How the Baby Boomers' Retirement Wave Distorts Model-Based Output Gap Estimates

Maik H. Wolters*

University of Jena, Kiel Institute for the World Economy, IMFS at Goethe University Frankfurt

May 24, 2018

Abstract

This paper illustrates based on an example the importance of consistency between the empirical measurement and the concept of variables in estimated macroeconomic models. Since standard New Keynesian models do not account for demographic trends and sectoral shifts, I propose adjusting hours worked per capita used to estimate such models accordingly to enhance the consistency between the data and the model. Without this adjustment, low frequency shifts in hours lead to unreasonable trends in the output gap, caused by the close link between hours and the output gap in such models. The retirement wave of baby boomers, for example, lowers U.S. aggregate hours per capita, which leads to erroneous permanently negative output gap estimates following the Great Recession. After correcting hours for changes in the age composition, the estimated output gap closes gradually instead following the years after the Great Recession.

Keywords: low frequency trends, demographic trends, hours per capita measurement, output gap estimates, DSGE models, Bayesian estimation

JEL-Codes: C54, E32, J11

*Friedrich-Schiller-University Jena, Carl-Zeiß Straße 3, 07743 Jena, Germany. E-Mail: maik.wolters@uni-jena.de

1 Introduction

While many papers deal with estimation methods for DSGE models, there are surprisingly few papers on the impact of the choice of observable time series, their measurement and time series characteristics for the estimation outcome and model-based analyses. Instead, often a standard set of observables is used that roughly matches the concept of variables in the model.

Guerron-Quintana (2010) shows, however, that the specific choice of observables has large effects on parameter estimates. A number of papers have considered that some data series might be imprecisely measured: Ireland (2004), Edge et al. (2008) and Gust et al. (2017) use measurement errors, Galí et al. (2012) and Justiniano et al. (2013) propose combining two wage measures with different properties and Boivin and Giannoni (2006) question whether economic variables can be properly measured by single indicators at all and introduce techniques to estimate DSGE models based on large datasets.

One important issue is how to deal with low frequency changes or trends in time series. Different detrending methods affect the business cycle properties of macroeconomic time series (see, e.g., Canova, 1998) and may distort parameter estimates of DSGE models (see, e.g., Canova and Ferroni, 2011; Canova, 2014; Sala, 2015; Sun and Tsang, 2017). Sala (2015) estimates a model in the frequency domain and shows that the presence of frequencies that the model is not intended to explain—in particular low-frequency dynamics—affect parameter estimates and forecasts obtained in the time domain. Related to this, I show, based on an example on the link between observable hours and output gap estimates, that low-frequency dynamics that the model is not intended to explain distort model-based analyses. Solutions have been proposed by Canova and Ferroni (2011) and Canova (2014). The former propose an estimation method that potentially eliminates the biases that detrending produces and the latter proposes a method to estimate based on raw data jointly model parameters and data trends that the model is not intended to explain.

Focusing specifically on hours worked, low frequency changes in labor supply have been analysed by several researchers. These can be caused, for example, by demographic trends, sectoral shifts between the public and private sector, changes in the tax code and changing preferences. The treatment of such low frequency components has large effects on VAR analyses (see, e.g., Christiano et al., 2003; Chari et al., 2005; Basu et al., 2006; Fernald, 2007; Francis and Ramey, 2009; Canova et al., 2010, on the technology-hours debate based on VARs).

Much less work has been conducted on the implications of using hours that include low frequency changes for the estimation of DSGE models. To my knowledge, Chang et al. (2007) are the only ones that have addressed the discrepancy between observed non-stationary hours and the stationarity assumptions of hours in standard models by using non-stationary labor supply shocks. Despite the possible non-stationarity of standard measures of hours per capita, they are regularly used for the estimation of DSGE models without adjusting the model accordingly or correcting the data to exclude low frequency movements that cannot be explained by the model.

I show that this can lead to incorrect findings of model-based analyses. In particular, I focus on the implications of the measurement of hours on model-based output gap estimates. Sala et al. (2010) show that there is a close link between hours and output gaps since hours are the main determinant of the labor wedge which in turn is the main determinant of the output gap in standard DSGE models. Dynamics of hours caused by sectoral or demographic shifts are thus falsely interpreted through the model's lens as inefficiencies in the labor market and cyclical variations. Hence, they are included in the output gap rather than interpreting them as a change in steady state hours. This can have large effects on output gap estimates. A number of recent papers document a persistently negative U.S. model-based output gap since the Great Recession (see, e.g. Barsky et al., 2014; Del Negro et al., 2015, 2017). I show that this is due to the retirement wave of the baby boomers lowering hours rather than a permanently depressed economy.

I correct hours per capita for low-frequency movements due to sectoral and demographic changes to retain only those dynamics that can be explained by the model. To do so, I follow Francis and Ramey (2009). First, I use total hours rather than hours in the private sector to exclude dynamics that are caused by shifts in hours between the private and the public sector. Second, I correct hours for the effects caused by the changing share of prime age workers in the working-age population due to the baby boomer cohort. For this, I use micro data on hours worked by different age groups and data on the age composition of the population.

The large decrease in private hours between 1960 and 1975 is corrected by including the increase in government hours over the same period. Low per capita hours between 1965 and 1990 and high per capita hours between 1990 and 2005 that are caused by the baby boomer cohort moving from being young and working few hours to the prime age worker group working more hours is corrected via the demographic adjustment. These corrections avoid unreasonable trends in the estimated output gap of a standard DSGE model.

An adjustment of hours is particular important for the last decade. Total hours decreased much less than hours in the private sector during the Great Recession, so that merely focusing on private hours will result in too pessimistic output gap estimates during that time. Even more important are recent demographic changes: the population share of people aged 65 and over has started to increase substantially around 2006. Hence, the beginning of the retirement wave of the baby boomer cohort coincides roughly with the beginning of the global financial crisis. People of ages 65 and over work substantially less than prime age workers so that aggregate hours have decreased which consecutively lowers output gap estimates after the financial crisis. Once I apply the demographic correction, adjusted hours increase after the financial crisis and the output gap does not remain persistently negative, but rather closes gradually until 2015. The resulting output gap estimates are similar to those from simpler state space models without observable hours (see, e.g., Kiley, 2015; Laubach and Williams, 2015).

The remainder of this paper proceeds as follows. Section 2 outlines the model, shows that the model-based output gap estimates are closely linked to hours and provides corresponding reasoning for this. In section 3, I first analyse the effects of sectoral and demographic changes on hours as well as the output gap and subsequently correct for these. Section 4 concludes.

2 The Link Between Hours and the Output Gap

In order to analyse the link between hours per capita and the output gap I use the DSGE model by Del Negro et al. (2015) due to its similarity to models frequently used at central banks. It is based on Smets and Wouters (2007) and is extended to include the financial accelerator by Bernanke et al. (1999).

2.1 Model and Estimation

Long-run growth is described by a neoclassical core model and business cycle fluctuations are generated by a variety of structural shocks combined with a number of nominal and real frictions. Nominal frictions include sticky prices and wages, price and wage indexation as well as the financial accelerator mechanism, while real frictions include habit formation, investment adjustment costs and capital utilization adjustment costs. Other specific features of the model are the non-separability of utility in consumption and leisure, the usage of the aggregator by Kimball (1995) which implies a non-constant elasticity of demand rather than the Dixit-Stiglitz aggregator and fixed costs in production. The model contains eight structural shocks and is fit to eight time series.

The model is estimated using Bayesian techniques. I use the same prior distribution as in Del Negro and Schorfheide (2013) and Del Negro et al. (2015). This is essentially also the same prior as used in Smets and Wouters (2007), except for a wider prior distribution for the steady state inflation rate and additional priors for the financial friction parameters. The sample goes from 1959Q1 to 2017Q1. The data series on per capita real output growth, consumption growth, investment growth, wage growth, inflation and the federal funds rate are constructed as in Smets and Wouters (2007). Following Del Negro et al. (2015), I use the difference between the Moody's Seasoned Baa Corporate Bond Yield and the 10-Year Treasury Note Yield at Constant Maturity to measure the credit spread. I further use four different measures of hours per capita that are described in detail in the following sections. They measure hours in the private sector, in the private nonfarm business (NFB) sector, total hours and total hours adjusted for changes in the age composition of the population, respectively. To account for the zero lower bound, I add measurement equations that link model-based interest rate expectations to financial market expectations and use anticipated monetary policy shocks as in Del Negro et al. (2015).[1]

I compute 500,000 draws from the Metropolis-Hastings algorithm of which 50,000 draws are disregarded as a burn in sample. The resulting parameter estimates are very similar to those in the literature. Parameter estimates change only slightly, but not significantly, when using different measures of hours per capita as observable. A reason for the insensitivity of parameter estimates with respect to different hours measures is that business cycle moments of these differ only slightly from each other as documented in the Appendix.[2] The linearized model equations, priors and posterior estimates are documented in the Appendix. Output gap estimates as depicted in the different figures in this paper are posterior mean estimates.

2.2 The Output Gap, the Labor Wedge and Hours per Capita

In order to understand the reasons for the strong link between hours and the output gap, I first analyse how the output gap and the labor wedge are connected and subsequently how the labor wedge is linked to hours per capita as in Sala et al. (2010). The output gap measures deviations of output from potential output, which refers to an allocation without nominal rigidities, i.e. with flexible prices and wages, without financial frictions, and without inefficient price and wage mark-up shocks. Thereby, the output gap reflects general inefficiencies, whereas the labor wedge measures inefficiencies that are specific to the allocation of labor (see e.g. Chari et al., 2007), i.e. the deviation of households' marginal rate of substitution (MRS) between consumption and leisure from the firms' marginal product of labor (MPL).

[1] I use expectations from the Blue Chip Financial Forecast Survey for the period from 1992 to 2011 and from the New York Fed's Survey of Primary Dealers from 2011 onwards. Interest rate expectations prior to 1992 are treated as unobserved.

[2] The estimates of σ_l, which characterizes the curvature of the disutility of labor (and would equal the inverse of the Frisch elasticity in absence of wage rigidities) are somewhat smaller when using one of the more volatile hours measures to estimate the model. A smaller σ_l can reconcile a higher volatility of hours with an unchanged volatility of real wages (see equation (14) in the Appendix).

The MRS, with variables denoted in percentage deviations from steady state, is given by:

$$mrs_t = \sigma_l L_t - \xi_t, \tag{1}$$

where σ_l denotes the inverse of the Frisch elasticity of labor supply, L_t hours worked per capita, and ξ_t the marginal utility of consumption. The MPL is given by:

$$mpl_t = \alpha(k_t^s - L_t), \tag{2}$$

where α denotes the share of capital in production and k_t^s capital services used in production.

The labour wedge is then:

$$\begin{aligned} wedge_t = mrs_t - mpl_t &= (\sigma_l + \alpha)L_t - \xi_t - \alpha k_t^s & (3)\\ &= (\sigma_l + \alpha)\left(L_t - L_{f,t}\right) - \left(\xi_t - \xi_{f,t}\right) - \alpha\left(k_t^s - k_{f,t}^s\right), & (4) \end{aligned}$$

where the subscript f denotes the allocation with flexible prices and wages. Equation (4) uses the fact that the labor wedge is zero in this allocation.

The output gap, x_t, can be written as:

$$x_t = y_t - y_{f,t} = \Phi\left[\alpha\left(k_t^s - k_{f,t}^s\right) + (1-\alpha)\left(L_t - L_{f,t}\right)\right], \tag{5}$$

where Φ captures the fixed cost in production.

Combining equations (4) and (5) shows the link between the output gap and the labor wedge:

$$x_t = \Phi\frac{1-\alpha}{\alpha+\sigma_l}\left[wedge_t + \left(\xi_t - \xi_{f,t}\right) + \frac{\alpha(1+\sigma_l)}{1-\alpha}\left(k_t^s - k_{f,t}^s\right)\right]. \tag{6}$$

If $(\xi_t - \xi_{f,t})$ and $(k_t^s - k_{f,t}^s)$ are small, then the output gap is mainly driven by inefficiencies in the labor market and according to equation (4), the labor wedge is mainly explained by hours.

Figure 1 shows in the upper part the output gap and its scaled components according to equation (6) and in the lower part the labor wedge and its components according to equation (3). The graph shows that hours are the main driver of the labor wedge, which in turn is the main driver of the output gap. The correlation is 0.96 between the output gap and the labor wedge and 0.92 between the labor wedge and hours.[3] In simpler models without physical capital, government spending, fixed costs in production and consumption habits, the output gap, the labor wedge and hours per capita are even exactly proportional (see Sala et al., 2010).

One can further show that the labor wedge is dominated by the dynamics in the MRS, while the dynamics of the MPL are much smaller. As the real wage is acyclical, it follows that the wage mark-up is the main driver for the inefficient labor allocation, while the price mark-up plays only a minor role.[4] Similar results have been found, for example, by Galí et al. (2007). Thus, the inefficient component can mainly be attributed to inefficient wage mark-up shocks and wage rigidities. These are needed to reconcile the volatile and strongly procyclical movements of hours and the MRS and the more stable and acyclical real wages.[5]

[3] The figure is based on the version of the model in which observable hours are measured using average hours in the NFB sector as in Smets and Wouters (2007), but the close connection between the output gap, the labor wedge and hours also holds when one of the other three hours measures considered in this paper is used.

[4] The labor wedge is related to the wage and price mark-up (μ_t^w and μ_t^p) as follows: $wedge_t = (mrs_t - w_t) + (w_t - mpl_t) = -\left(\mu_t^w + \mu_t^p\right)$.

[5] Many economists argue that the large role of wage mark-up shocks in explaining recessions is unsatisfactory (see, e.g., Shimer, 2009). DSGE models in which wage mark-up shocks play an important role are nevertheless frequently used in applied

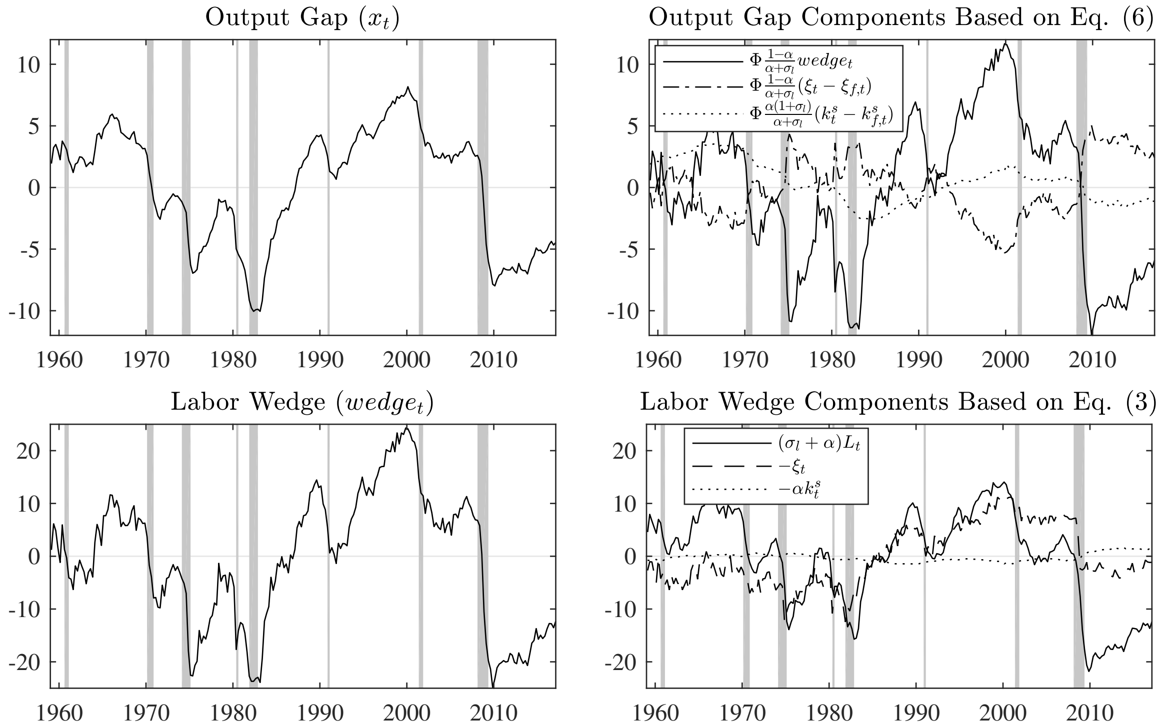

Figure 1: The output gap, the labor wedge and their components

Overall, the analysis shows that most dynamics of hours are interpreted by standard DSGE models as being inefficient and therefore hours are the main determinant of the labor wedge, which in turn is the main determinant of the output gap. Hence, it is important to measure hours precisely and in line with the model assumptions, i.e. by eliminating low-frequency components that the model is not intended to explain, because otherwise model-based output gap estimates will be distorted.

3 Low frequency Trends in Hours per Capita

In the following I show first that sectoral and demographic shifts lead to low frequency changes in hours, which consequently transmit to the output gap estimates, and subsequently correct hours for these changes.

3.1 Sectoral Shifts in Hours per Capita

The upper panel of figure 2 shows hours per capita in the private business sector, total hours per capita, total hours per capita with a demographic adjustment and a measure of hours in the NFB sector. All four measures are shown in percentage deviation from their mean. To arrive at per capita measures, I divide hours in the private business sector by the noninstitutional popoulation aged 16 and over and total hours by the same measure plus the number of military personnel. The demographic adjustment of the third hours measure is explained in detail in the next section. Finally, the NFB hours measure is computed by multiplying average weekly NFB hours with the employment-population rate. While this measure is computed differently than the other three hours measures and is therefore not directly comparable to the others, it is probably the most widely used measure of hours per capita in estimated DSGE models (see, e.g., Smets and Wouters, 2007; Christiano et al., 2011, among many others).

work. Therefore, the goal of this paper is to study how distortions in estimated output gaps can be avoided in these models

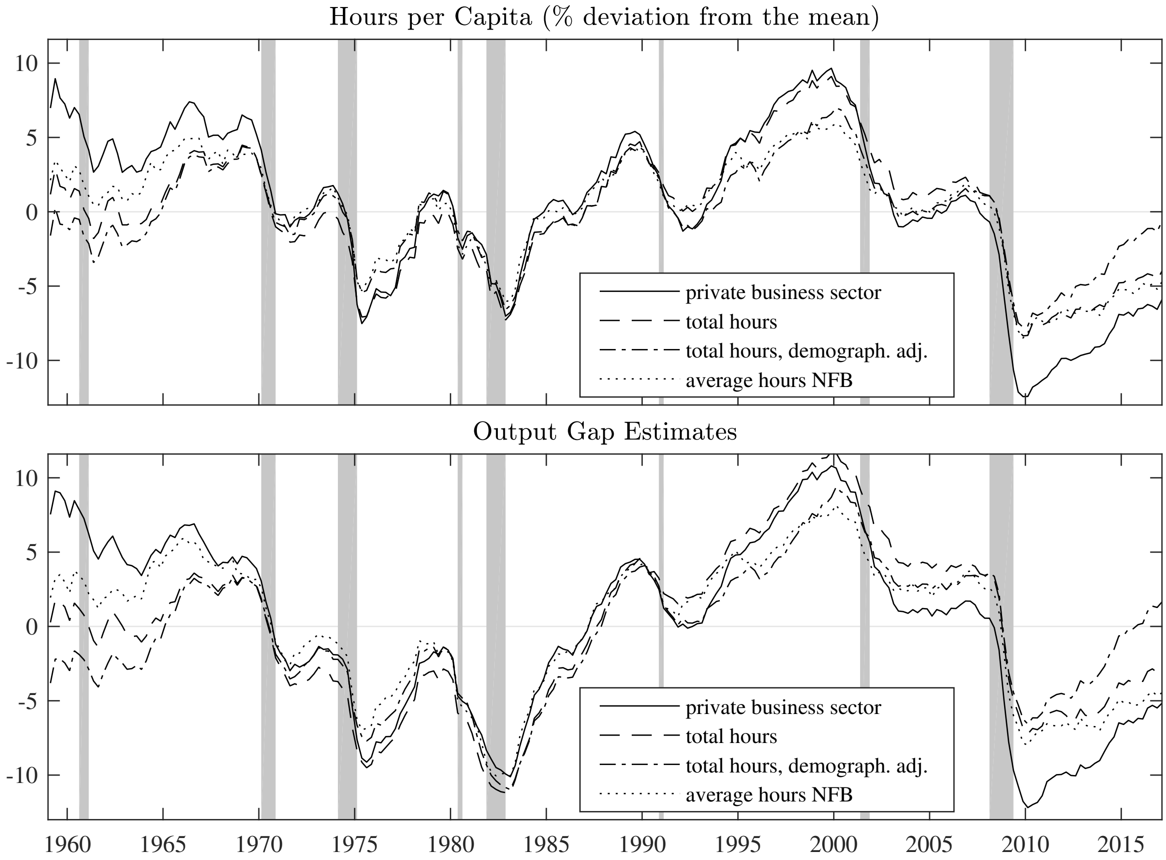

Figure 2: The Effects of Different Hours per Capita Measures on Output Gap Estimates

Hours in the private business sector decreased strongly between 1960 and 1975 in consequence of a decreasing share of hours worked in the the private business sector from 81% to 77%. The share of hours worked in the government and non-profit sector increased by the same amount, so that there is no such decline in total hours. There is only a small decline in NFB hours, because the largest decrease in hours in the private sector is caused by a reduction in farming hours.

Using hours in the private business sector as an observable leads to a downward trend in the output gap until 1975, while using total hours per capita instead leads to much more stable output gap estimates as shown in the lower panel of figure 2. Using hours in the NFB sector also avoids an unreasonable downward trend of the output gap at the beginning of the sample, but we will see later that this measure leads to large output gap distortions at the end of the sample.[6]

Since the share of hours in the private sector has been stable between 1975 and 2000, output gap estimates based on hours in the private sector and on total hours show similar dynamics during this period. From 2000 to 2010 another decrease in the share of private business hours to 75% has occurred, while again government and non-profit hours increased by the same amount. This trend is reflected in the output gap estimates, which are lower when using hours in the private business sector or the NFB sector compared to using total hours as an observable.

Hence, private hours are an inaccurate measure of aggregate hours per capita due to the observed sectoral shifts. In standard one-sector models the decline in the share of hours in the private business

rather than contributing to solving the general and well-known problems with some assumptions and features of them.

[6]To preserve clarity of the figure, probability bands are not shown. However, the difference between the preferred output gap measure based on total demographically adjusted hours and the ones based on hours in the private or the NFB sector are significant between 1959 and the late 1960s as well as between 2009 and 2017 (see figure 4) based on a 90% probability band that accounts for parameter and filter uncertainty.

sector leads to downward trends in the output gap which can be easily corrected for by using total hours per capita instead.

3.2 Demographic Trends

Figure 3 shows the population share of different age groups over time based on U.S. Census data. There are large changes caused mainly by the baby boomer cohort. This cohort led to an increase in the fraction of (young) individuals aging 16 to 21 between 1955 and 1985 and a decrease in the fraction of prime age individuals (ages 22-64) around the same time. As young workers work substantially less hours than prime age workers this decreased aggregate hours per capita. Afterwards, the baby boomer cohort increased the fraction of prime age workers in the working-age population which contributed to the large increase in aggregate hours per capita until this cohort started retiring from around 2005 onwards.

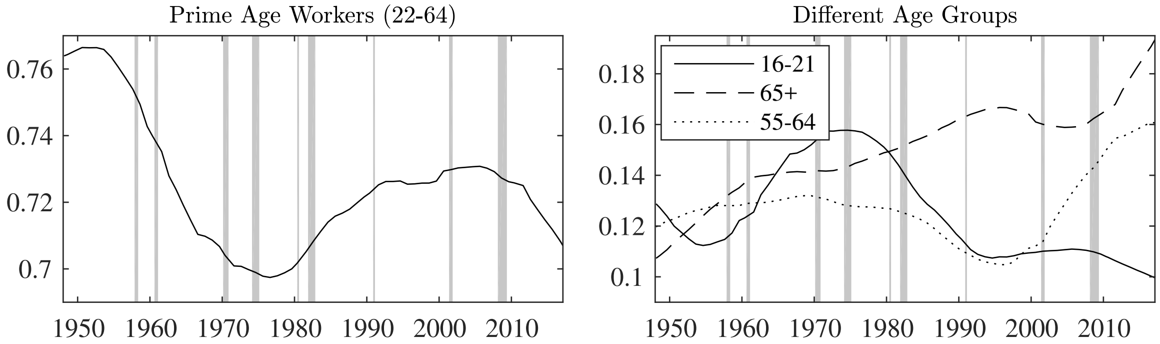

Figure 3: Age Composition of Population (Percentage of Population Ages 16 and Over)

These changes in aggregate hours caused by age-cohort effects cannot be explained by standard models. Therefore, I adjust hours per capita for low-frequency changes caused by demographic trends. The original hours per capita series H_t is adjusted for the cumulated chain-weighted changes in hours that are caused by demographic trends to obtain a corrected series $H_t^{demo.adj.}$ via the following formula:

$$H_t^{demo.adj.} = H_t - \sum_{\tau=t_0}^{t} \left[\sum_{i=1}^{8} \left(\frac{h_{i,\tau} + h_{i,\tau-1}}{2} \right) (\theta_{i,\tau} - \theta_{i,\tau-1}) \right], \tag{7}$$

where $h_{i,t}$ denotes hours per capita by age-group i in period t, $\theta_{i,t}$ denotes the share of age-group i of the noninstitutional population aged 16 and over, and t_0 denotes the first observation of the sample. This approach has been originally suggested by Shimer (1998) to correct the unemployment rate for demographic trends caused by the baby boomer cohort.[7] Francis and Ramey (2009) have applied this procedure to hours per capita. I use the same eight age groups as in Francis and Ramey (2009) (16-17, 18-21, 22-24, 25-34, 35-44, 45-54, 55-64, 65+), so that the demographically adjusted hours series is an update of theirs. I compile data on hours worked by the different age groups from the Integrated Public Use Microdata Series (IPUMS) dataset based on the American Community Survey. The dataset covers 1% of the U.S. population. Detailed information is provided in the Appendix.

The demographically adjusted total hours per capita series is shown as the dashed-dotted line in the upper panel of figure 2. By comparing it with the unadjusted total hours per capita series, it becomes apparent that demographic changes shifted hours upwards in the 1960s, downwards in the 1970s and

[7] Barnichon and Mesters (2017) propose an alternative methodology based on a dynamic factor model to correct the unemployment rate for demographic trends in order to account for a lowering of the unemployment rate of young workers caused by a higher fraction of high school graduates entering college, i.e. delayed labor force entry.

strongly upwards in the 1990s. The graph also shows that demographic shifts have contributed to the persistent decline of hours after the global financial crisis of 2008/2009, i.e. without demographic shifts, hours per capita would have moved back towards their long-run mean more rapidly. Overall, the dynamics of the demographically adjusted total hours series are muted compared to the unadjusted series. This means that demographic trends yield dynamics of hours that could falsely be interpreted as cyclical movements.

The lower panel of figure 2 includes the output gap estimate based on using the demographically adjusted total hours per capita series (dashed-dotted line). The downward demographic adjustment of hours in the 1960s and between 1990 and 2005 is reflected in less positive output gap estimates and the upward demographic adjustment of hours between 1970 and 1980 is reflected in less negative output gap estimates during the respective periods. Overall, the sectoral and demographic adjustments of hours per capita lead to more stable output gap estimates compared to using unadjusted hours in the private business sector as an observable.

3.3 Output Gap Estimates During and After the Great Recession

Finally, I analyse to which extent sectoral and demographic trends affect hours per capita and output gap estimates since 2007. This period is of special interest since a number of papers have reported persistently negative output gaps for the US economy while the start of the baby boomer cohort's retirement wave has large effects on hours per capita during the same period. Yet, ignoring the latter could lead to drawing the misleading conclusion that there has been a permanent slack in the US economy since the Great Recession.

The left panel of figure 4 shows the same four hours measures discussed previously for the period 2007-2017. The graph on the right panel shows the respective model-based output gap estimates for using the different hours measures as observable and in addition the output gap of the Congressional Budget Office (CBO). For the favored output gap estimate based on demographically adjusted total hours a 90% probability band accounting for parameter and filter uncertainty is shown in addition to the point estimate.

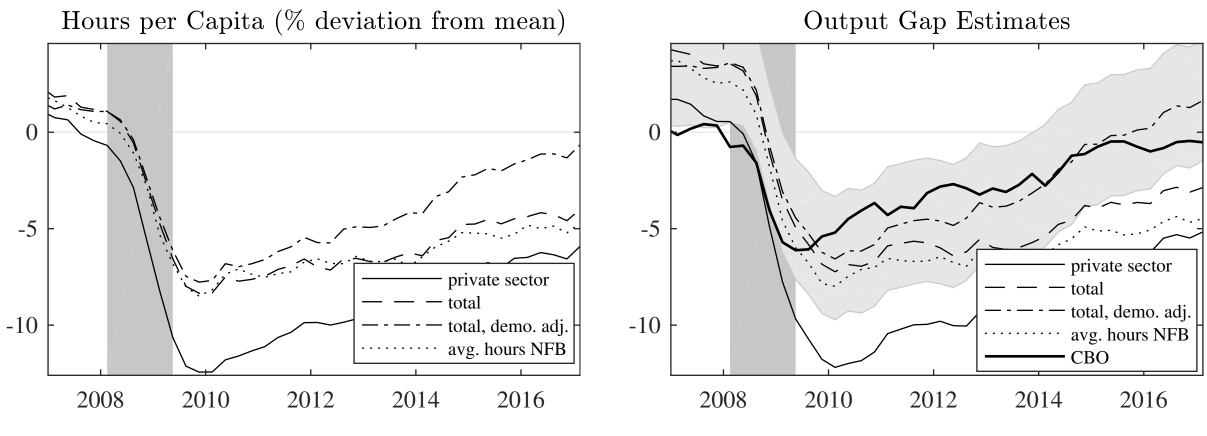

Figure 4: Output Gap Estimates and Hours (2007-2017)

First, it can be observed that sectoral shifts had a large effect on aggregate hours per capita during and after the Great Recession. Between 2008 and 2010, hours in the private sector decreased much more than total hours and remained lower afterwards as well. Government hours remained roughly constant during the Great Recession and hours in the non-profit sector even increased. In turn, the estimated output gap based on hours in the private sector fell up to -12% during the financial crisis, while the output gap based on total hours only decreased to -7%. Focusing on the private business sector only instead of using total hours during the recovery would create an overoptimistic impression since total hours increased more gradually compared to hours in the private business sector. Hence, sectoral shifts lead to an overestimation of fluctuations in hours worked and the output gap during and after the Great Recession if one focuses on the private business sector only instead of using total hours.

Second, the baby boomer cohort's retirement wave has a large effect on hours. The share of individuals aged 65+ has strongly increased since 2006, leading to a decline in the share of prime age workers (figure 3). Both, unadjusted and demographically adjusted total hours decreased by about 8% below their long-run mean in 2010. However, unadjusted hours remained highly negative and were still 4% below their long-run mean in 2017, while demographically adjusted hours increased faster.[8] The demographic effects on the estimated output gaps are even larger: despite the trough of the output gap based on both measures of total hours (adjusted and unadjusted) being similar, the analysis reveals that the output gap based on demographically adjusted hours has closed in 2015 and even turned positive thereafter, while the estimate based on unadjusted hours was still negative in 2017. The output gap estimate based on demographically adjusted hours is significantly higher than the other ones since 2014 and significantly higher than the one based on hours in the private sector even since 2008. The output gap based on the demographically adjusted total hours series is also much more in line with output gap estimates based on simpler state space models and the output gap estimates by the Congressional Budget Office (CBO) (thick black line in the right panel of figure 4) as documented in Kiley (2015) and Laubach and Williams (2015) than the permanently negative output gap estimates that have been found in the DSGE literature.[9]

The differences between the output gap estimates based on hours in the private business sector and those based on total demographically adjusted hours are large. However, instead of using hours in the private business sector to estimate DSGE models, the most common hours measure is based on average weekly hours in the NFB sector multiplied with the employment-population rate (dotted line). Unfortunately, it can also be observed for this measure that hours are lower than total and demographically adjusted total hours. Hence, output gap estimates based on average hours in the NFB sector have been too low after the Great Recession because they do not account for the dynamics of hours in the public sector and the beginning of the the baby boomer cohort's retirement wave. This output gap measure implies that output was 5% below potential in 2017, while the output gap based on hours in all sectors adjusted for demographic trends already turned positive.

For the structural adjustment detailed micro data on hours worked in different age groups is needed. Compiling this data is burdensome and probably not feasible for some economies. Hence, the question arises whether eliminating low-frequency trends based on HP-filtering the data can provide an approximation to the structural adjustment done in this paper. Francis and Ramey (2009) find using a VAR that the effects of technology shocks on hours HP-filtered with a parameter of 16,000 are similar to those on structurally adjusted hours. Unfortunately, when comparing the HP-filtered trend to the structural adjustment term, I find that the HP-filter adjustment is at most a very rough approximation. With an

[8]The changes in average hours worked by the different age groups cannot compensate for the change in the population structure since hours worked by individuals aged 65+ have increased only slightly from 4.5 hours per week in 2006 to 5.5 hours per week in 2017, while those of prime age workers even decreased from 29.5 in 2006 to 29 in 2017.

[9]The output gap estimates by Kiley (2015) and Laubach and Williams (2015) are even closer to the DSGE model-based output gap based on demographically adjusted hours than the one by the CBO as they turn positive around 2015, while the CBO estimate remains close to zero.

HP-parameter of 16,000 the adjustment of hours is much larger than the sectoral and demographic trends justify. With a larger HP-parameter the adjustment in the middle of the sample becomes closer to the structural one, but the end-of-sample distortions become worse. Hence, HP-filtering hours can ensure a stationary DSGE model-based output gap, but the interpretation becomes difficult, because it is unclear which low-frequency fluctuations are eliminated and possible new end-of-sample distortions are introduced.

4 Conclusion

The mismatch between the model assumptions and the data characteristics of hours per capita can lead to substantial distortions of estimated output gaps. I have shown that this problem is particularly severe in the 1960s, but also in the most recent period after the Great Recession. Insofar such estimates are used in the policy process at central banks, erroneously low output gap estimates after the Great Recession can have far reaching implications. The population share of individuals aged between 55 and 64 has steadily increased over the last decade (figure 3) which implies that the baby boomer cohort's retirement wave will continue and intensify over the next decade. To compute non-distorted model-based output gap estimates in the future, it will be crucial to adjust hours per capita for demographic trends or to model different demographic cohorts. Otherwise, DSGE model-based output gap estimates will be underestimated systematically at least over the next decade.

References

Barnichon, R., Mesters, G., 2017. On the demographic adjustment of unemployment. Review of Economics and Statistics, forthcoming.

Barsky, R., Justiniano, A., Melosi, L., 2014. The natural rate of interest and its usefulness for monetary policy. The American Economic Review 104, 37–43.

Basu, S., Fernald, J. G., Kimball, M. S., 2006. Are technology improvements contractionary? The American Economic Review 96, 1418–1448.

Bernanke, B., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. In: Taylor, J. B., Woodford, M. (Eds.), Handbook of Macroeconomics. Vol. 1C. North Holland, Amsterdam, pp. 1341–1393.

Boivin, J., Giannoni, M., 2006. DSGE models in a data-rich environment, NBER Working Paper No. 12772.

Canova, F., 1998. Detrending and business cycle facts. Journal of Monetary Economics 41, 475–512.

Canova, F., 2014. Bridging DSGE models and the raw data. Journal of Monetary Economics 67, 1–15.

Canova, F., Ferroni, F., 2011. Multiple filtering devices for the estimation of cyclical DSGE models. Quantitative Economics 2, 73–98.

Canova, F., López-Salido, D., Michelacci, C., 2010. The effects of technology shocks on hours and output: A robustness analysis. Journal of Applied Econometrics 25, 755–773.

Chang, Y., Doh, T., Schorfheide, F., 2007. Non-stationary hours in a DSGE model. Journal of Money, Credit and Banking 39, 1357–1373.

Chari, V., Kehoe, P. J., McGrattan, E. R., 2007. Business cycle accounting. Econometrica 75, 781–836.

Chari, V. V., Kehoe, P. J., McGrattan, E. R., 2005. A critique of structural VARs using real business cycle theory, Federal Reserve Bank of Minneapolis Working Paper 631.

Christiano, L., Eichenbaum, M., Vigfussion, R. J., 2003. What happens after a technology shock?, NBER Working Paper 9819.

Christiano, L., Trabandt, M., Walentin, K., 2011. DSGE models for monetary policy analysis. In: Friedman, B. M., Woodford, M. (Eds.), Handbook of Monetary Economics. Vol. 3a. Elsevier B.V., North-Holland., Ch. 7, pp. 285–367.

Cociuba, S. E., Prescott, E. C., Ueberfeldt, A., 2012. U.S. hours and productivity behavior using CPS hours worked data: 1947-III to 2011-IV, mimeo.

Del Negro, M., Giannoni, M., Gupta, A., and Erica Moszkowski, P. L., 2017. The FRBNY DSGE model forecast - February 2017, http://libertystreeteconomics.newyorkfed.org/2017/02/the-frbny-dsge-model-forecast-february-2017.html.

Del Negro, M., Giannoni, M. P., Schorfheide, F., 2015. Inflation in the Great Recession and New Keynesian models. American Economic Journal: Macroeconomics 7, 168–196.

Del Negro, M., Schorfheide, F., 2013. DSGE model-based forecasting. In: Elliott, G., Timmerman, A. (Eds.), Handbook of Economic Forecasting. Vol. 2. Elsevier, Ch. 2, pp. 57–140.

Edge, R. M., Kiley, M. T., Laforte, J.-P., 2008. Natural rate measures in an estimated DSGE model of the U.S. economy. Journal of Economic Dynamics and Control 32, 2512–2535.

Fernald, J. G., 2007. Trend breaks, long-run restrictions, and contractionary technology improvements. Journal of Monetary Economics 54, 2467–2485.

Francis, N., Ramey, V. A., 2009. Measures of per capita hours and their implications for the technology-hours debate. Journal of Money, Credit and Banking 41, 1071–1097.

Galí, J., Gertler, M., López-Salido, J. D., 2007. Markups, gaps, and the welfare cost of business fluctuations. Review of Economics and Statistics 89, 44–59.

Galí, J., Smets, F., Wouters, R., 2012. Unemployment in an estimated New Keynesian model. NBER Macroeconomics Annual 26, 329–360.

Guerron-Quintana, P. A., 2010. What you match does matter: the effects of data on DSGE estimation. Journal of Applied Econometrics 25, 774–804.

Gust, C., Herbst, E., López-Salido, D., Smith, M. E., 2017. The empirical implications of the interest-rate lower bound. The American Economic Review 107, 1971–2006.

Hamilton, J. D., 2018. Why you should never use the Hodrick-Prescott Filter. Review of Economics and Statistics forthcoming.

Ireland, P. N., 2004. A method for taking models to the data. Journal of Economic Dynamics and Control 28, 1205–1226.

Justiniano, A., Primiceri, G., Tambalotti, A., 2013. Is there a trade-off between inflation and output stabilization? American Economic Journal: Macroeconomics 5, 1–31.

Kiley, M. T., 2015. What can the data tell us about the equilibrium real interest rate?, Finance and Economics Discussion Series of the Federal Reserve Board 2015-077.

Kimball, M. S., 1995. The quantitative analytics of the basic monetarist model. Journal of Money, Credit and Banking 27, 1241–1277.

Laubach, T., Williams, J. C., 2015. Measuring the natural rate of interest redux, Hutchins Center on Fiscal and Monetary Policy at Brookings Working Paper 15.

Ruggles, S., Genadek, K., Goeken, R., Grover, J., Sobek, M., 2015. Integrated public use microdata series: Version 6.0 [machine-readable database], minneapolis: University of Minnesota.

Sala, L., 2015. DSGE models in the frequency domain. Journal of Applied Econometrics 30, 219–240.

Sala, L., Söderström, U., Trigari, A., 2010. The output gap, the labor wedge, and the dynamic behavior of hours, Sveriges Riksbank Working Paper 246.

Shimer, R., 1998. Why is the U.S. unemployment rate so much lower? In: Bernanke, B., Rotemberg, J. (Eds.), NBER Macroeconomics Annual. Vol. 13. MIT Press, pp. 11–61.

Shimer, R., 2009. Convergence in macroeconomics: The labor wedge. American Economic Journal: Macroeconomics 1, 280–297.

Smets, F., Wouters, R., 2007. Shocks and frictions in US business cycles: A Bayesian DSGE approach. The American Economic Review 97, 586–606.

Sun, X., Tsang, K. P., 2017. What cycles? Data detrending in DSGE models, SSRN Working Paper.

Appendix A: Data Sources

Average Weekly Hours in the Nonfarm Business Sector

- Source: US. Bureau of Labor Statistics, Series ID: PRS85006023. This hours measure is multiplied with the employment-population ratio to measure hours per capita.
- Employment: Civilian Employment (based on civilian noninstitutional population, persons 16 years and older), Source: US. Bureau of Labor Statistics, Series ID: LNS12000000.
- Population: Civilian Noninstitutional Population (persons 16 years of age and older), Source: US. Bureau of Labor Statistics, Series ID: LNU00000000.

Hours per Capita in the Private Business Sector

- Source: US. Bureau of Labor Statistics, available at: https://www.bls.gov/lpc/special_requests/us_total_hrs_emp.xlsx, one needs to add up the hours series for the nonfarm business sector and for the farm sector.
- Population: Civilian Noninstitutional Population (see description above).

Total Hours per Capita all Sectors

- Source: US. Bureau of Labor Statistics, available at: http://www.bls.gov/lpc/special_requests/us_total_hrs_emp.xlsx.
- Population: Noninstitutional Population (sum of civilian noninstitutional population and armed forces)
  - Civilian Noninstitutional Population (see description above).
  - Armed Forces: Data until end of 2011 is taken from data constructed by Cociuba et al. (2012); Data from 2012 onwards is taken from the Defense Manpower Data Center: https://www.dmdc.osd.mil/appj/dwp/dwp_reports.jsp (Active Duty Military Personnel by Service by Rank/Grade).

Total Hours per Capita all Sectors, Demographically Adjusted

- Until the fourth quarter of 2007 the series from Francis and Ramey (2009) is used. It is available on Valerie A. Ramey's website: http://econweb.ucsd.edu/ vramey/research/Francis-Ramey_JMCB_Data_09.xls. I have replicated the series and got almost identical numbers.
- Data for Total Hours per Capita all Sectors is described above.
- Data for the demographical adjustment (from 2008 onwards):
  - Population shares of different age groups: US Census Bureau, Annual Data is interpolated to quarterly:
    - 2008-2009: https://www.census.gov/popest/data/intercensal/national/nat2010.html.
    - 2010-2016: https://factfinder.census.gov/bkmk/table/1.0/en/PEP/2016/PEPAGESEX
    - 2017 (Projection): https://www.census.gov/population/projections/files/summary/NP2014-T9.xls.
  - Average hours of different age groups: I use Census data from the integrated public use microdata series (IPUMs) based on the yearly American Community Survey from 2007-2014 (Ruggles et al., 2015).
    - Calculating average hours worked per week: For each individual I multiply the number of hours per week (UHRSWORK) with the number of weeks worked and divide the result by 52. Afterwards, I take the mean for all individuals of each age group.

* The exact number of weeks worked (WKSWORK1) is only available until 2007. Afterwards, only intervals of the number of weeks worked are available in IPUMS (WKSWORK2). For 2007 both WKSWORK1 and WKSWORK2 are available. I compute for 2007 for each age group the mean of WKSWORK1 for each interval WKSWORK2. I then use this number as a proxy of the number of weeks worked for each interval in WKSWORK2 for the years after 2007.
* For 2016 and 2017 I approximate average hours worked by the different age groups with the values from 2015.
* Annual data is linearly interpolated to quarterly.

Appendix B: Model Equations

The model is so well known that I only describe the log-linearized equations and refer the reader for more details to Del Negro and Schorfheide (2013) and Del Negro et al. (2015). All variables in the following are expressed in log deviations from their non-stochastic steady state.

$\tilde{z}_t$ denotes the linearly detrended log productivity process and follows an autoregressive process: $\tilde{z}_t = \rho_z \tilde{z}_{t-1} + \sigma_z \epsilon_{z,t}$. Non-stationary variables are detrended by $Z_t = e^{\gamma t + \frac{1}{1-\alpha}\tilde{z}_t}$, where γ denotes the steady state growth rate. z_t denotes the growth rate of Z_t in deviations from γ and follows the process $z_t = \ln(Z_t/Z_{t-1}) - \gamma = \frac{1}{1-\alpha}(\rho_z - 1)\tilde{z}_{t-1} + \frac{1}{1-\alpha}\sigma_z \epsilon_{z,t}$.

The consumption Euler equation can be derived from combining the households' first order conditions for consumption and bond holdings and is given by:

$$c_t = c_1(c_{t-1} - z_t) + (1 - c_1)E_t[c_{t+1} + z_{t+1}] + c_2(L_t - E_t[L_{t+1}]) - c_3(R_t - E_t[\pi_{t+1}] + \epsilon_t^b). \quad (8)$$

The parameters are $c_1 = (he^{-\gamma})/(1 + he^{-\gamma})$, $c_2 = [(\sigma_c - 1)(w_* L_*/c_*)]/[\sigma_c(1 + he^{-\gamma})]$ and $c_3 = (1-he^{-\gamma})/[(1+he^{-\gamma})\sigma_c]$. h governs the degree of habit formation, σ_c is the inverse of the intertemporal elasticity of substition and parameters with a $*$ subscript denote steady state values. ϵ_t^b denotes an AR(1) shock process on the premium over the central bank controlled interest rate. Consumption is a weighted average of past and expected future consumption due to habit formation. Consumption depends on hours worked, L_t, because of their nonseparability in the utility function. The real interest rate and the shock term affect aggregate demand by inducing intertemporal substitution in consumption.

The investment Euler equation is given by:

$$i_t = i_1(i_{t-1} - z_t) + (1 - i_1)E_t[i_{t+1} + z_{t+1}] + i_2 q_t + \epsilon_t^i, \quad (9)$$

where $i_1 = 1/(1 + \beta e^{(1-\sigma_c)\gamma})$ and $i_2 = 1/((1 + \beta e^{(1-\sigma_c)\gamma})e^{2\gamma}\phi)$. β denotes the discount factor, ϕ the elasticity of the capital adjustment cost function, q_t Tobin's Q and ϵ_t^i an investment specific technology shock that follows an AR(1) process. Current investment is a weighted average of past and expected future investment due to the existence of capital adjustment costs. It is positively related to the real value of the existing capital stock. This dependence decreases with the elasticity of the capital adjustment cost function.

The law of motion for physical capital is given by:

$$k_t = k_1(k_{t-1} - z_t) + (1 - k_1)i_t + k_2 \epsilon_t^i, \quad (10)$$

where $k_1 = (1 - i_*/k_*)$ and $k_2 = i_*/k_*(1 + \beta e^{(1-\sigma_c)\gamma})e^{2\gamma}\phi$.

The introduction of financial frictions leads to a replacement of the standard arbitrage condition between the return to capital and the riskless rate with the two following conditions:

$$E_t\left[\tilde{R}_{t+1}^k - R_t\right] = b_t + \zeta_{sp,b}\left(q_t^k + k_t - n_t\right) + \sigma_{w,t} \quad (11)$$

and

$$\tilde{R}_t^k - \pi_t = q_1 r_t^k + q_2 q_t^k - q_{t-1}^k, \quad (12)$$

where $q_1 = r_*^k / \left(r_*^k + (1-\delta)\right)$ and $q_2 = (1-\delta)/\left(r_*^k + (1-\delta)\right)$. $\tilde{R}_t^k$ denotes the gross nominal return on capital for entrepreneurs and n_t denotes equity of entrepreneurs. $\sigma_{w,t}$ denotes an AR(1) shock process that captures mean-preserving changes in the cross-section dispersion of entrepreneurial equity. Equation (11) determines the spread between the expected return on capital and the riskless interest rate. Equation (12) shows that the real value of the existing capital stock is a positive function of the rental rate of capital and a negative function of the real interest rate and the external finance premium. The net worth of entrepreneurs evolves according to the following law of motion:

$$n_t = \zeta_{n,\tilde{R}^k}\left(\tilde{R}_t^k - \pi_t\right) - \zeta_{n,R}\left(R_{t-1} - \pi_t\right) + \zeta_{n,qK}\left(q_{t-1}^k + k_{t-1}\right) + \zeta_{n,n} n_{t-1} - \frac{\zeta_{n,\sigma_w}}{\zeta_{sp,\sigma_w}}\sigma_{w,t-1}. \quad (13)$$

Capital used in production depends on the capital utilization rate and the physical capital stock of the previous period as new capital becomes effective with a lag of one quarter:

$$k_t^s = k_{t-1} + u_t - z_t. \tag{14}$$

k_t^s denotes effective capital and u_t the capital utilization rate.

Household income from renting capital services to firms depends on r_t^k and changing capital utilization is costly so that the capital utilization rate depends positively on the rental rate of capital:

$$u_t = (1-\psi)/\psi r_t^k, \tag{15}$$

where $\psi \in [0,1]$ is a positive function of the elasticity of the capital utilization adjustment cost function.

Real marginal costs are given by:

$$mc_t = w_t + \alpha L_t - \alpha k_t, \tag{16}$$

where α is the income share of capital in the production function. The capital-labor ratio is the same across all firms:

$$k_t = w_t - r_t^k + L_t. \tag{17}$$

The production process is assumed to be determined by a Cobb-Douglas production function with fixed costs:

$$y_t = \Phi(\alpha k_t^s + (1-\alpha)L_t) + (\Phi - 1)/(1-\alpha)\tilde{z}_t. \tag{18}$$

The resource constraint is given by:

$$y_t = c_y c_t + i_y i_t + u_y u_t + \epsilon_t^g - 1/(1-\alpha)\tilde{z}_t, \tag{19}$$

where output y_t is the sum of consumption, c_t, and investment, i_t, weighted with their steady state ratios to output $c_y = c_*/y_*$ and $i_y = i_*/y_*$, the capital-utilization adjustment cost which depends on the capital utilization rate, u_t, and the steady state ratio of this cost to output $u_y = r_*^k k_*/y_*$, and an exogenous government spending shock ϵ_t^g. ϵ_t^g follows an AR(1) process and is also affected by the technology shock.

Monopolistic competition, Calvo-style price contracts, and indexation of prices that are not free to be chosen optimally combine to yield the following Phillips curve:

$$\pi_t = \pi_1 \pi_{t-1} + \pi_2 E_t[\pi_{t+1}] + \pi_3 mc_t + \epsilon_t^p, \tag{20}$$

with $\pi_1 = \iota_p / \left(1 + \beta e^{(1-\sigma_c)\gamma}\iota_p\right)$, $\pi_2 = \beta e^{(1-\sigma_c)\gamma} / \left(1 + \beta e^{(1-\sigma_c)\gamma}\iota_p\right)$, $\pi_3 = 1/\left(1 + \beta e^{(1-\sigma_c)\gamma}\iota_p\right) \left(1 - \beta e^{(1-\sigma_c)\gamma}\xi_p\right)(1-\xi_p) / (\xi_p(\Phi - 1)\epsilon_p + 1)$. This Phillips curve contains not only a forward-looking but also a backward-looking inflation term because of price indexation. Firms that cannot adjust prices optimally either index their price to the lagged inflation rate or to the steady-state inflation rate. Note, this indexation assumption ensures also that the long-run Phillips curve is vertical. ξ_p denotes the Calvo parameter, ι_p governs the degree of backward indexation, ϵ_p determines the curvature of the Kimball aggregator. The mark-up shock ϵ_t^p follows an ARMA(1,1) process.

A monopolistic labor market yields the condition that the wage mark-up μ_t^w equals the real wage minus the marginal rate of substitution mrs_t:

$$\mu_t^w = w_t - mrs_t = w_t - \left[\sigma_l L_t + \frac{1}{1-he^{-\gamma}}(c_t - he^{-\gamma}(c_{t-1} - z_t))\right], \tag{21}$$

where σ_l characterizes the curvature of the disutility of labor.

The wage Phillips-Curve ist given by:

$$w_t = w_1(w_{t-1} - z_t) + (1-w_1)E_t[w_{t+1} + z_{t+1} + \pi_{t+1}] - w_2\pi_t - w_3\pi_{t-1} - w_4\mu_t^w + \epsilon_t^w, \tag{22}$$

where $w_1 = 1/(1 + \beta e^{(1-\sigma_c)\gamma})$, $w_2 = (1 + \beta e^{(1-\sigma_c)\gamma}\iota_w)/((1 + \beta e^{(1-\sigma_c)\gamma}))$, $w_3 = \iota_w/(1 + \beta e^{(1-\sigma_c)\gamma})$, and $w_4 = 1/(1+\beta e^{(1-\sigma_c)\gamma})(1-\beta e^{(1-\sigma_c)\gamma}\xi_w)(1-\xi_w)/(\xi_w((\phi_w-1)\epsilon_w+1))$. The parameter definition is analogous to the price Phillips curve.

The monetary policy rule reacts to inflation, the output gap and the change in the output gap and incorporates partial adjustment:

$$R_t = \rho R_{t-1} + (1-\rho)(\phi_\pi \pi_t + \phi_x x_t) + \phi_{\Delta x}(x_t - x_{t-1}) + r_t^m. \tag{23}$$

r_t^m is a monetary policy shock that follows an AR(1) process. The output gap x_t is defined as the log difference between output and potential output.

Potential output is described by an allocation without nominal rigidities, i.e. with flexible prices and wages, without financial frictions, and without inefficient price and wage mark-up shocks and financial friction shocks. This allocation is obtained by setting $\xi_p = 0$, $\xi_w = 0$, $\epsilon_t^p = 0$ and $\epsilon_t^w = 0$ and replacing equations (11), (12), and (13) with

$$q_{f,t} = q_1 E_t\left[r_{f,t+1}^k\right] + (1-q_1)E_t\left[q_{f,t+1}\right] - r_{f,t} + \epsilon_t^b, \tag{24}$$

where $q_1 = r_*^k/\left(r_*^k + 1 - \delta\right)$. The f subscript denotes that this allocation refers to flexible prices and wages and $r_{f,t}$ denotes the real natural interest rate. This allocation is efficient except for the constant inefficiency caused by monopolistic competition.

In addition to equations (8) to (24) measurement equations that relate the model variables to the data are added and these are given by:

$$
\begin{aligned}
\textit{output growth} &= \gamma + 100\left(y_t - y_{t-1} + z_t\right) && (25)\\
\textit{consumption growth} &= \gamma + 100\left(c_t - c_{t-1} + z_t\right) && (26)\\
\textit{investment growth} &= \gamma + 100\left(i_t - i_{t-1} + z_t\right) && (27)\\
\textit{real wage growth} &= \gamma + 100\left(w_t - w_{t-1} + z_t\right) && (28)\\
\textit{hours} &= L_* + 100L_t && (29)\\
\textit{inflation} &= \pi_* + 100\pi_t && (30)\\
\textit{federal funds rate} &= R_* + 100R_t && (31)\\
\textit{spread} &= SP_* + 100E_t\left[\tilde{R}_{t+1}^k - R_t\right]. && (32)
\end{aligned}
$$

π_*, R_*, L_* and SP_* denote the steady state level of inflation, the federal funds rate, hours and the spread.

I further include four measurement equations that link model-based interest rate expectations with those from financial market participants to account for the zero lower bound on nominal interest rates and the effects of forward guidance:

$$\textit{federal funds rate expectations}_{\,t+k} = R_* + 100E_t\left[R_{t+k}\right], \qquad k = 1, ..., 4. \tag{33}$$

To make estimation feasible with these four additional measurement equations I augment the model with four anticipated monetary policy shocks. The monetary policy shock process is thus given by:

$$r_t^m = \rho_r r_{t-1}^m + \epsilon_t^r + \sum_{k=1}^{4} \epsilon_{t,t-k}^r. \tag{34}$$

ϵ_t^r is a standard monetary policy shock, where $\epsilon_t^r \sim N(0, \sigma_r^2)$, and $\epsilon_{t,t-k}^r$ are anticipated monetary policy shocks, where $\epsilon_{t,t-k}^r \sim N(0, \sigma_{k,r}^2)$. They are known to agents at time $t-k$, but affect the policy rule only at time t.

Appendix C: Estimated Parameters

Table 1: Estimated Structural Parameters

Prior				Posterior (Mean, 90% Interval)			
Param.	Density	Mean	St. Dev.	Hours BS	Hours Tot.	H. Demo. Adj.	Avg. H. NFBS
ξ_p	Beta	0.50	0.10	0.6988 [0.6218,0.7801]	0.6449 [0.5583,0.7366]	0.6665 [0.5754,0.7592]	0.6341 [0.5420,0.7220]
ι_p	Beta	0.50	0.15	0.2556 [0.1317,0.3762]	0.2655 [0.1382,0.3885]	0.2613 [0.1368,0.3793]	0.3016 [0.1717,0.4296]
ξ_w	Beta	0.50	0.10	0.6890 [0.6029,0.7779]	0.6772 [0.5882,0.7703]	0.7017 [0.6134,0.7916]	0.6777 [0.5914,0.7651]
ι_w	Beta	0.50	0.15	0.3387 [0.1641,0.5022]	0.3166 [0.1449,0.4785]	0.2772 [0.1251,0.4345]	0.3504 [0.1618,0.5342]
ψ	Beta	0.50	0.15	0.4632 [0.3340,0.5925]	0.4758 [0.3333,0.6260]	0.5070 [0.3592,0.6531]	0.4680 [0.3295,0.6092]
Φ	Normal	1.25	0.12	1.1565 [1.0618,1.2470]	1.33131 [1.1996,1.4281]	1.3723 [1.2531,1.4943]	1.3707 [1.2552,1.4902]
ϕ	Normal	4.00	1.50	3.6872 [2.4282,4.9197]	3.9104 [2.5912,5.1572]	4.0620 [2.7924,5.3420]	3.7233 [2.4257,4.9976]
σ_c	Normal	1.50	0.37	0.7984 [0.6452,0.9410]	0.7740 [0.5830,0.9652]	0.7147 [0.5571,0.8641]	0.7689 [0.5631,0.9721]
h	Beta	0.70	0.10	0.6032 [0.5281,0.6867]	0.5988 [0.5108,0.6949]	0.6292 [0.5490,0.7101]	0.5932 [0.4961,0.6922]
σ_l	Normal	2.00	0.75	1.8824 [1.1065,2.6566]	1.9061 [1.0571,2.7151]	2.1465 [1.2978,2.9883]	2.3521 [1.4437,3.2509]
ϕ_π	Normal	1.50	0.25	1.4069 [1.2666,1.5371]	1.4061 [1.2678,1.5398]	1.4062 [1.2637,1.5461]	1.4163 [1.2779,1.5606]
ρ	Beta	0.75	0.10	0.7797 [0.7426,0.8171]	0.7730 [0.7364,0.8109]	0.7858 [0.7499,0.8196]	0.7756 [0.7374,0.8129]
ϕ_x	Normal	0.12	0.05	0.0153 [0.0000,0.0276]	0.0174 [0.0001,0.0308]	0.0171 [0.0000,0.0312]	0.0194 [0.0000,0.0352]
$\phi_{\Delta x}$	Normal	0.12	0.05	0.2181 [0.1736,0.2647]	0.2298 [0.1800,0.2765]	0.2298 [0.1795,0.2791]	0.2323 [0.1830,0.2822]
π_*	Gamma	0.75	0.40	0.9465 [0.6816,1.2198]	0.9628 [0.6892,1.2373]	0.9562 [0.6806,1.2144]	0.9515 [0.6808,1.2244]
r_*	Gamma	0.25	0.10	0.2399 [0.1197,0.3562]	0.2608 [0.1302,0.3859]	0.2711 [0.1471,0.3963]	0.2591 [0.1252,0.3842]
L_*	Normal	0.00	2.00	0.6250 [-1.9669,3.2319]	0.2070 [-2.1017,2.5656]	0.2010 [-2.0856,2.4917]	0.2522 [-2.0604,2.5348]
γ	Normal	0.40	0.10	0.4803 [0.4341,0.5244]	0.4242 [0.3842,0.4651]	0.3912 [0.3532,0.4270]	0.4392 [0.4009,0.4796]
α	Normal	0.30	0.05	0.1432 [0.1160,0.1717]	0.1327 [0.1032,0.1611]	0.1376 [0.1073,0.1678]	0.1299 [0.1021,0.1566]
SP_*	Gamma	2.00	0.10	1.7790 [1.6466,1.9090]	1.7689 [1.6403,1.8991]	1.7618 [1.6344,1.8931]	1.7797 [1.6491,1.9099]
$\zeta_{sp,b}$	Beta	0.05	0.005	0.0577 [0.0505,0.0647]	0.0577 [0.0504,0.0650]	0.0574 [0.0502,0.0645	0.0572 [0.0501,0.0643]

Notes: The table shows priors and posterior estimates for different observable hours measures. Hours BS: hours in the private business sector, Hours Tot.: hours in all sectors, H. Demo. Adj.: hours in all sectors demographically adjusted, Avg. H. NFBS: average weekly hours in the nonfarm business sector multiplied with employment-population ratio. The discount factor β is indirectly given through the steady state real interest rate: $\beta = (1/(1 + r_*/100))$. The following parameters are fixed: $\delta = 0.025$, $g_* = 0.18$, $\phi_w = 1.5$, $\epsilon_w = 10$, $\epsilon_p = 10$. The steady-state default probability of entrepreneurs is $\bar{F}_* = 0.03$ and their survival rate is $\gamma_* = 0.99$.

Table 2: Estimated Shock Process Parameters

Prior				Posterior (Mean, 90% Interval)			
Param.	Density	Mean	St. Dev.	Hours BS	Hours Tot.	H. Demo. Adj.	Avg. H. NFBS
σ_z	InvG	0.10	2.00	0.6042 [0.5511,0.6552]	0.5326 [0.4856,0.5798]	0.5267 [0.4791,0.5712]	0.5240 [0.4459,0.5709]
σ_b	InvG	0.10	2.00	0.0206 [0.0168,0.0243]	0.0215 [0.0176,0.0253]	0.0224 [0.0175,0.0251]	0.0223 [0.0182,0.0263]
σ_g	InvG	0.10	2.00	2.7358 [2.5141,2.9560]	2.8214 [2.5887,3.0487]	2.8073 [2.5736,3.0319]	2.6618 [2.4469,2.8757]
σ_i	InvG	0.10	2.00	0.3702 [0.3105,0.4257]	0.3644 [0.3088,0.4174]	0.3602 [0.3094,0.4121]	0.3723 [0.3105,0.4347]
σ_r	InvG	0.10	2.00	0.1745 [0.1491,0.1999]	0.1803 [0.1548,0.2053]	0.1811 [0.1557,0.2066]	0.1759 [0.1496,0.2015]
σ_p	InvG	0.10	2.00	0.1621 [0.1372,0.1874]	0.1616 [0.1370,0.1862]	0.1569 [0.1332,0.1792]	0.1673 [0.1424,0.1919]
σ_w	InvG	0.10	2.00	0.4178 [0.3677,0.4664]	0.4198 [0.3704,0.4699]	0.4075 [0.3588,0.4557]	0.4190 [0.3667,0.4698]
σ_{σ_w}	InvG	0.05	4.00	0.0640 [0.0580,0.0696]	0.0639 [0.0580,0.0694]	0.0635 [0.0578,0.0693]	0.0628 [0.0572,0.0685]
$\sigma_{1,r}$	InvG	0.10	2.00	0.0743 [0.0621,0.0866]	0.0751 [0.0627,0.0869]	0.0745 [0.0620,0.0870]	0.0761 [0.0632,0.0894]
$\sigma_{2,r}$	InvG	0.10	2.00	0.0578 [0.0453,0.0697]	0.0570 [0.0454,0.0684]	0.0574 [0.0457,0.0691]	0.0586 [0.0457,0.0716]
$\sigma_{3,r}$	InvG	0.10	2.00	0.0353 [0.0306,0.0398]	0.0353 [0.0307,0.0398]	0.0355 [0.0308,0.0399]	0.0357 [0.0310,0.0402]
$\sigma_{4,r}$	InvG	0.10	2.00	0.0445 [0.0375,0.0509]	0.0430 [0.0363,0.0495]	0.0429 [0.0363,0.0494]	0.0427 [0.0362,0.0490]
ρ_z	Beta	0.50	0.20	0.9828 [0.9716,0.9941]	0.9784 [0.9652,0.9919]	0.9692 [0.9494,0.9888]	0.9748 [0.9581,0.9923]
ρ_b	Beta	0.50	0.20	0.9867 [0.9793,0.9939]	0.9874 [0.9801,0.9951]	0.9878 [0.9805,0.9953]	0.9879 [0.9808,0.9957]
ρ_g	Beta	0.50	0.20	0.9817 [0.9686,0.9951]	0.9827 [0.9712,0.9954]	0.9821 [0.9699,0.9953]	0.9853 [0.9751,0.9962]
ρ_i	Beta	0.50	0.20	0.8970 [0.8607,0.9335]	0.8916 [0.8549,0.9283]	0.8936 [0.8580,0.9300]	0.8958 [0.8604,0.9326]
ρ_r	Beta	0.50	0.20	0.4138 [0.3491,0.4793]	0.4091 [0.3482,0.4696]	0.3997 [0.3382,0.4626]	0.4233 [0.3603,0.4854]
ρ_p	Beta	0.50	0.20	0.9850 [0.9739,0.9968]	0.9706 [0.9480,0.9942]	0.9415 [0.8963,0.9860]	0.9808 [0.9652,0.9970]
ρ_w	Beta	0.50	0.20	0.9566 [0.9372,0.9767]	0.9606 [0.9421,0.9792]	0.9559 [0.9357,0.9770]	0.9507 [0.9297,0.9723]
ρ_{σ_w}	Beta	0.75	0.15	0.9929 [0.9860,0.9996]	0.9925 [0.9857,0.9994]	0.9932 [0.9868,0.9995]	0.9930 [0.9865,0.9995]
η_p	Beta	0.50	0.20	0.7386 [0.6262,0.8576]	0.7556 [0.6471,0.8675]	0.7637 [0.6625,0.8689]	0.8057 [0.7195,0.8974]
η_w	Beta	0.50	0.20	0.8376 [0.7670,0.9082]	0.8492 [0.7827,0.9221]	0.8553 [0.7861,0.9276]	0.8197 [0.7393,0.9008]
$\eta_{g,z}$	Beta	0.50	0.20	0.3298 [0.0684,0.5650]	0.3608 [0.0877,0.6288]	0.3564 [0.0801,0.6152]	0.5375 [0.2386,0.8358]

Notes: The table shows priors and posterior estimates for different observable hours measures. Hours BS: hours in the private business sector, Hours Tot.: hours in all sectors, H. Demo. Adj.: hours in all sectors demographically adjusted, Avg. H. NFBS: average weekly hours in the nonfarm business sector multiplied with employment-population ratio. The different σ-parameters denote the standard deviation of the structural shocks and the ρ-parameters the autocorrelation parameters. z: technology, b: risk-premium, g: government spending, i: marginal efficiency of investment, r: monetary policy, p: price mark-up, w: wage mark-up, σ_w: spread. η_p and η_w denote the additional MA-parameters in the price and wage mark-up ARMA shock processes. $\eta_{g,z}$ denotes the reaction of government spending to the technology shock. $\sigma_{k,r}$, $k = 1, ..., 4$, denote the standard deviations of anticipated monetary policy shocks.

Appendix D: Business Cycle Moments

Table 3: Business Cycle Moments of Different Hours per Capita Measures

Series	Std. Dev.	Rel. Std. Dev.	Corr. w. y_t	1^{st} Order Autocorr.
		Hamilton Projection Filter		
Output	3.20	1.00	1.00	0.90
Hours BS	3.55	1.11	0.84	0.89
Hours Tot.	2.89	0.90	0.86	0.89
H. Demo. Adj.	2.63	0.82	0.83	0.90
Avg. H. NFBS	2.57	0.80	0.85	0.90
		Hodrick-Prescott Filter		
Output	1.45	1.00	1.00	0.87
Hours BS	1.78	1.23	0.86	0.92
Hours Tot.	1.43	0.98	0.86	0.91
H. Demo. Adj.	1.42	0.98	0.86	0.91
Avg. H. NFBS	1.29	0.89	0.87	0.90
		Linearly Detrended		
Output	4.29	1.00	1.00	0.97
Hours BS	4.87	1.13	0.77	0.99
Hours Tot.	4.27	0.99	0.83	0.99
H. Demo. Adj.	3.26	0.76	0.82	0.98
Avg. H. NFBS	3.41	0.79	0.83	0.98

Notes: The table shows business cycle moments of output and hours based on different detrending methods. The Hamilton Projection Filter refers to Hamilton (2018). Hours BS: hours in the private business sector, Hours Tot.: hours in all sectors, H. Demo. Adj.: hours in all sectors demographically adjusted, Avg. H. NFBS: average weekly hours in the nonfarm business sector multiplied with employment-population ratio.