frac{a_r}{2}\sum_{i=1}^{2}\left(r_{t-i} - r^*_{t-i}\right) + \varepsilon^1_t, \qquad (1)$$

where $\tilde{y}$ denotes the output gap, r denotes the real effective federal funds rate, r^* denotes the natural real rate of interest, and ε^1_t is a statistical error with a standard deviation of σ_1 included to capture noise in the data. The terms a_1 and a_2 measure the persistence of output gap deviations, while a_r measures the sensitivity of the output gap to the real interest rate gap.

As with the IS equation, Laubach and Williams specify several features of the data when modeling the Phillips curve. First, they incorporate eight quarters of lagged inflation, as U.S. inflation can be slow to adjust to policy changes (Christiano, Eichenbaum, and Evans). Second, they incorporate oil and import prices as control variables, as factors outside of the output gap can also have an effect on inflation. Finally, they incorporate the output gap with a one-quarter lag, consistent with the idea that prices are slow to adjust to slack in the economy. The Phillips curve that enters the model is expressed mathematically as:

$$\pi_t = \sum_{i=1}^{8} b_i \pi_{t-i} + b_y \tilde{y}_{t-1} + b_{imp} \pi_t^{imp} + b_{oil} \pi_{t-1}^{oil} + \varepsilon_t^2 , \tag{2}$$

where π denotes the quarterly inflation rate as measured by the price index for personal consumption expenditures excluding food and energy, $\tilde{y}$ denotes the output gap, π^{oil} denotes oil import price inflation, π^{imp} denotes inflation in core import prices, and ε_t^2 is a statistical error with a standard deviation of σ_2 included to capture noise in the data. Laubach and Williams impose the restrictions that $\sum b_i = 1$ and that the coefficients on lags two through four are equal as are the coefficients on lags five through eight during the estimation. The coefficients b_{imp} and b_{oil} measure the effect of changes in import and energy prices on core inflation, while b_y measures the sensitivity of inflation to changes in the output gap.

Determinants of the natural real rate of interest

Standard models of economic growth predict that the natural real rate varies positively with the economy's trend growth rate, denoted here by *g*, leading Laubach and Williams to specify:

$$r_t^* = c_g g_t + z_t ,$$

where c_g measures the sensitivity of the natural rate to trend growth. Laubach and Williams include the *z* term to capture other factors that are difficult to quantify but may affect the natural rate through aggregate demand channels, including expectations of fiscal deficits, the health of household and firm balance sheets, and demand emanating from abroad.

We augment Laubach and Williams' expression for r^* to include the term premium, *tp*, and the risk premium, *rp*, from bond markets. Specifically, we specify the natural real rate as:

$$r_t^* = c_g g_t + z_t + c_{tp} tp_t + c_{rp} rp_t .$$

Neither the term premium nor the risk premium are perfectly observable, so we employ commonly used estimates instead. For the term premium, we use the estimate for the 10-year U.S. Treasury security from Adrian, Crump, and Moench (2013a).[7] For the risk premium, we use the difference between Moody's index of BAA corporate bonds and the 10-year constant-maturity U.S. Treasury security. The coefficients c_{tp} and c_{rp} measure the potential influence that term and risk premiums have on r^*. We expect both coefficients to be negative.

Finally, we specify the statistical process for the unobserved variables in the model, which include z, other unobservable demand factors that affect r^*; y^*, the natural log of potential output; and g, the trend growth rate. Following Laubach and Williams, we assume these unobserved variables evolve according to:

$$z_t = z_{t-1} + \varepsilon_t^3, \tag{3}$$

$$y_t^* = y_{t-1}^* + g_{t-1} + \varepsilon_t^4, \tag{4}$$

and

$$g_t = g_{t-1} + \varepsilon_t^5. \tag{5}$$

In each of these equations, the terms ε_t^3, ε_t^4, and ε_t^5 are unexpected shocks to the unobserved aggregate demand factor, the natural log of potential output, and trend growth with standard deviations equal to σ_3, σ_4, and σ_5, respectively.[8]

Estimates of the natural real rate of interest

Our model estimates reveal that a decline in bond premiums increases the natural real rate of interest. Table 1 reports the full set of parameter estimates and standard errors. The first column of results shows estimates from our unrestricted model. As expected, the coefficient on the risk premium, $c_{rp} = -0.78$, is negative, suggesting a lower risk premium would yield a higher natural real rate. The coefficient on the term premium, $c_{tp} = -1.54$ is also negative, giving empirical weight to Bernanke's and Stein's views that reductions in the term premium raise the natural real rate. The coefficients on the risk and term premiums are both near –1, suggesting bond premiums may have an economically significant effect on r^*. Finally, the coefficient on trend growth, $c_g = 5.69$, is positive, as expected. The magnitude of the coefficient

Table 1

Parameter Estimates for Natural Real Rate Model

Parameter	Unrestricted model	Preferred model	Model without bond premiums
a_1	1.65*** (0.16)	1.62*** (0.12)	1.66*** (0.10)
a_2	–0.75*** (0.14)	–0.71*** (0.11)	–0.72*** (0.10)
a_r	–0.06** (0.03)	–0.07*** (0.02)	–0.05*** (0.02)
b_1	0.56*** (0.06)	0.56*** (0.06)	0.55*** (0.06)
b_2	0.34*** (0.08)	0.34*** (0.08)	0.34*** (0.08)
b_y	0.11** (0.05)	0.11** (0.05)	0.12*** (0.04)
b_{imp}	0.03*** (0.01)	0.03*** (0.01)	0.03*** (0.01)
b_{oil}	0.003** (0.001)	0.003*** (0.001)	0.003** (0.001)
c_g	5.69 (8.63)	4.00	4.00
c_{tp}	–1.55* (0.81)	–1.00	0.00
c_{rp}	–0.78 (1.27)	–1.00	0.00
σ_1	0.25*** (0.10)	0.27*** (0.09)	0.27*** (0.08)
σ_2	0.80*** (0.04)	0.80*** (0.04)	0.80*** (0.04)
σ_4	0.64*** (0.05)	0.63*** (0.05)	0.63*** (0.05)
Log likelihood	–519.61	–519.84	–522.10
Null hypothesis for likelihood ratio test	—	Unrestricted model = Preferred model	Preferred model = Model without bond premiums
P-value for likelihood ratio test	—	0.92	0.10

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

Notes: All models are estimated via maximum likelihood from 1962:Q1 to 2016:Q3. Details regarding the estimation procedure are available in Appendix A. Standard errors are in parentheses.

suggests that annualized trend growth ($c_g/4$) affects the natural real rate (expressed in annualized percentage points) nearly one for one.[9]

The second column of results in Table 1 shows our preferred estimation results, which restrict the parameters so that $c_g = 4$ and $c_{rp} = c_{tp} = -1$. The likelihood ratio test, which compares how well the unrestricted model fits the data compared with this restricted version of the model, reveals that these restrictions cannot be rejected by the data. The restriction that $c_g = 4$ implies that changes in trend growth have a one-for-one effect on the natural real rate; this restriction emerges from many macroeconomic models and is supported within our framework by the estimates in Laubach and Williams. The restriction that $c_{rp} = c_{tp} = -1$ also emerges from theoretical models of the macroeconomy, such as in the model developed by Smets and Wouters. This restriction implies that changes in bond yields, emanating from both term and risk premiums, have a one-for-one negative effect on r^*. The relative fit of this preferred model suggests that bond premiums may have an equal and economically significant influence on the natural real rate when compared with trend growth.

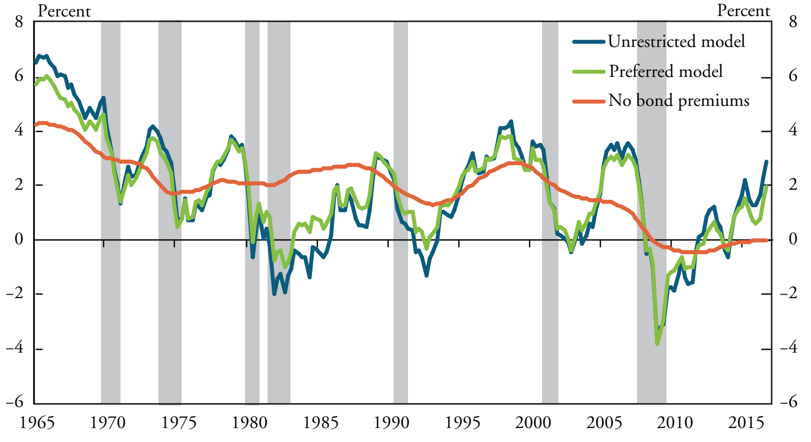
We also find some evidence against a version of the model that removes bond premiums from the estimation of the natural real rate. In particular, the third column of results in Table 1 shows estimates from a model that restricts, $c_{rp} = c_{tp} = 0$, thereby eliminating bond premiums as a determinant of the natural real rate. Chart 1 plots these estimates alongside two other estimates of the natural real rate series: our unrestricted estimate and our preferred estimate. The chart shows very little difference between our unrestricted and preferred estimates. However, the estimate without bond premiums differs significantly from the other two. A more formal comparison using a likelihood ratio test reveals that the model fit deteriorates when risk and term premiums are excluded, suggesting they are important determinants of the natural real rate.[10] As a result, the remainder of this section focuses on our preferred model estimates.

The cyclicality of the natural real rate

Our preferred estimate of r^* is procyclical, rising in economic expansions and declining in recessions. The cyclicality of the natural real rate reflects that bond premiums are countercyclical. Chart 2 plots the

Chart 1

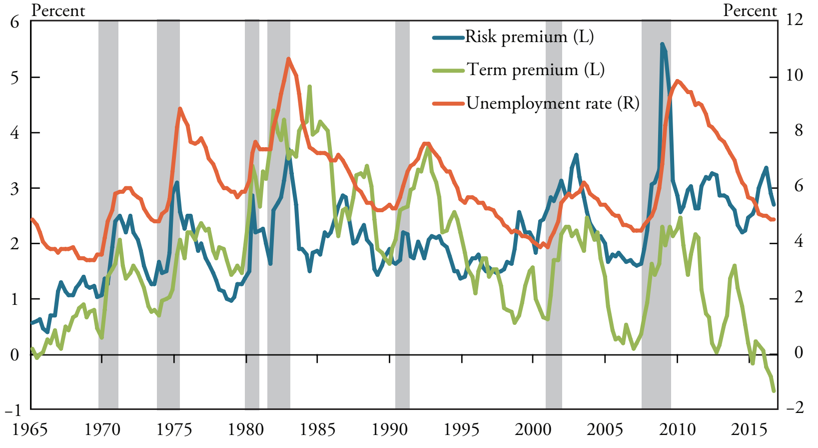
Natural Real Rate Estimates



Note: Gray bars denote NBER-defined recessions.
Sources: Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Federal Reserve Bank of New York, Board of Governors of the Federal Reserve System, Moody's, National Bureau of Economic Research (NBER), and authors' calculations. All data sources accessed through Haver Analytics.

Chart 2

The Cyclicality of Bond Premiums



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unemployment rate alongside the term and risk premiums to illustrate that bond premiums tend to follow the unemployment rate: they rise in and around recessions and decline in expansions. The driving forces behind risk and term premiums can offer some insight into why this pattern emerges.

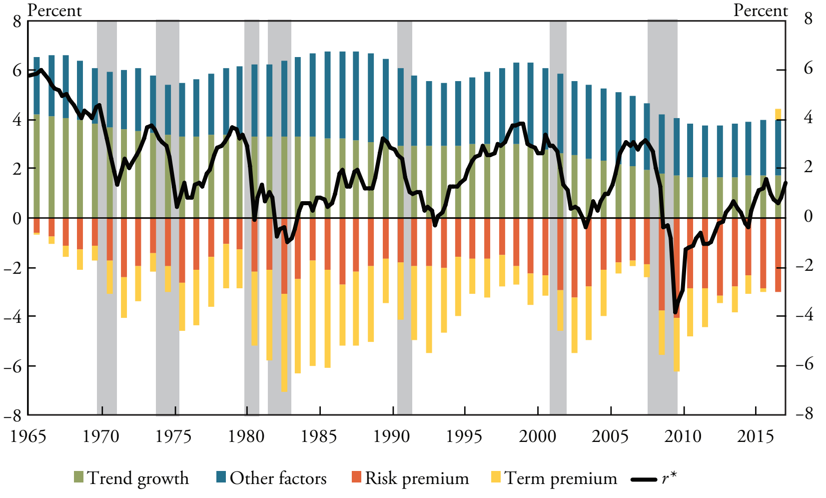
Risk premiums arise from both the risk of default investors face in corporate debt markets and their tolerance for bearing such risks. Both factors tend to make risk premiums strongly countercyclical. Slowing economic growth (as in recessions) can weigh on firms' balance sheets, increasing their risk of defaulting on corporate bonds and thereby increasing risk premiums. In addition, Gilchrist and Zakrajšek (2012) show that declining investor sentiment toward risks is associated with slowing economic activity and may perhaps play a causal role in propagating economic downturns.

Similarly, the term premium arises, in part, from the risk that realized short-term interest rates could differ from their expected future values. Prior to the 1990s, the primary risk for bond holders was unexpected inflation, which eats into the purchasing power of a bond's nominal coupon payments. But today, the primary risk may be uncertainty related to the near-term growth outlook. Adrian, Crump, and Moench (2013b) show the term premium is highly correlated with measures of interest rate uncertainty. As a consequence, term premiums rise in recessionary periods along with other financial market measures of uncertainty such as the Chicago Board of Exchange's Volatility Index (VIX) and, the counterpart for U.S. government bond markets, the Merrill Lynch Option Volatility Estimate (MOVE) index.[11]

Decomposing factors that drive the natural real rate

Our model posits four variables that affect the natural real rate: the term premium (*tp*), the risk premium (*rp*), trend growth (*g*), and other aggregate demand factors (*z*). Chart 3 plots the natural real rate over bars showing the contribution of each component to the natural real rate. While term and risk premiums made strong negative contributions to the natural rate during the 2007–09 financial crisis and recession, they have since ebbed from their post-recession highs, leading to a rise in r^*. However, the level of r^* has been weighed down by trend

Chart 3
Contributions of Components to the Natural Real Rate



Note: Gray bars denote NBER-defined recessions.
Sources: BEA, BLS, Federal Reserve Bank of New York, Board of Governors of the Federal Reserve System, Moody's, NBER, and authors' calculations. All data sources accessed through Haver Analytics.

growth and other aggregate demand factors despite easing financial market conditions during the economic recovery.

The economy's rate of trend growth has persistently declined since the end of the 20th century. We estimate that the economy's trend growth rate has slowed from 3 percent per year in the mid-1990s—a period of rapid technological advancement and adoption—to 2 percent in the mid-2000s and to just 1.7 percent in the mid-2010s. This decline in potential growth is consistent with the observation by Stock and Watson (2016) that demographic forces due to an aging U.S. population, together with the slowing rate of growth in output per worker, are acting as a headwind to economic growth. By our estimates, the reduction in the economy's long-run growth capacity has reduced the natural real rate by 1.3 percentage points since the mid-1990s.

Our estimate of the economy's potential growth rate from this top-down approach aligns well with the estimate from the Congressional Budget Office (CBO). The CBO regularly publishes estimates of the U.S. economy's potential growth rate using a growth accounting perspective. In particular, the CBO attempts to estimate the economy's productive capacity based on sectoral data and then aggregates this back to a measure of aggregate output. This bottom-up approach predicts that the growth rate of potential output was about 1.6 percent in the third quarter of 2016, very near our estimate of 1.7 percent for the same period.

In addition to the decline in trend growth, latent aggregate demand factors, captured by the z term in the natural real rate equation, also appear to be acting as a headwind to r^* in recent years. Interpreting the factors influencing z is difficult, because by assumption, this variable captures components of aggregate demand that are unobservable. One often-cited factor restraining the economy during the most recent expansion is the stance of fiscal policy. Although government spending supported GDP growth in the initial years of the recession, it became a drag on growth in subsequent years (Bernanke 2012a; Yellen; Stock and Watson 2016).

Our estimate of z seems to be capturing the stance of fiscal policy among other possible elements of aggregate demand. Chart 4 plots our time-series of z_t against the two-year centered moving average of government spending's (arithmetic) contribution to GDP growth to capture not only past spending, but also its contributions to aggregate growth over the next year. The two series are tightly correlated over our estimation sample. This suggests that during much of the economic expansion, past and expected future reductions in government spending have contributed to weak aggregate demand and thereby weighed on the natural rate.

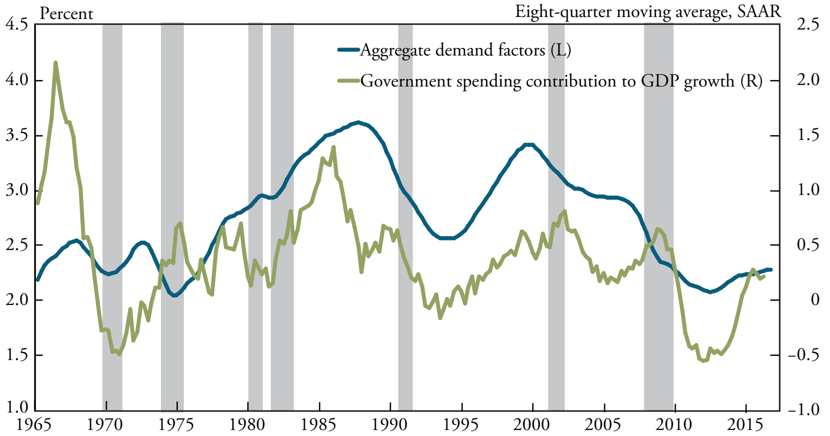
Uncertainty in our estimates of r^*

One caveat to our interpretations is that our estimate of the natural real rate is not very precise. Chart 5 shows our point estimate surrounded by 90 percent confidence bands. The average range between the upper and lower confidence band is about 5 percentage points, but in the most recent period, the range exceeds 7 percentage points. In other words, the uncertainty associated with our estimate of the natural rate is high on average, but especially high for the most recent estimate. Another source of uncertainty, not captured in Chart 5, is model specification. For example, when Laubach and Williams change the specification of the latent aggregate demand process, the resulting estimate of the natural rate becomes more cyclical.

These uncertainties are not unique to our estimates. Any model-based approach can produce imprecise estimates that vary substantially with

Chart 4

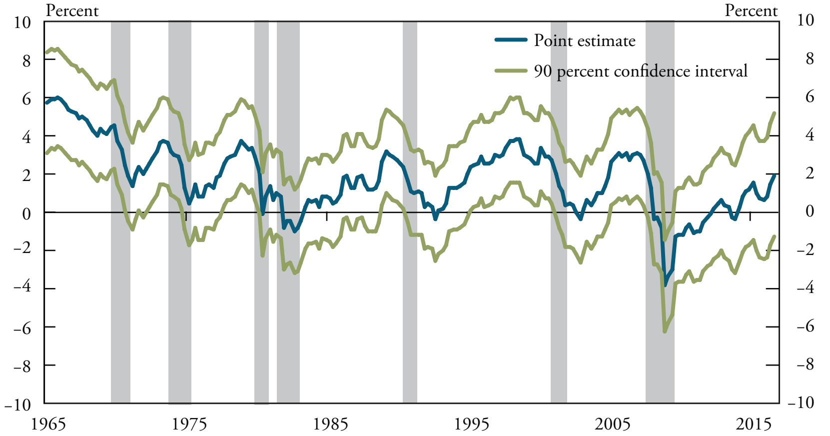
The Link between Aggregate Demand Factors and Fiscal Policy



Note: Gray bars denote NBER-defined recessions.
Sources: BEA, BLS, Federal Reserve Bank of New York, Board of Governors of the Federal Reserve System, Moody's, NBER, and authors' calculations. All data sources accessed through Haver Analytics.

Chart 5

Uncertainty Surrounding the Natural Real Rate



Note: Gray bars denote NBER-defined recessions.
Sources: BEA, BLS, Federal Reserve Bank of New York, Board of Governors of the Federal Reserve System, Moody's, NBER, and authors' calculations. All data sources accessed through Haver Analytics.

different vintages of data and different model specifications (Laubach and Williams; Clark and Kozicki; Holston, Laubach, and Williams). As Clark and Kozicki point out, these issues make statistical estimates of the real rate less reliable in practical policy applications. To address this shortcoming, we develop an alternative, data-driven estimate of the natural real rate as a cross-check on our model-based analysis.

III. A Data-Driven Approach to Estimating the Natural Real Rate of Interest

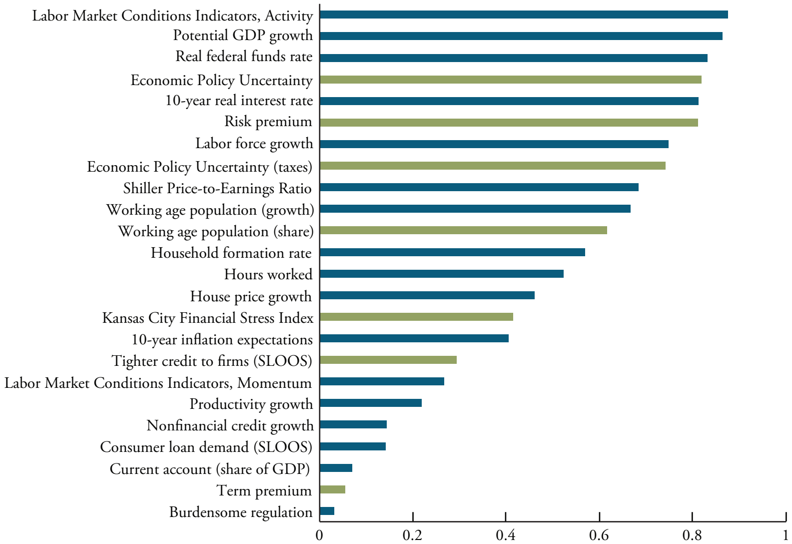
To derive an alternative estimate of the natural real rate, we look for a common component across numerous variables that economists and policymakers have associated with the natural real rate. This approach removes the uncertainty surrounding model specification, as it requires us to make minimal assumptions.

We estimate what we call "the natural real rate factor," denoted by f, using a statistical technique called principle component analysis. Principle component analysis enables us to consolidate information across 24 variables plausibly related to the natural real rate, including long-term real interest rates, trend-growth estimates from the CBO, demographic trends, measures of economic policy uncertainty, measures of the U.S. credit and housing cycle, cyclically adjusted price-to-earnings ratios as a measure of investor sentiment, measures of the supply of global savings into U.S. financial markets, a measure of government regulations, and both quantitative and qualitative measures of the ease or tightness of U.S. financial markets (which include the risk and term premium used in our model-based estimate). The natural real rate factor is constructed as a weighted average of the 24 variables. The complete list of variables, along with a description of any transformations, is included in Appendix B.

Since the variables have very different units, means, and standard deviations, each variable is first normalized to have a mean equal to zero and a standard deviation equal to one. As a result, our estimate of the natural real rate factor, f, also has a mean of zero and a standard deviation of one. Therefore, a reading of $f = 0$ means the natural real rate equals its historical average, while the historical average of our r^* estimate is about 2 percent.

Chart 6

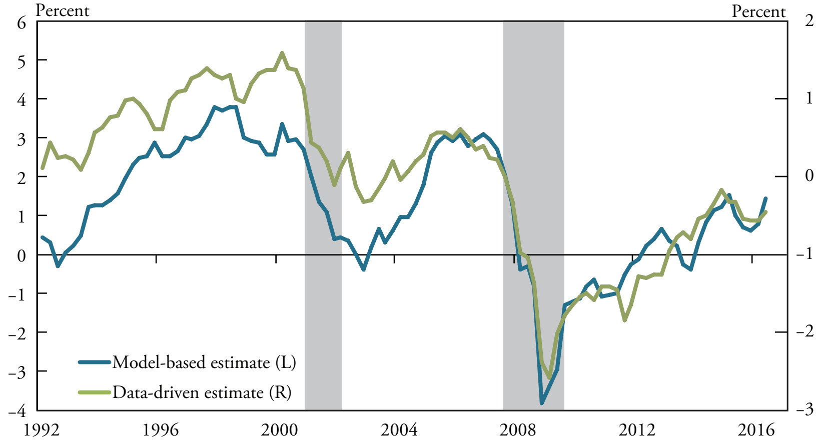
Factor Loadings for the Natural Real Rate Factor (*f*)



Note: Blue bars denote a positive factor loading, while green bars denote a negative factor loading.
Sources: BLS; Board of Governors of the Federal Reserve System; Federal Reserve Bank of New York; Federal Reserve Bank of Kansas City; Moody's; Census Bureau; Bank for International Settlements; Case-Shiller; Robert Shiller; CBO; National Federation of Independent Business (NFIB); Commerce Department; Baker, Bloom, and Davis; Survey of Professional Forecasters (SPF); and authors' calculations. All data sources accessed through Haver Analytics.

To illustrate the relationship between the 24 variables and *f*, Chart 6 reports the factor loadings—that is, the correlation between the normalized variable and *f*. The chart ranks the variables by the size of the absolute value of the correlation. Blue bars denote a positive factor loading, while green bars denote a negative factor loading. As expected, consistent with the model-based estimate of r^*, the correlation between the term and risk premium and our natural rate factor is negative. Also as expected and consistent with the model-based estimate, growth in real potential GDP is positive and has the second largest correlation with *f*. The Federal Reserve Bank of Kansas City's Labor Market Conditions Indicators (LMCI) Activity index, a broad measure of labor market conditions, has the largest correlation with *f*, presumably reflecting the cyclicality of r^*. Finally, the correlation between *f* and three three other measures of financial conditions—the Kansas City Financial Stress Index (a broad measure of financial stress), the share of banks

Chart 7
Comparing Our Two Estimates of the Natural Real Rate



Notes: Gray bars denote NBER-defined recessions.
Sources: BLS; Board of Governors of the Federal Reserve System; Federal Reserve Bank of New York; Federal Reserve Bank of Kansas City; Moody's; Census Bureau; Bank for International Settlements; Case-Shiller; Robert Shiller; CBO; NFIB; Commerce Department; Baker, Bloom, and Davis; SPF; and authors' calculations. All data sources accessed through Haver Analytics.

reporting tighter standards for commercial loans, and the growth rate of nonfinancial credit—indicate tighter credit conditions reduce f.

Although our approaches to estimating r^* and f are vastly different, they yield similar interpretations of the natural rate. To compare these two estimates of the natural real rate on the same chart, Chart 7 plots r^* on the left axis and f on the right axis. Our data-driven estimate of the natural real rate closely tracks our model-based estimate with a correlation coefficient of 0.89. And much like our model-based estimate, the data-driven estimate was still running below its historical average as of the second quarter of 2016.

The similar conclusions reached from both a model-based and data-driven approach provide some confidence in our assessment of the natural real rate in recent decades. In particular, both estimates are highly cyclical, rising in expansions and falling in recessions. Both estimates also reached their sample lows during the recent financial crisis but have trended up in recent years. In all, the timing and magnitude of the movements are broadly consistent with our previous analysis linking the ease or tightness of financial conditions to the natural real rate. Since r^* and f are so highly correlated, we focus on r^*, which has a meaningful level interpretation for the natural real rate, for the remainder of the article.

IV. Movements in the Natural Real Rate and Events in Financial Markets

Many factors can influence bond premiums—and, in turn, the natural real rate of interest. To illustrate this, Chart 8 highlights how r^* has been influenced by four prominent events that significantly changed the ease or tightness of U.S. financial market conditions: changes in the supply of global savings (often referred to as the "global savings glut"), the global financial crisis, changes in expectations about the size of the Fed's balance sheet that occurred in spring 2013 (an event now referred to as the "taper tantrum"), and the 2014 oil price collapse.

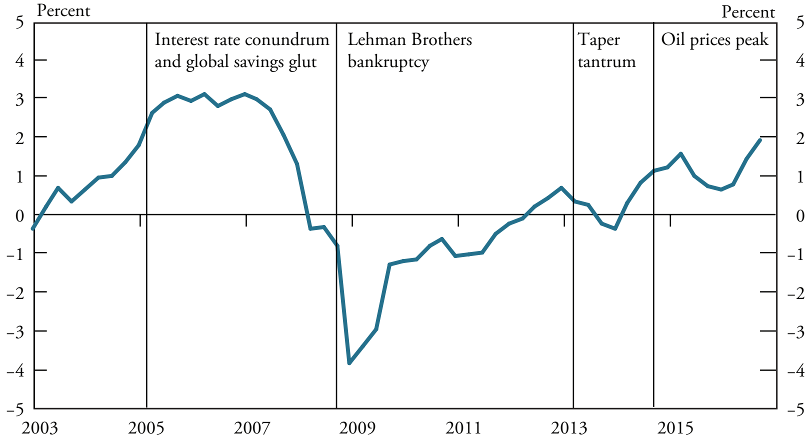
The global savings glut

From June 2004 to February 2005, the FOMC increased the target federal funds rate by 150 basis points, but the yield on the 10-year Treasury security fell by more than 50 basis points. At the time, then-Chair Greenspan called the diverging paths of long-term and short-term rates a "conundrum." In 2007, then-Chair Bernanke proposed the global savings glut as an explanation for the puzzling decline in long-term rates. Bernanke hypothesized that a global savings imbalance led to large inflows of foreign savings into U.S. capital markets, driving up the price of both safe and risky assets and thereby lowering their yield.

Consistent with Bernanke's hypothesis, the term premium fell by more than 2 percentage points from 2004 to 2006, while risk premiums declined by nearly 0.5 percentage point. Together, these declines led to a more than 2.5 percentage point increase in our estimate of r^*. Warnock and Warnock use data on foreign official purchases of U.S. securities to show that foreign purchases lowered the yield on the 10-year Treasury security during 2004–06 by more than 80 basis points. Moreover, they find that foreign purchases have larger effects on BAA-rated U.S. corporate bonds than Treasury securities, suggesting foreign inflows also played a role in depressing risk premiums during these years. This evidence, viewed through the lens of our model of the natural real rate, suggests that an influx of foreign funds into U.S. capital markets applied meaningful upward pressure on the natural real rate over this period.

Chart 8

The Natural Real Rate and Changes in U.S. Financial Market Conditions



Sources: BEA, BLS, Federal Reserve Bank of New York, Board of Governors of the Federal Reserve System, Moody's, NBER, and authors' calculations. All data sources accessed through Haver Analytics.

The global financial crisis

Our estimate of the natural real rate fell precipitously over the 2006–08 period. The sharpest decline came in the fourth quarter of 2008, when the global financial crisis intensified. A full discussion of the events that increased turmoil in financial markets over this period is beyond the scope of this article; instead, we focus on some clearly identifiable events in the second half of 2008 that led to a sharp rise in bond premiums.

In September 2008, the Federal Housing Finance Agency placed Fannie Mae and Freddie Mac into conservatorship, Lehman Brothers filed for bankruptcy, and the Federal Reserve extended AIG an $85 billion rescue package. This sequence of events amplified already high risk aversion, sending the risk premium to a post-war high.

The term premium remained elevated throughout September but reached new highs in October due in large part to increased uncertainty over the policy response to the unfolding crisis. As the financial crisis intensified, the Federal Reserve voted to cut its target for the federal funds rate by 50 basis points in a coordinated move with other central banks. The rate reduction, which was announced after an unscheduled conference call, sparked uncertainty over the timing and size of further interest rate cuts. As a result, measures of near-term expected interest rate volatility, such as the MOVE index, rose sharply along with the term premium. Tense political negotiations over the Troubled Asset Relief Program (TARP) added further policy uncertainty. The initial TARP bill failed to pass the House of Representatives, raising concerns in financial markets over how long it would take Congress to agree on a policy response.

The rise in term and risk spreads during the crisis was associated with what was arguably the largest tightening in U.S. financial conditions since the Great Depression. Our estimate of the natural real rate commensurately declined to nearly –4 percent in the fourth quarter of 2008. Although we estimate that the natural real rate became negative in the four previous recessions, the unusually large decline suggests that deeply negative policy rates would have been needed to fully stabilize the economy. Therefore, through the lens of our model, unconventional monetary policy can be viewed as an attempt to reduce the output gap by narrowing the real rate gap when the natural real rate is deeply negative and nominal interest rates have reached their effective lower bound.

The taper tantrum

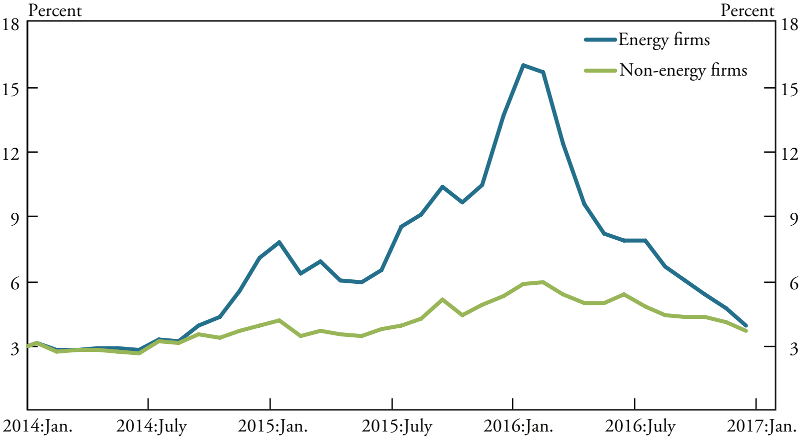
One of the most vivid illustrations of the link between the FOMC's balance sheet and the natural rate came in the spring of 2013. Unlike previous QE programs, the Federal Reserve's third round of asset purchases (referred to as QEIII) was an open ended bond-buying program with no preset size or end date. In May 2013, then-Chair Bernanke suggested during congressional testimony that the current pace of asset purchases might be tapered in the "next few meetings" if the U.S. economy continued to improve. Bernanke reiterated this assessment in a press conference after the June FOMC meeting. Together, these comments pulled forward the expected timing of reductions in the monthly flow of asset purchases and increased uncertainty about when policy accommodation would be reduced.[12] As a result, financial markets tightened considerably during this time. From May to June 2013, the term premium jumped nearly 40 basis points and continued to rise through the end of the year, at which time the FOMC began tapering asset purchases. Our estimate of the natural real rate declined nearly 1 percentage point over the second half of 2013 due to this rise in the term premium.

The 2014 oil price collapse

A 70 percent collapse in oil prices from 2014 to 2016 sent energy firms into financial distress and tightened overall financial conditions. From 2011 to mid-2014, West Texas Intermediate (WTI) oil prices averaged about $100 per barrel. But growing U.S. oil production, together with the November 2014 announcement that the Organization of the Petroleum Exporting Countries (OPEC) was not willing to play the role of swing producer, sent prices tumbling by 60 percent in just one year. After recovering to around $60 per barrel in mid-2015, spot prices for WTI fell again on the heels of an announced agreement with Iran that would enable the country to once again supply global markets with oil. Prices continued to fall through 2015, breaching $30 per barrel in early 2016 amid growing concerns that demand for oil was faltering. At the same time, concerns about China were growing as its economy transitioned to a more consumer-oriented growth model.[13]

The risk premium rose nearly 120 basis points from the peak in oil prices in the second quarter of 2014 to the trough in the first quarter of 2016. Corporate bond spreads peaked in 2016:Q1 as creditors grew concerned that low oil prices would hamper oil producers' ability to repay their debt. Comments in the January 2016 Senior Loan Officer Opinion Survey noted oil and gas producers as a particular industry of concern and cited the energy industry as one reason for tightening credit standards on commercial loans. Capital markets tightened similarly over this period. Chart 9 shows that the rise in risk spreads was initially concentrated in the energy sector but spilled over to non-energy firms as well, thereby tightening overall credit conditions. Consequently, our estimate of the natural real rate declined throughout 2015. After cresting at nearly 1.5 percentage points to start the year, by the end of 2015, the natural real rate had fallen to an estimated 0.5 percentage point.[14] As oil prices rose through 2016, risk spreads narrowed for both energy and non-energy firms, and r^* recovered.

Chart 9
Risk Premiums During the 2014–16 Oil Price Collapse



Sources: Board of Governors of the Federal Reserve System, Bank of America, and authors' calculations. All data sources accessed through Haver Analytics.

V. Conclusion

Recent estimates of the natural real rate of interest show a persistent decline from its historical average of about 2 percent. The prospect of a persistently low natural real rate of interest has numerous ramifications for monetary policy makers. For example, as lower rates are required to keep the economy operating at potential, encounters with the effective lower bound may become more frequent and longer lasting. Widely cited estimates from Laubach and Williams' model, which links the natural real rate to both the economy's trend growth rate and persistent aggregate demand factors, suggest the natural real rate of interest has been declining for several decades and is currently near zero. However, the model does not explicitly account for the influence of financial market conditions on the natural real rate.

In this article, we augment the Laubach and Williams model with measures of bond premiums to capture the relationship between U.S. capital markets and the natural real rate of interest. We find evidence of a meaningful negative relationship between term and risk premiums and the natural real rate. To the extent that some of the recent movements in bond premiums can be traced to the FOMC's asset purchases, our findings suggest a link between the FOMC's balance sheet and the level of the natural real rate of interest. However, a multitude of non-monetary factors can also drive bond premiums. Therefore, a broader interpretation of our results is that changes in financial market conditions, emanating from changes in the risk appetite of investors or the supply of global savings, may require a monetary policy response.

In addition to our model-based estimate, we also provide a data-driven estimate of the natural real rate. This alternative approach produces a natural real rate factor, f, that is highly correlated with our model-based estimate of r^* but requires few modeling assumptions. The strong correlation between f and r^*—despite very different estimation techniques—further supports our interpretation of the link between financial market conditions and the natural real rate.

Our resulting estimates of the natural real rate are much more cyclical than most other estimates of r^*. While we estimate that the U.S. economy's rate of potential growth has been steadily declining for several decades, the time variation in financial market conditions outweighs this long-term decline in trend growth. As a consequence, our natural real rate estimates fell sharply during and after the recent recession, but have also risen steadily in line with the recovery and ongoing economic expansion. Nevertheless, a sustained return of r^* to its historical average seems unlikely due to the apparent deceleration in trend growth over the past 20 years.

Appendix A
Model Estimation Details

In this appendix, we describe the estimation strategy for our model-based estimates of the natural real rate. Equations (1)–(5) in the text form the basis of a state-space model, with equations (1) and (2) serving as the measurement equations and equations (3), (4), and (5) serving as the transition equations. In principle, this state-space model can be directly estimated via maximum likelihood using the Kalman filter. However, in practice, the estimates of σ_3 and σ_5 are typically pushed to zero due to the so-called "pile-up" problem (Stock). Therefore, we follow Laubach and Williams and peg the signal to noise ratios:

$$\lambda_z = \frac{|a_r|}{\sqrt{2}} \frac{\sigma_3}{\sigma_1} = 0.058 \text{ and } \lambda_g = \frac{\sigma_5}{\sigma_4} = 0.042$$

These values for λ_z and λ_g are the estimated values from Laubach and Williams, who use a multistep estimation procedure. First they model potential GDP as a random walk with drift so that trend growth is a constant. With this specification, they find an estimate of λ_g by performing a structural break test on the intercept term in a regression of the growth rate of potential GDP on a constant and then use the look-up table (Table 3) in Stock and Watson (1998). They then use this estimate of λ_g in a second-stage estimation that assumes z_t is constant to similarly arrive at an estimate of λ_z. In particular, they perform a structural break test on the intercept term in a regression of the resulting output gap series on two lags of itself and a two-quarter average of the lagged real rate and then use the look-up table (Table 3) in Stock and Watson (1998).

With Laubach and Williams' estimates of λ_z and λ_g in hand, we estimate the state-space model via maximum likelihood using the Kalman filter. The estimation is performed in RATS version 9.0. All results reported in the figures are calculated using the smoothed (two-sided) states. The model is estimated from 1962:Q1 through 2016:Q3.

The data used in the estimation are as follows. We measure output as 100 times the natural log of real GDP. Inflation is the annualized quarterly percent change of the core PCE price deflator (prior to 1959, we use the PCE price deflator, since the core PCE price deflator is not available). For the control variables in the Phillips curve, we measure import price movements by the difference between the annualized quarterly percent change in the price deflator for non-petroleum imports and inflation, and we measure oil-price movements by the difference between the change in the import price of crude oil and inflation. The import and oil price series are obtained from Laubach and Williams' regular updates reported on the Federal Reserve Bank of San Francisco website. We calculate the real federal funds rate as the difference between the nominal effective federal funds rate and a statistical forecast of inflation over the next year using an AR(3) model estimated over a 10-year rolling window. Prior to 1965, we use the Federal Reserve Bank of New York's discount rate series instead of the nominal effective federal funds rate, since the funds rate regularly falls below the discount rate over this period.

Appendix B

Data-Driven Natural Real Rate Estimation Details

In this appendix, we list each variable used in our factor analysis. In addition, we also provide the source for each variable along with any transformations made to the variables. All variables that are available daily or monthly are first averaged to a quarterly frequency before further calculations. The data we use can be generally classified into one of 10 categories:

Real interest rates

- Real long-term interest rate: The yield on the 10-year constant-maturity U.S. Treasury security (BOG) minus the median SPF forecast for 10-year-ahead CPI inflation (SPF).
- Real federal funds rate: The nominal effective federal funds rate (BOG) minus the year-over-year percent change in the CPI inflation rate (BLS).
- Long-term inflation expectations: The median forecast for 10-year-ahead CPI inflation (SPF).

Real trend growth

- The quarterly year-over-year percent change in potential GDP (CBO).

Real economic activity

- The year-over-year percent change in real output per hour in the nonfarm business sector (BLS).
- The year-over-year percent change in aggregate weekly hours of production and nonsupervisory employees (BLS).
- The year-over-year percent change in the civilian labor force (BLS).
- LMCI: Activity (KC Fed)
- LMCI: Momentum (KC Fed)

Uncertainty

- Economic Policy Uncertainty Index (Baker, Bloom, and Davis)
- Economic Policy Uncertainty Index: Tax Code Expirations sub index (Baker, Bloom, and Davis)

Demographics

- The year-over-year percent change in the civilian population ages 16–64 (BLS).
- The 16–64 civilian population divided by the civilian population (BLS).
- The year-over-year percent change in the number of households (Commerce Department).

Asset prices

- The year-over-year percent change in the market value of credit outstanding to the nonfinancial sector (BIS) minus the year-over-year percent change in the CPI inflation rate (BLS).
- The year-over-year percent change in the S&P CoreLogic Case-Shiller Home Price Index (S&P) minus the year-over-year percent change in the CPI inflation rate (BLS).
- The cyclically adjusted price to earnings ratio for the S&P 500 (Robert Shiller).

Supply and demand for loans

- Net percentage of domestic respondents tightening standards for C&I loans to small firms (SLOOS).
- Net percentage of domestic respondents reporting stronger demand for consumer loans (SLOOS).

Financial market conditions

- Federal Reserve Bank of Kansas City Financial Stress Index.
- Risk premium: The difference between Moody's index of BAA corporate bonds (Moody's) and the 10-year constant-maturity U.S. Treasury security (BOG).
- Term premium: The estimate for the 10-year U.S. Treasury security (Adrian, Crump, and Moench 2013a).

Government regulation

- Percentage of firms reporting government regulation as their single most important problem (NFIB).

Global savings glut

- U.S. current account as a share of GDP (BEA).

All series are obtained from Haver Analytics. The natural rate factor is the first principle component of the standardized version of these 24 variables.

Endnotes

[1]Gilchrist and Zakrajšek (2013) use a different estimation approach but also find that QE announcements that lowered yields on government bonds led to a reduction in the overall level of credit risk in the economy. In addition, Hamilton and Wu find that shifting the composition of the FOMC's balance sheet toward longer-maturity Treasury securities could lower term and risk premiums using a term-structure model.

[2]In a recent paper, Carlstrom, Fuerst, and Paustian more carefully model the theoretical underpinnings of the term premium and find the same normative prescription for monetary policy makers: changes in the term premium should be offset by changes in policy rates.

[3]Doh presents a careful overview of the arguments for and against central banks counteracting swings in asset prices, including risk spreads.

[4]Since the slope of the yield curve is composed of the term premium and the difference between expected future short-term rates and current short-term rates, this finding is consistent with the stylized fact that a downward sloping (inverted) yield curve is a harbinger of a recession.

[5]The real effective federal funds rate is also unobservable, since nominal interest rates have to be adjusted for inflation expectations (which are themselves not readily observable). However, following Laubach and Williams, we proxy inflation expectations using, at each point in time, a statistical forecast of inflation over the next year. Therefore, our estimation treats the real effective federal funds rate as a known quantity.

[6]The term "accelerationist" is used to describe this relationship, because a positive output gap is associated with rising inflation and hence an accelerating price level.

[7]We use Adrian, Crump, and Moench's (2013) estimate of the term premium, rather than Kim and Wright's estimate, because the model estimation begins in 1962.

[8]The estimation procedure pegs the values of σ_3 and σ_5 following Laubach and Williams. More details are available in Appendix A.

[9]The standard errors in the equation for the natural real rate should be interpreted with caution. In particular, since z_t is non-stationary (follows a random walk), spurious correlations could be driving the results (Granger and Newbold; Laubach and Williams).

[10]The p-value for the likelihood ratio test comparing our preferred model with the model without bond premiums suggests that removing bond premiums does not alter the fit by a statistically significant amount. However, if we specify the model with a single parameter governing the effects of bond premiums by restricting c_{tp} to equal c_{rp}, a restriction that cannot be rejected by the data, then

we can easily reject the model that excludes bond premiums with a high degree of statistical significance.

[11]The VIX measures the implied uncertainty over the stock market during the next 30 days according to options prices.

[12]The April 2013 Survey of Primary Dealers suggests financial market participants expected the FOMC to reduce its pace of asset purchases sometime in 2014. However, by July, the expected timing of tapering had been pulled forward to September 2013.

[13]Nie (2016) provides a summary of this expected transition and potential outcomes for Chinese growth.

[14]While risk premiums continued to rise in the first quarter of 2016, term-premiums fell as well that quarter due to concerns of the growth prospects for major emerging market economies which resulted in demand for safe U.S. Treasuries. These safe-haven flows helped to prevent a further decline in the natural rate at the start of 2016.

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Crowdedness, Centralized Employment, and Multifamily Home Construction

By Jordan Rappaport

After the 2007–08 financial crisis, both multifamily and single-family home construction collapsed. But multifamily home construction, unlike single-family construction, has since rebounded strongly. During the first half of 2016, multifamily home starts rose to their highest level since the late 1980s. However, this recent aggregate strength varied considerably across metropolitan areas. While multifamily construction boomed in several metros, such as Austin, TX; Charlotte, NC; Nashville, TN; and Des Moines, IA; it remained weak in many others, such as San Antonio, TX; Pittsburgh, PA; Memphis, TN; and Chicago, IL.

In this article, I examine potential drivers behind the recent variation in multifamily construction and find that factors related to population, population density, and centralized employment played important roles. More specifically, I find multifamily construction was stronger in metropolitan areas that had lower average population density, one or two neighborhoods with especially high population density relative to other neighborhoods, and relatively similar population density across remaining neighborhoods. I also find that multifamily construction was stronger in metropolitan areas with larger populations and in those with employment more concentrated in the city center. These relationships

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appear to primarily capture differences in metros' productivity, urban amenities, and availability of land for development.

Section I describes the variation in recent multifamily construction across metropolitan areas, including its relationship to the variation in single-family construction and population growth. Section II documents and interprets multifamily construction's correlations with metropolitan population, population density, and centralized employment. Section III highlights how multifamily construction's relationships with population, population density, and centralized employment differ in the city and suburban portions of metros.

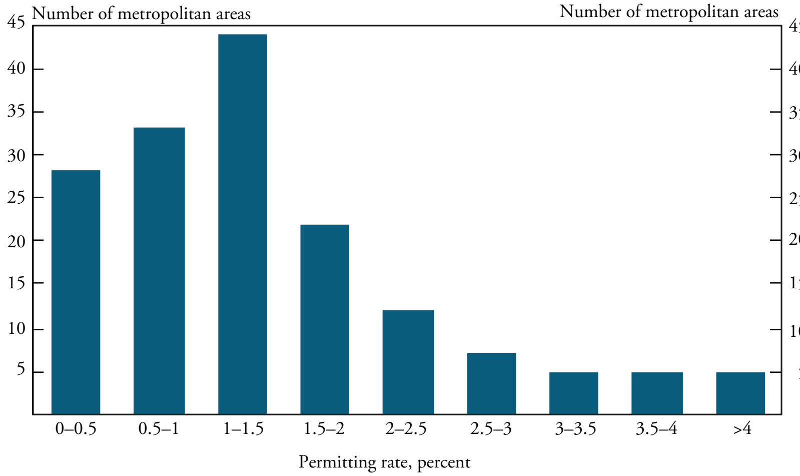
I. The Varying Strength of Multifamily Construction

To compare the strength of multifamily construction across metropolitan areas of different sizes and with different compositions of multifamily and single-family housing, I measure the rate of multifamily construction as the ratio of permits for new multifamily home units (specifically, individual apartments) to existing multifamily home units. Most places in the United States require a permit to construct a new house or apartment, and the Census Bureau conducts an annual census of the more than 20,000 local jurisdictions that issue such permits.[1] I calculate the number of multifamily permits issued in each metro during 2013–15 by summing the number of permits issued for home units in residential structures with five or more units. For each metro, I then divide average annual permits by the number of homes in structures with five or more units in 2010. The resulting multifamily permitting rate during 2013–15 can be interpreted as an average annual rate of gross investment.

To keep the analysis manageable, I limit the data set to metropolitan areas with a 2010 population of at least 250,000. I also exclude metros with a large number of college students relative to the total population, as college enrollment appears to drive especially strong multifamily permitting. The resulting data set includes 161 metros.[2]

Chart 1 shows that the multifamily permitting rate during 2013–15 varied considerably in strength across these metropolitan areas. In 28 metros, multifamily permitting plodded along at a less than 0.5 percent annual rate. But in 15 other metros, permitting boomed at an annual rate of more than 3 percent.[3]

Chart 1
Distribution of Multifamily Permitting Rates, 2013–15



Notes: The multifamily permitting rate is calculated as the average annual number of permits during 2013–15 for housing units in structures with five or more housing units divided by the number of such units in 2010. The distribution is over the 161 metro areas with populations over 250,000 in 2010 for which I could calculate the number of permits excluding metropolitan areas with less than 10,000 multifamily units in 2010 and excluding those with college student enrollment to population ratios in 2010 above 10 percent. The mean and standard deviation of the multifamily permitting rate for the included metros are 1.4 and 1.0 percent, respectively.
Sources: Census Bureau and author's calculations.

The similarities among the 15 booming metros are not obvious (Table 1). They are located throughout the country—in the South, Midwest, and West. They range in population from under 400,000 people to almost 6 million. And they specialize in a wide range of industries, including high tech (Austin, TX, and San Jose, CA), leisure (Charleston, SC, and Orlando, FL), financial services (Charlotte, NC, and Des Moines, IA), energy (Houston, TX), and manufacturing (Wilmington, NC, and Springfield, MO).

But these metros—and metros with strong multifamily construction more broadly—do share two features: strong single-family construction and fast population growth. Austin, for example, had the highest rate of multifamily permitting during 2013–15, the third highest rate of single-family permitting during 2013–15, and the fastest rate of population growth from 2010 to 2015 (see Table A-3). These positive relationships among multifamily construction, single-family construction, and population growth are perhaps unsurprising: multifamily and single-family construction are driven by many of the same factors, including population growth. In addition, strong population

Table 1

15 Metropolitan Areas with the Strongest 2013–15 Rate of Multifamily Permitting

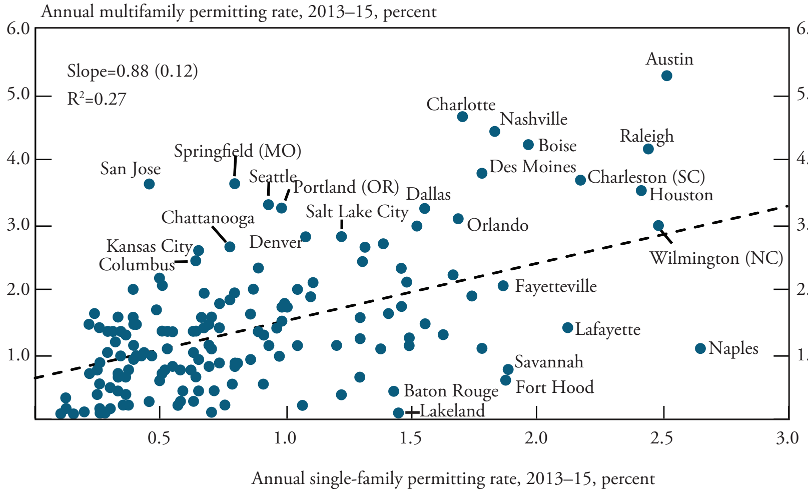
Rank	Metro	Multifamily permitting rate (percent)	Average annual multi-family permits (2013–15)	Multifamily housing units (2010)	Population (2010)
1	Austin-Round Rock, TX	5.3	9,900	186,000	1,716,000
2	Charlotte-Gastonia-Concord, NC-SC	4.7	6,200	134,000	1,758,000
3	Nashville-Davidson-Murfreesboro, TN	4.5	5,400	121,000	1,590,000
4	Boise City-Nampa, ID	4.2	1,000	23,000	617,000
5	Raleigh-Cary, NC	4.2	3,500	85,000	1,130,000
6	Des Moines, IA	3.8	1,600	44,000	570,000
7	Charleston-North Charleston, SC	3.7	1,900	50,000	665,000
8	San Jose-Sunnyvale-Santa Clara, CA	3.6	5,900	161,000	1,837,000
9	Springfield, MO	3.6	900	26,000	437,000
10	Houston-Baytown-Sugar Land, TX	3.5	20,500	584,000	5,947,000
11	Seattle-Tacoma-Bellevue, WA	3.3	12,600	379,000	3,440,000
12	Dallas-Fort Worth-Arlington, TX	3.3	20,800	636,000	6,372,000
13	Portland-Vancouver-Beaverton, OR-WA	3.3	6,400	195,000	2,226,000
14	Orlando, FL	3.1	6,700	215,000	2,134,000
15	Wilmington, NC	3.0	800	26,000	362,000

Notes: Multifamily permitting rate is constructed as average annual permits to construct new multifamily units during 2013–15 divided by total existing multifamily housing units in 2010. Permits to convert existing structures to multifamily use are not included. Permit and housing unit numbers are rounded. Housing units are classified as multifamily if they are in structures with five or more units. A full ranking is included in Table A-2.

growth requires vigorous home construction, typically both single-family and multifamily.

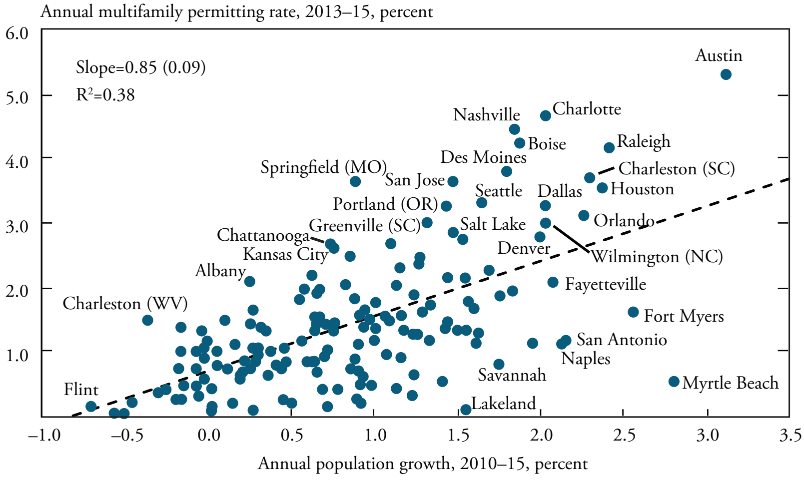
Chart 2 shows that multifamily construction tends to be strong where single-family construction is strong. The chart plots metros' multifamily permitting rate during 2013–15 against their single-family permitting rate during 2013–15.[4] The dotted line shows the best-fit linear relationship based on a simple regression. Its positive slope implies that a metro with a 1 percentage point higher single-family permitting rate than another metro is associated with a 0.88 percentage point higher multifamily permitting rate. The correlation is moderately tight, with the variation in metros' single-family permitting rates accounting for 27 percent of the variation in metros' multifamily permitting rates (as measured by the regression's R-squared).[5]

Chart 2
Multifamily Permitting versus Single-Family Permitting



Notes: Metros are labeled with the name of their largest city. Dashed line shows the best fit based on a linear regression. The corresponding coefficient, standard error, and fit are reported in the top left corner. The chart does not show Myrtle Beach, which had single-family and multifamily permitting rates of 3.5 percent and 0.6 percent, respectively.
Sources: Census Bureau and author's calculations.

Chart 3
Multifamily Permitting versus Population Growth



Notes: Metros are labeled with the name of their largest city. Dashed line shows the best fit based on a linear regression. The corresponding coefficient, standard error, and fit are reported in the top left corner.
Sources: Census Bureau and author's calculations.

However, several metropolitan areas have multifamily permitting considerably above or below the rate their single-family permitting predicts. For example, actual multifamily permitting considerably exceeded its predicted rate in San Jose, CA; Springfield, MO; Charlotte, NC; and Austin, TX. In contrast, actual multifamily permitting fell considerably short of its predicted rate in Lakeland, FL; Fort Hood, TX; Savannah, GA; and Naples, FL. Both exceptions suggest that the factors driving multifamily permitting can sometimes differ significantly from those driving single-family permitting.

Chart 3 shows that multifamily construction tends to be strong where population growth is strong. The chart plots metros' multifamily permitting rate during 2013–15 against their annual rate of population growth from 2010 to 2015. The positive slope of the best-fit linear relationship implies that a metro with population growth that is 1 percentage point higher than another metro is expected to have a multifamily permitting rate that is 0.85 percentage point higher. The correlation is moderately tight, with the variation in population growth across metros accounting for almost 40 percent of the variation in the multifamily permitting rate.[6]

However, much like the correlation with single-family permitting, several metros have actual multifamily permitting considerably above or below the rate their population growth predicts. For example, actual multifamily permitting considerably exceeded the permitting rate predicted by population growth in Charlotte, NC; Nashville, TN; and Springfield, MO. In contrast, actual multifamily permitting fell considerably short of predicted multifamily permitting in Myrtle Beach, SC, and Lakeland, FL. Rapid population growth in these metros was made possible by strong single-family construction and, possibly, the re-occupancy of previously vacant single-family and multifamily housing units.

II. The Types of Metropolitan Areas Where Multifamily Construction Has Been Strongest

Multifamily construction's positive relationships with single-family construction and population growth give only limited insight into what drove the recent boom. While the relationships suggest the boom was driven by more than just a shift in preferences toward living in apartments rather than houses, they fail to identify more fundamental similarities among metros with strong multifamily construction as well as the underlying forces behind them.

To get a better sense of the types of metros where multifamily construction has boomed, I examine multifamily construction's relationships with several measures of population density, population, and centralized employment. These characteristics evolve slowly over time, making it easier to identify the forces driving their relationships with multifamily construction. In addition, I show that several of these relationships are also shared by single-family construction and population growth, suggesting similar forces are driving them.

Metropolitan population density

Population density, a measure of crowdedness, varies considerably within metropolitan areas. In metros with a population of at least 500,000 in 2010, the most-crowded census tract had, on average, a population density 60 times that of the least-crowded census tract within the non-rural portion of the metro.[7] In the New York City, Chicago, and San Francisco metros, this ratio exceeded 300. When the rural portions of metropolitan areas are included, this ratio is multiplied manyfold. Consequently, raw measures of average population density that divide total metro population by total land area can be highly misleading. For example, measured this way, the average population density of the Las Vegas metro in 2010 was just 250 persons per square mile. But this masks the fact that 90 percent of the Las Vegas metro's population lived in a census tract with a density of at least 1,500 persons per square mile.

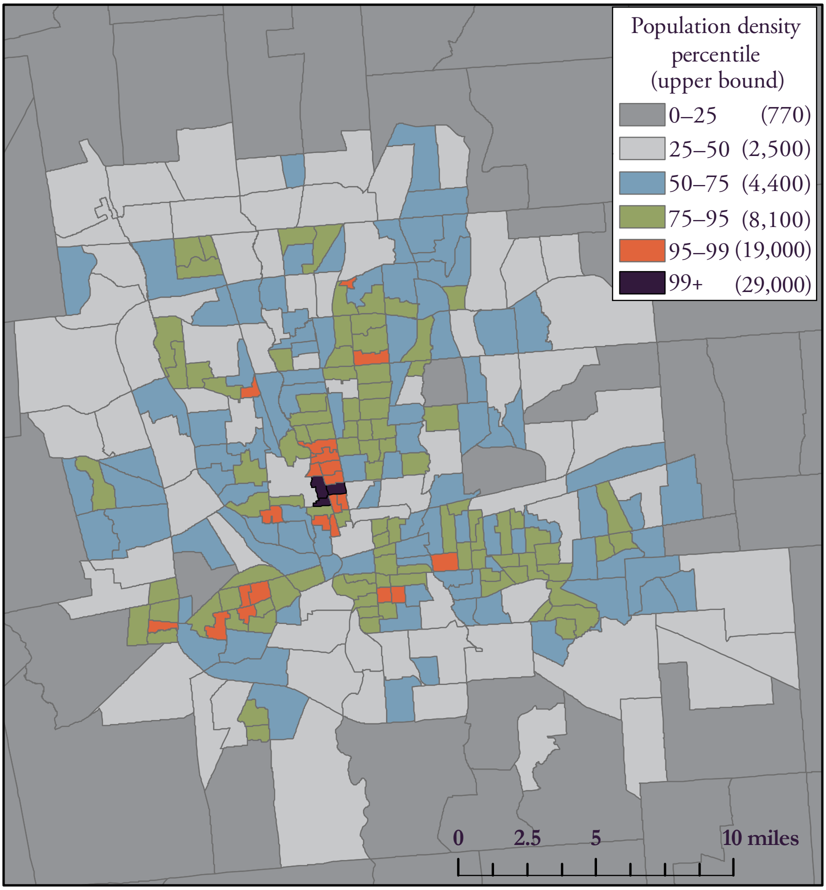
A more meaningful measure of average metropolitan population density is its median or 50th percentile density—that is, the tract density at or below which at least 50 percent of a metro's population lives.[8] For example, Las Vegas's median density in 2010 was 6,200 persons per square mile: half of its population lived in census tracts at or below this density, and half lived in census tracts at or above this density.

Multifamily construction's relationship with population density, however, is not just with median density but rather with the entire distribution of population density within metropolitan areas.[9] I jointly measure this internal distribution by three characteristics: median (50th percentile) population density, the increase from the log of 50th percentile density to the log of 95th percentile density, and the increase from the log of 95th percentile density to the log of 99th percentile density. The increase from the 50th percentile to the 95th percentile, or 95th/50th percentile density, captures how steeply population density increases across the more crowded tracts within a metropolitan area. This change in log density is proportional to the ratio of 95th percentile to 50th percentile density, which ranged from an average of 2 (among the 10 metros in which it was lowest in 2010) to an average of 15 (among the 10 metros in which it was highest). Analogously, 99th/95th percentile density captures how steeply population density increases across the *most* crowded tracts within a metropolitan area. The ratio of 99th percentile to 95th percentile density ranged from an average only slightly above 1 (almost no increase) to an average of almost 3.[10]

To give a sense of variation in density within a metro area, Map 1 shows the spatial distribution of population density in and around the settled portion of the Columbus metropolitan area in 2010. Census tracts with population density at or below the 25th percentile, shaded in dark gray, surround the settled portion, extending out to the border of the metro approximately 10 miles in each direction beyond what is shown. Most tracts in this range are made up primarily of agricultural land. Tracts with population density from the 25th to 50th percentiles, shaded light gray, are primarily located at the periphery of the settled portion, with a number of tracts near the center of Columbus also having low density in this range. Tracts with population density from the 50th to 75th percentiles and from the 75th to 95th percentiles, respectively shaded blue and green, make up most of the interior of the settled portion. Tracts with density from the 95th to 99th percentiles, shaded orange, are primarily located near the center of Columbus, with some also scattered among medium density tracts five to 10 miles from the center. Finally, the three tracts with the highest density, shaded purple, are located in the center, adjacent to each other and to tracts with population density nearly as high.

The measures I use to describe the internal distribution of population density can be thought of as taking place moving from the periphery of Columbus' settled portion to its center. The 95th/50th percentile density corresponds to the increase in density moving inward from the least-crowded blue tracts to the least-crowded orange tracts. The 99th/95th percentile density corresponds to the increase in

Map 1
Distribution of Population Density in Columbus, OH, 2010



Notes: Map shows the distribution of population density across census tracts in the Columbus, OH, metropolitan area. Values in parentheses are the upper-bound population densities of each percentile range (measured as persons per square mile). The Columbus metropolitan area as delineated by the OMB during the 2000s extends about 15 miles east and west of the displayed area and about 20 miles north and south. Almost all of the area not shown has a population density below the 25th percentile. Tracts with population density at the 25th percentile or higher account for 13 percent of the Columbus metro's total land area.
Sources: Census Bureau and author's calculations.

density moving inward from the least-crowded orange tracts to the least-crowded purple tract.

Table 2 reports the partial correlations of multifamily permitting with each of these three population density variables and with metro population. In other words, the table reports the correlation between

Table 2
Multifamily Permitting, Population, and Population Density

Explanatory variable	All metros (1)	Smaller metros (2)	Larger metros (3)
ln(population)	0.27** (0.11)	0.69 (0.43)	0.29 (0.18)
ln(median density)	−0.29* (0.16)	−0.11 (0.16)	−0.41* (0.24)
ln(95th percentile density)− ln(50th percentile density)	−0.69*** (0.16)	−0.33* (0.18)	−0.90*** (0.24)
ln(99th percentile density)− ln(95th percentile density)	1.42*** (0.33)	1.58*** (0.38)	1.36*** (0.47)
Observations	161	62	99
R^2	0.23	0.27	0.20
Adjusted R^2	0.21	0.22	0.17

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level
Notes: The dependant variable is the average annual rate of multifamily permitting during 2013–15. Population and population density are measured in 2010. Smaller metros are those with populations from 250,000 to 500,000. Larger metros are those with populations of at least 500,000. Regressions also include a constant. Standard errors are in parentheses.

multifamily permitting and each variable while controlling for variations in the other three variables. In addition to results using the full sample of 161 metropolitan areas, I include results from separate regressions that use only the smaller metros (those with populations from 250,000 to 500,000) and only the larger metros (those with populations above 500,000). Doing so allows me to capture underlying forces that may affect smaller and larger metros differently.

Multifamily permitting is positively correlated with metro population, especially among smaller metropolitan areas. The estimated coefficient from the regression using the full sample implies that a metro with population 1 log point higher than another, equivalent to a 2.7 times larger population, is expected to have a 0.27 percentage point higher multifamily permitting rate. This difference is economically significant, representing just over one-quarter of the standard deviation of the multifamily permitting rate across all metros. The correlation is more than twice as strong for small metros, as measured by the estimated coefficient.[11]

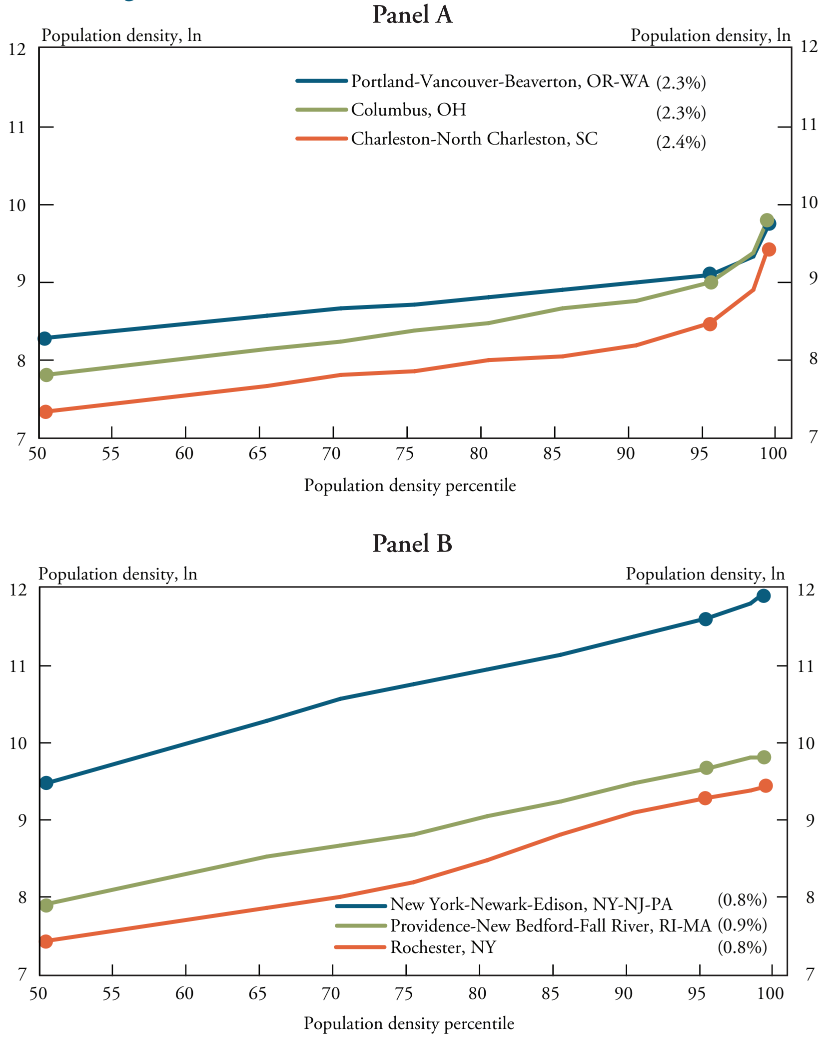
Taking account of its positive relationship with size, multifamily permitting is negatively correlated with median population density. This correlation is primarily driven by the larger metros in the sample. The negative coefficient on median density for larger metros is statistically and economically significant, implying that a metro with 1 log point higher median density than another is expected to have a 0.41 percentage point lower rate of multifamily permitting. This difference represents one-third of the standard deviation among the larger metros. In contrast, the coefficient for smaller metros is close to zero, suggesting that multifamily permitting and median population density are uncorrelated among metros with populations from 250,000 to 500,000. Importantly, multifamily permitting's negative partial correlation with median density holds only when controlling for population. Otherwise, the positive relationship with population masks the negative relationship with median density.

For both smaller and larger metros, multifamily permitting is negatively correlated with the increase in population density from the 50th to 95th percentiles and positively correlated with the increase in density from the 95th to 99th percentiles. In each of the three regressions, the negative coefficients on 95th/50th percentile density and positive coefficients on 99th/95th are statistically and economically significant. The negative partial correlation with 95th/50th percentile density is considerably stronger for the larger metros. A large metro with a 1 log point larger increase in density from the 50th to 95th percentile is expected to have a 0.90 percentage point lower multifamily permitting rate.

To illustrate these relationships, Panel A of Chart 4 shows distributions of population density associated with relatively strong multifamily permitting. Specifically, it shows the density profiles of Portland, OR; Columbus, OH; and Charleston, SC. Each metro has a relatively modest increase in population density from the 50th to 95th percentiles and a relatively steep increase in population density from the 95th to 99th percentiles. Based on the coefficients from the regression using the larger metros, a small 95th/50th percentile density and large 99th/95th percentile density contribute to relatively high rates of multifamily permitting. In addition, the higher median population densities of Portland and Columbus compared with Charleston (indicated by the height of their 50th percentile density markers) are associated with weaker multifamily permitting. However, this negative contribution from median population density is mostly offset by a positive contribution from the larger populations of Portland and Columbus, leaving the predicted multifamily permitting rates for all three metros a few tenths above 2 percent.

Chart 4

Distribution of Population Density and Predicted Multifamily Permitting



Notes: Numbers in parentheses are the predicted mulitfamily permitting rates based on each metro's population and population density multiplied by the corresponding coefficients for the regression using only larger metros reported in column 3 of Table 2. Markers indicate log population density at the 50th, 95th, and 99th percentiles.
Sources: Census Bureau and author's calculations.

Panel B of Chart 4 shows density profiles associated with relatively weak multifamily permitting. In the New York City, NY; Providence, RI; and Rochester, NY, metros, population density increases rather steeply from the 50th to 95th percentiles and increases moderately relative to other metros from the 95th to 99th percentiles. Based on the coefficients from the regression using the larger metros, a large 95th/50th percentile density and small 99th/95th percentile density contribute to relatively weak multifamily permitting. The negative contribution to permitting from New York City's higher median population density relative to Providence and Rochester is mostly offset by a positive contribution from its larger population, leaving the predicted multifamily permitting rate for all three metros a few tenths below 1 percent. Overall, differences in the internal distributions of population density predict 1.5 percentage points lower multifamily permitting rates for the New York City, Providence, and Rochester metros than for the Portland, Columbus, and Charleston metros.

Centralized employment

Another characteristic that varies considerably across metropolitan areas is the extent to which jobs are concentrated in a central location rather than spread more diffusely across the metro. More centralized employment may boost demand for nearby home construction among workers seeking shorter commute times. Recent research shows that more centralized employment may also increase firms' productivity, thereby boosting population growth and construction throughout a metropolitan area (Brinkman, Coen-Pirani, and Sieg).

I measure the centralization of employment by the share of employment in 2000 that took place in each metro's central business district (CBD), defined to encompass the traditional "downtown" of the largest city within a metropolitan area as well as nearby neighborhoods with dense employment.[12] For the larger metros in my sample, the CBD share of employment ranged from an average of less than 2 percent (among the 10 metros where it was lowest) to an average of 25 percent (among the 10 metros where it was highest).

Table 3 reports results from regressions of multifamily permitting, single-family permitting, and population growth on population, population density, and the CBD employment share. I limit the analysis

Table 3
Multifamily Permitting, Single-Family Permitting, and Population Growth

Explanatory variable	Multifamily permitting rate, 2013–15 average (1)	Single-family permitting rate, 2013–15 average (2)	Population growth rate, 2010–15 average (3)	Multifamily permitting rate, 2013–15 average (4)
ln(population)	0.25 (0.17)	0.09 (0.08)	0.16 (0.11)	0.08 (0.13)
ln(median density)	−0.56** (0.24)	−0.50*** (0.11)	−0.24* (0.15)	−0.30* (0.19)
ln(95th percentile density)–ln(50th percentile density)	−1.08*** (0.24)	−0.71*** (0.11)	−0.86*** (0.15)	−0.19 (0.22)
ln(99th percentile density)–ln(95th percentile density)	1.17** (0.46)	0.25 (0.21)	0.45 (0.28)	0.71** (0.36)
CBD share of employment	4.22*** (1.36)	1.38** (0.62)	1.71** (0.85)	2.46** (1.07)
Population growth rate (2010–15 average)				1.03*** (0.13)
Observations	99	99	99	99
R^2	0.27	0.34	0.31	0.57
Adjusted R^2	0.24	0.31	0.27	0.54

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level
Notes: Regressions are for metropolitan areas with a population of at least 500,000. The dependent variable for each regression is listed in the top row. Permitting is the average annual rate during 2013–15. Population growth is the average annual rate during 2010–15. Regresssions also include a constant. Standard errors are in parentheses.

to the larger metros, as multifamily construction is uncorrelated with centralized employment among the smaller metros.[13]

The results from the baseline specification in column 1 show that multifamily permitting has a strong positive correlation with centralized employment. The estimated coefficient on the CBD employment share implies that a metro with a CBD employment share 10 percentage points higher than another metro, representing less than one standard deviation, is expected to have 0.4 percentage point higher multifamily permitting. For example, Las Vegas, NV; New York City, NY; and Des Moines, IA—which have CBD shares close to 30 percent—are expected to have 1 percentage point higher multifamily permitting rates than Los Angeles, CA; Oklahoma City, OK; and Tucson, AZ—which have CBD shares close to 7 percent. Controlling for the CBD share leaves multifamily permitting's partial correlations with population and density largely unaffected.

The baseline specification of centralized employment, together with population and the three measures of population density, does a fairly good job predicting the rate of multifamily construction in the larger metropolitan areas. Variation in the baseline variables accounts for more than one-quarter of the variation in multifamily permitting, as measured by the R-squared statistic.[14] Chart 5 plots each metro's actual 2013–15 multifamily permitting rate against its predicted value based on the baseline coefficients. Differences in actual versus predicted permitting, measured by the vertical distance of each dot to the dashed line, were driven by forces unrelated to the baseline characteristics. Austin, TX; Charlotte, NC; Nashville, TN; and Boise, ID, stand out as metros with actual multifamily permitting considerably above the rate the baseline variables predict. In a similar vein, Sacramento, CA, and New Orleans, LA, stand out as metros with actual multifamily permitting considerably below their predicted rates.

Importantly, the predictive power of population, population density, and centralized employment does not mean that their variations across metropolitan areas *caused* the variations in multifamily construction. A better interpretation is that underlying forces interacted with the varying characteristics to drive varying multifamily construction.

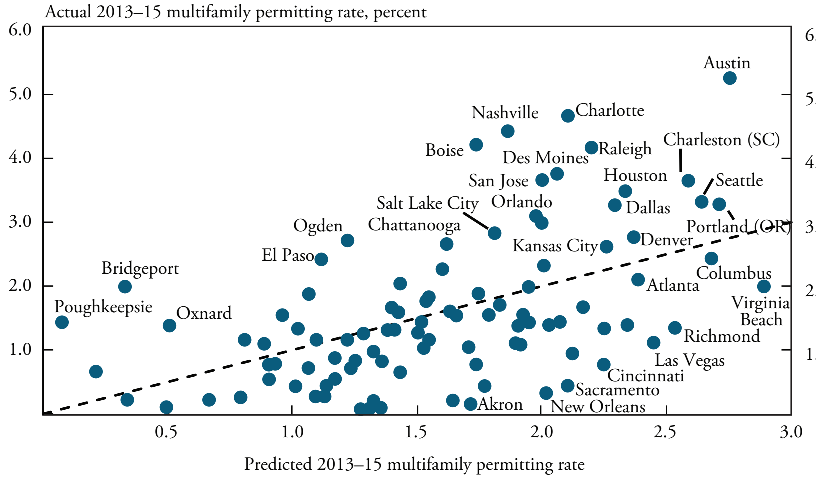
Underlying forces

Designing policies to shape, prepare for, and respond to multifamily housing development critically depends on identifying the forces driving multifamily construction's relationships with population, population density, and centralized employment. Single-family construction and population growth largely parallel multifamily construction's relationships with the baseline characteristic (Table 3, columns 2 and 3), suggesting that the forces driving the multifamily relationships also drive the single-family and population growth relationships. Most obviously, such forces may directly affect population growth, thereby indirectly affecting multifamily construction and single-family construction.

Multifamily permitting's positive relationship with population was likely driven indirectly (through the channel of population growth) by the higher productivity and greater amenities of many larger metros.[15] Considerable research has documented a positive relationship between productivity and metro size. Larger size, as measured by either

Chart 5

Actual versus Predicted Multifamily Permitting in Larger Metropolitan Areas



Notes: Metros are labeled with the name of their largest city. The horizontal axis measures the multifamily permitting rate predicted by the regression reported in column 1 of Table 3. Dashed line shows where the actual permitting rate equals the rate predicted by the regression.
Sources: Census Bureau and author's calculations.

employment or population, can increase firms' productivity as well as the wages they pay by allowing for better matching between workers and firms, more specialized professional support services, more innovation from collaboration among firms that sell to each other, and greater competition among firms in the same industry (Duranton and Puga; Combes and Gobillion). Larger size also increases a metro's amenities—for example, by allowing for a greater variety of restaurants, live entertainment, outdoor activities, education opportunities, and places of worship (Glaeser, Kolko, and Saiz; Diamond).[16] Conversely, many metros became large due to exogenous sources of high productivity and amenities, such as a central location and nice weather (Rappaport 2008b).

Multifamily permitting's positive relationship with centralized employment was also likely driven in part (through the channel of population growth) by higher firm productivity and the accompanying higher wages. Much of the productivity benefit of size is thought to occur by firms interacting with each other in close proximity, and a considerable portion of the higher average productivity of firms located in larger metros reflects the higher productivity of firms located in the CBD itself (Rosenthal and Strange; Brinkman, Coen-Pirani, and Sieg). Firms located elsewhere in the metro may also benefit from interactions with high-productivity firms in the CBD—for example, by working with CBD firms that offer specialized professional services (Brinkman). Notably, single-family construction, which typically takes place away from CBDs, is also positively related to centralized employment. While this relationship may seem less intuitive, it is consistent with the conclusion that permitting's positive relationship with centralized employment works through the channel of population growth; specifically, by attracting residents from other metros rather than from elsewhere in the same metro.

At the same time, some of the forces driving multifamily permitting's positive relationship with centralized employment appear to be doing so by attracting residents who live elsewhere in the same metro to move near the CBD, possibly to cut commute times.[17] In particular, multifamily permitting remains positively related with CBD employment even after taking account of its strong positive relationship with population growth (Table 3, column 4). Adding population growth to the baseline regression is meant to capture any forces that operate by attracting people from other metros, and the estimated coefficient on it, which is close to 1, implies that multifamily permitting responds approximately proportionally to population inflows. The estimated coefficients on the baseline characteristics in this regression should thus primarily capture forces that shift demand between single-family and multifamily housing as well as among different neighborhoods within the same metro.

Multifamily permitting's negative partial correlation with median population density was likely driven by the supply of land suitable for new residential development. Metros with higher average population density typically have higher average land prices, requiring developers to charge higher average rents and sales prices for newly constructed units. Controlling for other metropolitan characteristics, higher rents and prices dissuade people from moving into more crowded metros, depressing population growth and thereby multifamily construction. Bolstering this interpretation, single-family permitting is also negatively related to median density. Higher average land prices make newly constructed homes less affordable for existing residents, which may explain the portions of multifamily and single-family constructions' negative correlations with median density that remain after controlling for population growth.[18]

Multifamily permitting's negative relationship with 95th/50th percentile density was likely driven by a similar supply consideration. A steeper increase in density from the 50th to 90th percentile is associated with a steeper increase in land prices; this in turn likely boosts rents for newly constructed multifamily units in high-density neighborhoods relative to moderate-density neighborhoods. The resulting negative effect on multifamily permitting appears to arise solely from discouraging population inflows (multifamily permitting is uncorrelated with 95th/50th percentile density when controlling for population growth). To the extent that individuals considering moving to a metro prefer to live in denser neighborhoods, higher relative rents in these neighborhoods may push down population growth for the entire metro area. Consistent with this interpretation, multifamily permitting and population growth across larger metros were also negatively related to the increase in density from the 25th to the 50th percentile (not shown).

Conversely, a smaller increase in density from the 50th to the 95th percentiles may make it possible to construct less expensive multifamily units close to high-density neighborhoods. A smaller increase in 95th/50th percentile density partly reflects pockets of lightly used land in census tracts that otherwise have relatively high population density. Land in these pockets—typically occupied by small businesses, surface parking, vacant buildings, and undeveloped lots—is likely to cost less than land elsewhere within the same census tract.[19]

Lastly, multifamily permitting's positive relationship with the increase in density from the 95th to the 99th percentiles was likely driven by the urban amenities often found near spikes in population density. Urban amenities—such as pedestrian access to varied restaurants, cafes, bars, and small retailers—increase housing demand nearby. Consistent with this interpretation, recent research finds that young professionals have been increasingly choosing to live near CBDs with high levels of urban amenities (Couture and Handbury; Baum-Snow and Hartley). This attraction to urban amenities appears to primarily draw residents from elsewhere in the same metro. Specifically, the coefficient on 99th/95th percentile density is only moderately smaller when controlling for population growth (column 4 versus column 1). However, urban amenities are also likely to attract population inflows from other metros. The coefficient on 99th/95th percentile density in the population regression is relatively large and differs from zero at the 12 percent level, only slightly above the 10 percent benchmark for rejecting that population growth is uncorrelated with 99th/95th percentile density.

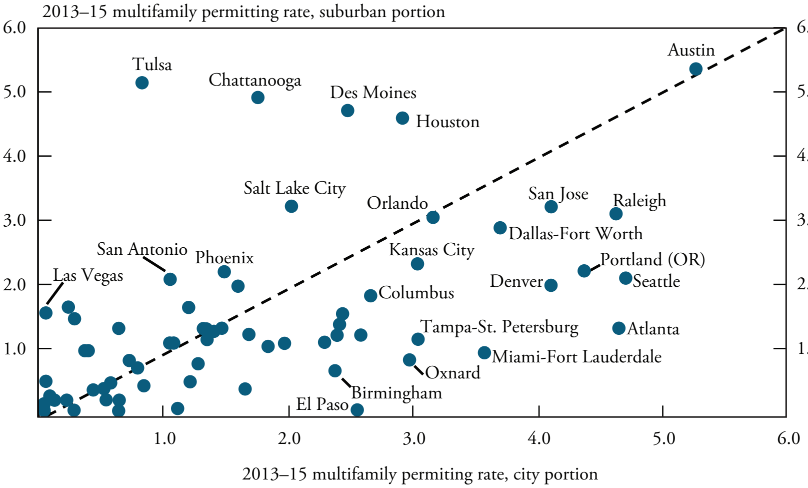
III. Multifamily Construction in Cities and Suburbs

The increasing popularity of living near CBDs with high amenities suggests that the forces driving construction in the city and suburban portions of metropolitan areas may differ. Indeed, separate regressions for each of these portions show that city and suburban multifamily permitting's relationships with 99th/95th percentile density differ significantly. However, city and suburban multifamily permitting have relatively similar relationships with three of the four other baseline characteristics: population density, 95th/50th percentile density, and the CBD employment share. Furthermore, their apparent difference with respect to the final baseline characteristic, population, may be misleading.

To capture potential differences between city and suburban construction, I calculate separate permitting rates for the city and suburban portions of 67 of the larger metropolitan areas (those whose largest municipality had a population of at least 150,000 in 2000 and for which I am able to distinguish the location of permits). The city portion of each metro includes its largest municipality and, in a few cases, its second- and third-largest ones. For example, I include St. Paul in the city portion of the Minneapolis metro and Tacoma and Bellevue in the city portion of the Seattle metro. The remainder of each metro constitutes its suburban portion.[20]

Recent multifamily permitting was, on average, equally strong in the city and suburban portions of these metros. Chart 6 plots the 2013–15 rates of multifamily permitting in the suburbs against their rates in the cities. The dashed line delineates where the suburban and city permitting rates are equal. Metros above the line had stronger suburban permitting; those below the line had stronger city permitting. In almost two-thirds of the 67 metros, the city and suburban rates were within 1 percentage point of each other. Among the remaining metros, slightly more experienced stronger multifamily permitting in the city. Atlanta had especially strong multifamily permitting in the city relative to the

Chart 6
Suburban versus City Multifamily Permitting



Notes: Metros are labeled with the name of their largest city. Dashed line shows where the multifamily permitting rates in the city portion and suburban portion of the metro are equal. Below the dashed line, the city permitting rate exceeds the suburban permitting rate. Chart does not show Boise, ID, which had respective permitting rates of 2.5 percent and 8.7 percent in the city and suburban portions.
Sources: Census Bureau and author's calculations.

suburbs; Tulsa and Chattanooga had especially strong multifamily permitting in the suburbs relative to the city.[21]

Table 4 reports results from regressions of multifamily and single-family permitting in the city and suburban portions of metros on metropolitan population, metropolitan population density, and metropolitan centralized employment.[22] As with the analysis of underlying forces in the previous section, the single-family partial correlations help interpret the multifamily ones.

The most important difference between the city and suburban multifamily regressions is that city permitting's positive relationship with 99th/95th percentile density is large and statistically significant whereas suburban permitting's positive relationship with 99th/95th percentile density is small and not statistically significant. This contrast bolsters the interpretation that spikes in 99th/95th density reflect urban amenities that attract people to live nearby.

Another difference between the two multifamily regressions is that city permitting has a positive, statistically significant relationship with metro population, while suburban permitting appears largely unrelated

Table 4

Multifamily and Single-Family Permitting in Cities and Suburbs

Explanatory variable	Multifamily permitting rate, 2013–15 average		Single-family permitting rate, 2013–15 average	
	City portion (1)	Suburban portion (2)	Primary city portion (3)	Suburban portion (4)
ln(population)	0.51** (0.26)	0.15 (0.32)	0.06 (0.09)	0.14 (0.14)
ln(median density)	−0.53 (0.36)	−0.97** (0.44)	−0.24* (0.13)	−0.65*** (0.19)
ln(95th percentile density)− ln(50th percentile density)	−1.19*** (0.43)	−1.51*** (0.53)	−0.60*** (0.15)	−0.97*** (0.23)
ln(99th percentile density)− ln(95th percentile density)	1.53** (0.62)	0.39 (0.76)	0.08 (0.22)	0.08 (0.33)
CBD share of employment	4.63** (2.10)	7.54*** (2.60)	0.38 (0.75)	2.82** (1.12)
Observations	67	67	67	67
R^2	0.33	0.21	0.21	0.29
Adjusted R^2	0.27	0.15	0.15	0.23

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level
Notes: The dependant variable for each column is listed in the top row. Endnote 24 describes the sensitivity of the suburban mulitfamily partial correlations with population and CBD employment and the suburban single-family partial correlation with CBD employment. Regressions also include a constant. Standard errors are in parentheses.

to population. However, the suburban estimate may be misleading, as it reflects permitting rates in just a handful of metros. An alternative methodology that is less sensitive to the exact sample of metros included in a regression finds a strong, positive relationship between suburban multifamily permitting and metro population.[23]

The remaining relationships of city and suburban multifamily permitting with 50th percentile density, 95th/50th percentile density, and CBD employment differ only moderately. For each of the three pairs, the magnitude of city permitting's partial correlation is moderately smaller than suburban permitting's partial correlation, but the difference is not statistically significant. More importantly, the large, positive partial correlations of suburban multifamily and single-family permitting with the CBD employment share bolster the interpretation that centralized employment boosts construction because of the higher productivity associated with it. Further bolstering this productivity interpretation, suburban population growth also has a strong positive relationship with CBD employment (not shown).[24]

IV. Conclusions

Multifamily home construction has rebounded strongly since the financial crisis, but some metropolitan areas have experienced stronger construction than others. I identify five characteristics that account for much of the variation in the recent strength of multifamily construction and discuss some underlying forces that may be driving the relationships. Specifically, I find that multifamily construction during 2013–15 was stronger in larger metropolitan areas, less crowded metropolitan areas, and in metropolitan areas with more centralized employment. Additionally, I find that multifamily construction was stronger in metropolitan areas where population density increased less steeply across the more crowded tracts and more steeply across the most crowded tracts.

Several underlying forces are likely driving these relationships. Productivity and amenities tend to be higher in larger metropolitan areas, attracting population inflows that boost multifamily construction. Productivity also tends to be higher in metropolitan areas with more centralized employment, attracting population inflows that boost multifamily home construction. More centralized employment may also allow nearby multifamily construction to better meet demand for shorter commute times. Urban amenities are likely to be high near spikes in population density, attracting residents from other parts of the metro as well as other metros, thereby boosting multifamily home construction. And lower average crowdedness and a less steep increase in population density across the more crowded tracts of a metro likely reflect more land available for development and lower land prices, boosting multifamily construction both directly and by attracting population inflows.

Understanding the forces driving multifamily construction is important in designing effective policies for metropolitan development. For example, policies that support centralized employment may boost productivity, attracting firms and residents from elsewhere in the country and thereby increasing residential construction throughout a metropolitan area. The resulting increase in metropolitan population may itself reinforce high productivity and amenities. Similarly, policies that promote urban amenities, whether in the city or suburbs, may attract young adults from elsewhere in the metro and from other metros, accelerating nearby multifamily development. In contrast, policies that seek to encourage multifamily development by cutting commute time without taking into account nearby urban amenities may prove unsuccessful.

Of course, the forces driving multifamily construction in the future may differ. Young adults primarily drove the recent rebound in multifamily construction, but members of the baby boom generation are increasingly likely to affect demand as they age (Rappaport 2015). In 2021, the leading edge of the baby boom turns 75, the age at which downsizing to multifamily homes typically picks up. For seniors who are retired, amenities are likely to be a more important consideration than productivity and wages in choosing where to live. Some amenities—such as nice weather and adjacency to the ocean and mountains—are clearly beyond the scope of public policy. But public policy may be able to help shape other amenities—for example, through zoning policies that support the development of neighborhoods that mix multifamily housing, urban amenities, assisted-living arrangements, and proximity to where seniors' children and grandchildren live.

In the longer term, technological innovation is also likely to affect multifamily home construction. The pace at which self-driving cars are adopted will be especially important. Self-driving cars are likely to ameliorate long commutes, potentially supporting single-family construction in peripheral suburbs. However, reduced parking needs due to self-driving cars may considerably benefit both multifamily construction in dense urban areas and centralized employment. While it is unclear which of these competing forces will dominate, both lower the broadly construed costs of living in larger metropolitan areas and will thus favor residential construction in larger metros over residential construction in smaller ones.

Appendix
Additional Tables

Table A-1
Metropolitan Summary Statistics

Explanatory variable	All metropolitan areas (161 metros with population of at least 250,000)			
	Mean	Standard deviation	Minimum	Maximum
Multifamily permitting rate (2013–15)	1.42	1.02	0	5.29
Single-family permitting rate (2013–15)	0.87	0.60	0.10	3.51
Population growth rate (2010–15)	0.85	0.74	–0.71	3.12
ln(population)	13.60	0.92	12.43	16.75
ln(median density)	7.51	0.70	5.62	9.49
ln(95th percentile density)–ln(50th percentile density)	1.39	0.52	0.60	3.03
ln(99th percentile density)–ln(95th percentile density)	0.38	0.23	0.05	1.77
CBD share of employment (percent)	0.14	0.09	0	0.50
Population (2010)	1,391,040	2,202,287	251,133	18,897,109
50th percentile density (persons/square mile)	2,333	1,806	275	13,196
95th percentile density (persons/square mile)	9,426	10,561	1,737	113,988
99th percentile density (persons/square mile)	14,519	16,630	2,883	159,209
95th/50th percentile density	4.71	3.34	1.82	20.62
99th/95th percentile density	1.51	0.49	1.05	5.87
Multfamily permits (2013–15 average)	2,107	4,879	0	44,231
Single-family permits (2013–15 average)	3,045	4,358	88	36,611
Multifamily housing units (2010)	124,439	282,938	10,479	2,811,815
Single-family housing units (2010)	375,899	477,087	63,482	3,223,449
College and graduate enrollment	79,043	140,181	6,692	1,184,677
College and graduate enrollment to population (ratio)	0.059	0.013	0.027	0.096

Note: CBD share of employment is not available for three of the smaller metros.

Table A-1(continued)

Explanatory variable	Smaller metropolitan areas (62 metros with population 250,000–500,000)			
	Mean	Standard deviation	Minimum	Maximum
Multifamily permitting rate (2013–15)	1.15	0.71	0	3.62
Single-family permitting rate (2013–15)	0.86	0.68	0.10	3.51
Population growth rate (2010–15)	0.68	0.73	−0.71	2.80
ln(population)	12.78	0.20	12.43	13.11
ln(median density)	7.12	0.62	5.62	8.52
ln(95th percentile density)–ln(50th percentile density)	1.52	0.54	0.60	2.90
ln(99th percentile density)–ln(95th percentile density)	0.34	0.22	0.05	1.08
CBD share of employment (percent)	0.13	0.10	0	0.50
Population (2010)	362,816	70,288	251,133	494,593
50th percentile density (persons/square mile)	1,481	942	275	5,016
95th percentile density (persons/square mile)	6,680	4,777	1,737	27,611
99th percentile density (persons/square mile)	9,597	7,357	2,883	37,702
95th/50th percentile density	5.40	3.74	1.82	18.23
99th/95th percentile density	1.44	0.38	1.05	2.93
Multfamily permits (2013–15 average)	275	222	0	928
Single-family permits (2013–15 average)	953	719	88	3,433
Multifamily housing units (2010)	23,050	11,261	10,479	73,723
Single-family housing units (2010)	112,799	25,044	63,482	177,537
College and graduate enrollment	18,636	6,654	6,692	39,258
College and graduate enrollment to population (ratio)	0.06	0.014	0.027	0.096

Note: CBD share of employment is not available for three of the smaller metros.

Table A-1 (continued)

Explanatory variable	Larger metropolitan areas (99 metros with population of at least 500,000)			
	Mean	Standard deviation	Minimum	Maximum
Multifamily permitting rate (2013–15)	1.59	1.15	0.03	5.29
Single-family permitting rate (2013–15)	0.88	0.55	0.16	2.52
Population growth rate (2010–15)	0.96	0.73	–0.57	3.12
ln(population)	14.11	0.82	13.15	16.75
ln(median density)	7.76	0.63	5.76	9.49
ln(95th percentile density)–ln(50th percentile density)	1.30	0.50	0.63	3.03
ln(99th percentile density)–ln(95th percentile density)	0.41	0.24	0.10	1.77
CBD share of employment (percent)	0.14	0.08	0	0.48
Population (2010)	2,034,978	2,612,977	514,098	18,897,109
50th percentile density (persons/square mile)	2,867	2,006	316	13,196
95th percentile density (persons/square mile)	11,146	12,654	2,800	113,988
99th percentile density (persons/square mile)	17,601	19,822	3,250	159,209
95th/50th percentile density	4.28	3.00	1.87	20.62
99th/95th percentile density	1.56	0.54	1.10	5.87
Multfamily permits (2013–15 average)	3,254	5,948	8	44,231
Single-family permits (2013–15 average)	4,356	5,117	316	36,611
Multifamily housing units (2010)	187,934	346,475	15,874	2,811,815
Single-family housing units (2010)	540,668	547,725	143,141	3,223,449
College and graduate enrollment	116,874	168,229	12,539	1,184,677
College and graduate enrollment to population (ratio)	0.061	0.012	0.028	0.094

Note: CBD share of employment is not available for three of the smaller metros.

Table A-2
City and Suburban Summary Statistics

Explanatory variable	Mean	Standard deviation	Minimum	Maximum
Primary city portion of metropolitan area				
Multifamily permitting rate (2013–15)	1.75	1.37	0	5.26
Single-family permitting rate (2013–15)	0.47	0.45	0.01	1.84
Population growth rate (2010–15)	0.88	0.83	–0.97	2.69
Multfamily permits (2013–15 average)	1,719	2,462	0	11,144
Single-family permits (2013–15 average)	747	1,019	13	5,236
Multifamily housing units (2010)	76,504	84,377	9,018	466,872
Single-family housing units (2010)	139,727	104,759	17,989	455,631
Population (2010)	579,638	495,767	142,308	2,697,650
Suburban portion of metropolitan area				
Multifamily permitting rate (2013–15)	1.60	1.56	0	8.70
Single-family permitting rate (2013–15)	1.02	0.71	0.26	3.18
Population growth rate (2010–15)	1.01	0.73	–0.08	3.24
Multfamily permits (2013–15 average)	1,639	2,205	0	9,816
Single-family permits (2013–15 average)	4,329	5,082	272	31,375
Multifamily housing units (2010)	111,513	141,697	1,754	812,370
Single-family housing units (2010)	460,942	411,079	28,163	1,909,513
Population (2010)	1,583,919	1,477,705	151,953	6,773,707
Primary city share of metropolitan total				
Multfamily permits (2013–15 average)	0.50	0.26	0	1.00
Single-family permits (2013–15 average)	0.16	0.17	0.01	0.89
Multifamily housing units (2010)	0.48	0.21	0.13	0.96
Single-family housing units (2010)	0.28	0.16	0.05	0.85
Population (2010)	0.31	0.16	0.08	0.81
Metropolitan area characteristics				
ln(population)	14.29	0.76	13.15	16.06
ln(median density)	7.89	0.56	6.61	9.00
ln(95th percentile density)– ln(50th percentile density)	1.21	0.40	0.63	2.43
ln(99th percentile density)– ln(95th percentile density)	0.41	0.26	0.10	1.77
CBD share of employment (percent)*	0.15	0.07	0	0.31

Note: Sample comprises 67 metropolitan areas with populations of at least 500,000 that meet additional criteria described in the text.

Table A-2 (continued)

Explanatory variable	Mean	Standard deviation	Minimum	Maximum
Population	2,158,023	1,827,596	514,453	9,461,105
50th percentile density (person/square mile)	3,067	1,589	740	8,133
95th percentile density (person/square mile)	10,386	6,493	3,115	35,537
99th percentile density (person/square mile)	16,695	13,196	3,635	79,072
95th/50th percentile density	3.67	1.77	1.87	11.35
99th/95th percentile density	1.57	0.62	1.10	5.87

Note: Sample comprises 67 metropolitan areas with populations of at least 500,000 that meet additional criteria described in the text.

Table A-3

Multifamily Permitting by Metropolitan Area

	Multifamily housing				Single-family housing		Population growth	
Metropolitan area	Rank	Permit rate	Average annual permits	Housing units (2010)	Rank	Permit rate	Rank	Growth rate
Austin, TX	1	5.3	9,850	186,000	3	2.5	1	3.1
Charlotte, NC	2	4.7	6,220	134,000	17	1.7	12	2.0
Nashville, TN	3	4.5	5,380	121,000	13	1.8	17	1.9
Boise City, ID	4	4.2	960	23,000	9	2.0	16	1.9
Raleigh, NC	5	4.2	3,540	85,000	5	2.4	4	2.4
Des Moines, IA	6	3.8	1,650	44,000	14	1.8	19	1.8
Charleston, SC	7	3.7	1,850	50,000	7	2.2	6	2.3
San Jose, CA	8	3.6	5,850	161,000	116	0.5	34	1.5
Springfield, MO	9	3.6	930	26,000	70	0.8	77	0.9
Houston, TX	10	3.5	20,500	584,000	6	2.4	5	2.4
Seattle, WA	11	3.3	12,620	379,000	55	0.9	23	1.7
Dallas, TX	12	3.3	20,790	636,000	21	1.6	13	2.0
Portland, OR	13	3.3	6,370	195,000	52	1.0	38	1.4
Orlando, FL	14	3.1	6,690	215,000	18	1.7	7	2.3
Wilmington, NC	15	3.0	800	26,000	4	2.5	11	2.0
Greenville, SC	16	3.0	1,180	39,000	23	1.5	42	1.3
Salt Lake City, UT	17	2.8	2,270	80,000	39	1.2	33	1.5
Denver, CO	18	2.8	8,760	313,000	44	1.1	14	2.0
Ogden, UT	19	2.7	540	20,000	32	1.4	31	1.5
Chattanooga, TN-GA	20	2.7	760	28,000	72	0.8	87	0.7
Corpus Christi, TX	21	2.7	820	31,000	34	1.3	57	1.1
Kansas City, MO-KS	22	2.6	3,560	136,000	90	0.6	84	0.8
El Paso, TX	23	2.5	1,120	45,000	35	1.3	78	0.9
Columbus, OH	24	2.4	3,790	155,000	92	0.6	44	1.3
Huntsville, AL	25	2.4	570	24,000	28	1.5	45	1.3
Indianapolis, IN	26	2.3	3,010	130,000	61	0.9	54	1.1
McAllen, TX	27	2.3	460	20,000	19	1.7	22	1.7
Eugene, OR	28	2.2	500	23,000	111	0.5	101	0.6
Atlanta, GA	29	2.1	9,620	454,000	42	1.1	29	1.6
Clarksville, TN-KY	30	2.1	240	12,000	26	1.5	35	1.4
Fayetteville, AR	31	2.1	640	31,000	12	1.9	10	2.1

Notes: Metropolitan area column lists the largest city in each metro area. Permit rates and average annual permits are calculated during 2013–15. Population growth rates are calculated over 2010–15.

Table A-3 (continued)

	Multifamily housing				Single-family housing		Population growth	
Metropolitan area	Rank	Permit rate	Average annual permits	Housing units (2010)	Rank	Permit rate	Rank	Growth rate
Albany, NY	32	2.1	1,220	59,000	110	0.5	123	0.3
Omaha, NE	33	2.0	1,360	67,000	46	1.0	56	1.1
Spokane, WA	34	2.0	720	36,000	62	0.9	80	0.8
Bridgeport, CT	35	2.0	1,370	69,000	125	0.4	94	0.7
Virginia Beach, VA	36	2.0	2,560	129,000	67	0.8	104	0.6
Green Bay, WI	37	1.9	390	20,000	86	0.7	95	0.7
Sarasota, FL	38	1.9	1,520	80,000	16	1.7	18	1.8
Phoenix, AZ	39	1.9	6,460	343,000	43	1.1	20	1.8
Columbus, GA	40	1.9	370	20,000	73	0.8	47	1.2
Fayetteville, NC	41	1.8	400	22,000	49	1.0	106	0.5
Little Rock, AR	42	1.8	790	44,000	76	0.7	74	0.9
Colorado Springs, CO	43	1.8	770	43,000	27	1.5	27	1.6
Asheville, NC	44	1.8	330	18,000	48	1.0	61	1.0
Tampa, FL	45	1.7	5,060	292,000	51	1.0	40	1.3
Boston, MA-NH	46	1.7	7,480	447,000	113	0.5	66	1.0
Washington, DC	47	1.7	11,010	664,000	63	0.9	26	1.6
Trenton, NJ	48	1.6	480	30,000	154	0.2	122	0.3
Cape Coral, FL	49	1.6	1,340	83,000	31	1.4	3	2.6
San Diego, CA	50	1.6	5,280	328,000	123	0.4	43	1.3
New York, NY	51	1.6	44,230	2,812,000	138	0.3	99	0.6
Minneapolis, MN	52	1.6	4,720	300,000	79	0.7	60	1.1
Reno, NV	53	1.6	640	41,000	37	1.3	52	1.2
Louisville, KY-IN	54	1.6	1,340	86,000	87	0.7	93	0.7
Tulsa, OK	55	1.5	900	58,000	50	1.0	71	0.9
Charleston, WV	56	1.5	180	12,000	156	0.2	157	–0.4
Salem, OR	57	1.5	330	22,000	84	0.7	65	1.0
Columbia, SC	58	1.5	710	48,000	22	1.5	58	1.1
Poughkeepsie, NY	59	1.5	540	37,000	120	0.4	133	0.1
San Francisco, CA	60	1.5	7,170	494,000	121	0.4	36	1.4
Shreveport, LA	61	1.4	320	22,000	54	1.0	124	0.3
Greensboro, NC	62	1.4	780	54,000	85	0.7	83	0.8
Winston-Salem, NC	63	1.4	500	35,000	75	0.7	91	0.7
Lafayette, LA	64	1.4	220	16,000	8	2.1	37	1.4
Oxnard, CA	65	1.4	620	44,000	147	0.3	97	0.7

Notes: Metropolitan area column lists the largest city in each metro area. Permit rates and average annual permits are calculated during 2013–15. Population growth rates are calculated over 2010–15.

Table A-3 (continued)

	Multifamily housing				Single-family housing		Population growth	
Metropolitan area	Rank	Permit rate	Average annual permits	Housing units (2010)	Rank	Permit rate	Rank	Growth rate
Honolulu, HI	66	1.4	1,680	121,000	105	0.5	67	0.9
Birmingham, AL	67	1.4	990	72,000	97	0.6	116	0.3
Knoxville, TN	68	1.4	600	44,000	59	0.9	85	0.7
Norwich, CT	69	1.4	210	16,000	134	0.3	151	–0.2
Los Angeles, CA	70	1.4	19,570	1,439,000	140	0.3	81	0.8
Richmond, VA	71	1.4	1,180	86,000	60	0.9	62	1.0
Baltimore, MD	72	1.4	3,070	226,000	104	0.6	100	0.6
Montgomery, AL	73	1.4	270	20,000	93	0.6	144	0.0
Miami, FL	74	1.3	12,900	956,000	109	0.5	28	1.6
Santa Rosa, CA	75	1.3	320	24,000	144	0.3	86	0.7
Lexington, KY	76	1.3	510	38,000	57	0.9	51	1.2
Philadelphia, PA	77	1.3	5,270	399,000	131	0.4	115	0.3
Jacksonville, FL	78	1.3	1,520	116,000	20	1.6	32	1.5
Oklahoma City, OK	79	1.3	1,000	77,000	25	1.5	24	1.6
Riverside, CA	80	1.3	2,370	188,000	91	0.6	50	1.2
Pensacola, FL	81	1.3	340	27,000	38	1.3	46	1.3
Buffalo, NY	82	1.2	740	63,000	139	0.3	139	0.0
San Antonio, TX	83	1.2	1,750	149,000	47	1.0	8	2.2
Bakersfield, CA	84	1.2	290	25,000	56	0.9	63	1.0
Duluth, MN-WI	85	1.2	200	17,000	126	0.4	140	0.0
Olympia, WA	86	1.2	180	16,000	41	1.2	41	1.3
Harrisburg, PA	87	1.1	370	33,000	82	0.7	105	0.6
Augusta, GA	88	1.1	260	23,000	24	1.5	72	0.9
Naples, FL	89	1.1	820	74,000	2	2.7	9	2.1
Las Vegas, NV	90	1.1	2,380	214,000	33	1.4	25	1.6
St. Louis, MO-IL	91	1.1	1,840	167,000	106	0.5	130	0.2
Kennewick, WA	92	1.1	150	13,000	15	1.8	15	2.0
Allentown, PA-NJ	93	1.1	430	40,000	122	0.4	121	0.3
Albuquerque, NM	94	1.1	540	50,000	81	0.7	110	0.5
Atlantic City, NJ	95	1.1	240	22,000	117	0.4	142	0.0
Memphis, TN-MS-AR	96	1.1	1,000	94,000	96	0.6	117	0.3
South Bend, IN-MI	97	1.0	180	17,000	143	0.3	134	0.1
Hickory, NC	98	1.0	120	12,000	118	0.4	152	–0.2
Syracuse, NY	99	1.0	440	43,000	133	0.3	146	–0.1

Notes: Metropolitan area column lists the largest city in each metro area. Permit rates and average annual permits are calculated during 2013–15. Population growth rates are calculated over 2010–15.

Table A-3 (continued)

Metropolitan area	Multifamily housing				Single-family housing		Population growth	
	Rank	Permit rate	Average annual permits	Housing units (2010)	Rank	Permit rate	Rank	Growth rate
Hagerstown, MD	100	1.0	120	12,000	53	1.0	88	0.7
Roanoke, VA	101	1.0	210	21,000	119	0.4	113	0.4
Manchester, NH	102	1.0	300	30,000	114	0.5	118	0.3
Vallejo, CA	103	0.9	210	22,000	88	0.6	59	1.1
Bremerton, WA	104	0.9	130	14,000	64	0.9	90	0.7
Pittsburgh, PA	105	0.9	1,300	141,000	124	0.4	143	0.0
Stockton, CA	106	0.9	260	29,000	77	0.7	53	1.2
Beaumont, TX	107	0.9	180	21,000	65	0.8	119	0.3
Salinas, CA	108	0.9	210	24,000	148	0.3	76	0.9
Portland, ME	109	0.9	260	30,000	66	0.8	108	0.5
Cedar Rapids, IA	110	0.9	150	18,000	69	0.8	102	0.6
Tucson, AZ	111	0.8	650	76,000	68	0.8	103	0.6
Evansville, IN-KY	112	0.8	170	20,000	103	0.6	126	0.2
Fort Wayne, IN	113	0.8	220	26,000	83	0.7	98	0.6
Rochester, NY	114	0.8	550	68,000	127	0.4	135	0.0
Savannah, GA	115	0.8	200	25,000	10	1.9	21	1.8
Cincinnati, OH	116	0.8	1,250	158,000	107	0.5	112	0.4
Wichita, KS	117	0.8	250	32,000	101	0.6	111	0.4
Grand Rapids, MI	118	0.8	350	46,000	98	0.6	79	0.9
Erie, PA	119	0.8	110	15,000	152	0.3	153	–0.2
New Haven, CT	120	0.7	530	71,000	155	0.2	147	–0.1
Mobile, AL	121	0.7	160	22,000	108	0.5	132	0.1
Milwaukee, WI	122	0.7	1,070	145,000	136	0.3	125	0.3
Davenport, IA	123	0.7	160	23,000	129	0.4	127	0.2
Spartanburg, SC	124	0.7	80	12,000	36	1.3	73	0.9
Lancaster, PA	125	0.7	160	24,000	94	0.6	96	0.7
Chicago, IL	126	0.7	6,190	939,000	135	0.3	128	0.2
York, PA	127	0.6	90	14,000	112	0.5	114	0.4
Killeen, TX	128	0.6	110	18,000	11	1.9	48	1.2
Reading, PA	129	0.6	100	17,000	146	0.3	129	0.2
Fresno, CA	130	0.6	290	52,000	58	0.9	68	0.9
Hartford, CT	131	0.6	560	98,000	151	0.3	141	0.0
Port St. Lucie, FL	132	0.5	210	39,000	71	0.8	39	1.4

Notes: Metropolitan area column lists the largest city in each metro area. Permit rates and average annual permits are calculated during 2013–15. Population growth rates are calculated over 2010–15.

Table A-3 (continued)

Metropolitan area	Multifamily housing				Single-family housing		Population growth	
	Rank	Permit rate	Average annual permits	Housing units (2010)	Rank	Permit rate	Rank	Growth rate
Myrtle Beach, SC	133	0.5	310	59,000	1	3.5	2	2.8
Canton, OH	134	0.5	60	13,000	142	0.3	148	–0.1
Anchorage, AK	135	0.5	110	24,000	99	0.6	64	1.0
Toledo, OH	136	0.5	220	47,000	137	0.3	149	–0.1
Deltona, FL	137	0.5	200	44,000	78	0.7	69	0.9
Sacramento, CA	138	0.4	640	145,000	89	0.6	55	1.1
Baton Rouge, LA	139	0.4	190	43,000	30	1.4	92	0.7
Detroit, MI	140	0.4	1,240	291,000	130	0.4	137	0.0
Brownsville, TX	141	0.4	90	21,000	40	1.2	82	0.8
Utica, NY	142	0.4	60	14,000	153	0.2	155	–0.3
Huntington, WV	143	0.4	40	11,000	159	0.1	156	–0.3
New Orleans, LA	144	0.3	240	77,000	95	0.6	49	1.2
Peoria, IL	145	0.3	60	18,000	115	0.5	145	–0.1
Scranton, PA	146	0.3	50	19,000	100	0.6	154	–0.2
Jackson, MS	147	0.3	80	30,000	45	1.1	109	0.5
Palm Bay, FL	148	0.3	120	48,000	74	0.8	75	0.9
Cleveland, OH	149	0.3	440	173,000	132	0.4	150	–0.2
Providence, RI	150	0.2	260	117,000	128	0.4	131	0.2
Worcester, MA	151	0.2	120	54,000	102	0.6	107	0.5
Binghamton, NY	152	0.2	20	12,000	160	0.1	158	–0.5
Modesto, CA	153	0.2	30	16,000	150	0.3	70	0.9
Akron, OH	154	0.2	80	46,000	141	0.3	136	0.0
Flint, MI	155	0.1	40	27,000	157	0.2	161	–0.7
Ocala, FL	156	0.1	10	10,000	80	0.7	89	0.7
Springfield, MA	157	0.1	50	51,000	149	0.3	120	0.3
Lakeland, FL	158	0.1	20	25,000	29	1.4	30	1.5
Dayton, OH	159	0.1	40	52,000	145	0.3	138	0.0
Youngstown, OH	160	0.0	10	27,000	158	0.2	160	–0.6
Rockford, IL	161	0.0	0	18,000	161	0.1	159	–0.5

Notes: Metropolitan area column lists the largest city in each metro area. Permit rates and average annual permits are calculated during 2013–15. Population growth rates are calculated over 2010–15.

Table A-4
Multifamily Permitting in City and Suburban Portions of Metro Areas

Primary city	City portion				Suburban portion			
	Rank	Permitting rate (2013–15)	Average annual permits (2013–15)	Housing units (2010)	Rank	Permitting rate (2013–15)	Average annual permits (2013–15)	Housing units (2010)
Austin, TX	1	5.3	7,370	140,000	2	5.4	2,490	46,000
Seattle-Tacoma-Bellevue, WA	2	4.7	8,230	174,000	13	2.1	4,390	205,000
Atlanta. GA	3	4.7	4,970	107,000	32	1.3	4,650	347,000
Raleigh, NC	4	4.6	2,720	59,000	8	3.1	820	26,000
Portland-Vancouver, OR-WA	5	4.4	4,110	94,000	12	2.2	2,260	102,000
San Jose, CA	6	4.1	3,040	74,000	6	3.3	2,810	86,000
Miami-Fort Lauderdale, FL	7	3.6	5,140	144,000	46	1.0	7,760	812,000
Orlando, FL	8	3.2	1,780	56,000	9	3.1	4,920	159,000
Kansas City, MO	9	3.0	1,600	53,000	10	2.4	1,950	83,000
Tampa-St. Petersburg, FL	10	3.0	2,610	86,000	37	1.2	2,450	206,000
Oxnard, CA	11	3.0	350	12,000	48	0.8	270	32,000
Houston, TX	12	2.9	11,140	383,000	5	4.6	9,350	201,000
Columbus, OH	13	2.7	3,030	114,000	21	1.8	760	41,000
Boston-Cambridge, MA	14	2.6	3,800	147,000	36	1.2	3,690	300,000
El Paso, TX	15	2.6	1,120	44,000	66	0.0	0	2,000
Boise City, ID	21	2.5	420	17,000	1	8.7	540	6,000
Virginia Beach-Norfolk-Newport News, VA	22	2.4	1,450	60,000	25	1.6	1,100	70,000

Table A-4 (continued)

Primary city	City portion				Suburban portion			
	Rank	Permitting rate (2013–15)	Average annual permits (2013–15)	Housing units (2010)	Rank	Permitting rate (2013–15)	Average annual permits (2013–15)	Housing units (2010)
Washington, DC	23	2.4	3,750	155,000	27	1.4	7,260	509,000
Omaha, NE	24	2.4	1,090	45,000	34	1.3	270	22,000
Birmingham, AL	25	2.4	700	30,000	51	0.7	290	42,000
Minneapolis-St. Paul, MN	26	2.3	2,540	111,000	39	1.1	2,170	189,000
Salt Lake City, UT	27	2.0	530	26,000	7	3.2	1,740	54,000
San Diego, CA	28	2.0	3,640	185,000	41	1.1	1,640	143,000
Philadelphia, PA	29	1.8	2,230	122,000	43	1.1	3,040	278,000
Chattanooga, TN	30	1.7	350	20,000	4	4.9	410	8,000
San Francisco-Oakland, CA	31	1.7	3,920	231,000	35	1.2	3,250	262,000
Bakersfield, CA	32	1.7	250	15,000	57	0.4	40	10,000
Little Rock, AR	33	1.6	360	22,000	15	2.0	430	21,000
Phoenix, AZ	34	1.5	2,340	158,000	11	2.2	4,120	184,000
Greensboro, NC	35	1.5	580	40,000	31	1.3	190	14,000
Knoxville, TN	36	1.4	410	29,000	33	1.3	190	14,000
Oklahoma City, OK	37	1.3	670	50,000	38	1.2	330	28,000
Richmond, VA	38	1.3	430	32,000	29	1.4	750	55,000
Baltimore, MD	39	1.3	870	66,000	28	1.4	2,200	160,000
Pittsburgh, PA	40	1.3	460	36,000	49	0.8	840	105,000
Grand Rapids, MI	41	1.2	180	15,000	52	0.5	170	31,000

Table A-4 (continued)

Primary city	City portion				Suburban portion			
	Rank	Permitting rate (2013–15)	Average annual permits (2013–15)	Housing units (2010)	Rank	Permitting rate (2013–15)	Average annual permits (2013–15)	Housing units (2010)
Jacksonville, FL	42	1.2	1,040	87,000	23	1.7	480	29,000
Tucson, AZ	43	1.1	650	58,000	67	0.0	0	18,000
Albuquerque, NM	44	1.1	500	46,000	40	1.1	40	3,000
San Antonio, TX	45	1.0	1,370	132,000	14	2.1	370	17,000
St. Louis, MO-IL	46	1.0	430	41,000	42	1.1	1,400	125,000
Chicago, IL	47	0.9	3,990	467,000	55	0.5	2,210	472,000
Tulsa, OK	48	0.8	400	48,000	3	5.2	490	10,000
Wichita, KS	49	0.8	220	28,000	50	0.7	30	4,000
Rochester, NY	50	0.7	170	23,000	47	0.8	380	45,000
Toledo, OH	51	0.6	160	25,000	59	0.3	60	22,000
Stockton, CA	52	0.6	110	18,000	30	1.4	150	11,000
New Orleans, LA	53	0.6	210	34,000	64	0.1	30	43,000
Fresno, CA	54	0.6	220	37,000	53	0.5	80	14,000
Baton Rouge, LA	55	0.5	150	28,000	60	0.3	40	15,000
Sacramento, CA	56	0.5	220	44,000	56	0.4	420	101,000
Cincinnati, OH	57	0.4	210	54,000	45	1.0	1,040	105,000
Milwaukee, WI	58	0.4	230	62,000	44	1.0	840	83,000
Riverside-San Bernardino, CA	59	0.3	110	38,000	26	1.5	2,250	150,000
Modesto, CA	60	0.3	30	9,000	65	0.0	0	7,000

Table A-4 (continued)

Primary city	City portion				Suburban portion			
	Rank	Permitting rate (2013–15)	Average annual permits (2013–15)	Housing units (2010)	Rank	Permitting rate (2013–15)	Average annual permits (2013–15)	Housing units (2010)
Buffalo, NY	61	0.2	50	21,000	22	1.7	690	41,000
Worcester, MA	62	0.2	50	21,000	62	0.2	70	33,000
Providence, RI	63	0.1	20	16,000	61	0.2	240	102,000
Cleveland, OH	64	0.1	30	40,000	58	0.3	410	133,000
Las Vegas, NV	66	0.0	0	65,000	24	1.6	2,380	149,000
Jackson, MS	65	0.0	0	14,000	54	0.5	80	16,000
Springfield, MA	67	0.0	0	15,000	63	0.1	50	36,000

Endnotes

[1]The Census Bureau survey excludes permits to renovate a residential structure or to convert a structure from commercial to residential use, which may understate multifamily construction in older and more crowded metropolitan areas as well as in the city portion of metropolitan areas relative to the suburban portion.

[2]I use the 2003 delineation of Core-Based Statistical Areas (CBSAs) from the Office of Management and Budget (OMB), which is based on the 2000 decennial census. In addition, I combine the Denver and Boulder CBSAs to keep the delineation unchanged over time. The threshold of 250,000 as the cutoff population for inclusion in the analysis is arbitrary. I drop the five metros that had fewer than 10,000 multifamily units in 2010, reflecting that multifamily permitting rates in these metros are especially sensitive to idiosyncratic factors. I also drop 14 metros where college and graduate student enrollment in 2000 exceeded 10 percent of total metro population. Especially high multifamily permitting rates in some of these metros was likely driven by students. The 14 metros are Ann Arbor, MI; Durham, NC; Fort Collins, CO; Gainesville, FL; Kalamazoo, MI; Lansing, MI; Lincoln, NE; Lubbock, TX; Madison, WI; Provo, UT; San Luis Obispo, CA; Santa Barbara, CA; Santa Cruz, CA; and Tallahassee, FL.

[3]The mean and standard deviation of the multifamily permitting rate across the 161 metros is 1.6 percent and 1.3 percent, respectively. Summary statistics for all variables are reported in Table A-1. Only one metro, Rockford, IL, had zero permitting.

[4]I construct the single-family permitting rate analogously to the multifamily permitting rate—that is, I divide average annual single-family permits during 2013–15 by the number of single-family units in 2010.

[5]The correlation between multifamily and single-family permitting is considerably tighter across large metropolitan areas, specifically those with a population of at least 500,000. For these metros, regressing multifamily permitting on single-family permitting gives a slope of 1.42 with standard error 0.15 and an R-squared value of 0.47. Performing the same exercise for metros with populations from 250,000 to 500,000 gives a slope of 0.29 with standard error 0.13 and an R-squared value of 0.08.

[6]Regressing the multifamily permitting rates of the 161 metros on their population growth rate (and a constant) gives a coefficient of 0.85 with standard error 0.09 and R-squared value 0.38. The correlation between multifamily permitting and population growth is tighter in metros with a population of at least 500,000. For these metros, regressing multifamily permitting on population growth gives a coefficient of 1.12 with standard error 0.11 and an R-squared value of 0.51. For smaller metros—those with populations from 250,000 to 500,000—the analogous regression gives a coefficient of 0.36 with standard error 0.12 and R-squared value of 0.13.

[7]Census tracts are relatively small areas delineated by the Census Bureau that typically encompass from 1,000 to 8,000 residents. I construct the ratio of most-dense to least-dense census tract using 500 persons per square mile (0.78 persons per acre) as the minimum for all metros, a lower threshold that the Census Bureau uses to classify a census tract as part of an "urbanized area." Actual minimum tract density in metros is considerably lower, reflecting that the OMB delineates CBSAs as combinations of whole counties, thereby including considerable agricultural and unsettled land. The vast majority of land in most CBSAs has a population density below 500 persons per square mile (Rappaport 2014).

[8]A metro's average population density can also be measured by the population-weighted mean of the densities of all its census tracts. Doing so is equivalent to thinking of a metro's residents as each experiencing the density of the tract in which they live and then calculating the simple mean of experienced density across all residents. "Raw" population density—total population divided by total land—is average population density as experienced by parcels of land tracts (Glaeser and Kahn; Rappaport 2008a).

[9]Regressions on metro population and median density with no other measures of population density falsely suggest that multifamily permitting is unrelated to median density.

[10]I use the 99th percentile rather than maximum density as the top bound, as there is considerable idiosyncratic variation in the increase in density between the two. Multifamily permitting's partial correlations with the increase in density from the 95th percentile to maximum density have the same sign as its correlations with the increase from 95th to 99th percentile density. But coefficient estimates are typically less precise using maximum density, and for some sets of observations and additional controls, the magnitude of the estimated coefficient is considerably smaller.

[11]Simple regressions of multifamily permitting on only log population for the three groups of metros give coefficients with similar magnitude and statistical significance to those reported in Table 2.

[12]There is no consensus definition for metros' CBD. For this analysis, I define the CBD as the combination of all census tracts with an employment density of at least 8,000 workers per square mile in 2000 that are within five miles of the centroid of a metro's largest primary city as returned by Google Earth (Holian and Kahn; Rappaport 2014). Data to calculate employment density is from the Census Transportation Planning Product (CTTP) 2000, which re-tabulates the 2000 decennial census by place of work. I use the 2000 CTTP rather than the most recent one, based on data from the combined 2006–10 American Community Surveys, because its sample size is considerably larger.

[13]Multifamily construction's lack of correlation with centralized employment for the smaller metros may reflect mismeasurement. Specifically, the algorithm I use to identify CBD tracts may poorly delineate CBDs in smaller metros because its threshold employment density of 8,000 workers per square mile is inappropriately high.

[14]The R-squared statistic rises from 0.27 under the baseline specification reported in column 1 of Table 3 to 0.33 when including fixed effects for the four census regions and to 0.37 when including fixed effects for the nine census divisions. In both cases, estimated coefficients remain very close to those in the baseline specification.

[15]The population growth regression estimates the coefficient on log population to be 0.16 with a standard error of 0.11, which is statistically significant only at the 13 percent level (Table 3, column 3). Running the same regression for the full sample of 161 metros yields a coefficient on log population of 0.17 with a standard error of 0.08, which is statistically significant at the 5 percent level. The increase in statistical confidence captures that average population growth in the larger metros significantly exceeds average population growth in the smaller metros. An analogous regression establishes that population growth is uncorrelated with log population among the smaller metros.

[16]A different possibility is that an unrelated characteristic may have affected population growth for many years prior to 2010, causing some metros to become larger than others. If this same characteristic continued to affect population growth from 2010 to 2015, population growth could be positively correlated with population without there necessarily being a causal relationship between the two. While I cannot rule out this different possibility, regressions analogous to those reported in Tables 2 and 3 that include population and population density measured in 2000 give similar estimates to the regressions using population and population density measured in 2010. Separately, net inflows of population should eventually stop once they sufficiently increase housing costs and commuting congestion to offset higher wages and amenities. Once this occurs, population growth would be uncorrelated with initial population (Rappaport 2016; Desmet and Rappaport). The recent positive correlation of population growth with population suggests that the productivity and amenity benefits of size may have increased over the last few decades.

[17]Couture and Handbury argue that the increase in young professionals living near CBDs during the 2000s was driven more by demand for proximity to urban amenities than by demand to cut commute times. Specifically, they find that the increase in young professionals living near CBDs during the 2000s was positively correlated with the number of bars and restaurants near CBDs and that many of the young professionals living near CBDs "reverse" commuted to less central work locations. My interpretation regarding the desire to cut commute times reflects that my regressions control for the increase in population density from the 95th to the 99th percentile, which is likely to capture a significant portion of the urban amenities (specifically, bars and restaurants near CBDs) that Couture and Handbury measure. In particular, CBDs with nearby spikes in population density seem likely to have more nearby bars and restaurants.

[18]Regressing single-family permitting on the baseline characteristics and population growth yields a coefficient on median density of 0.35 with standard error of 0.06, which is statistically significant at the 1 percent level. The same regression

estimates a coefficient on 95th/50th percentile density of –0.19 with standard error 0.07, which is statistically significant at the 1 percent level. The estimated coefficients on the remaining three baseline characteristics are relatively small and do not statistically differ from zero.

[19]More precisely, the final cost of developing new multifamily units in such pockets—including land acquisition, demolition, and construction—is likely to be lower than the cost of developing multifamily units in tracts with uniformly high population density.

[20]Based on subjective criteria, I combine pairs of municipalities as the city portion of nine metro areas: Dallas-Fort Worth, Miami-Fort Lauderdale, Boston-Cambridge, San Francisco-Oakland, Riverside-San Bernardino, Minneapolis-St. Paul, Denver-Boulder, Tampa-St. Petersburg, and Portland-Vancouver. I combine three municipalities each as the city portion of Seattle-Tacoma-Bellevue and Virginia Beach-Norfolk-Newport News. I exclude the New York City metro from the analysis because of the especially large number of municipalities that arguably should be included in its city portion.

[21]The suburban multifamily permitting rate in Boise (not shown) exceeded the city multifamily permitting rate by more than 6 percentage points (8.7 percent versus 2.5 percent). The best-fit linear relationship of the suburban multifamily permitting rate against the city multifamily permitting rate has an intercept of 0.67 with a standard error of 0.28, a slope of 0.53 with a standard error of 0.12, and an R-squared of 0.22. Aggregate multifamily permits for the 67 metro areas were split approximately evenly between the city and the suburban portions.

[22]Values of these characteristics describe the entire metropolitan area rather than just the city or suburban portion. Hence, they are identical to each other in the two regressions as well as to the values used in the metropolitan regression reported in Section II.

[23]A robust regression, as implemented with Stata's "rreg" command and default settings, uses an iterative algorithm to downweight observations that disproportionately affect estimated coefficients. A robust regression of suburban multifamily permitting on the specification in Table 4 yields a coefficient on log population of 0.39 with an associated standard error of 0.17, which statistically differs from zero at the 5 percent level. The robust suburban regression also estimates a considerably smaller coefficient on the CBD employment share than the value reported in column 2 of Table 4, but the coefficient is nevertheless large and statistically significant. All other coefficients reported in Table 4 are qualitatively similar using robust regressions.

[24]Regressing suburban population growth on the explanatory variables reported in Table 4 yields a coefficient on the CBD employment share of 3.19 with a standard error of 1.19, which is statistically significant at the 1 percent level.

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Identifying State-Level Recessions

By Jason P. Brown

Although the U.S. economy is in its eighth year of expansion since the Great Recession, some states are nevertheless in recession. The timing of states entering an economic downturn often differs from the nation as a whole: the onset and duration of recessions depend on factors that typically differ in each business cycle. A global recession such as the Great Recession is often widespread, dampening economic growth across most regions and sectors of the United States. But other downturns may be more concentrated. For example, in the 2001 recession, the manufacturing sector was hit especially hard.

States with higher concentrations in specific sectors may enter downturns earlier than other states—and may remain in them longer. For example, energy-producing states in the Tenth Federal Reserve District entered a recession in 2015 and 2016 following the 70 percent decline in the price of oil from June 2014 to February 2016. In contrast, most non-energy-producing states experienced moderate but steady growth over the last two years. Energy-producing states have a larger share of employment and output in the oil and gas sector; as a result, declining or sustained low oil prices can decrease exploration and

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drilling, decrease activity in other sectors, and thereby dampen overall economic activity.

In this article, I use two approaches to determine whether the seven states of the Tenth District are in a recession. The first approach is helpful for identifying regional recessions retrospectively over the last four decades, while the second approach is more helpful for identifying regional recessions in real time. When applied to the seven states of the Tenth District, both approaches indicate that Oklahoma and Wyoming entered downturns in early to mid-2015. The second approach suggests Kansas and New Mexico entered recessions beginning in late summer 2016. On average, recessions in energy-producing states occur more frequently but are typically shorter than recessions in non-energy-producing states.

Section I discusses some of the measurement issues involved in identifying regional recessions compared with national recessions. Section II uses an algorithm to identify the timing and duration of past regional recessions. Section III develops a formal model that categorizes state-level economic activity into two regimes—low growth/recession and high growth/expansion. This approach allows me to identify in real time when states slip into recession.

I. The Challenges of Identifying State Recessions

Identifying economic turning points for individual states is challenging for a number of reasons. First, while the National Bureau of Economic Research (NBER) Business Cycle Dating Committee identifies national recessions, neither it nor any other comparable organization dates state-level recessions. Moreover, the NBER has no fixed timeline for determining recession dates and often announces the beginning of a recession a year or more after it occurs. Second, timely state-level economic indicators are limited. The broadest measure, gross state product, is only available quarterly and is published with a lag of around six months (versus one month for advance estimates of U.S. gross domestic product). Similarly, quarterly measures of state-level personal income are published with about a three-month lag. Although monthly labor market indicators are available at the state and metropolitan level from the Bureau of Labor Statistics' Current Employment Statistics and Current Population Survey, it is not obvious which set or combination of indicators would be best to monitor and summarize state-level economic activity.

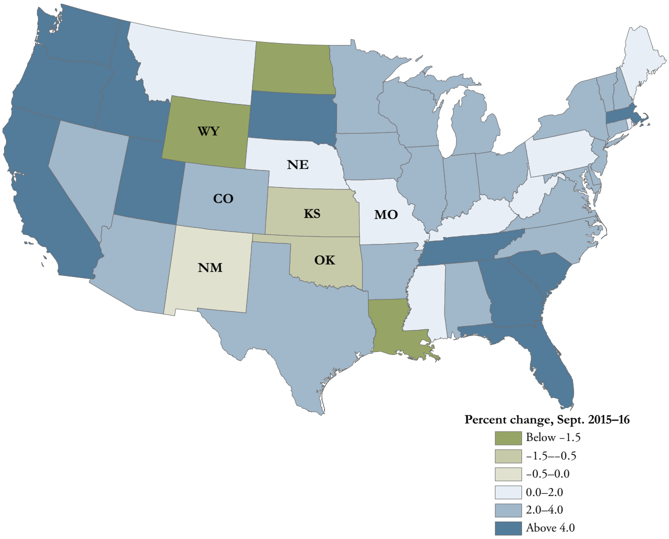
One possible alternative is the Federal Reserve Bank of Philadelphia's state coincident index, a timely and comprehensive measure of each state's economic activity. The Philadelphia Fed's coincident index captures each state's current economic conditions by combining four state-level indicators—nonfarm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and wage and salary disbursements deflated by the consumer price index (U.S. city average). The trend for each state's index is set equal to the trend of its real GDP. Each month, the Bank releases an updated version of each state's entire index that also includes the most recent month for which data are available. These regular updates are important, because the underlying state-level data can be subject to substantial revision.

Changes in the coincident index suggest that several states in the Tenth District experienced declining economic activity over the past year. Map 1 shows that the energy-producing states in the District, namely Oklahoma, Wyoming, Kansas, and New Mexico, accounted for four of six states in the entire country where economic activity declined from September 2015 to September 2016 (the other two states were North Dakota and Louisiana, also energy-producing states). Map 2 shows that the pace of decline accelerated in some states beginning in the middle of 2016. From June to September 2016, economic activity declined faster in Kansas and New Mexico than in Oklahoma or Wyoming.

Growth in each state's index may be a useful indicator for measuring state-level business cycles. However, growth alone is not enough to identify recessions. The next two sections discuss two approaches for identifying state-level recessions. I first use the Bry-Boschan method, as it is a standard and simple approach for identifying turning points in economic indicators. The Bry-Boschan method—like the NBER—typically dates recessions with a substantial lag. As a result, I also use a Markov regime-switching model, which is more complex but offers more flexibility to identify state-level recessions in real time.

Map 1

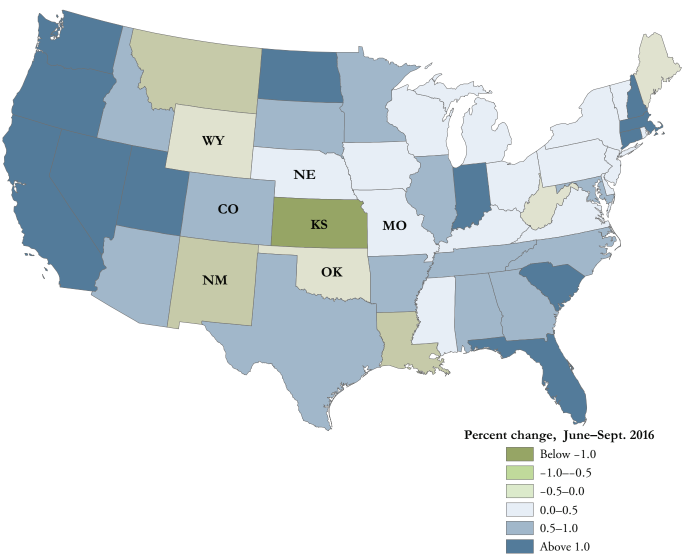
Growth in the Economic Activity Index by State, September 2015 to September 2016



Sources: Federal Reserve Bank of Philadelphia and author's calculations.

Map 2

Growth in the Economic Activity Index by State, June 2016 to September 2016



Sources: Federal Reserve Bank of Philadelphia and author's calculations.

II. Using the Bry-Boschan Method to Identify U.S. Recessions

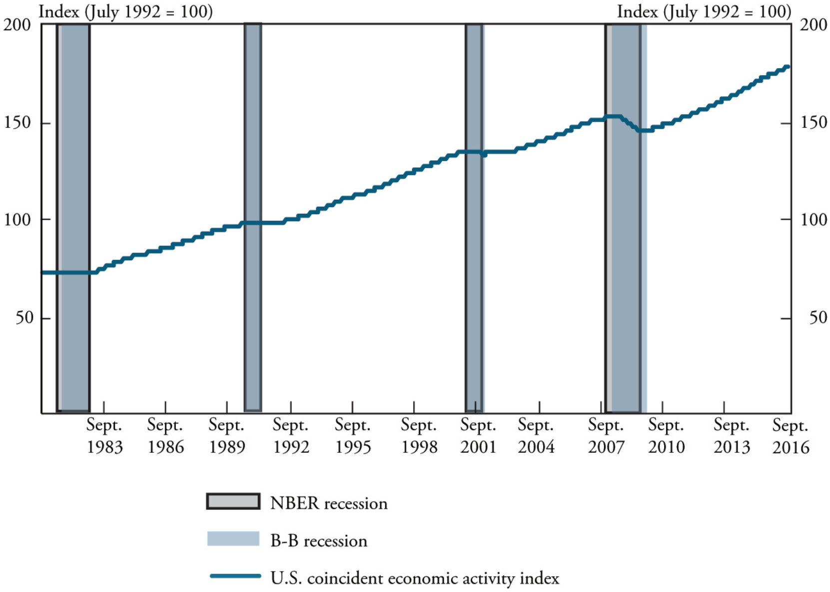
The Bry-Boschan (B-B) method is a popular approach to business cycle dating because it is straightforward and easy to implement. The B-B method is designed to identify the peaks and troughs in the level of a time series—in other words, the turning points between economic expansions and contractions. To do so, the algorithm requires users to specify not only a window of time over which to identify these turning points but also a minimum length of time for each phase (expansion or contraction) and cycle (the period between two peaks or two troughs). I use a window of 12 months, where each phase is at least six months, and a complete cycle is 24 months. As the algorithm rolls through the data, it looks six months ahead and six months behind each month to identify local minima and maxima. When the algorithm discovers local minima or maxima, it determines whether they are possible turning points. Candidate turning points satisfy two conditions: phases are at least six months long and complete cycles are at least 24 months long.[1]

As a result of these imposed conditions, however, the B-B algorithm may be limited in identifying turning points in real time—its accuracy improves as time passes and more data in the series are available to satisfy the cycle constraint. For example, if a downturn occurred in the last few months of available data, the B-B algorithm would not likely identify it until a full six months had passed.

To gain some confidence in applying the B-B method to regional data using the Philadelphia Fed's state coincident index, I first apply the method to the Bank's national coincident index (calculated in the same way as the state indexes) and compare the results with the NBER's dating of past U.S. recessions. The B-B method is unlikely to exactly identify the NBER-defined recessions, as the process used by the Business Cycle Dating Committee is somewhat subjective. The Committee does not have a fixed rule or algorithm for identifying expansions and recessions but instead applies its judgement when dating business cycles. As a result, it is unlikely that applying any particular fixed algorithm to a coincident indicator of economic activity will exactly replicate the NBER's dating.

Nevertheless, the turning points identified by both the B-B method and the NBER are similar for most recessions. Chart 1 shows the

Chart 1
U.S. Business Cycles



Sources: NBER, Federal Reserve Bank of Philadelphia, and author's calculations.

Table 1
Difference in Dating of U.S. Recessions

Recession	Timing relative to NBER (months)	
	Enter	Exit
1981–82	1	0
1990–91	1	1
2000–01	0	2
2008–09	3	4
Average	1.25	1.75

Note: A positive number indicates that the B-B algorithm identified the U.S. economy entering/exiting a recession later than the NBER.
Sources: NBER, Federal Reserve Bank of Philadelphia, and author's calculations.

U.S. coincident index from September 1980 to September 2016. The gray shading indicates NBER-defined recessions, while the light blue shading shows recessions determined by the B-B algorithm. In most cases, the shading overlaps. For a more detailed comparison, Table 1 reports the time difference (measured in months) between the B-B method's entry and exit dates for the last four recessions and those dated by the NBER. Averaging across recessions, the B-B method suggests the United States entered or exited a recession 1.5 months later than the official NBER designation. Thus, applying the B-B method to the U.S. coincident index appears to produce similar business cycle dates as the NBER, offering some confidence in dating regional recessions with a similar method.

Using the B-B method to identify state-level recessions

Given the relative success of the B-B method in replicating NBER recession dates at the national level, I use the B-B method and state-level coincident indexes to identify business cycles in Tenth District states. I start the analysis in 1979, the first year for which state coincident indexes are available. Table 2 summarizes the number, duration, and time spent in state-level recessions for the seven states of the Tenth District. Over the past four decades, each District state spent more time in recession than did the United States (52 months). From April 1979 to September 2016, the United States was in recession 12 percent of the time. In contrast, Missouri was in recession about 27 percent of the time, followed closely by Oklahoma at 24 percent. Over the period of analysis, all District states had four to five recessions except Wyoming, which had six. The average recession duration was shortest in Nebraska (15 months) and longest in Missouri (31 months). For the United States as a whole, the average recession duration was 13 months.

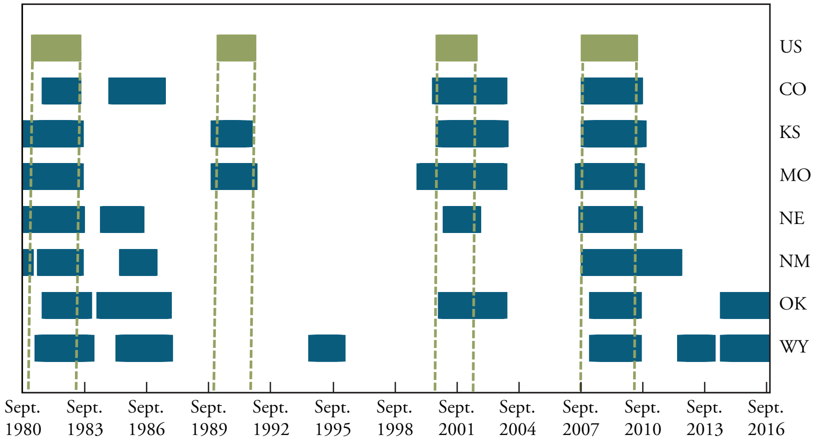
Chart 2 illustrates that the timing of District states entering recessions often differs from the United States as a whole (see Appendix Table A-1 for a list of all recession entry and exit dates). Kansas, Missouri, and Nebraska tend to enter downturns before the United States as a whole. The states with the most oil and gas production (New Mexico, Oklahoma, and Wyoming) typically enter recessions later than the United States but also exit them later. Notably, none of the states in the Tenth District has exited a recession before the nation.

Table 2
Summary of Recessions by District State

State	Number of months in recession	Time in recession (percent)	Number of recessions	Average duration (months)
Colorado	79	17.6	4	20
Kansas	88	19.6	5	18
Missouri	122	27.1	4	31
Nebraska	76	16.9	5	15
New Mexico	74	16.4	4	18
Oklahoma	107	23.8	5	22
Wyoming	91	20.2	6	14
United States	52	11.6	4	13

Sources: Federal Reserve Bank of Philadelphia and author's calculations.

Chart 2
Timing of District versus U.S. Recessions



Note: U.S. recessions in the chart correspond to turning points identified by the B-B method for a more direct comparison of state-level recessions using the same method.
Sources: Federal Reserve Bank of Philadelphia and author's calculations.

In addition, some Tenth District states experienced recessions that the United States as a whole never entered. Colorado, Nebraska, New Mexico, Oklahoma, and Wyoming experienced a state-level recession during 1985–86 while the United States was in a period of general expansion. Around this time, a steep decline in the price of oil caused drilling and production to halt and overall economic activity in oil- and gas-producing states to slow. As a result, the energy-producing states in the Tenth District experienced a downturn while the rest of the nation continued to grow. Nebraska's recession was likely due to the slowdown in agriculture that occurred around the same time.

Oklahoma and Wyoming experienced additional state-level recessions. Wyoming had short downturns in 1995 and 2013 coinciding with declines in coal prices (1995) and coal production (2013). And Oklahoma and Wyoming both entered recessions at the beginning of 2015: oil prices declined steeply in the second half of 2014, leading to significant declines in economic activity in both states.

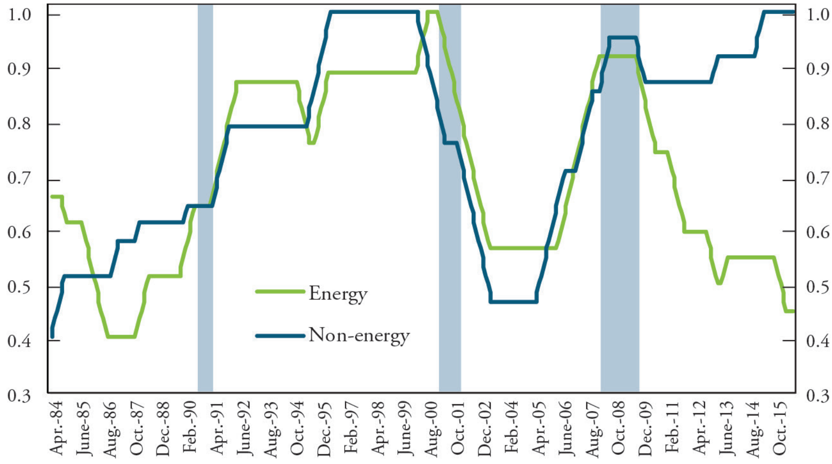
Synchronization of state business cycles

Certain economic shocks can affect the entire energy sector, causing energy-producing states to become more synchronized—that is, more likely to be in the same phase of the business cycle—than non-energy producing states. Less apparent, however, is whether this exposure to sector-specific shocks causes energy-producing states to become less synchronized with U.S. business cycles than non-energy-producing states. To address this issue, I construct measures of synchronization of District states with each other and with the United States, grouping states into energy and non-energy-producing categories. These measures indicate whether each group of states is in the same phase of the business cycle (expansion or recession) as the other group and the overall U.S. economy.

One way to measure the degree to which turning points across states are synchronized is to calculate an index of concordance as used by Harding and Pagan. An index of concordance measures the share of time two data series spend in the same phase of expansion or contraction at the same time.[2] The overall value of the index is bounded between 0 and 1, with larger values indicating a higher level of synchronicity between two states. An exact reading of 1 would indicate that two states were in the exact same phases of the business cycle in each month over the sample period.

Chart 3

Energy versus Non-Energy States' Concordance with U.S. Business Cycles



Notes: The concordance is the share of time over a five-year window in which the energy states (New Mexico, Oklahoma, and Wyoming) and the non-energy states (Colorado, Kansas, Missouri, and Nebraska) were in the same phase of the business cycle as the United States. Blue shading represents U.S. recessions identified using the B-B method.
Sources: Federal Reserve Bank of Philadelphia and author's calculations.

Given the potential similarities between energy-producing states, I calculate concordance indexes for two groups: New Mexico, Oklahoma, and Wyoming (energy-producing states) and Colorado, Kansas, Missouri, and Nebraska (non-energy-producing states).[3] I then determine how long each group of states spent in the same phases of the business cycle with the United States and with each other.

In general, Tenth District states were much more synchronized during periods of economic expansion. Chart 3 shows a five-year rolling window of the concordance measure. In the 1990s, both groups of states experienced robust and prolonged growth. As a result, it is not surprising that the non-energy states were perfectly synchronized with the United States for most of the mid- to late-1990s. Conversely, both energy and non-energy states were less synchronized during and after U.S. recessions, since District states entered and exited phases at different times.

On average, the non-energy-producing states were synchronized with the United States 77 percent of the time, while the energy-producing states were synchronized with the nation only 70 percent of the time. The difference between the two groups is most likely due to oil price shocks that energy-producing states were subject to outside of nationwide recessions. Synchronization between the energy-producing states and the United States reached its lowest point (0.4) in the mid-1980s during an oil supply shock. Synchronization between the energy-producing states and the nation remained low following the Great Recession and moved lower yet into 2016. Unlike synchronization across countries, synchronization across states seems to be driven by the sectors of the economy affected most during a downturn, with each recession being unique.

III. Identifying Regional Recessions in Real Time

Although the B-B method appears to be an effective way to identify past state-level recessions, it is less useful in identifying recessions in real time. As such, I use a Markov regime-switching model (proposed by Hamilton) to identify more recent turning points. The Markov regime-switching model is more complex than the B-B method, but it does not require a specific window of time to be pre-selected for each phase in the business cycle. This flexibility allows it to more closely identify the start of recessions.

The model, which is widely used in business cycle dating, provides an alternative way to identify turning points by allowing the average growth rate to switch between different regimes (for example, between a high-growth and low-growth regime). The timing of these regimes and the growth rates within them are then estimated from the data. The model can be expressed as:

$$Y_t = c\,(S_t) + \phi Y_{t-1} + \varepsilon_t, \tag{1}$$

where Y_t is the month-to-month growth in the state-level coincident index, c represents the mean growth rate that switches between high or low average growth regimes (S_t), ϕ is the autoregressive coefficient on previous growth Y_{t-1}, and ε_t accounts for differences in growth not captured by the model.[4] The model can be generalized to allow regime-switching in the persistence of growth (L_t) and in the volatility of growth (V_t) as shown by:

$$Y_t = c\,(S_t) + \phi(L_t)\,Y_{t-1} + \sigma(V_t)\varepsilon_t. \tag{2}$$

With this specification, each state can be in one of eight possible regime combinations. The variables S_t, L_t, and V_t allow the average growth rate to be high or low, the persistence of growth to be high or low, and the volatility of growth to be high or low at each point in time depending upon the regime. Each of the regimes across the variables are assumed to be independent of one another. While it need not be the case, the low average growth regime turns out to indicate when a state is in recession. In addition, while more than two regimes can be considered for each variable—such as high, medium, and low for each regime type (see Foerster and Choi)—I consider only two, because it is more consistent with economies being in expansions or recessions.

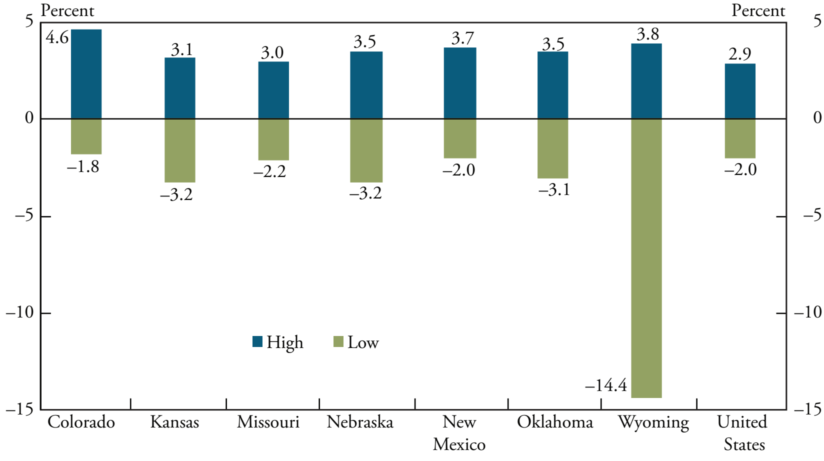
Moving from one regime to another is assumed to follow a Markov process, where the regime at a given point in time depends on the probability of being in that same regime in the previous period. In this case, P_{hh}^{c} and P_{ll}^{c} measure the probability that the state economy will be in the high or low average growth regime if it was in that regime in the previous period. Similarly, P_{hl}^{c} and P_{lh}^{c} measure the probability of switching from the high to low or low to high growth regimes. The expected duration of remaining in a regime is approximated by $1/\left(1-P_{ll}^{c}\right)$ for the low growth/recession regime and by $1/\left(1-P_{hh}^{c}\right)$ for the high growth/expansion regime.

Average growth regimes

Persistence and volatility in growth are important for determining regime probabilities, but seem to matter less in explaining growth for most states. As a result, the subsequent discussion focuses primarily on the average growth regime. The average growth rate in the high-growth and low-growth regimes differs greatly across states. Chart 4 reports annualized growth rates by state.[5] Colorado has the highest average growth in the high-growth regime (4.6 percent), as well as the highest average growth in the low-growth regime (–1.8 percent) compared with other District states. These results are consistent with Colorado's persistent and faster growth in the region. Following Colorado, Wyoming has the next highest average growth in the high-growth regime (3.8 percent). However, Wyoming has the lowest growth of all Tenth District states in the low-growth regime (–14.4 percent). This result is striking but consistent with Owyang, Piger, and Wall, who estimate a nearly –15.0 percent growth rate in Wyoming's low-growth regime from 1979 to 2002.[6]

In addition, Wyoming's growth is more volatile than most District states (Table A-1). One explanation for this volatility may be Wyoming's share of economic activity from the mining sector, which is among the

Chart 4
Average Annualized Growth by Regime



Sources: Federal Reserve Bank of Philadelphia and author's calculations.

highest in the nation (Brown). Lower or higher volatility in growth is consistent with previous findings that regions that depend more on resource extraction are more subject to boom-bust cycles and slower growth over time (Jacobsen and Parker).

The remaining District states have similar growth rates in the high-growth (3.0 to 3.7 percent) and low-growth (–2.0 to –3.2 percent) regimes. For comparison, U.S. average growth is 2.9 percent in the high-growth regime and –2.0 percent in the low-growth regime. Of all the Tenth District states, Missouri is the most similar to U.S. average growth by regime. Missouri is also the District state with the most similar industrial composition to the nation (Federal Reserve Bank of Kansas City).

Both expansion and recession phases of the states' business cycles are persistent. However, the probability of a state remaining in a high-growth regime or expansion is higher than remaining in the low-growth regime or recession (Table 3). Kansas and Wyoming have the highest probability of remaining in an expansion phase in a given month at 0.985, with an expected duration of 67 months. During a downturn, Kansas and Missouri have the highest probability of remaining in recession at around 0.96, with an expected duration of just over two years.

Table 3
Regime Probabilities and Expected Duration

State	Expansion		Recession	
	Probability of remaining	Expected duration (months)	Probability of remaining	Expected duration (months)
Colorado	0.977	43	0.922	13
Kansas	0.985	67	0.960	25
Missouri	0.981	53	0.961	25
Nebraska	0.971	34	0.849	7
New Mexico	0.958	24	0.839	6
Oklahoma	0.956	23	0.883	9
Wyoming	0.985	67	0.875	8

Note: Expected duration is calculated by $1/(1-P_{hh}^{c})$ for expansion and $1/(1-P_{ll}^{c})$ for recession.

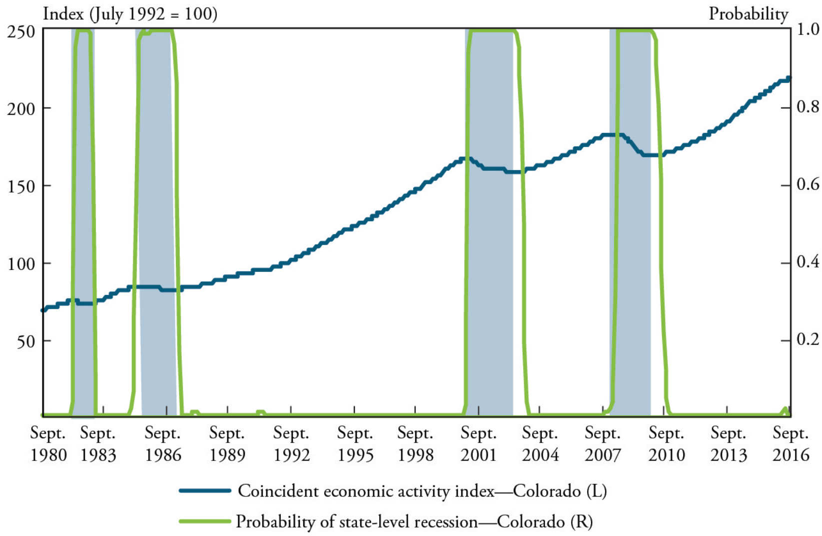
The estimated expected duration of recessions in each District state ranged from eight to 25 months. With the exception of Wyoming, the Markov regime-switching model indicates that energy-producing states spend less time in both expansionary and recessionary phases than non-energy states. The estimated ranges nearly match the phase and cycle lengths (12 and 24 months, respectively) used in the B-B method; the close fit suggests the cycle length estimated from the Markov regime-switching model could be used to set parameters for the B-B method.

Comparing two methods of business-cycle dating

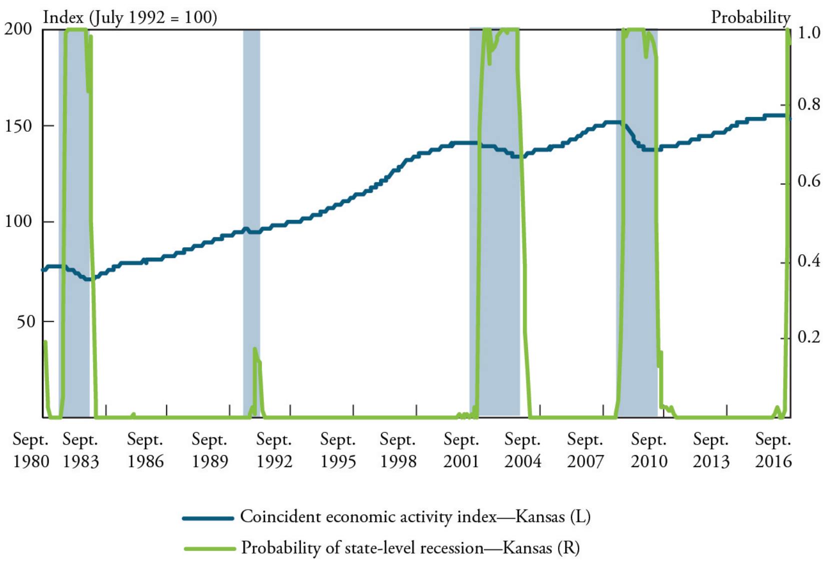
The B-B and Markov regime-switching methods identify many of the same recessions, though the exact dates of the turning points can differ by a few months. Chart 5, Panels A–G illustrate the business cycles identified for each state in the Tenth District under both methods. The shaded regions denote recessionary periods identified by the B-B algorithm, the blue line shows the state-level coincident index, and the green line shows the probability of recession from the Markov regime-switching model. A reading above 0.5 indicates the low-growth regime consistent with a recessionary period. The panels in Chart 5 show that, generally, the Markov regime-switching model identifies the same recessions as the B-B method. For example, the green line in Panel A borders the recessions identified by the blue shading, suggesting that both methods identified recessions in Colorado in 1981–82, 1985–86, 2001, and 2008–09. However, the two methods differ with respect to

Chart 5
Business Cycles of Tenth District States

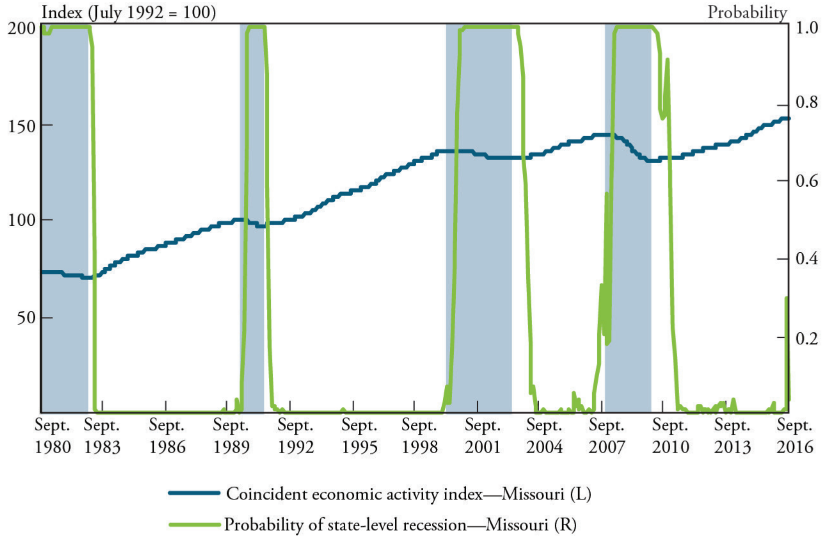
Panel A: Colorado



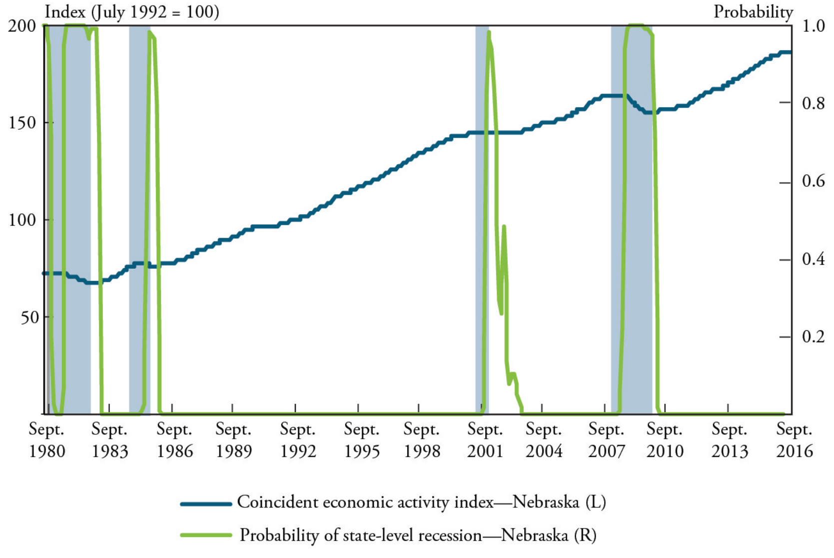
Panel B: Kansas



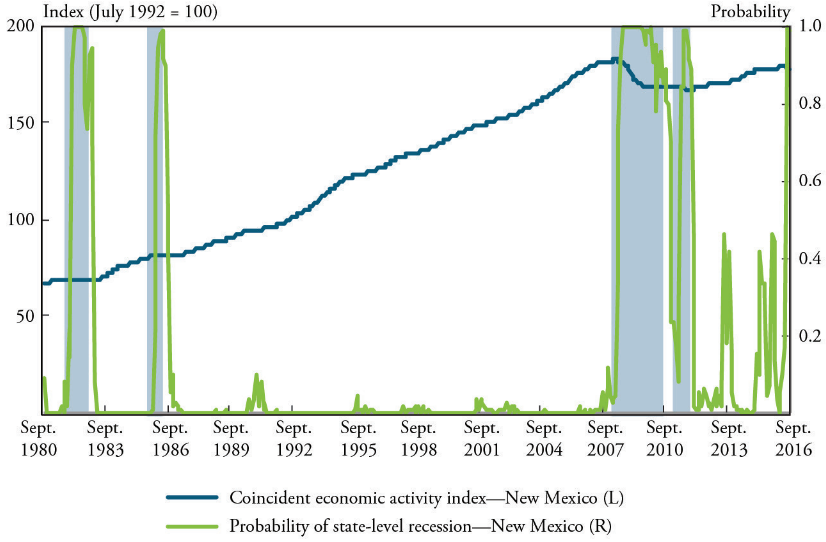
Panel C: Missouri



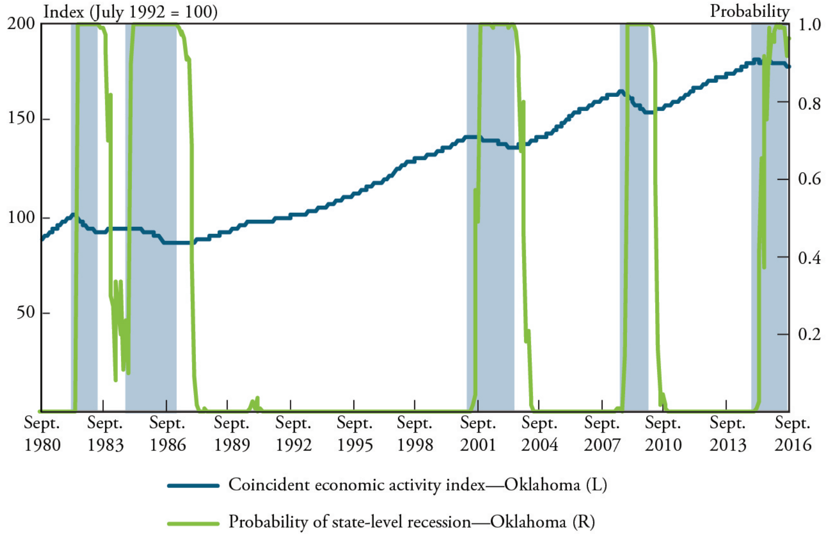
Panel D: Nebraska



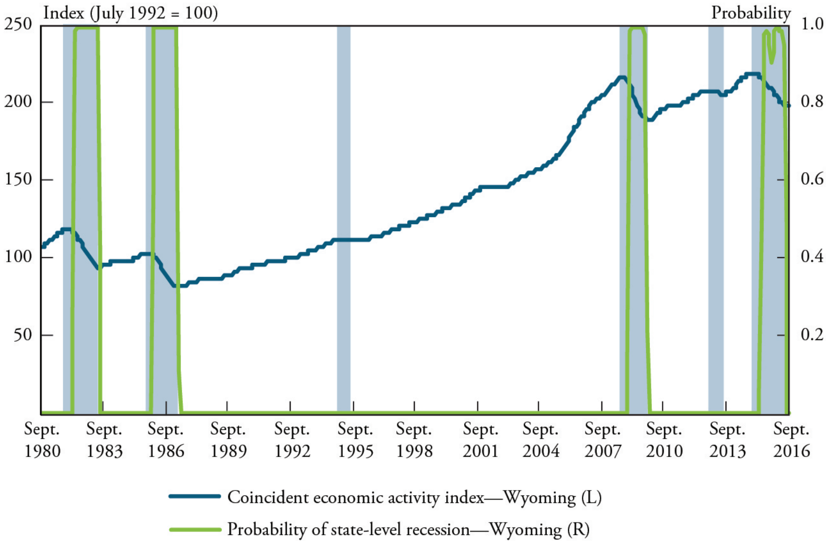
Panel E: New Mexico



Panel F: Oklahoma



Panel G: Wyoming



Sources: Federal Reserve Bank of Philadelphia and author's calculations.

Table 4

Contemporaneous Recession Dating

State	2015–16			
	B-B Enter	RS Enter	B-B Exit	RS Exit
Colorado				
Kansas		Aug.-16		?
Missouri				
Nebraska				
New Mexico		July-16		?
Oklahoma	Jan.-15	May-15	?	?
Wyoming	Jan.-15	June-15	?	July-16

Note: Question mark indicates that the state was still in recession as of September 2016.
Sources: Federal Reserve Bank of Philadelphia and author's calculations.

timing. In general, the regime probabilities identify downturns slightly later than the B-B method.

In addition, only the Markov regime-switching model identified the start of recessions in early to mid-2016 in Kansas (Panel B) and New Mexico (Panel E). The blank entry for Kansas and New Mexico in the "B-B Enter" column of Table 4 shows that the B-B method did not identify these more recent recessions. The most likely reason is that not enough time had passed to satisfy the cycle-length constraint of six months: the B-B method would likely not identify these recessions until January or February 2017.

While there could be numerous causal factors for recent state recessions, changes in oil prices are likely a main driver. Over the past couple of years, the price of oil fell substantially mostly due to changes in expectations of future oil demand relative to available supply (Davig and others). Oil price declines are a plausible explanation for recent recessions in New Mexico, Oklahoma, and Wyoming (given their relative dependence on the oil and gas sector) and may be a contributing factor in Kansas as well. As of September 2016, Kansas, New Mexico, and Oklahoma still appeared to be in recession, with Wyoming possibly exiting in the prior months (Table 4). It is worth noting, however, that the most recent readings of the coincident index can be subject to (generally small) revisions.

According to the Markov regime-switching model, the most recent downturns occurred in New Mexico (July 2016) and Kansas (August 2016). The rise in the recession probability in both states follows several months of slowing growth and then declining economic conditions in those states. The B-B method did not identify these recessions, likely because of the cycle- and phase-length constraints. However, as time passes, the B-B method will likely identify a turning point. Both methods have unique advantages in dating state-level recessions: the B-B method can more precisely identify recessions after they occur, while the Markov regime-switching model may offer a better real-time indication of recessions.

IV. Conclusion

States and regions may enter economic downturns even when the nation as a whole continues to grow. The energy-producing states in the Tenth Federal Reserve District, for example, have often diverged from the United States as a whole over the past 35 years. In the mid-1980s, Oklahoma, New Mexico, and Wyoming entered recessions due to an oil supply shock that dramatically reduced the price of oil. More recently, a similar phenomenon has occurred, as global supply and demand for oil are out of balance. The subsequent drop in oil prices and oil-related activity hit Wyoming first followed by Oklahoma, New Mexico, and Kansas. As of September 2016, Oklahoma, New Mexico, and Kansas were still in recession, with Wyoming appearing to exit in late summer.

The combined results from two recession dating methods show that Tenth District states spend more time in recession compared with the United States as a whole. Moreover, the results show that energy-producing states typically enter and exit national recessions later and have more frequent (but shorter) recessions than non-energy-producing states. While both methods are useful in identifying state-level recessions, the Markov regime-switching model appears better than the Bry-Boschan method in identifying recessions in real time.

Appendix

Additional Tables

Table A-1

Timing of District State Recessions

State	1981–82		1990–91		2001		2008–09	
NBER dated	Enter	Exit	Enter	Exit	Enter	Exit	Enter	Exit
United States	Aug.-81	Nov.-82	Aug.-90	Mar.-91	Apr.-01	Nov.-01	Jan.-08	June-09
B-B dated								
United States	Sep.-81	Nov.-82	Sep.-90	Apr.-91	Apr.-01	Jan.-02	Apr.-08	Oct.-09
Colorado	Mar.-82	Nov.-82			Feb.-01	June-03	Apr.-08	Jan.-10
Kansas	July-81	Dec.-82	May-90	Feb.-91	Apr.-01	July-03	Apr.-08	Mar.-10
Missouri	Apr.-79	Dec.-82	May-90	May-91	May-00	June-03	Jan.-08	Feb.-10
Nebraska	Mar.-81	Jan.-83			Aug.-01	Mar.-02	Mar.-08	Jan.-10
New Mexico	Dec.-81	Dec.-82					Apr.-08	Sep.-10
Oklahoma	Mar.-82	May-83			May-01	June-03	Sep.-08	Dec.-09
Wyoming	Nov.-81	June-83					Sep.-08	Dec.-09

Sources: NBER, Federal Reserve Bank of Philadelphia, and author's calculations.

Table A-2

Timing of District State Recessions

State	Average growth regime		Auto-correlation regime		Volatility regime	
	High	Low	High	Low	High	Low
Colorado	0.0038*** (39.971)	−0.0015*** (−7.989)	−0.0022 (−0.044)	−0.0965*** (−2.017)	2.9e-06*** (3.452)	--
Kansas	0.0026*** (23.759)	−0.0027*** (−4.634)	0.1090 (1.008)	0.0509 (1.106)	9.8e-06** (2.554)	4.6e-06*** (4.675)
Missouri	0.0025*** (18.356)	−0.0018*** (−14.031)	0.0177 (0.411)	−0.0031 (−0.080)	3.4e-06*** (4.224)	--
Nebraska	0.0029*** (33.926)	−0.0027*** (−9.015)	0.0639 (0.558)	0.0465 (1.608)	5.6e-06 (1.486)	2.8e-06*** (3.640)
New Mexico	0.0031*** (24.226)	−0.0017*** (−6.521)	0.1665*** (3.866)	−0.0105 (−0.200)	2.9e-06*** (3.109)	--
Oklahoma	0.0029*** (18.968)	−0.0026*** (−9.973)	−0.0022 (−0.032)	−0.0249 (−0.447)	5.2e-06*** (4.408)	--
Wyoming	0.0032*** (16.987)	−0.0120*** (−44.486)	0.0269 (0.516)	0.0232 (0.551)	9.7e-06*** (6.775)	--
United States	0.0024*** (43.765)	−0.0017*** (−13.176)	0.0784*** (3.260)	−0.0071 (−0.092)	1.1e-06** (2.190)	

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

Note: T-statistics are reported in parentheses.
Sources: NBER, Federal Reserve Bank of Philadelphia, and author's calculations.

Endnotes

[1]Results are robust to changes in the window, cycle, and phase. However, if the time period for the phase is made too short, the algorithm tends to identify more turning points. In both recessions and expansions, brief reversals in economic activity may occur. As a result, setting the parameters to time periods too short could lead to false positive indications of recessions.

[2]The index of concordance between state i and j is: $IC_{ij}=n^{-1}\left(\sum_{t=1}^{T} P_{it}P_{jt} + \left(1-P_{it}\right)\left(1-P_{jt}\right)\right)$, where $P_{it} = P_{jt} = 1$ indicates that states i and j are in expansion, $P_{it} = P_{jt} = 0$ indicates the states are in recession at time t, and n is the total number of time periods.

[3]Colorado and Kansas do produce oil and gas but on a much smaller scale than New Mexico, Oklahoma, and Wyoming.

[4]Owyang, Piger, and Wall; and Hamilton and Owyang use a similar model to investigate business-cycle phases in U.S. states.

[5]Complete results of the Markov regime-switching model are reported in Appendix Table A-2.

[6]Owyang, Piger, and Wall's estimate of Wyoming average month-over-month growth in the low-growth regime is –1.246 , which is –14.95 percent at an annualized rate.

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