Macroeconomic Dynamics, **21**, 2017, 1426–1453. Printed in the United States of America.
doi:10.1017/S1365100515000917

ESTIMATING THE NATURAL RATE OF HOURS

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This paper proposes an alternative measure for the slack of the aggregate labor market. The natural rate of hours holds valuable information about the state of the labor market that is not reflected by conventional measures, such as the equilibrium rate of unemployment, because it takes the intensive margin into account and is robust to variations in labor force participation. We set up and estimate a multivariate unobserved-components model using information on GDP, inflation, and hours worked, and apply it to the United States and Germany. The estimated hours gap outperforms conventional unemployment gap measures in a Taylor rule by formal model comparison.

Keywords: Natural Rate, Unobserved-Components Model, Taylor Rule

1. INTRODUCTION

Knowing how far a country's labor market deviates from its equilibrium level is of great relevance for various reasons. The sign and magnitude of the labor market gap provide valuable information to better predict output growth and the impact of monetary policy. Central banks take some form of natural rate estimate into account when evaluating the state of the economy. For instance, the Federal Reserve Open Market Committee (FOMC) estimates the "long-run normal rate of unemployment," as published quarterly in the FOMC's Summary of Economic Projections.[1]

The most widely used indicators for the state of the labor market are the nonaccelerating inflation rate of unemployment (NAIRU) and the corresponding gap. The idea of a natural rate of unemployment was pioneered by Friedman (1968) and Phelps (1968), who claim that unemployment is at its natural level when neither inflationary nor deflationary pressure emanates from the labor market. The existence of a constant NAIRU was questioned after the oil price shocks of the

For helpful comments we thank Freddy Heylen, Gerdie Everaert, Irina Panovska, and participants at the 20th SNDE Annual Symposium, the CMR Lunch Seminar at the University of Cologne, the 7th ifo Workshop on Macroeconomics and the Business Cycle, and the Baltic Sea Colloquium. Hauke Vierke acknowledges financial support from the Friedrich-Ebert-Stiftung and from Ghent University's Special Research Fund (BOF). Address correspondence to: Tino Berger, University of Goettingen, Platz der Goettinger Sieben 3, 37036 Goettingen, Germany; e-mail: tino.berger@wiwi.uni.goettingen.de.

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1970s, as unemployment remained high even after inflation had stabilized. More recently, the NAIRU has been assumed to be a function of labor market institutions and real macroeconomic variables such as real interest rates or productivity growth and hence to be time-varying.

Using the NAIRU as an indicator for the state of the aggregate economy assumes that the unemployment rate captures the most relevant changes in the labor market. In this paper we argue that labor force participation (extensive margin) and hours worked (intensive margin) play an important role in the adjustment process, such that additional information, other than the unemployment rate, can help to estimate the natural level more precisely. During the Great Recession, Germany reacted to the severe decline in GDP with a widespread short-time work program. To avoid layoffs, employees agreed with firms to work less and received a subsidized wage allowance. The scope of underemployment in Germany, with about 1.5 million short-time workers at maximum, was concealed by a relatively stable unemployment rate during the crisis. However, hours worked dropped by 3.3%; i.e., the adjustment occurred along the intensive margin. Moreover, changes in labor force participation can alter the unemployment rate, even if the overall employment level stays constant. If many discouraged workers exit the labor force after a severe recession, the unemployment rate overestimates the state of the labor market. There is an ongoing debate on the determinants of the decline in U.S. labor force participation and its impact on employment dynamics. Fujita (2014) argues that both long-run and cyclical factors have driven the decline and that the number of discouraged workers has certainly risen during the recent recession. Whether these marginally attached workers play an important role in the unemployment rate is not clear-cut: Davig and Mustre-del Rio (2013) find that reentry of the "shadow labor supply" will only have a modest impact on the unemployment rate. Ravikumar and Shao (2014) construct an alternative unemployment rate that accounts for the reentry of discouraged workers. This series is only slightly higher than the official series and exhibits a similar trend. However, according to Romero (2012), the number of around 900,000 discouraged workers at the end of 2013 is severely underestimated, as this only includes people who have searched for a job within the past year. In contrast, 3.2 million workers generally want a job but stopped looking more than one year ago. Zandweghe (2012) argues that the current cyclical gap between the actual and trend labor force participation rate is likely to hold back the return of the unemployment rate to its long-run level. Hence, the dynamics of hours worked and labor force participation may have important implications for the state of the labor market. By exclusively focusing on unemployment as the labor market indicator, this information is neglected.

In this paper, we take a fresh look at the adjustment dynamics of various labor market variables over the business cycle in the United States and Germany. The main focus is on the estimation of an additional indicator for the state of the labor market that captures movements along the extensive and intensive margin. We estimate the natural ratio of total hours to potential hours and find a meaningful correlation between the proposed indicator and other macroeconomic variables.

We demonstrate the implications of our alternative labor market gap for the conduct of monetary policy. A Taylor rule based on the hours gap as the relevant labor market indicator leads to a better model fit and is not subject to parameter instability. We find strong support for the hours-based rule using formal model comparison.

The remainder of the paper is structured as follows: Section 2 shows the adjustment dynamics of key labor market variables over the business cycle. Section 3 introduces the hours ratio as an alternative variable of aggregate movements in the labor market. Section 4 lays down a stylized structural time series model used to estimate the natural rate of hours. Section 5 describes the data and the Bayesian estimation procedure. Results are given in Section 6. We demonstrate the importance of our findings for monetary policy via a Taylor rule in Section 7. Section 8 gives a conclusion.

2. LABOR MARKET ADJUSTMENT

This section analyzes the adjustment dynamics of key labor market variables over the business cycle. Particular attention is paid to changes over time and across countries in the response of (i) the employment-to-population ratio, (ii) the unemployment rate, (iii) labor force participation, and (iv) hours worked after a recession. We focus on the United States and Germany. The United States is known to have a flexible labor market, whereas Germany represents the more rigid European labor market regime. The focus in the following graphical analysis is on the role of the extensive margin for the United States and the intensive margin for Germany.

Figure 1 shows the evolution of the U.S. unemployment rate, the labor force participation rate, and the employment-to-population ratio during business cycles over the period from 1973 to 2012. Each graph plots the series until the 20th quarter after the peak date. All variables are displayed in deviations from their value at the business cycle peak.[2]

After the first two recessions, the unemployment rate and the employment-to-population ratio evolve symmetrically and follow a V-shaped pattern; i.e., both series return to their prerecession levels shortly after a sharp turning point. Labor force participation stagnates for some time, but starts to increase right after the trough. This suggests that the decline in the unemployment rate during the recoveries was driven by additional job creation and not by people exiting the labor force. During the recession in the 1990s the unemployment rate and the employment-to-population ratio exhibit a U-shaped pattern. Although this recession was less severe in terms of absolute changes, it took longer time for both series to return to their prerecession level. The early 2000s recession shows an incomplete U-pattern, as neither the unemployment rate nor the employment-to-population ratio returns to its prerecession level during the recovery. However, the absolute change is larger for the employment-to-population ratio. In contrast to the recessions of the 1970s and 1980s, the labor force participation rate steadily decreased throughout

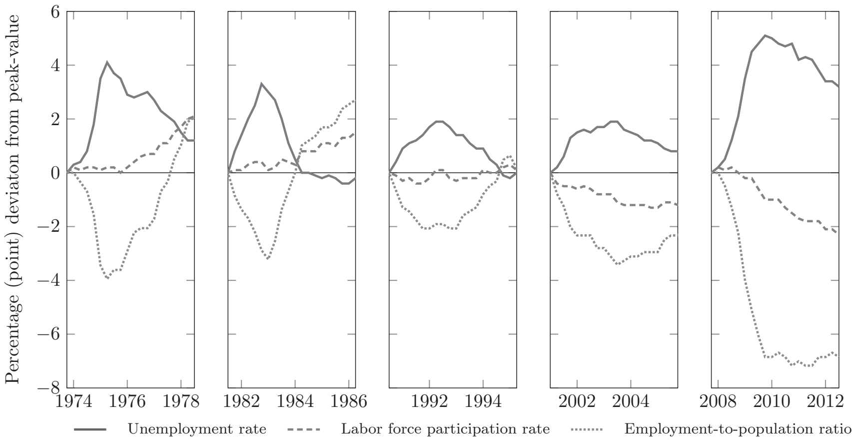

FIGURE 1. Labor market indicators over business cycles: United States.

this cycle. Thus, the rather moderate increase in the unemployment rate suggests that fewer people actively looked for a job.[3] Regarding the most recent recession, all three labor market indicators exhibit changes that are substantially larger in magnitude than in previous recessions in the sample. In contrast to former periods, the employment-to-population follows an L-shaped pattern; i.e., employment stagnates at its recession level and without any sign of recovery. The unemployment rate, however, evolved in a very different way. Although the magnitude of changes in these two variables was very similar over the previous recessions, changes in the unemployment rate were considerably smaller during the most recent recession. Moreover, the declining unemployment rate after 2010:Q1 coincides with a steep decline in labor force participation. Thus, the decline in the unemployment rate may not be interpreted as a recovery of the labor market as such, but as the result of fewer people joining the labor market. The increased importance of the extensive margin in the recent recession and to a lesser extent in the early 2000s recession implies that the deviation of the unemployment rate from a natural level such as the NAIRU is too small and does not reflect all dimensions of the aggregate labor market. Even if one still believes in the NAIRU as an important piece of information, its relation to other labor market variables such as the labor force participation rate and the employment-to-population ratio has changed over time. The latter point on its own is relevant to the conduct of monetary policy.

Turning to the German labor market, there is a remarkable difference in the magnitude between the different cycles within Germany and compared with the United States. Figure 2 shows the evolution of the German unemployment rate, hours worked, and the employment-to-population ratio during business cycles over the period from 1973 to 2013.

The first four cycles deliver clear evidence on how business cycle shocks left permanent scars on the German economy as the unemployment rate initially

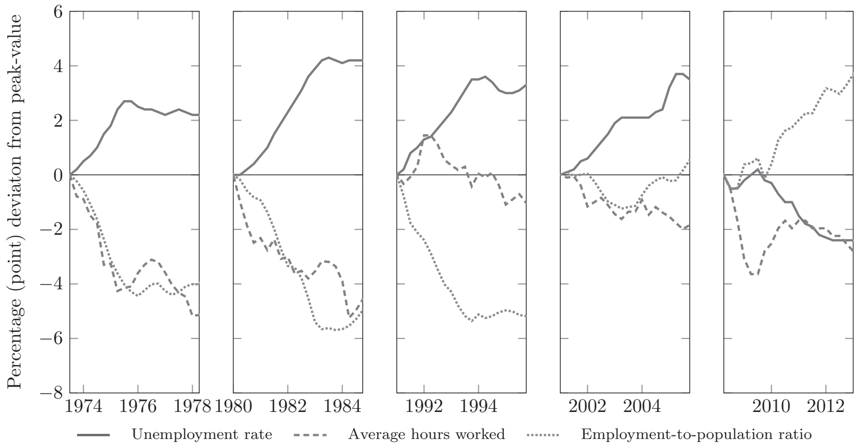

FIGURE 2. Labor market indicators over business cycles: Germany.

increased and then stagnated on a new plateau. Similarly, employment exhibits an L-shaped pattern during the first three recessions, but employment dynamics is very different for the recession in the early 2000s, as job losses are small and employment recovers quickly. The fact that the unemployment rate increases despite growing employment can be explained by German labor market reforms that led to a broader definition of the unemployed population.[4] The picture for the 2008 recession is drastically different from those for previous cycles, as the unemployment rate increases only slightly and only for a few quarters before it continues to decrease permanently. Similarly, the recession does not alter the upward trend in employment notably. Almost all of the adjustment occurs along the intensive margin of the labor market. Hours worked plunge sharply in Germany, but recover just as fast. The series for hours worked over all five recessions also points to the important distinction between trend and cyclical movements. The hours series exhibits a distinct downward trend movement in Germany over the full sample, but the very last recession is a distinct example of a temporary decrease in the number of hours worked. This is the result of short-time work arrangements during the crisis in Germany—a feature of the labor market not captured by the official unemployment rate.

The importance of the intensive margin for the adjustment process on the labor market also appears in cross-country comparisons. Ohanian and Raffo (2012) document that in many OECD countries about half of the adjustment occurs along the intensive margin. In fact, different dynamics in hours worked might be one reason that the unemployment rate reacted so differently across countries during the Great Recession. Table 1 shows the changes in GDP, the unemployment rate, the employment level, and hours per employed person from peak to trough.

Although the size of the GDP shock is larger for Germany, the United States experienced a stronger reaction of the labor market, with a larger increase in the

TABLE 1. Labor market adjustment during the Great Recession

	Change from peak to trough	
	Germany 08:Q1–09:Q2	United States 07:Q4–09:Q2
GDP %	−6.0	−4.1
Unemployment rate pp.	−0.1	4.4
Employment (level) %	0.3	−4.8
Avg. hours per empl. pers. %	−3.3	−1.5

unemployment rate and a bigger drop in employment. The intensive margin appears to be less important for the adjustment process. In contrast, Germany experienced only a slight movement in the (un)employment series (with a counterintuitive sign). Hours per employed person, however, were reduced substantially during the recession. This can be explained by the short-time work program, which was set up to avoid mass layoffs during the crisis. Hence, solely looking at the NAIRU could be misleading for the case of Germany.

In sum, the adjustment of labor markets differs across countries and has changed over time. Using the unemployment rate as the predominant labor market indicator (i) leaves out the intensive margin and (ii) is sensitive to shifts in labor force participation. Hence, using the natural rate of hours, as estimated from a structural time-series model, provides a more realistic picture of the state of the labor market.

3. MEASURING EMPLOYMENT IN HOURS WORKED

An indicator that takes the intensive margin into account and is robust to movements along the extensive margin is the ratio of aggregate hours worked to potential hours in an economy within one year. It is also known as the *employment rate in hours*[5] and is given by

$$\text{hours rate} = \frac{\text{hours per employed person} \times \text{employment}}{1920 \times \text{population at working age}}. \tag{1}$$

This indicator combines different dimensions of the labor market. Fewer hours worked show up as a lower number, thus capturing movements along the intensive margin. Changes in the participation rate affect the numerator in (1). However, changes in labor force participation that do not correspond to changes in the employment level, i.e., unemployed persons who give up looking for a job, will not shift the hours rate. This is different from the unemployment rate, which would decrease if unemployed people exited the labor force. Although changes in unemployment can be induced by very different factors with very different implications, changes in the hours rate are always linked to an increase (or decrease) in overall labor utilization. For the calculation of potential hours, we assume a workweek of

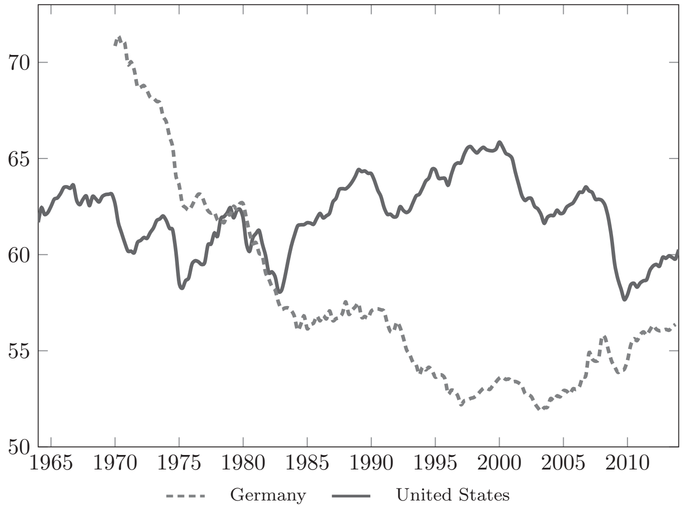

FIGURE 3. Overall employment measured in hours.

40 hours and 48 workweeks, which results in 1920 potential hours per capita and per year.[6]

Figure 3 shows hours series for both countries considered here. Germany starts at a much higher employment level than the United States, but exhibits a persistent downward trend until the early 2000s. For example, in 1970:Q1 Germans worked about 71% of potential hours whereas Americans worked about 63%. Since the early 1980s, the United States has reached a permanently higher employment level (in hours) than Germany. More recently, the two series exhibit convergence. Differences in the hours rate are substantially smaller than 20 years ago. Moreover, the United States exhibits more pronounced cyclical swings whereas the German series seems to be driven mainly by structural or long-run factors. The cross-country differences are the subject of a large literature. Whereas some authors emphasize the role of labor and product market characteristics such as employment protection legislation, union power, wage bargaining systems, and barriers to entry, other studies highlight the influence of fiscal policy, particularly the differences in the level and composition of taxes and government expenditures [see Berger and Heylen (2011)]. However, the focus here is not on the mean of the series but on cyclical movements around its long-run trend. In particular, the series for hours is decomposed into a long-run trend and a cyclical component. To the best of our knowledge, all previous studies of this subject have focused on the unemployment rate.

4. EMPIRICAL MODEL

This section lays down a structural time series model to estimate the natural rate of hours.[7] The empirical model borrows from the recent NAIRU literature;

https://doi.org/10.1017/S1365100515000917 Published online by Cambridge University Press

i.e., we estimate the time-varying natural rate within a multivariate unobserved-components (UC) model that treats the equilibrium rate and its corresponding gap as latent variables. The latent variables as well as the model parameters are jointly estimated using a Gibbs sampling procedure.

Laubach (2001) introduced the structural UC model in order to estimate the NAIRU. In his bivariate model, a Phillips curve is used to link the unobserved unemployment gap to changes in the rate of inflation. The model is structural in the sense that, by using a Phillips curve, the resulting equilibrium rate of unemployment is consistent with the stochastic law of motion for the latent variables that have been specified, and with a zero unemployment gap when inflation is stable. The latter point distinguishes NAIRU estimates based on an UC model from purely statistical trend–cycle decompositions.

Since Laubach (2001), the literature has extended the modeling framework in several dimensions. Common to most of the recent NAIRU estimates is that they rely on multivariate UC models; i.e., the latent variables are identified using information contained in various macroeconomic aggregates.[8] In fact, Basistha and Startz (2008) show that using additional information from multiple indicators that share a similar cycle with the unemployment rate cuts in half uncertainty about the estimate as measured by variance.

This paper's model is based on the assumption that the series for total hours shares a common cyclical component with the two other variables considered, namely inflation and output.[9] First, the employment–inflation relation is presented. A standard Phillips curve relation expresses realized inflation as the sum of current expectations of future inflation and the labor market gap. Denoting the inflation rate in period t by π_t and defining the labor market gap,[10] h_t^c, as the deviation of total hours, h_t, from their natural level, h_t^*, the Phillips curve can be written as

$$\pi_t = E_t(\pi_\infty) + \theta(L)(h_t - h_t^*) + \varepsilon_t^\pi, \tag{2}$$

where ε_t^π is a Gaussian zero-mean white noise error term, θ is the slope coefficient of the Phillips curve, and the lag polynomial is defined as $\theta(L) = \theta_0 + \theta_1 L + \cdots + \theta_q L^q$. Inflation expectations are not observed and thus have to be proxied. Often, a backward-looking or accelerationist curve is assumed; i.e., lagged inflation is used as a proxy for inflation expectations [see, e.g., Laubach (2001); Fabiani and Mestre (2004)]. Instead of assuming backward-looking expectations, this paper follows Morley et al. (2015) and proxies the expectation term by a stochastic trend. In theoretical work, Cogley and Sbordone (2008) and Goodfriend and King (2009) derive versions of the New Keynesian Phillips curve (NKPC) that incorporate a time-varying inflation trend, so that the inflation gap rather than the level of inflation is influenced by the real activity gap. In empirical studies, the forward-looking NKPC can be reconciled with the data once inflation is allowed to have a stochastic trend [see Nelson and Lee (2007); Piger and Rasche (2008)]. The inflation trend, π_t^*, is assumed to follow a driftless random walk,[11]

$$\pi_t^* = \pi_{t-1}^* + \eta_t^\pi, \tag{3}$$

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where η_t^{π} is a Gaussian zero-mean white noise error term. Similarly, real GDP is decomposed into a stochastic trend and a cyclical component. Trend output, g^*, is assumed to follow a random walk with drift. The cyclical component in output is linked to the hours gap through a stylized production function, which states that deviations of output from its trend are correlated with the hours gap,[12]

$$g_t = g_t^* + \omega(L)h_{t-1}^c + \varepsilon_t^g, \tag{4}$$

$$g_t^* = \gamma + g_{t-1}^* + \eta_t^g, \tag{5}$$

where ε_t^g and η_t^g are Gaussian zero-mean white noise error terms and the lag polynomial is defined as $\omega(L) = \omega_0 + \omega_1 L + \cdots + \omega_q L^q$.

In (4) the output gap reacts to previous periods' hours gaps. However, the direction of causality may also run the other way around. Indeed, most studies relating the unemployment rate to output assume a lagged reaction of the unemployment gap to the output gap. As Knotek (2007) has shown for the United States, the correlation between current unemployment and past output has gained importance over time. However, because the labor market series used in our model incorporates both employment (in persons) and hours worked, the dynamic relationship is not clear-cut. In fact, hours worked are considered a leading indicator. For instance, Kydland and Prescott (1990) and Cooley and Prescott (1995) investigate the U.S. business cycle and find that although employment lags output, hours worked slightly lead it. Fiorito and Kollintzas (1994) use data for the G7 and show that for most countries employment is a lagged and hours is a leading or coincident indicator.[13]

To close the model, we have to specify the stochastic law of motion for the natural rate and the hours gap. The latter is specified as a stationary autoregressive process. Denoting the natural rate by h_t^* and cyclical hours by h_t^c, the dynamics for employment can be written as

$$h_t = h_t^* + h_t^c, \tag{6}$$

$$h_t^* = \mu + h_{t-1}^* + \eta_t^h, \tag{7}$$

$$h_t^c = \phi(L)h_{t-1}^c + \nu_t, \tag{8}$$

where η_t^h and ν_t are Gaussian zero-mean white noise error terms and the lag polynomial is defined as $\phi(L) = \phi_0 + \phi_1 L + \cdots + \phi_q L^q$.

5. DATA AND ESTIMATION METHODOLOGY

5.1. Data

We use quarterly data from 1964:Q1 to 2013:Q4 for the United States and from 1970:Q1 to 2013:Q4 for Germany. The inflation series is obtained by taking first differences of the log of the seasonally adjusted Consumer Price Index (CPI) at an annualized rate. Output is the log of real gross domestic product at constant local prices. The hours series is calculated according to (1). Details on the data sources are given in Appendix A.

5.2. Estimation Methodology

The outlined model can in principle be estimated using the Kalman filter and the maximum likelihood (ML) technique. Instead of using ML, we estimate the model using Gibbs sampling. For our purposes, the Gibbs sampler has a number of advantages over standard ML estimation. First, it directly provides an entire distribution of all parameters and states, allowing us to analyze the uncertainty around our state estimates.[14] Second, by specifying prior distributions for the variance parameters, which are strictly positive, we avoid the so-called pile-up problem.[15] Third, by using prior information, we downweight the likelihood function in regions of the parameter space that are inconsistent with out-of-sample information and/or in which the structural model is not interpretable.

The Gibbs sampler splits the model parameters and unobserved components into blocks that are conditional on each other in order to draw sequentially from the conditional distribution. After a sufficiently large number of iterations, the algorithm produces draws from the joint posterior distribution of all parameters and states. Thus, the credible bands around the states combine filter and parameter uncertainty.

Gibbs sampling. Denote the model parameters by $\psi = \{\phi, \theta, \omega, \sigma_{\varepsilon^\pi}, \sigma_{\varepsilon^g}, \sigma_{\eta^h}, \sigma_{\eta^\pi}, \sigma_{\eta^g}, \sigma_\nu, \gamma, \mu\}$. The posterior density of interest is $p(h^c, h^*, \pi^*, g^*, \psi | h, \pi, g)$. Given an arbitrary set of starting values $(h^c_{\{0\}}, h^*_{\{0\}}, \pi^*_{\{0\}}, g^*_{\{0\}}, \psi_{\{0\}})$, the algorithm consists of the following blocks:

1. Sample the unobserved components $(h^c_{\{1\}}, h^*_{\{1\}}, \pi^*_{\{1\}}, g^*_{\{1\}})$ from $p(h^c, h^*, \pi^*, g^* | h$ $\pi, g, \psi_{\{0\}})$ according to observation equations (2), (4), and (6) and state equations (3), (5), (7), and (8).
2. Sample the parameters ψ from $p(\psi_{\{1\}} | h, \pi, g, h^c_{\{1\}}, h^*_{\{1\}}, \pi^*_{\{1\}}, g^*_{\{1\}})$.

Sampling from these blocks can then be iterated J times and, after a sufficiently long burn-in period B, the sequence of draws $(B + 1, \ldots, J)$ approximates a sample from the virtual posterior distribution. Details on the exact implementation can be found in Appendix B.

Priors. Normal priors are used for all slope parameters, whereas inverted gamma-2 distributions are used for all variance parameters. As stated in the preceding, the main motivation for setting these priors is to downweight the likelihood function in regions of the parameter space that are inconsistent with out-of-sample information and/or in which the structural model is not interpretable. Previous estimates as well as economic theory give us an idea of the approximate value of the model's parameters. However, using previous studies to set priors should be done with caution, particularly if these studies consider the same time period. We therefore use previous estimates only as a rough indication for the prior means, but choose the prior variance fairly loosely. Prior beliefs about the parameters and

TABLE 2. Parameter estimates for the United States: Hours-based model

	Prior			Posterior		
	Parameter	Belief	Strength	Mean	5%	95%
Employment	ϕ_1	1.4	0.0001	1.322	1.154	1.447
	ϕ_2	−0.6	0.0001	−0.411	−0.489	−0.318
	σ_ν	0.7	0.1	0.416	0.377	0.460
	$\sigma_{\eta h}$	0.1	0.1	0.128	0.091	0.184
Inflation	$\Sigma\theta_i$	1.0	0.0001	0.951	−0.160	2.024
	$\sigma_{\eta\pi}$	0.25	0.1	0.541	0.388	0.729
	$\sigma_{\varepsilon\pi}$	1.0	0.0001	1.748	1.576	1.947
Output	$\Sigma\omega_i$	1.5	0.0001	1.538	0.717	2.254
	$\sigma_{\eta g}$	0.7	0.1	0.651	0.547	0.774
	$\sigma_{\varepsilon g}$	0.1	0.0001	0.815	0.684	0.961
	γ	0.7	0.0001	0.745	0.665	0.822

the strength of these beliefs are given in the tables in Section 6. We express the strength of the priors as a fraction of the sample precision. For many parameters the strength is set to 0.0001, implying that prior information is proportionate to 0.01% of the in-sample information. We apply slightly more informative priors only for the standard deviations of trend and cycle components, which are proportionate to 10% of the sample information. For example, the prior mean of 0.7 for $\sigma_{\eta g}$ implies that 95% of all shocks to potential output lie between -1.4% and +1.4% per quarter. The prior belief about the AR coefficients implies a hump-shaped pattern of the labor market gap. Moreover, we assume positive signs on the hours–output relation and the slope of the Phillips curve, implying that above-trend inflation is associated with a positive output gap and a positive inflation gap.

In estimating the model, a lag order q of two is chosen, which is in line with the literature [see, e.g., Laubach (2001); Domenech and Gomez (2006); Basistha and Startz (2008)] and sufficient for quarterly data.[16]

6. RESULTS

6.1. United States

Table 2 shows the posterior mean for all model parameters, along with the 5th and 95th percentiles of the posterior distributions. The AR coefficients imply a highly persistent cyclical component, as the posterior of the sum is close to one. The estimated standard deviation for cyclical shocks is substantially larger than that for permanent shocks. The slope of the Phillips curve is 0.95, which indicates that a labor market gap of 1% leads to a deviation of actual from trend inflation of roughly the same size. However, the 90% credible interval also contains the value of zero. The output–employment relation is somewhat stronger. with a mean estimate of 1.5. The drift in trend output, which represents the average growth rate

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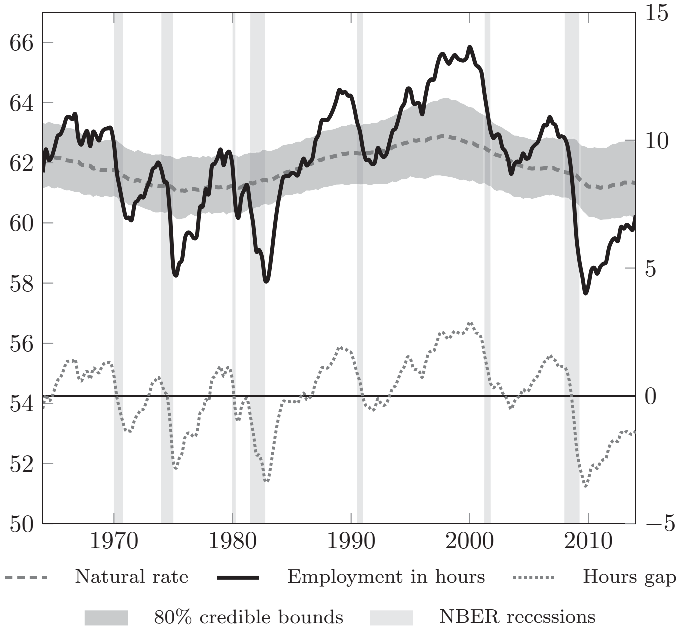

FIGURE 4. Natural rate and hours gap: United States.

of potential GDP, is very close to what is commonly found in the literature and the credible interval is quite narrow.

Figure 4 plots the hours series, the mean estimate of the natural rate (left scale), and the corresponding hours gap (right scale). Shaded areas indicate recessions of the U.S. economy. The natural rate exhibits moderate long-run swings with two turning points. The rather steep decline within the first years of the sample can be explained by a large-scale withdrawal of prime-age men from the U.S. labor force. This withdrawal is associated with a rapid expansion of the social security programs [see Parsons (1980)]. The first turning point occurs in the late 1970s, when the initial downward trend reversed and the natural rate started to increase for about two decades. The continuing decrease in male labor force participation was then offset by growing participation of women, who increased their hours devoted to market work rapidly until the late 1980s. This expansions slowed down in the 1990s, as described by Juhn and Potter (2006). Despite important shifts in hours worked between different labor market subgroups, aggregate hours appear relatively stable over the sample [see McGrattan and Rogerson (2004)]. The second turning point lies in the late 1990s, when the labor force participation of women started to stagnate and failed to offset the ongoing decline of male participation. The impact of the Great Recession on the natural rate is rather moderate, because the model ascribes most of the movements in the original hours series to the cyclical component. Recently, the natural rate of hours has been at roughly the

TABLE 3. Parameter estimates for the United States: Unemployment-based model

	Prior			Posterior		
	Parameter	Belief	Strength	Mean	5%	95%
Unemployment	ϕ_1	1.4	0.0001	1.437	1.273	1.570
	ϕ_2	−0.6	0.0001	−0.528	−0.612	−0.429
	σ_ν	0.7	0.1	0.355	0.321	0.393
	$\sigma_{\eta u}$	0.1	0.1	0.105	0.081	0.142
Inflation	$\Sigma\theta_i$	−1.5	0.0001	−1.028	−2.247	0.139
	$\sigma_{\eta\pi}$	0.25	0.1	0.554	0.409	0.744
	$\sigma_{\varepsilon\pi}$	1.0	0.0001	1.740	1.574	1.923
Output	$\Sigma\omega_i$	−1.5	0.0001	−1.595	−2.443	−0.729
	$\sigma_{\eta g}$	0.7	0.1	0.628	0.529	0.753
	$\sigma_{\varepsilon g}$	0.1	0.0001	0.787	0.663	0.934
	γ	0.7	0.0001	0.736	0.664	0.808

same level as in the 1970s. The estimated labor market gap of 3.5% during the trough of the last recession is larger than ever before.

We compare our alternative measure of the labor market gap with a conventionally estimated unemployment gap. To estimate the unemployment gap, we replaced the hours series with the U.S. civilian unemployment rate and estimated the model as outlined in Section 4.[17] Parameter estimates for the unemployment-based model are given in Table 3.

A visual comparison of the gap measures is given in Figure 5.[18] Both gap series pick up the same business cycle turning points and match the NBER recession dates. Although for some periods the gaps are almost identical, the hours gap moves outside the 80% credible bound of the unemployment gap in other periods. These differences are large for the recession in the early 1970s as well as for most of the 1990s. The hours gap implies that the deviation from the long-run labor market level in the 1990s was larger than standard unemployment measures suggested. Regarding the Great Recession, both gap measures peak at about the same level but diverge during the most recent observations. Although the unemployment gap is almost zero by the end of 2013, the hours gap is still as large as 1.5%.

As differences in the gaps can lead to substantially different policy choices, one would like to have a statistical measure for these differences. Thus, we compute the difference of the unemployment and the hours gap in each iteration of the Gibbs sampler, resulting in an empirical distribution of the gap difference at each quarter. At times where the intensive and the extensive margin of the labor market become more important, we find that the 90% credible interval does not include zero.[19]

However, the fact that the credible interval contains zero in many other periods should not be interpreted as evidence that the gaps are not different from each other.

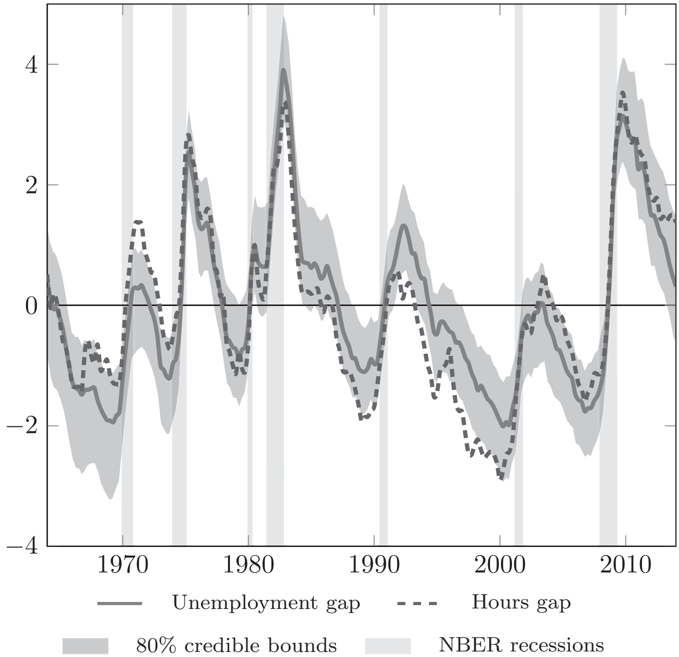

FIGURE 5. Hours gap and unemployment gap: United States.

In fact, although nonoverlapping confidence bounds ensure significant differences, the reverse is not true, as shown by Schenker and Gentleman (2001).

Central banks might in general be interested in the complete distribution of relevant variables, but they will ultimately base their policy choices on some type of average value, i.e., the mean or mode of the distribution. Thus, differences in the mean estimate can have different policy implications. We demonstrate the policy implications of the two different gap estimates via a Taylor-rule exercise in Section 7.

6.2. Germany

The posterior distributions of the model parameter for Germany are given in Table 4. In comparison to the United States, permanent shocks to the labor market are larger, reflecting more rigid labor market institutions. The slope of the Phillips curve is similar to that for the United States, but again the credible intervals are larger. The estimated production function coefficients, which display the correlation between the output and the labor market gap, sum up to 2.5 on the average, with the estimate being significantly different from zero. One notable feature of the German economy is the lower output drift, which implies a yearly growth rate of potential GDP of 2.2% as compared to 3% for the United States.

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TABLE 4. Parameter estimates for Germany: Hours-based model

	Prior			Posterior		
	Parameter	Belief	Strength	Mean	5%	95%
Employment	ϕ_1	1.4	0.0001	0.747	0.518	0.960
	ϕ_2	−0.6	0.0001	0.123	−0.037	0.291
	μ	0	0.0001	−0.083	−0.120	−0.047
	σ_ν	0.7	0.1	0.409	0.358	0.465
	$\sigma_{\eta h}$	0.1	0.1	0.266	0.187	0.344
Inflation	$\Sigma\theta_i$	1.0	0.0001	1.176	0.178	2.212
	$\sigma_{\eta\pi}$	0.3	0.1	0.372	0.273	0.488
	$\sigma_{\varepsilon\pi}$	1.0	0.0001	1.165	1.047	1.296
Output	$\Sigma\omega_i$	1.5	0.0001	2.451	1.074	3.948
	$\sigma_{\eta g}$	0.7	0.1	0.889	0.699	1.089
	$\sigma_{\varepsilon g}$	1.0	0.0001	1.229	1.039	1.451
	γ	0.5	0.0001	0.541	0.427	0.656

Figure 6 shows the German hours series, the mean estimate of the natural rate of hours (left scale), and the corresponding hours gap (right scale). The natural rate follows the three-decade-long decline in total hours that ended in the mid-2000s. Since then, trend hours have picked up again and are now back to the pre-1991 recession level. Although most of the cyclical swings in total hours appear rather persistent, the downturn in hours during the latest recession stands out as severe but short-lived. Almost all of the dynamics during this recession is explained by the transitory component, whereas the natural rate continues to increase at a prerecession pace.

To compare the hours gap with the unemployment gap, we rerun the model and replace hours with the rate of unemployment. Parameter estimates for the unemployment-based model are given in Table 5.

The resulting gap is compared with the hours gap in Figure 7. During the first two downturns and the following recoveries, the unemployment and hours gaps evolve symmetrically, implying that cyclical changes in hours worked and labor force participation had less of a role to play. The picture is somewhat different for the last three recessions. During the cycles in the 1990s and early 2000s, the unemployment gap is larger (by as much as two percentage points) than the hours gap. Conversely, the hours gap is larger during the most recent recession, which is the result of nationwide short-time work arrangements. Only looking at the unemployment rate as the relevant labor market indicator would not provide a complete picture of the state of the German labor market. This becomes even more clear if one compares the magnitude of the two gap measures over time. The cyclical increase in the unemployment rate during the latest recession is small compared with those in former periods. The recessions in the 1980s, 1990s, and early 2000s led to much larger shifts of the unemployment rate away from its

TABLE 5. Parameter estimates for Germany: Unemployment-based model

	Prior			Posterior		
	Parameter	Belief	Strength	Mean	5%	95%
Unemployment	ϕ_1	1.4	0.0001	0.971	0.657	1.258
	ϕ_2	−0.6	0.0001	−0.083	−0.338	0.180
	μ	0	0.0001	0.032	0.006	0.058
	σ_ν	0.7	0.1	0.349	0.308	0.395
	$\sigma_{\eta u}$	0.1	0.1	0.182	0.118	0.271
Inflation	$\Sigma\theta_i$	−1.5	0.0001	−0.713	−2.140	0.675
	$\sigma_{\eta\pi}$	0.3	0.1	0.391	0.285	0.525
	$\sigma_{\varepsilon\pi}$	1.0	0.0001	1.251	1.116	1.402
Output	$\Sigma\omega_i$	−1.5	0.0001	−1.731	−3.806	0.319
	$\sigma_{\eta g}$	0.7	0.1	0.962	0.770	1.177
	$\sigma_{\varepsilon g}$	1.0	0.0001	1.395	1.176	1.650
	γ	0.5	0.0001	0.532	0.405	0.655

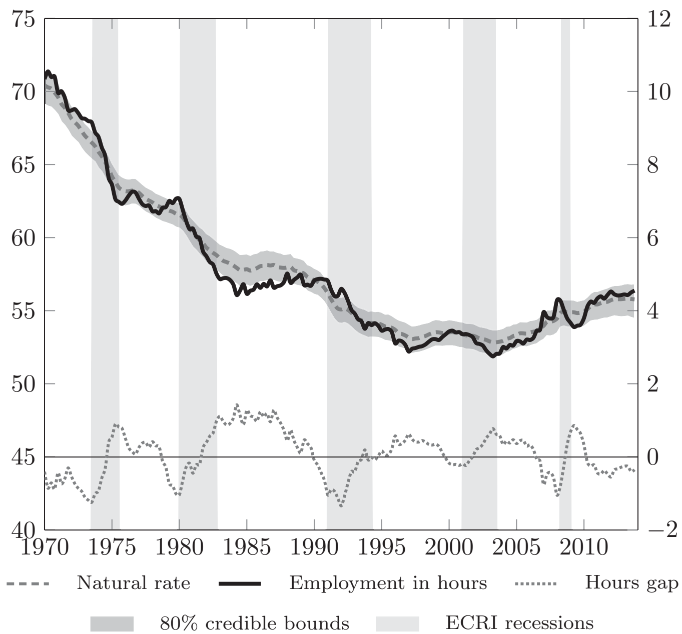

FIGURE 6. Natural rate and hours gap: Germany.

long-run trend. In contrast, the hours gap reacts much more strongly. This finding does not come as a surprise. As outlined in Section 2, unemployment stayed almost constant during the Great Recession in Germany, but aggregate hours worked declined.

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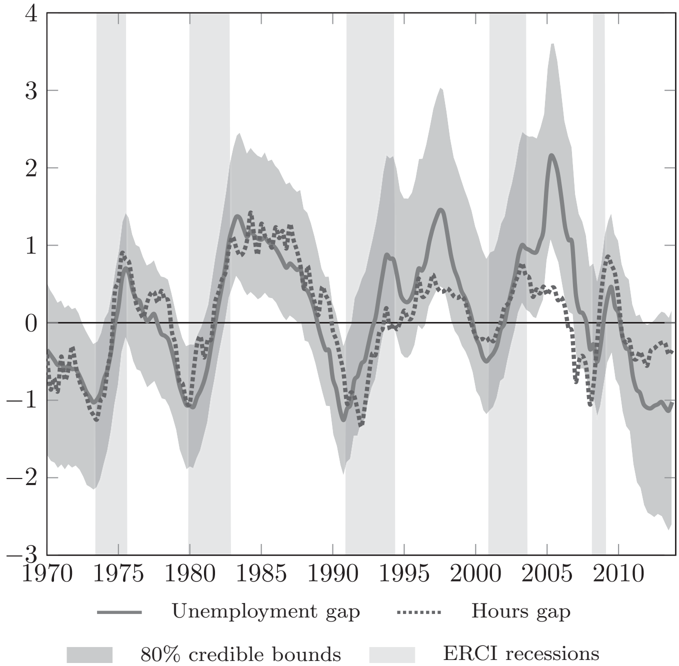

FIGURE 7. Hours gap and unemployment gap: Germany.

7. AN HOURS-BASED TAYLOR RULE

In a seminal paper, Taylor (1993) argued that changes in the federal funds rate (FFR) can be explained by a simple policy rule. According to this rule, central bankers set the nominal interest rate as a reaction to deviations of inflation from the inflation target and deviations of output from potential output. Given the assumption of a constant inflation target and a constant equilibrium real interest rate, such a rule can be estimated as a regression of the FFR on a constant, some measure of inflation, and a measure of the real activity gap. The latter variable is often proxied by the unemployment gap [see, e.g., Ball and Moffitt (2001); Mankiw (2001); Lansing (2006, 2008); Rudebusch (2009, 2010)].

To demonstrate the policy implications of the hours gap, we estimate a standard Taylor rule relationship for the United States and analyze whether the hours gap can provide additional information to explain central bank behavior. The hours-based Taylor rule is compared with an unemployment-based model using a Bayes factor. The Taylor rule in a regression equation takes the following form:

$$r_t = \beta_0 + \beta_1 \pi_t^{\mathrm{PCE}} + \beta_2 \mathrm{gap}_t + \varepsilon_t, \tag{9}$$

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TABLE 6. OLS Taylor rule estimates

		Hours gap	Unemployment gap
Constant	β_0	2.415***	3.269***
Inflation	β_1	1.800***	1.805***
Gap	β_2	1.676***	−1.428***
$\overline{R}^2$		0.88	0.65
Log-likelihood		−93.31	−138.65
		QA-breakpoint test on β_2	
Date		1994:Q2	2001:Q2
MaxF		4.41	47.66***
ExpF		1.07	20.08***
AveF		1.69	13.30***

*** Significant at the 1% level.

where r_t is the United States FFR, π_t^{PCE} is inflation measured by Core Personal Consumption Expenditure, gap_t is either the hours gap or the unemployment gap estimated in Section 6.1, and ε_t is a Gaussian zero-mean white noise error term. We run the regression using OLS for data from 1987:Q1 to 2007:Q4; i.e., we choose the same starting date as Taylor, but extend the sample just until the start of the Great Recession.[20] The estimated coefficients are given in Table 6.

All coefficients are statistically significant and have the expected sign; i.e., the FED raises the target rate when the labor market is above its natural level. This is the case for negative unemployment gaps or positive hours gaps. The estimated coefficients for the unemployment-based rule are similar to values typically found in the literature. For example, Rudebusch (2009) estimates an inflation coefficient of 1.3 and an unemployment gap coefficient of −2.0, whereas Ball and Moffitt (2001) report the inflation coefficient as ranging between 1.3 and 2.0 and the gap coefficient between −1.7 and −2.0. Importantly, the hours-based Taylor rule has considerably higher explanatory power regarding the FED policy, with an adjusted R^2 of 0.88 compared with 0.65 when the unemployment gap is used.

7.1. Model Comparison

In this section, we test whether the hours gap outperforms the unemployment gap in the Taylor rule. The two models are compared using a Bayes factor. Specifically, we denote the hours-based Taylor rule as model M_1 and the unemployment-gap-based Taylor rule as model M_2. We follow Kass and Raftery (1995) and use the Schwarz criterion to approximate the (log) Bayes factor, given by

$$\log B_{12} \approx \mathrm{ll}(D|M_1) - \mathrm{ll}(D|M_2) - \frac{1}{2}(d_1 - d_2)\log(n), \qquad (10)$$

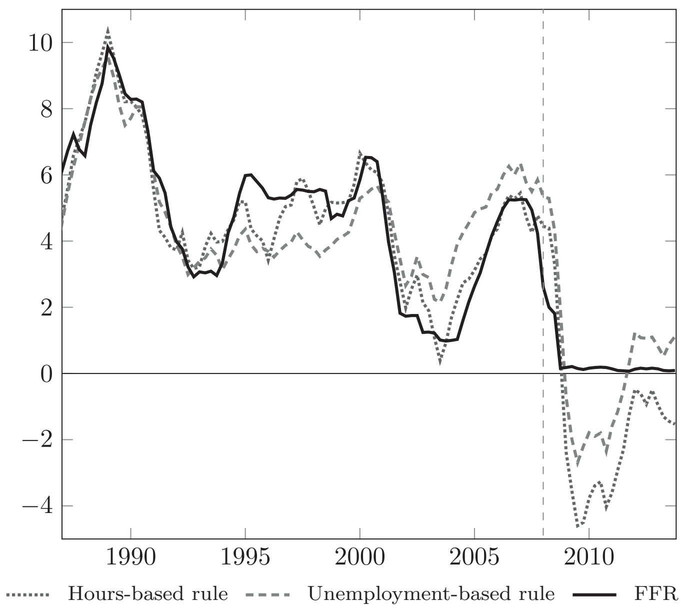

FIGURE 8. Taylor rule estimates.

where ll denotes the maximum of the log-likelihood function, d the number of parameters, and n the sample size.[21] When we evaluate the hours-based model, M_1, against the unemployment-based model, M_2, we find that $2 \times \log B_{12} = 90.7$. According to Kass and Raftery (1995), any value greater than 10 represents strong evidence against the alternative model. Thus, the Taylor rule with the hours gap is the model favored by the data.[22]

The better fit of the hours-based rule is visible in Figure 8, which shows the FFR along with the fitted series from both Taylor rules.

The vertical dashed line marks the end of the sample; hence observations right from this line shed light on the policy implications of both rules during the recent crisis and recovery. We emphasize that the hours-gap-based rule is superior in explaining monetary policy during most of the 1990s and 2000s. The unemployment-gap-based rule leads to substantially lower rates between 1994 and 2000 and higher rates for the period from 2001 to 2008.[23] This is in fact not new to the literature: Rudebusch (2006) estimates a simple Taylor rule model for 1987:Q4–2004:Q4 and finds similar deviations between the fitted and the actual series. He corrects for this fact by adding lagged endogenous variables. Lansing (2006) presents a Taylor rule with fixed coefficients, which also leads to lower rates during the 1990s and higher rates the early 2000s. When the coefficients are estimated using OLS, Lansing (2008) finds that the FFR is consistently above the estimated rule from 1995 to 1998 and below the rule from 2003 to

2008. Adding stock market variables leads to a better-fitting rule. Similar findings on the classic Taylor rule are presented by Orphanides (2003) and Rudebusch (2009).

Large deviations from the policy rule could also point to nonlinearities in the form of parameter instability. Lee et al. (2015) estimate a "Meta-Taylor rule" via Bayesian model averaging techniques, where the weights on inflation and the output gap are allowed to change over time. The authors report a doubling of the gap coefficient for the "mid-Greenspan" era that started in 1994. This is seen as the result of the central bank's desire to avoid overheating of the economy. However, parameter stability can be restored by using the hours gap as a slack measure. We perform a Quandt–Andrews breakpoint test on the gap coefficient for one single break at an unknown point in time. Results are given in the lower half of Table 8. The null hypothesis of no break is rejected for the unemployment-gap-based rule. Results point to a significant change in the reaction of the central bank to unemployment deviations in 2001. For the hours-gap-based rule the null cannot be rejected at the usual significance levels.[24]

A Taylor rule with the hours gap as the relevant measure of real activity does not suffer from parameter instability as the unemployment gap-based-rule does. Measuring labor market slack not only along the employment margin, but also along the intensive margin, helps to explain central bank behavior even on the basis on a simple two-variable Taylor rule.

Additional evidence in favor of the hours gap as an alternative indicator is given by the performance of the two rules during the recent crisis and recovery. Both series fail terribly in explaining the FFR during the recession, as the FED hit the zero lower bound (ZLB). However, since the end of 2011, the unemployment-gap-based rule would have called for monetary tightening, whereas the hours-gap-based rule still favors accommodative policies. In 2013:Q4, the two rules differ by about 2.5 percentage points, which is tremendous in central bank terms. We notice that this number should be interpreted with caution in the presence of the ZLB, as important nonlinearities may arise. However, the fact that both rules differ in the sign of the desired policy rate is already revealing. We take the Taylor rule exercise as evidence that central banks in fact consider more measures than the unemployment rate when evaluating the state of the labor market. As James Bullard (2013), President and CEO of the Federal Reserve Bank of St. Louis, explained in January 2013:

> Although some focus on the unemployment rate, it is only one aspect of the labor market. By itself, this indicator is an incomplete measure of overall labor-market health. . . . Along with payroll employment and the unemployment rate, the FOMC monitors the labor force participation rate, which has been a very important factor in recent years. ... Changing practices in labor markets could bring more people into part-time and temporary work; from that point of view, hours might be

a better indicator of the state of the labor market than simply counting the number of jobs.

8. CONCLUSION

This paper argues that because of changes in the process of adjustment to shocks of key labor market variables, the unemployment rate does not capture all important dimensions of the aggregated labor market. We propose the hours rate as an alternative indicator that takes into account adjustments along the intensive margin and is robust to changes along the extensive margin. The natural rate of hours and the corresponding hours gap are estimated from a multivariate UC model for the United States and Germany. We utilize additional information contained in inflation and output to reduce the uncertainty around the natural rate estimate. A Phillips curve is used to derive the number of hours worked at which inflation stabilizes. The hours gap is linked to the output gap via a reduced-form production function equation.

For both countries, the natural rate of hours evolves smoothly and picks up long-run trends in employment. The estimated labor market gaps are very persistent and follow the usual business cycle turning points. Results for Germany point to a strong impact of the recent crisis on the labor market. The widespread use of short-time work arrangements, concealed by a relatively stable unemployment rate, is picked up as a cyclical drop in hours. For the United States, we find that the labor market gap due to the crisis is severe, although our model assigns most of it to cyclical and not structural factors.

We demonstrate the policy implications of our findings via a Taylor rule estimation. A policy rule based on the hours gap as the relevant labor market indicator outperforms an unemployment-gap-based rule in explaining the FED. Bayesian model comparison favors the hours-gap-based model. Depending on whether the unemployment or the hours gap is taken into account, policy rules give very different advice on whether to end expansionary monetary policy in the United States.

NOTES

1. In January 2012, two and one-half years after the end of the Great Recession, FED chairman Ben Bernanke argued as to whether or not an increase in long-term unemployment has caused a shift in the natural rate of unemployment. Bernanke concluded that the unemployment rate of 8.5% was well above any natural rate estimate, so that sustaining an accommodative stance of monetary policy would be within the scope of the FED's dual mandate [Bernanke (2012)].
2. We use the peak and trough dates provided by the National Bureau of Economic Research for the United States and the Economic Cycle Research Institute for Germany throughout this paper.
3. Juhn and Potter (2006) argue that unemployment during the early 2000s has led to more or less permanent withdrawal from the labor market.
4. In January 2005 the number of unemployed persons shot up to about 5 million people, mainly because previous welfare recipients were classified as "capable of working" and thus counted as unemployed.

5. The employment rate in hours has previously been used as an indicator for the aggregate labor market by Dhont and Heylen (2008) and Berger and Heylen (2011).

6. The number of potential hours per year may be affected by labor market legislation and thus varies over time and countries. Infrequent changes in potential hours would change the long-run mean of the hours rate. Because the aim of our econometric approach is to extract cyclical swings from long-run movements, this should not affect our results. Nevertheless, we check the robustness of the results regarding the choice of potential hours.

7. We refer to the equilibrium level of the hours rate as the natural rate of hours.

8. Domenech and Gomez (2006) focus on the United States and estimate a model in which the latent variables are identified using information contained in inflation, unemployment, output, and investment. Berger (2011) estimates a trivariate UC model for the aggregate Euro area NAIRU with special emphasis on correlated shocks and structural breaks in the trend components of output and unemployment.

9. We included the investment ratio as an additional variable in a previous version of the paper. However, as the series does not deliver much information beyond what is already contained in the output series, we stick to the trivariate model.

10. We will refer to this as the hours gap.

11. Atkeson and Ohanian (2001) show that U.S. inflation is well described by a random walk.

12. This corresponds to the Okun's law approach used in the NAIRU literature, in which the cyclical in output is linked to the unemployment gap [see, e.g., Fabiani and Mestre (2004)].

13. We also estimated the model with a standard specification, i.e., one where the labor market gap reacts to lagged values of the output gap, and find that the results are nearly identical. The results of this exercise are not reported but are available upon request.

14. In the classical ML approach, filter and parameter uncertainty can be calculated, but it is not obvious how to combine them.

15. See Kim and Kim (2013) for simulation-based evidence that supports Bayesian estimation for UC models over ML.

16. Alternatively, we estimated the model with more than two lags. As additional lags have not found to be significant and the results were similar, we only report results for the AR(2) model.

17. Alternatively, we used NAIRU series from the CBO or OECD to calculate the unemployment gap. This leads to even more pronounced differences between the hours and the unemployment gap.

18. For better comparison, the hours gap has been multiplied by minus one. Thus, positive gaps imply that the labor market performs below its trend level.

19. This is the case for the times around 1992 and 1997.

20. We do not include more recent observations, as we would have to deal with the zero lower bound in our analysis. Moreover, we estimated the same equation with a smaller sample starting in 1995, which led to very similar results.

21. A Bayes factor is a ratio of marginal likelihoods, which are often difficult to calculate. In many cases, the marginal likelihood may not have a closed form solution.

22. To check the robustness of this result, we estimated the Taylor rule using the Gibbs sampler with uninformative priors and calculated the Bayes factor directly via the marginal likelihood, as described in Chib (1995). We find that $2 \times \log B_{12} \approx 93$, confirming the results based on the Schwarz criterion.

23. In principle, these deviations could also be driven by the fact that our model for estimating unemployment gap is misspecified. Therefore, we ran an alternative Taylor regression and replaced our model-based unemployment gap with the official CBO gap. However, the fitted series are almost identical, and results are not reported. We conclude that the deviations of the FFR from the unemployment-based rule are driven by factors not captured by the unemployment gap.

24. A Bai–Perron test for an unknown number of breaks cannot reject the null of no break for the hours-based rule, but confirms a significant break for the unemployment-based rule in 2001.

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APPENDIX A: DATA DESCRIPTION

All data are on a quarterly basis. When seasonal adjusted series were not available, we followed the X-12-ARIMA approach.

- Hours worked: The U.S. data on average hours worked are taken from the Bureau of Labor Statistics, BLS (via Datastream, code USHKIP..O). For Germany we make use of a dataset provided by Ohanian and Raffo (2012) and add more recent data provided by the Federal Statistical Office (via Datastream, code BDHOURPBQ).

- Employment: Data on U.S. civilian employment are taken from the BLS (via Datastream, code USEMPTOTO). Data on German employment are collected from the German Bundesbank (via Datastream, code BDUSBA14O).
- Population at working age: Data on U.S. civilian noninstitutional population are taken from the BLS (via Datastream, code USCV....P). For Germany we use population data provided by Ohanian and Raffo (2012) and add more recent data from OECD Main Economic Indicators (via Datastream, code BDQLFT32P).
- Inflation: We use the Consumer Price Index from the BLS (via FRED, code CPIAUCSL). German data are taken from the OECD's Main Economic Indicators (via Datastream, code BDQCP009F).
- Gross domestic product: Real GDP data for the United States are taken from the U.S. Bureau of Economic Analysis (via FRED, code GDPC1). In the case of Germany, data are taken from the IMF International Financial Statistics (via Datastream, code BDI99BVRG)
- Unemployment rate: The U.S. civilian unemployment rates are taken from the BLS (via Datastream, code USUN%TOTQ). The German unemployment rates are taken from the OECD Main Economic Indicators (via Datastream, code BDQLRT28Q).
- Recession dates: For the United States, the peak and trough dates are defined by the NBER Business Cycle Dating Committee. For Germany, we use dates from the Economic Cycle Research Institute (ECRI).

APPENDIX B: GIBBS SAMPLING ALGORITHM

In this paper we follow a Bayesian approach and apply a Gibbs sampling procedure to estimate our model. This Appendix gives details of the algorithm, which relies on stepwise sampling of the unobserved states (h^*, π^*, y^*, h^c) and the model's hyperparameters $(\phi, \theta, \omega, \sigma_{\varepsilon^\pi}, \sigma_{\varepsilon^g}, \sigma_{\eta^h}, \sigma_{\eta^\pi}, \sigma_{\eta^g}, \sigma_\nu, \gamma, \mu)$. The model's general state space form is given by

$$y_t = Z\alpha_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{i.i.d. } N(0, H), \tag{B.1}$$

$$\alpha_t = d + T\alpha_{t-1} + K\eta_t, \qquad \eta_t \sim \text{i.i.d. } N(0, Q), \tag{B.2}$$

where y_t is a $p \times 1$ vector of observations and α_t an unobserved $m \times 1$ state vector. The matrices Z, T, K, H, and Q and the vector d are assumed to be known (conditioned upon) and the error terms ε_t and η_t are assumed to be serially uncorrelated and independent of each other at all points in time. As equations (B.1)–(B.2) constitute a linear Gaussian state space model, the unknown state variables in α_t can be filtered using the standard Kalman filter. Within the classical approach the hyperparameters could be estimated via maximum likelihood based on a prediction error decomposition. As these estimates are taken as true values when the unobserved components are filtered, confidence intervals do not reflect parameter uncertainty, but only filtering uncertainty. The Bayesian approach allows jointly estimating the states and hyperparameters and thus leads to credible intervals that take into account both sources of uncertainty. Given an initial guess for the hyperparameters, we start by filtering and sampling the unobserved components.

B.1. BLOCK 1: FILTERING AND SAMPLING THE UNOBSERVED COMPONENTS

The model given by (2)–(8) can be cast into the following state space form:

$$\underbrace{\begin{bmatrix} h_t \\ \pi_t \\ g_t \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & \theta_1 & \theta_2 \\ 0 & 0 & 1 & \omega_1 & \omega_2 \end{bmatrix}}_{Z} \underbrace{\begin{bmatrix} h_t^* \\ \pi_t^* \\ g_t^* \\ h_t^c \\ h_{t-1}^c \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} 0 \\ \varepsilon_{\pi t} \\ \varepsilon_{gt} \end{bmatrix}}_{\varepsilon_t}, \tag{B.3}$$

$$\underbrace{\begin{bmatrix} h_t^* \\ \pi_t^* \\ g_t^* \\ h_t^c \\ h_{t-1}^c \end{bmatrix}}_{\alpha_t} = \underbrace{\begin{bmatrix} \mu \\ 0 \\ \gamma \\ 0 \\ 0 \end{bmatrix}}_{\mathrm{d}} + \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & \phi_1 & \phi_2 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{\mathrm{T}} \underbrace{\begin{bmatrix} h_{t-1}^* \\ \pi_{t-1}^* \\ g_{t-1}^* \\ h_{t-1}^c \\ h_{t-2}^c \end{bmatrix}}_{\alpha_{t-1}} + \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_{\mathrm{K}} \underbrace{\begin{bmatrix} \eta_t^h \\ \eta_t^\pi \\ \eta_t^g \\ \nu_t \end{bmatrix}}_{\eta_t}, \tag{B.4}$$

with

$$H = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \sigma_{\varepsilon^\pi}^2 & 0 \\ 0 & 0 & \sigma_{\varepsilon^g}^2 \end{bmatrix} \text{ and } Q = \begin{bmatrix} \sigma_{\eta^h}^2 & 0 & 0 & 0 \\ 0 & \sigma_{\eta^\pi}^2 & 0 & 0 \\ 0 & 0 & \sigma_{\eta^g}^2 & 0 \\ 0 & 0 & 0 & \sigma_\nu^2 \end{bmatrix}.$$

We make use of the standard Kalman filter to compute the vector of unobserved components at every point in time. Initial values are given by the unconditional distribution in the case of the stationary component and are set to arbitrary values with large initial variance in the case of nonstationary components. The state vector α_t is sampled from its conditional distribution via the multimove Gibbs sampler of Shephard (1994) and Carter and Kohn (1996).

B.2. BLOCK 2: SAMPLING THE HYPERPARAMETERS

Conditioning on the unobserved components sampled in Block 1, the hyperparameters can be expressed as unknown parameters in the standard static linear regression model,

$$y_t = b' x_t + u_t, \quad u_t \sim \mathcal{N}\left(0, \sigma^2\right), \tag{B.5}$$

where x_t and b are $(\ell \times 1)$ vectors. The matrix version of (B.5) is $y = Xb + u$ with obvious notations X ($T \times \ell$ matrix), y and u ($T \times 1$ vectors). We follow the approach outlined in Bauwens et al. (1999, pp. 56–61). Prior information is represented through the following normal-inverted gamma-2 density:

$$\varphi\left(b, \sigma^2\right) = f_{\mathrm{NIg}}\left(b, \sigma^2 | b_0, M_0, s_0, V_0\right), \tag{B.6}$$

https://doi.org/10.1017/S1365100515000917 Published online by Cambridge University Press

with the prior information being summarized by the hyperparameters $(b_0, m_0, \sigma_0^2, v_0)$. First, b_0 is the prior belief about the coefficient vector b with corresponding prior strength $M_0 = m_0 M$ such that m_0 is defined as being the prior precision proportional to the sample precision matrix $M = X'X$. Second, σ_0^2 is the prior belief about the error variance σ^2, such that $s_0 = \sigma_0^2 V_0$ is the prior belief about the residual sum of squares s, with V_0 being the corresponding prior strength, defined as $V_0 = v_0 T$, where v_0 is the prior degrees of freedom proportional to the sample size T.

The posterior density of b and σ^2 in the linear regression model (B.5) with prior density (B.6) is a normal-inverted gamma-2 distribution,

$$\varphi\left(b, \sigma^2 | y, X\right) = f_{\text{NIg}}\left(b, \sigma^2 | b_*, M_*, s_*, V_*\right), \tag{B.7}$$

with hyperparameters defined by

$$\begin{aligned} M_* &= M_0 + X'X, \\ b_* &= M_*^{-1}\left(M_0 b_0 + X'X\widehat{b}\right), \\ s_* &= s_0 + s + \left(b_0 - \widehat{b}\right)'\left[M_0^{-1} + \left(X'X\right)^{-1}\right]^{-1}\left(b_0 - \widehat{b}\right), \\ V_* &= V_0 + T, \end{aligned}$$

where $\widehat{b}$ is the LS estimator for b in (B.5). Sampling b and σ^2 from the posterior distribution (B.7) can then be done separately from

$$b \sim \mathcal{N}\left(b_*, \frac{s_*}{V_* - 2} M_*^{-1}\right), \tag{B.8}$$

$$\sigma^2 \sim IG_2\left(V_*, s_*\right). \tag{B.9}$$

If $X = [.]$, the posterior density in (B.7) reduces to

$$\varphi\left(\sigma^2 | y, X\right) = f_{\text{Ig}}\left(\sigma^2 | s_*, V_*\right), \tag{B.10}$$

with $s_* = s_0 + s$ and V_* as defined earlier.

The hyperparameters can then be sampled according to the following scheme:

- Obtain the posterior distribution of γ and $\sigma_{\eta^g}^2$ in (5) conditioning on g_t^* by using (B.7), setting $y_t = g_t^* - g_{t-1}^*$ and $x_t = 1$ in (B.5). Next, sample γ and $\sigma_{\eta^g}^2$ from (B.8) and (B.9), respectively.
- Obtain the posterior distribution of ϕ and σ_ν^2 in (8) conditioning on h_t^c by using (B.7), setting $y_t = h_t^c$ and $x_t = [h_{t-1}^c, h_{t-2}^c]$ in (B.5). Next, sample ϕ and σ_ν^2 from (B.8) and (B.9), respectively. Resample ϕ and σ_ν^2 in case the coefficients imply a nonstationary process.
- Obtain the posterior distribution of μ and $\sigma_{\eta^h}^2$ in (7) conditioning on h_t^* by using (B.7), setting $y_t = h_t^* - h_{t-1}^*$ and $x_t = 1$ in (B.5). Next, sample $\sigma_{\eta^h}^2$ from (B.8) and (B.9), respectively. For the model with $\mu = 0$, set $x_t = [.]$ and sample $\sigma_{\eta h}^2$ from (B.9).
- Obtain the posterior distribution of $\sigma_{\eta^\pi}^2$ in (3) conditioning on π_t^* by using (B.10), setting $y_t = \pi_t^* - \pi_{t-1}^*$ and $x_t = [.]$ in (B.5). Next, sample $\sigma_{\eta^\pi}^2$ from (B.9).

- Obtain the posterior distribution of θ and $\sigma^2_{\varepsilon\pi}$ in (2) conditioning on π^*_t and h^c_t by using (B.7), setting $y_t = \pi_t - \pi^*_t$ and $x_t = [h^c_t, h^c_{t-1}]$ in (B.5). Next, sample θ and $\sigma^2_{\varepsilon\pi}$ from (B.8) and (B.9), respectively.
- Obtain the posterior distribution of ω and $\sigma^2_{\varepsilon g}$ in (4) conditioning on g^*_t and h^c_t by using (B.7), setting $y_t = g_t - g^*_t$ and $x_t = [h^c_t, h^c_{t-1}]$ in (B.5). Next, sample ω and $\sigma^2_{\varepsilon g}$ from (B.8) and (B.9), respectively.

We repeat these steps iteratively 10,000 times and discard the first 5,000 draws as a burn-in sample.