# The Shifts in Lead-Lag Properties of the US Business Cycle*


Joshua Brault†
Carleton University
& Ottawa-Carleton GSE

Hashmat Khan‡
Carleton University
& Ottawa-Carleton GSE


August 2, 2019


**Abstract**

We document shifts in the lead-lag properties of the US business cycle since the mid-1980s. Specifically, (i) the well-known inverted-leading-indicator-property of real interest rates has completely vanished; (ii) labour productivity switched from positively leading to negatively lagging output and labour inputs over the cycle; and (iii) the unemployment rate shifted from lagging productivity negatively to leading positively. Many contemporary business cycle models produce counterfactual cross-correlations revealing that popular frictions and shocks provide an incomplete account of business cycle comovement. Determining the underlying sources of these shifts in the lead-lag properties is therefore a promising direction for future research.



*Key words*: Business Cycles, Cross-Correlations, Lead-Lag, DSGE Models, Interest Rates, Productivity, Hours, Employment, Unemployment
*JEL classification*: E24, E32, E43



*First draft: February 8, 2018. We thank Michelle Alexopolous, Paul Beaudry, Neville Francis, Dana Galiza, Christopher Gunn, Alok Johri, Lilia Karnizova, Minjoon Lee, David Munro, Andreas Pollak, Franck Portier, Jean-François Rouillard, Matthew Shapiro, Malik Shukayev, John Tsoukalas, conference participants at the News, Information and Expectations in Macroeconomics Workshop (University of Glasgow, May 11, 2018), AWSOME II Conference (McMaster University, May 22, 2018), CMFW (Carleton University, May 25, 2018), Canadian Economic Association Conference (Montreal, June 1-3, 2018), 2nd Research Conference of the Macroeconomic Modelling and Model Comparison Network (MMCN, Hoover Institution, Stanford, June 7-8, 2018), and seminar participants at the University of Alberta, Bank of Canada, Bank of England, Middlebury College, University of Saskatchewan, and University College London, for comments.



†Department of Economics, D886 Loeb, 1125 Colonel By Drive, Carleton University, Ottawa, Canada. *E-mail:* joshua.brault@carleton.ca. Tel: +1.613.520.2600 (ext 3057).

‡Corresponding author. Department of Economics, D891 Loeb, 1125 Colonel By Drive, Carleton University, Ottawa, Canada. *E-mail:* hashmat.khan@carleton.ca. Tel: +1.613.520.2600 (ext 1561).

# 1 Introduction

Stylized facts and regularities in the cyclical behaviour of macroeconomic aggregates continue to guide contemporary business cycle research. Models of the business cycle either seek to directly account for these stylized statistical properties or use them as evaluation criteria in determining the suitability of models aimed at studying a variety of topics such as the welfare costs of business cycles, the sources of business cycles, the role of economic policies, or asset prices. In this context, two popular types of comovements characterize aggregate fluctuations. Contemporaneous correlations with output indicating pro-, counter- or acyclicality, and the largest absolute magnitude of cross-correlations with output (or another reference variable) indicating leads and lags. This latter type of business cycle comovement has been emphasized in the literature since Blanchard and Watson (1986) and Kydland and Prescott (1990). Changes in the economy's structure, institutions, policies, and exogenous shocks can all impinge upon both types of comovements. While the recent business cycle literature has extensively studied *shifts* in contemporaneous correlations after the onset of the Great Moderation period in the mid-1980s, the shifts in the second type of comovement have either received less attention or have gone unexplored.[1]

The main contributions of our paper are twofold. First, we document shifts in the cross-correlations (also referred to as phase shifts) among macroeconomic variables in the post-World War II US business cycle since the mid-1980s. We focus on the real interest rate—a key intertemporal price in decision-making—and labour market quantities, namely, labour productivity, labour inputs, and the unemployment rate. These shifts in the cross-correlations indicating leading or lagging properties are, by definition, larger in absolute magnitude than the contemporaneous correlations reflecting the presence of important empirically relevant mechanisms not captured by contemporaneous comovements alone. Second, we study a va-

[1]Shifts in volatility and responses of macroeconomic variables to business cycle shocks have also been studied in the literature but these moments are not the focus of our paper.

riety of contemporary Dynamic Stochastic General Equilibrium (DSGE) models and show that they all produce counterfactual lead-lag patterns relative to US data. Even models that successfully explain the shifts in contemporaneous correlations display counterfactual lead-lag properties. We discuss important challenges for model development and evaluation for future research aimed at improving our understanding of comovement—a central feature of the US business cycle.

We use the Hodrick and Prescott (1980, 1997) (HP) filter as a baseline to obtain the cyclical component of the data. The advantage of using the HP filter is that it facilitates comparisons with the previous literature that has also used the same filter. We then consider the cyclical components based on three alternative filters, namely, Baxter and King (1999), Christiano and Fitzgerald (2003), and Hamilton (2018). The two time periods we consider are 1948-1984 (the pre-1985 period) and 1985-2016 (the post-1985 period). This sample split has been widely studied in the literature in the context of declining volatility and cyclicality of macroeconomic variables associated with the onset of the Great Moderation period.[2] We summarize the four major lead-lag shifts between the pre- and post-1985 periods as follows:

First, *real interest rates positively lag output.* Real interest rates display a 'Positive Lagging Property' (PLP). They strongly lag output by three quarters with positive signs. The well known inverted-leading-indicator property of real interest rates documented by King and Watson (1996) has completely vanished. We find a remarkable stability of the evidence for PLP. We show that the PLP of the real interest rate holds for ex-ante and ex-post real rates, for different prices deflators, and for filtered or unfiltered real interest rates. Importantly, we document that the shift from leading to lagging, and the sign switch, has also occurred in the nominal interest rate. Second, *labour productivity negatively lags output.* Labour productivity has shifted from leading the cycle with a positive sign to lagging with

[2] See, for example, Hall (2007), Stiroh (2009), Galí and Gambetti (2009), Barnichon (2010), Fernald and Wang (2016), Daly et al. (2017), Galí and van Rens (2017), and Garin, Pries and Sims (2018).

a negative sign. Output per hour lags by four quarters and output per person lags by five quarters. Third, *labour inputs negatively lead labour productivity.* Total hours worked have shifted from lagging output per hour by three quarters with a positive sign to leading by two quarters with a negative sign. Employment has shifted from lagging output per person by three quarters with a positive sign to leading by four quarters with a negative sign. Fourth, *the unemployment rate positively leads labour productivity.* The unemployment rate shifted from negatively lagging output per hour by three quarters and output per person by two quarters to positively leading output per hour by two quarters, and output per person by four quarters.

We conduct extensive checks to establish that these properties are in fact robust post-1985 US business cycle stylized facts. They suggest business cycle comovement of the real interest rate along with labour productivity and labour market variables has experienced a substantial shift in the lead-lag properties. Interestingly, such a shift is not present in investment data. For example, the well known property that residential investment leads the US business cycle is also present in the post-1985 data.

In light of the new lead-lag stylized facts listed above, an immediate question is: how do the properties of simulated data from existing Dynamic Stochastic General Equilibrium (DSGE) models compare with their empirical counterparts? We provide a few selected examples. For real interest rate dynamics we consider simulated data from Smets and Wouters (2007), Iacoviello (2005), and Basu and Bundick (2017), respectively. Our rationale is that these models have frictions and shocks that are embedded in a many contemporary DSGE models, and therefore, provide a useful reference point. For labour productivity and labour input dynamics, we consider simulated data from the models in Galí and van Rens (2017) and Garin, Pries and Sims (2018), respectively. Our rationale is that since these models successfully explain the decline in the procyclicality of labour productivity after the mid-1980s, they provide a natural benchmark to determine their intrinsic lead-lag properties relative to the stylized facts reported above. Finally, for the unemployment rate and labour productivity dynamics we consider simulated data from Barnichon (2010). Our rationale is that this model studies the change in the contemporaneous correlation of unemployment and labour productivity after the mid-1980s and, therefore, is well-suited to examine the cross-correlations between the same two variables.

While our rationales for selecting DSGE models are clear, it is important to note that none of these models were developed to match cross-correlations. Therefore, if it turns out that a particular model does match the lead-lag pattern, then it would be explaining something it was not designed to and that will reveal the strength of the proposed mechanism. On the other hand, if it turns out that a particular model does not match the lead-lag structure then that would provide important information for researchers toward developing new models to explain the stylized facts we have documented.

As we discuss in detail, our comparative analysis reveals that all the models we consider produce counterfactual lead-lag properties (both qualitatively and quantitatively) relative to their empirical counterparts in the post-1985 data. By extension, we hypothesize that this assessment applies to a wide class of contemporary DSGE models. This finding raises many important challenges and suggests promising areas for future research aimed at understanding business cycle comovement and improving DSGE models.

Our paper is related to three strands of literature on business cycles. First, recent business cycle literature has focused on the shifts in the unconditional contemporaneous correlations that indicate the pro-, counter-, or acyclical nature of certain macroeconomic variables (in particular, labour productivity, unemployment, labour inputs) and their volatility (see, for example, Hall (2007), Stiroh (2009), Galí and Gambetti (2009), Barnichon (2010), Fernald and Wang (2016), Daly et al. (2017), Galí and van Rens (2017), Garin, Pries and Sims (2018)). This literature, however, has not examined shifts in the lead-lags properties of these variables over the business cycle which is the objective of our paper.

Second, our paper is related to a large body of literature, starting at least since Backus, Kehoe and Kydland (1992), that has either motivated or evaluated models based on cross-correlations and lead-lag properties.[3] The primary focus of this literature is to consider cross-correlations over the whole sample period of study.[4] By contrast, we focus on the shifts in cross-correlations across the pre- and post-1985 sample split that coincides with the widely studied onset of the Great Moderation in the US economy.

Finally, our paper is related to current research on business cycles that is motivated by comovement properties of macroeconomic variables. The focus, however, has been on the first type of comovement, namely contemporaneous correlations, and not the lead-lag properties. Our findings suggest that for a complete explanation of US business cycle comovement both types should be simultaneously considered for motivating new models and their evaluation. We provide two examples to support our point. The first example is Jordà, Schularick and Taylor (2016) who emphasize the correlations between credit growth and output growth. Using their data, we calculated the cross-correlations between credit growth and output growth across the subsamples 1948-1984 and 1985-2013. As it turns out, there has been a shift in the lead-lag pattern in 13 of the 17 countries in their data.[5] The second example is Angeletos (2017), who advances the research agenda on demand-driven business cycle models where higher-order uncertainty is the source of frictional coordination among agents. The motivating facts are based on comovements (contemporaneous correlations) and he notes that the contemporaneous correlation between output and labour productivity is approximately zero (see Figure 2 in Angeletos (2017) based on the 1960-2015 period). This

[3]Section 3 in the Online Appendix provides a comprehensive list of contributions in the literature that have studied business cycle cross-correlations.

[4]A few exceptions are Backus, Kehoe and Kydland (1994) who consider pre- and post-1972 data and Dotsey, Lantz and Scholl (2003) who consider sub-samples between 1955 and 1996. Gavin and Kydland (2000) consider pre- and post-1979 sub-samples.

[5]These results are reported in Tables 16 and 17 in the Online Appendix. If we consider cross-correlations using Jordà, Schularick and Taylor (2016) data set for HP filtered data, 12 of the 17 countries exhibit a lead-lag switch. These results are reported in Tables 18 and 19 in the Online Appendix.

assessment, however, misses the picture revealed in the lead-lag shifts in labour productivity over the cycle since the onset of the Great Moderation period in the US economy. Specifically, while the contemporaneous correlation is close to zero even in the post-1985 period, labour productivity, measured as output per hour, lags output negatively by four quarters with a cross-correlation of $-0.61$. By definition, the leads and lags denote the largest absolute cross-correlations, which are often substantially larger than the contemporaneous correlations, suggesting empirically relevant business cycle forces at work that are not reflected in contemporaneous correlations alone.

The rest of this paper is organized as follows. Section 2 presents the data and documents the shifts in the lead-lag properties of the real interest rate and the three labour market variables. It also provides a comparison with properties based on simulated data from DSGE models. Section 3 assesses the robustness of the properties. Section 4 concludes.

# 2 Shifts in Lead-Lag Properties

In this section we present the data and the shifts in the lead-lag properties of four macroeconomic series. We also provide a comparison of lead-lag properties when looking through the lens of recent DSGE models. The set of models includes those with a focus on the changes in contemporaneous correlations since the onset of the Great Moderation period in the mid-1980s.

## 2.1 Data

We use quarterly data obtained from the Federal Reserve Bank of St. Louis Economic Database (FRED).[6] We employ two different measures of output in the paper, namely, real Gross Domestic Product (GDP) and nonfarm business sector real output, to allow a

[6] A more detailed description of the data is provided in the Online Appendix.

comparison with the model-based results in the literature. Our baseline measure of the real interest rate is the 3-month Treasury bill secondary market rate minus one period ahead ex-post inflation, where inflation is defined as the annualized log difference of the GDP deflator. We also consider alternative measures of the real interest rate which are described in Section 6 in the Online Appendix. The two measures of labour productivity are nonfarm business sector real output per hour and per person. Total hours and employment are the hours and employment of all persons in the nonfarm business sector, respectively. Finally, the unemployment rate is defined as the civilian unemployment rate.

We perform standard transformations of the variables prior to examining the cross-correlations. Specifically, we take the natural log of all variables (excluding the real interest rates and the unemployment rate). Throughout our analysis, the HP filter smoothing parameter for quarterly data is 1600. The baseline cyclical data is computed by detrending the entire sample prior to splitting into pre- and post-1985. In the robustness section we document that the results presented herein are not sensitive to detrending each sample independently. We present the main empirical findings on the shifts in cross-correlation and the lead-lag properties below.[7]

## 2.2 Real Interest Rates Positively Lag Output

We define the real interest rate as

$$\text{Real Interest Rate}_{\mathbf{t}} = \begin{cases} \text{3-Month T-Bill}_t - \pi^F_{t+1} : \text{Ex-Ante} \\ \text{3-Month T-Bill}_t - \pi_{t+1} : \text{Ex-Post} \end{cases}$$

where $\pi^F_{t+1}$ and $\pi_{t+1}$ are the one-period-ahead forecast of the inflation rate and the one-period-ahead actual inflation rate, respectively. We use the GDP deflator to construct $\pi_{t+1}$. For

[7]Table 1 in the Online Appendix presents all the cross-correlations that we discuss in this section.

$\pi^F_{t+1}$ we consider a variety of methods. First, we use an in-sample 3 variable VAR consisting of inflation, unemployment, and the nominal interest rate to forecast inflation (as in Stock and Watson (1999)). By construction, the in-sample VAR contains future information via the estimated parameters, therefore we also consider recursive and rolling window VARs (with a window length of 40 quarters). Finally, we use consumer price index estimates from the Survey of Professional Forecasters as a measure of expected inflation.

Figure 1 shows the cross-correlations between HP filtered output, $Y_t$, and leads and lags of the HP filtered real interest rate, denoted as $R_t$.[8] Specifically, Corr$(Y_t, R_{t+k})$: $k = \{-5, -4, ..., 0, ..., 4, 5\}$, where a negative $k$ indicates correlations between past real interest rates and current output and a positive $k$ indicates correlations between future real interest rates and current output. The largest correlation in absolute terms determines the lead-lag property of a given series relative to another. This cross-correlation is represented by the solid black dots.[9]

Panel (a) shows that in the pre-1985 period, the ex-post real interest rate was strongly negatively correlated with future output, and was countercyclical. This is the well-known Inverted Leading Indicator Property (ILP) of real interest rates documented by King and Watson (1996).[10]

Panel (b) shows that in the pre-1985 data the nominal interest rate also displayed a strong negative correlation with future output. In sharp contrast, the ILP for both the ex-post real interest rate and nominal interest rate has completely vanished in the post-1985 data. The real interest rate lags output by three quarters with a positive sign and the nominal interest rate lags output by one quarter with a positive sign. The real interest rate in the post-1985

[8] The results are nearly identical if we do not filter the real interest rate. These are shown in Tables 6 and 7 in the Online Appendix.

[9] All leads and lags discussed in the paper are statistically significant against the null hypothesis $H_0 : \rho_{i,j} = 0$.

[10] Similar properties of interest rates dynamics are documented in Fiorito and Kollintzas (1994) (Table 3), Chari, Christiano and Eichenbaum (1995) (Figure 3), Beaudry and Guay (1996) (Table 2), and Stock and Watson (1999) (Table 2).

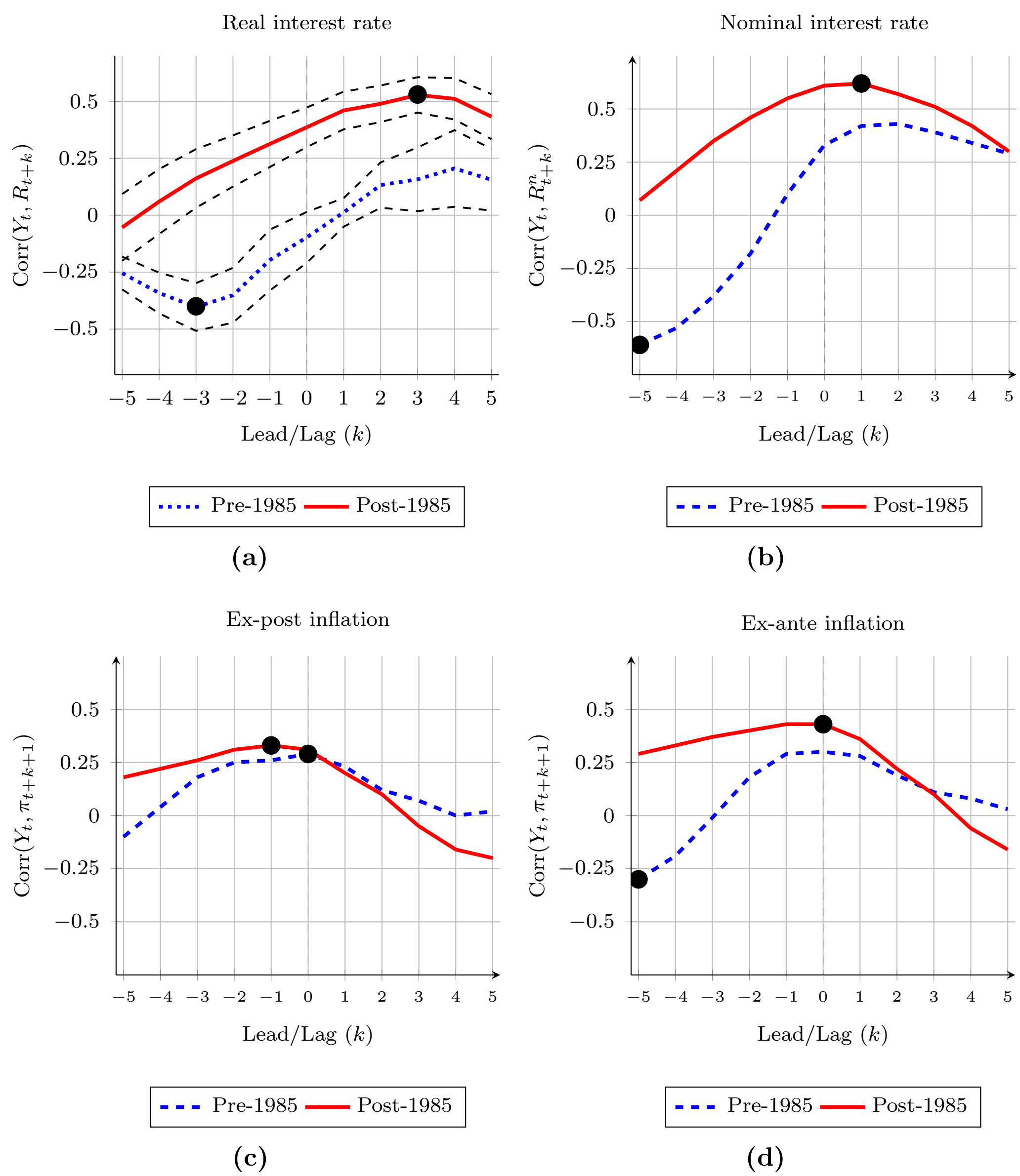



Figure 1: Cross-correlations between output, the real interest rate, the nominal interest rate, ex-post and ex-ante inflation

*Note*: Ex-post and ex-ante inflation measures are at time $t+1$. Ex-post and ex-ante inflation are generated from the GDP deflator, the ex-ante measure is based on in-sample VAR forecasts. The black dashed bands represent one standard deviation confidence bands computed using GMM. For more information on computing standard errors, see Section 2 in the Online Appendix.

data is also strongly procyclical. We refer to this shift in business cycle dynamics of the real interest rate as the 'Positive Lagging Property' (PLP).

Panels (c) and (d) show the cross-correlation between output and one period ahead ex-post and ex-ante inflation. The cross-correlation properties of the ex-post inflation rate remain relatively unchanged while the cross-correlation for ex-ante inflation has become positively correlated with future output. These findings suggest that changes in the conduct of monetary policy is likely to be central in understanding the shifts in real interest rate dynamics.

We now provide further evidence that this switch from ILP to PLP is a robust stylized fact of the post-1985 real interest rate dynamics. The PLP of real interest rates also exists in the 1985I-2007IV sample, the Great Moderation period. This evidence (as shown in Table 8 in the Online Appendix) indicates that PLP is not driven by the zero-lower-bound on the federal funds rate reached in the aftermath of the Great Recession in the US. Furthermore, the findings are also robust to alternative measures of the real interest rate such as alternative price indexes for inflation (CPI, PCE, Core CPI), using the federal funds rate as the measure of the nominal interest rate, and estimates of the nominal interest rate in the absence of the zero-lower-bound from Wu and Xia (2016) (as shown in Tables 6 and 7 in the Online Appendix).

The evidence we document here is related to two previous studies. The first is by Dotsey, Lantz and Scholl (2003) who find that over the 1947-1996 period, the ex-ante real interest based on the GDP deflator measure of inflation is procyclical and lags output but displays the ILP property when the expected inflation measure is based on the CPI. They also find that ex-ante and ex-post real interest rates display different properties. Additionally, they find inconclusive lead-lag patterns in various sub-samples. While their preferred measure of the ex-ante real rate based on the GDP deflator displays PLP, their overall findings paint a mixed picture of the business cycle relationship between real interest rates and output. We

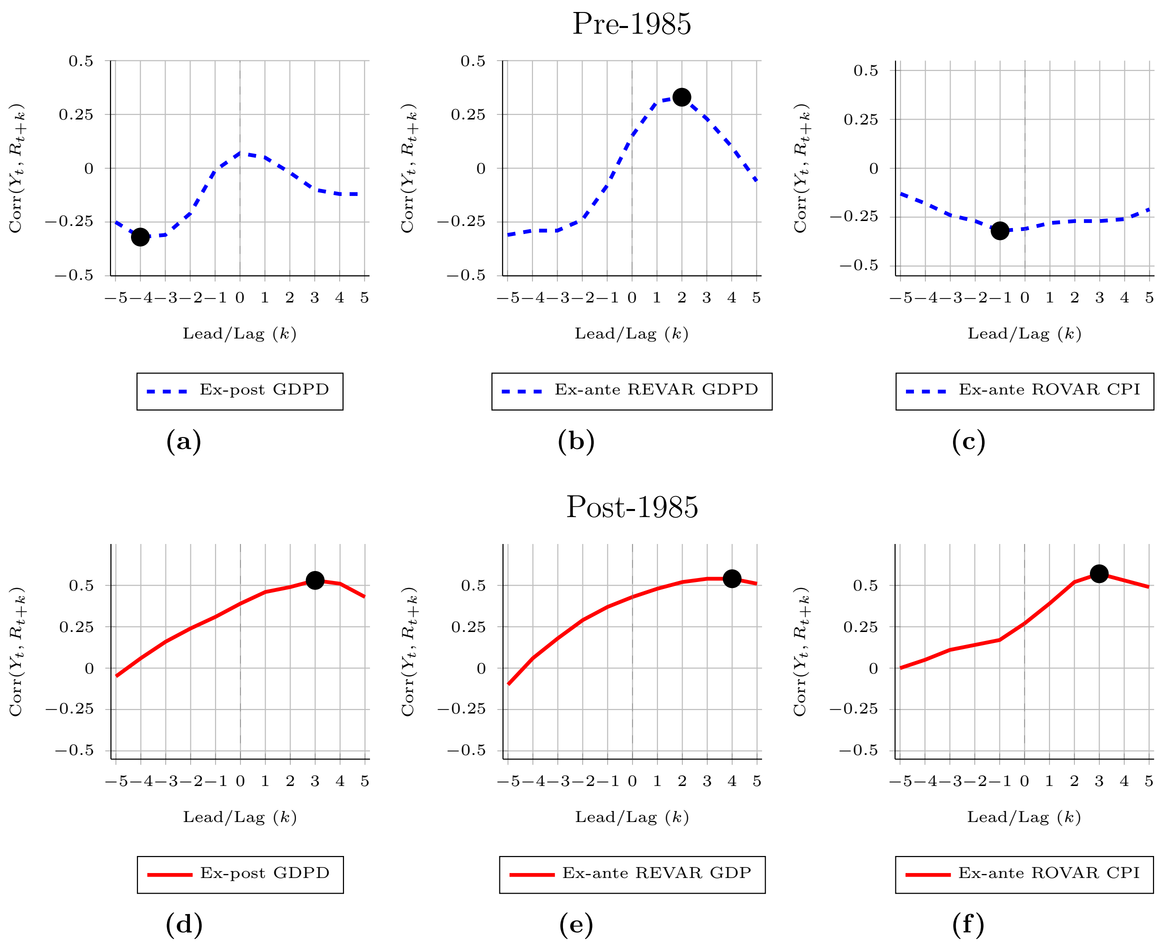



Figure 2: Ex-post and ex-ante real interest rates pre- and post-1985

*Note*: Ex-ante REVAR real interest rate is computed using estimates of expected inflation from the recursive VAR. Ex-ante ROVAR real interest rate is computed using estimates of expected inflation from the rolling VAR. The rolling window is set to 40 quarters. Pre-1985 cross-correlations are computed on data from 1956III:1984IV to avoid small sample VAR estimates.

concur with Dotsey, Lantz and Scholl (2003) in that the presence of ILP in the real interest rate data is largely related to the inflation instability during the 1970s. However, we find that in the post-85 data, that the relationship is remarkably robust to a variety of considerations. Both ex-ante and ex-post real interest rates display PLP, and real rates using both CPI and GDP based inflation measures display PLP. Figure 2 establishes that the various sources of instability noted in Dotsey, Lantz and Scholl (2003) are not present in the post-1985 data.

Thus, we conclude that the post-1985 data is consistent on the cyclical relationship between real interest rates and output, and represent a key stylized fact of business cycles.

The second study by Mertens (2010) investigates the relationship between real interest rates and output conditional on a variety of shocks. In particular, Mertens (2010) finds that the correlation between the real interest rate and output conditional on an identified technology shock is positive during the 1955-2006 period, and that ILP is driven by permanent shocks to inflation during the 1970s. He finds that real interest rates exhibit a leading indicator property conditional on the technology shock but with a positive sign.[11] This interpretation is, however, incorrect. The conditional correlation pattern documented in Mertens (2010) matches the post-1985 unconditional pattern as shown in Figure 1 but it is a *lagging* rather than a leading relationship. The robust evidence that we have established shows that real interest rates exhibit PLP in the post-1985 data.

We now examine real interest rate-output dynamics through the lens of a variety of DSGE models and compare it with the evidence. In this context, our approach follows King and Watson (1996) who also presented a variety of models that were all unable to account for the ILP. This has been a long-standing puzzle in the literature. While this property was attributed to monetary shocks, Boldrin, Christiano and Fisher (2001) presented a technology shock driven two-sector real business cycle model with consumption habits and limited labour mobility that accounted for the ILP. Recently, Pintus, Wen and Xing (2017) present a model, building on Kiyotaki and Moore (1997), in which self-fulfilling belief shocks redistribute income away from lenders to borrowers during booms. Although their objective is to provide a theoretical rationale for the ILP, they do not provide a quantitative comparison of model-based cross-correlations with those in the data. However, the post-1985 evidence we document poses a new challenge to the research aimed at explaining ILP since it no longer

[11] Mertens (2010) states *"Conditional on an identified technology shock, the real interest rate is procyclical and a positive leading indicator."*

exists in the data. Business cycle dynamics of real interest rates are characterized by PLP.[12]

The right panel of Figure 3 shows the cross-correlation based on the simulated data from a standard Real Business Cycle (RBC) model.[13] Interestingly, the procyclicality of real interest rates in the post-1985 data is, at least qualitatively, consistent with that based on this simulated data. While it is known that the model does not produce any lead-lag pattern between the real interest rate and output, the purpose of showing it here provides a useful perspective. The same challenge that the RBC model faced in matching ILP applies to matching PLP in the post-1985 data. Moreover, the mechanisms discussed in Boldrin, Christiano and Fisher (2001) and Pintus, Wen and Xing (2017) produce ILP, and therefore, by construction, cannot explain the PLP of real interest rates.

To investigate the real interest rate-output cross-correlations based on DSGE models developed more recently, we consider three models which have structural features—frictions and shocks—that are embedded in many contemporary DSGE models. These are Smets and Wouters (2007), Iacoviello (2005), and Basu and Bundick (2017).[14] The bottom row in Figure 3 shows the cross-correlations based on data simulated from these models, respectively.

Panel (c) shows the cross-correlations based on the simulated data from the Smets and Wouters (2007) model estimated for 1966I:1984IV and 1985I:2007IV. It is perhaps not well recognized that the Smets and Wouters (2007) model did in fact generate ILP. The presence of consumption habits, a mechanism explored in Boldrin, Christiano and Fisher (2001), helped explain ILP. The Smets and Wouters (2007) model-based ILP is, however, counterfactual relative to the post-1985 evidence of PLP shown in panel (a).

[12]Pintus, Wen and Xing (2018) study global financial linkages and the comovement of economic activity across countries. Their model, however, produces countercyclical real interest rate which runs counter to the the procyclical real rate in the the post-1985 data.

[13]We consider a frictionless version of the RBC model (See Cooley and Hansen (1995)).

[14]Section 4 in the Online Appendix provides links to replication codes for each of the models discussed. For each model we generate 1000 simulations of 1280 observations, dropping the first 1000 observations to control for initial starting condition issues. We compute cross-correlations for each sample and take the median cross-correlation across the 1000 samples.

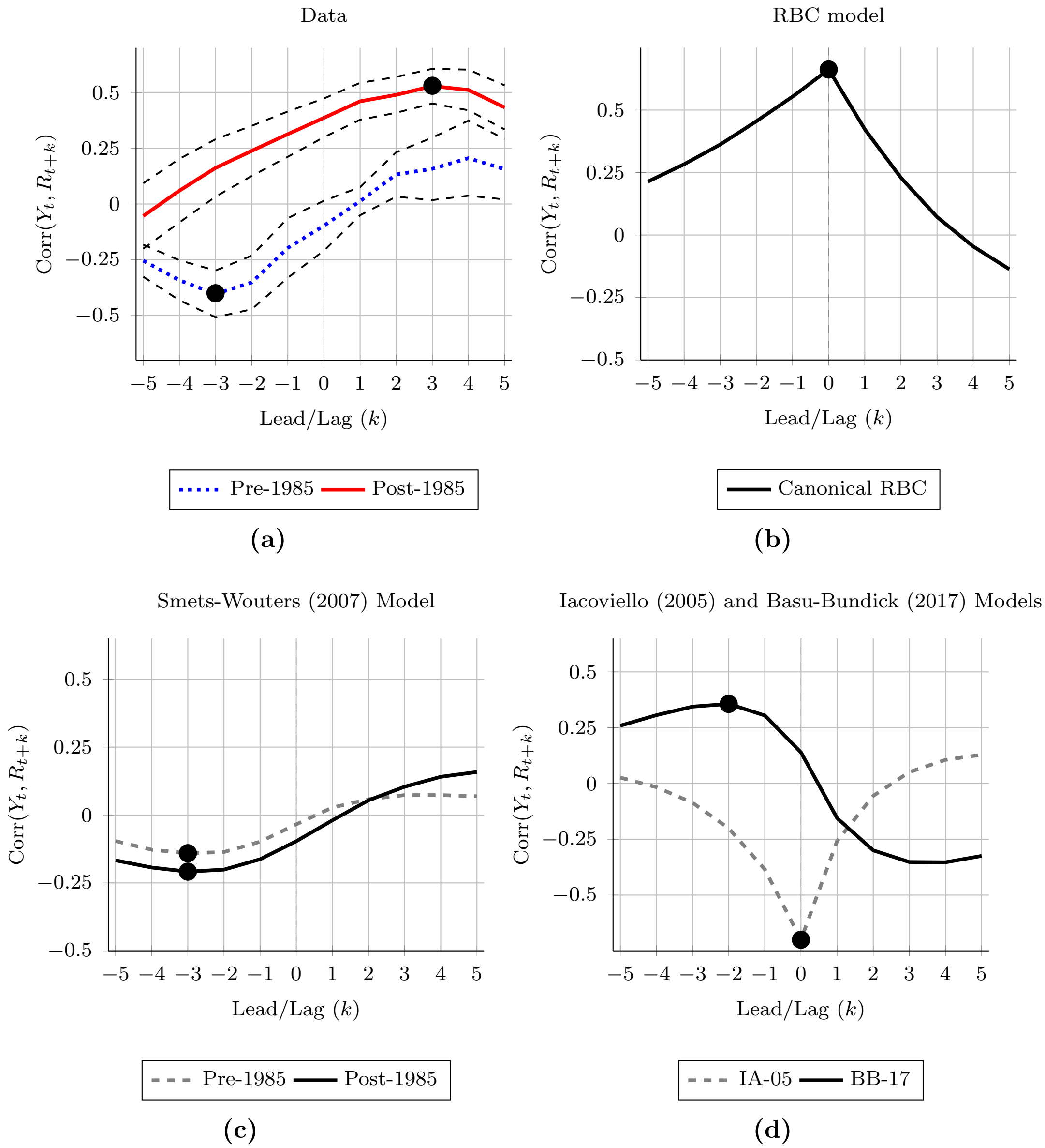



Figure 3: Cross-correlations between output and real interest rate

*Note*: $k$ denotes the number of leads (negative values) or lags (positive values) between real interest rate and output, $Y_t$. The correlations at the black dashed line represent the contemporaneous correlations. Black solid circles denote the largest cross- or contemporaneous correlation that occurs at the $k$th lead/lag, $\max |\{\mathrm{Corr}(Y_t, R_{t+k}), k = -5, -4, ..., 0, ..., 4, 5\}|$. Both actual and model-simulated output and real interest rates are HP filtered. For Smets and Wouters (2007) we estimate the pre-1985 model on data spanning from 1966I:1984IV and the post-1985 on data spanning from 1985I:2007IV. The black dashed bands represent one standard deviation confidence bands computed using GMM. For more information on computing standard errors, see Section 2 in the Online Appendix.

Next, we examine the cross-correlations based on the simulated data from the Iacoviello (2005) model of housing that has two types of households—patient and impatient—and an endogeneous borrowing constraint tied to the value of housing faced by the impatient agent. This model framework has been widely used in studying the role of monetary and fiscal policies in the presence of durable (housing) goods. As shown in panel (c), the real interest rate-output cross-correlations based on the simulated data do not match either the ILP in the pre-1985 data or the PLP in the post-1985 data.[15] The largest correlation implied by the model is contemporaneous. The model also implies that the real interest rate is highly countercyclical which contradicts the post-1985 data. The final example is Basu and Bundick (2017) who study the role of countercyclical markups, sticky prices, and monetary policy in producing contractionary comovement among macroeconomic aggregates after an increased uncertainty about the future. We generate simulated data from their model and compute the real interest rate-output cross-correlations. In the present context, although their model generates a positive contemporaneous correlation between output and the real interest rate consistent with that observed in the post-1985 data, the lead-lag pattern turns out to be counterfactual. In their model, real interest rates lead output by one quarter and with a positive sign.

Based on the comparison between the cross-correlations in the post-1985 data and the models, we conclude that a broad class of contemporary DSGE models do not match the PLP—the defining property of real interest rates over the business cycle in the post-1985 data. Identifying new mechanisms to explain the positive lagging property of real interest rates is, therefore, an important research direction.

Previously, Boldrin, Christiano and Fisher (2001) provided an explanation for the ILP of real interest rates in a model with intersectoral rigidities and consumption habits. Models with these features, however, cannot explain the PLP in the post-1985 period. Through a set

[15] The Iacoviello (2005) model does not have consumption habits.

of examples, we made the point that a broad class of contemporary DSGE models featuring a variety of mechanisms also do not produce PLP. This property of real interest rates is a serious challenge to developing a DSGE model-based explanation.

## 2.3 Labour Productivity Negatively Lags Output

Panels (a) and (b) in Figure 4 show the cross-correlations between output and labour productivity, $LP_t$, where the latter variable is measured as output per hour and output per person, respectively. The cross-correlations in the figure represent $\text{Corr}(Y_t, LP_{t+k})$: $k = \{-5, -4, ..., 0, ..., 4, 5\}$.

While the decline in the procyclicality of labour productivity has been widely discussed in the literature, the post-1985 data show a prominent inverted lagging property of labour productivity over the cycle. Labour productivity shifted from leading the cycle in the pre-1985 period with a positive sign to lagging by at least a year with a negative sign. The absolute magnitude of these cross-correlations are substantially larger than the contemporaneous correlations, indicating the presence of a strong business cycle relationship not captured by comovement alone.

A natural question is: Do models that can either qualitatively or quantitatively explain the decline in the procyclicality of labour productivity also account for the lead-lag shift in the data that we have documented in panel (a) of Figure 4? To answer this question we consider two recent contributions to the literature, Galí and van Rens (2017) and Garin, Pries and Sims (2018). Both models have successfully explained the decline in the procylicality of labour productivity.

The main mechanism discussed in Galí and van Rens (2017) is the decline in turnover reflecting reduced hiring frictions since the mid-1980s as a force behind the vanishing procyclicality of labour productivity. Panel (c) shows the cross-correlations based on the simulated data where we set the separation rate $\delta = 0.35$ for the pre-1985 period and $\delta = 0.15$ for the post-1985 period, as in Galí and van Rens (2017).

Consistent with the results in Galí and van Rens (2017), the diminished procyclicality of labour productivity is evident in panel (c). This exercise, however, also reveals that the model produces counterfactual cross-correlations for the two sub-samples. The model implies a contemporaneous correlation that is the largest in absolute value in both periods. We, therefore, conclude that the same mechanism—the decline in turnover—as developed in Galí and van Rens (2017), cannot account either qualitatively or quantitatively for (i) the switch from labour productivity leading output to lagging output and (ii) the switch in sign from positive to negative cross-correlation as shown in panel (a) of Figure 4.

The second example is Garin, Pries and Sims (2018) who develop a model in which they show that the importance of sectoral shocks relative to aggregate shocks can account for the decline in the procyclicality of labour productivity in the US economy. We use the simulated data from their model to compute cross-correlations between labour productivity and output.[16] Panel (d) of Figure 4 shows the cross-correlations for the pre- and post-1985 period. While the model can clearly account for the decline in the procyclicality of labour productivity, it produces a counterfactual cross-correlation pattern between output and labour productivity. The cross-correlations based on the simulated data are very close to zero for the post-1985 calibration in Garin, Pries and Sims (2018).

There is little work in the literature that has addressed the lead-lag properties of labour productivity over the US business cycle. An early contribution by Burnside and Eichenbaum (1993) discussed the ability of the factor-hoading model to generate dynamic correlations between labour productivity and output.[17] The presence of factor hoarding behaviour, however, causes labour productivity to lead output, as noted in Burnside (1998). This means that

[16] We thank Eric Sims and Julio Garin for providing us with the replication code for their paper.

[17] See Figure 3 in Burnside and Eichenbaum (1993) based on US data from 1955I - 1992IV. The discussion of cross-correlations is omitted in the published version (Burnside and Eichenbaum (1996)).

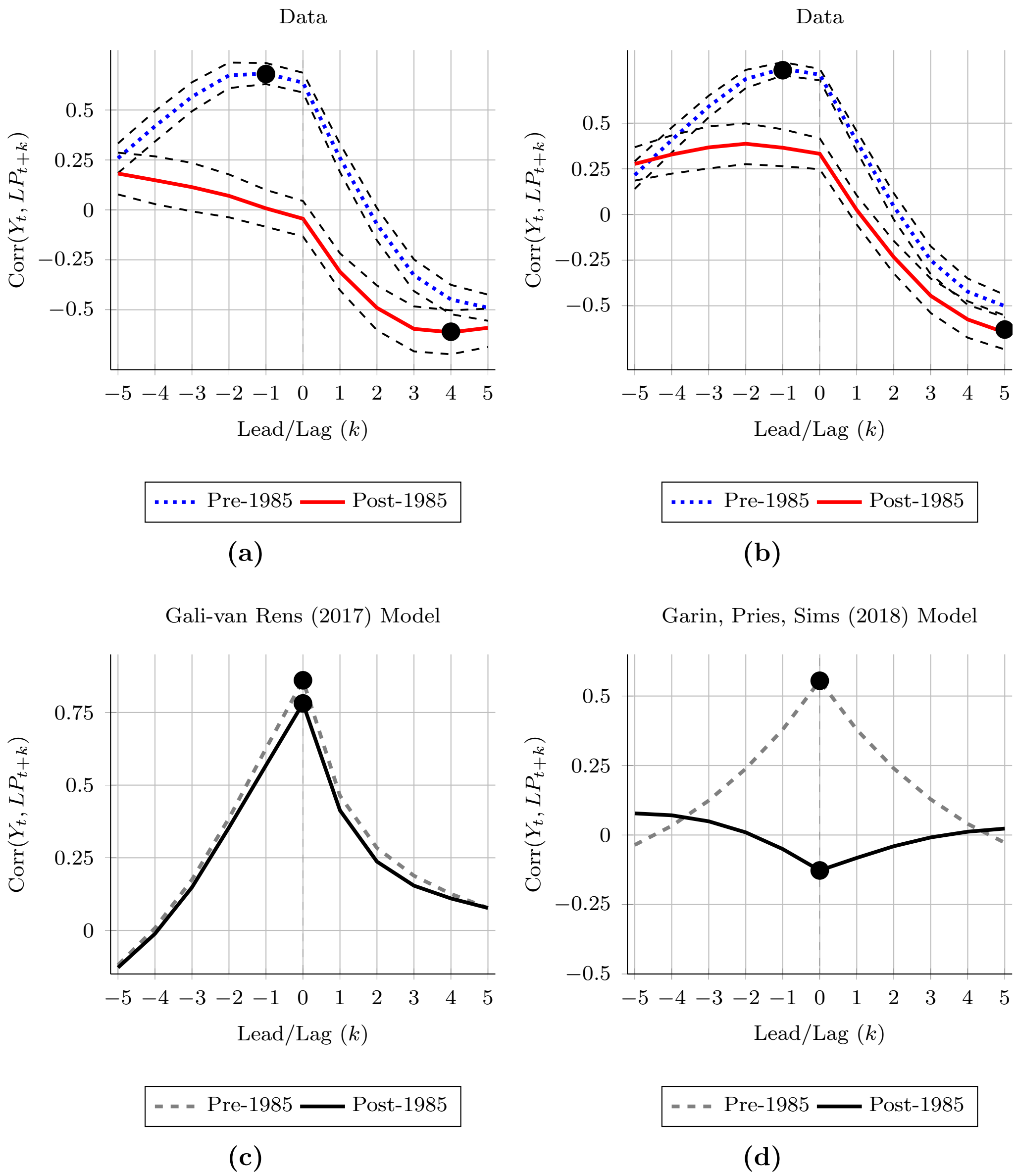
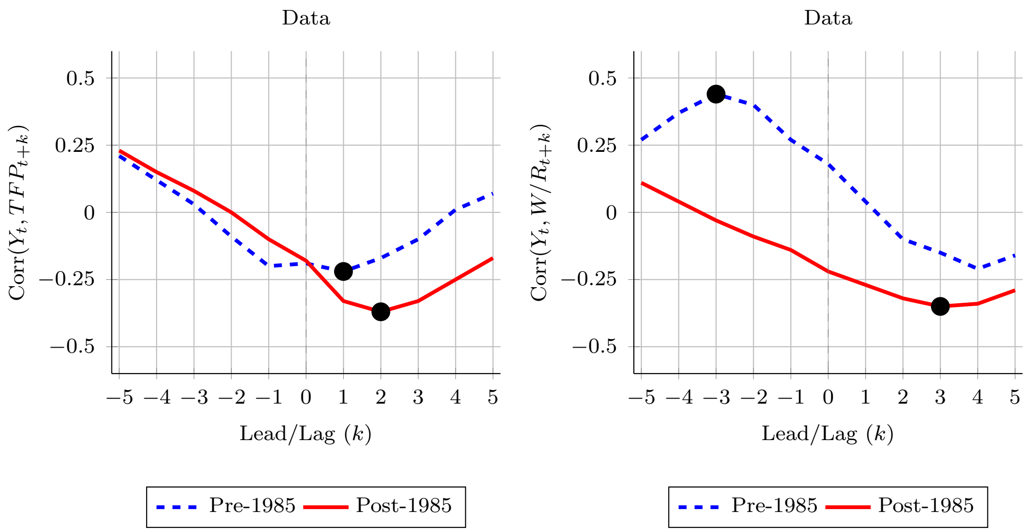



Figure 4: Cross-correlations between output and labour productivity

*Note*: $k$ denotes the number of leads (negative values) or lags (positive values) between output and labour productivity. The correlations at the black dashed line represent the contemporaneous correlations. Black solid circles denote the largest cross- or contemporaneous correlation that occurs at the $k$th lead/lag, $\max|\{\text{Corr}(Y_t, LP_{t+k}), k = -5, -4, ..., 0, ..., 4, 5\}|$. Actual data and model data in Garin et al. (2018) and Galí and van Rens (2017) are HP filtered. The black dashed bands represent one standard deviation confidence bands computed using GMM. For more information on computing standard errors, see Section 2 in the Online Appendix.

changes in factor-hoarding are unlikely to explain the negatively lagging labour productivity over the business cycle in the post-1985 period.

In summary, existing models and mechanisms that have been used to explain the declining procyclicality of labour productivity do not account for its changing role in the lead-lag property over the business cycle. In light of the new evidence from the post-1985 period shown in panel (a) of Figure 4, explaining the shift in labour productivity from leading positively to lagging negatively is an important direction for future research.




**(a)** **(b)**

Figure 5: Cross-correlations of output with total factor productivity (Fernald (2014)) and wage-interest ratio

*Note*: $k$ denotes the number of leads (negative values) or lags (positive values) of either $TFP$ or $W/R$ with respect to output. Black solid circles denote the largest cross- or contemporaneous correlation that occurs at the $k$th lead/lag, $\max|\{\text{Corr}(Y_t, \text{TFP}_{t+k}), k = -5, ..., 0, ..., 5\}|$ or $\max|\{\text{Corr}(Y_t, \text{W/R}_{t+k}), k = -5, ..., 0, ..., 5\}|$.

To further understand the forces underlying the shift in the lead-lag properties of labour productivity, consider the following constant-returns-to-scale production function expressed in terms of labour productivity

$$\ln\left(\frac{Y}{H}\right) = \ln A + \ln\left(f\left(\frac{K}{L}\right)\right) = \ln A + \ln\left(\phi\left(\frac{W}{R}\right)\right)$$

where $Y/H$ is labour productivity per hour, $A$ is Total Factor Productivity (TFP), $K/L$ is the capital services to labour ratio, and $W/R$ is the real wage to real interest rate ratio. The second equality imposes the equilibrium condition in perfectly competitive factor markets. This decomposition allows us to examine if the shifts in labour productivity have occurred either through changes in forces driving TFP or those related to input markets reflected in factor prices, or both. We use Fernald (2014) data on utilization-adjusted TFP growth, convert it to a log level series, and then apply the HP filter to compute the cross-correlations. As shown in Panel (a) in Figure 5 TFP displayed a negative lagging property in the pre-1985 data relative to output over the business cycle, with Corr$(Y_t, TFP_{t+1}) = -0.22$ . In the post-1985 data, this negative lagging property became more enhanced, with Corr$(Y_t, TFP_{t+2}) = -0.37$. So, although there is no shift in the lead-lag property, the stronger negative lagging property is consistent with the pattern observed for labour productivity. In both sub-samples, TFP has a negative contemporaneous correlation. Panel (b) shows that the factor price ratio displayed a strong positive leading property in the pre-1985 data with Corr$(Y_t, (W/R)_{t-3})$ $= 0.44$. This property shifted to a strongly lagging factor price ratio with a negative sign, Corr$(Y_t, (W/R)_{t+3}) = -0.35$. The factor price ratio also shifted from slightly procyclical to countercyclical. The shifts in the factor price comovement properties suggest that changes in factor market dynamics since the post-1985 period may have contributed to the negative lagging property of labour productivity, with the TFP dynamics enhancing this pattern.

## 2.4 Labour Inputs Negatively Lead Labour Productivity

The dynamic relationship between total hours worked and productivity features prominently in a large body of business cycle research (see, for example, Benhabib, Rogerson and Wright (1991), Christiano and Eichenbaum (1992), Galí (1999) for early contributions). Panels (a) and (b) in Figure 6 show two sets of cross-correlations. The first is between total hours worked, $H_t$, and output per hour. The second is between total employment, $E_t$, and output per worker. In the pre-1985 data, total hours worked lagged output per hour by three quarters and with a positive sign, $\text{Corr}(LP_t, H_{t+3}) = 0.62$. In the post-1985 data, however, this relationship has switched with total hours worked leading output per hour by two quarters. Employment also leads output per person by four quarters. Both of these cross-correlations have a negative sign, $\text{Corr}(LP_t, H_{t-2}) = -0.67$ and $\text{Corr}(LP_t, E_{t-4}) = -0.62$, respectively. The contemporaneous correlations between labour input and labour productivity measures have also switched signs from positive to negative. In particular, they have switched from $\text{Corr}(LP_t, H_t) = 0.21$ in the pre-1985 sample to $-0.53$ in the post-1985 sample for output per hour.[18] Similarly, they switched from $\text{Corr}(LP_t, E_t) = 0.24$ to $-0.27$ for output per person.

The pre-1985 evidence of total hours worked lagging output per worker is consistent with the evidence reported in Figure 6 of Burnside and Eichenbaum (1993). They show that the factor hoarding model does a good job of matching the cross-correlations. The switch in the lead-lag property, with total hours worked leading output per worker with a negative sign in the post-1985 data, however, suggests that the factor hoarding behaviour of firms cannot reconcile this evidence. We now examine the cross-correlations between labour productivity and employment through the lens of the Galí and van Rens (2017) and Garin, Pries and Sims (2018) models. Panel (c) shows the cross-correlations based on the simulated data from Galí and van Rens (2017). The model qualitatively matches the decrease in contemporaneous

[18] This shift in contemporaneous correlation is similar to that reported in Galí and van Rens (2017), Table 1.

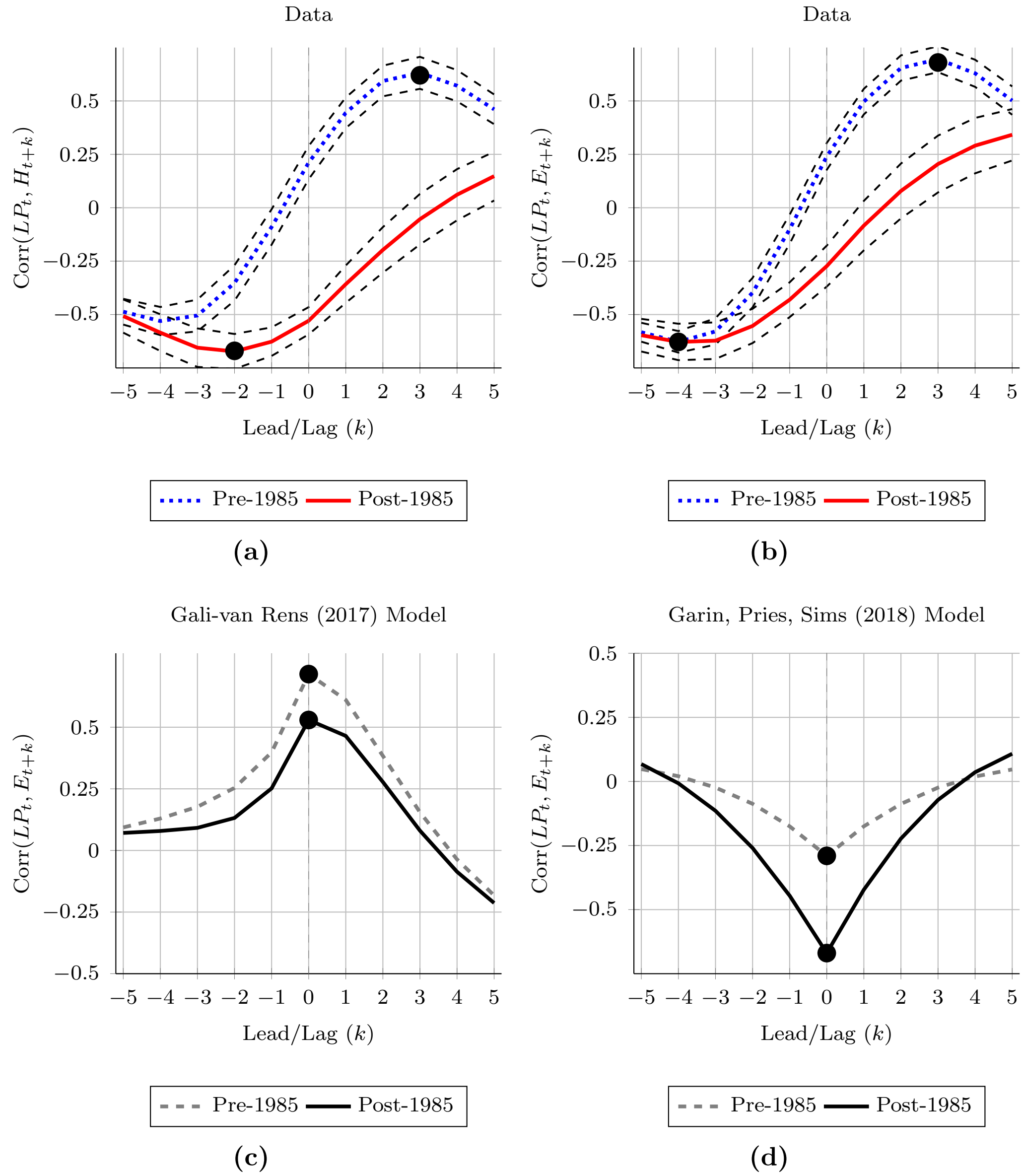



Figure 6: Cross-correlations between labour productivity and labour inputs

*Note*: $k$ denotes the number of leads (negative values) or lags (positive values) between labour productivity and labour inputs. The correlations at the black dashed line represent the contemporaneous correlations. Black solid circles denote the largest cross- or contemporaneous correlation that occurs at the $k$th lead/lag, $\max |\{\text{Corr}(LP_t, \text{Labour Input}_{t+k}), k = -5, ..., 0, ..., 5\}|$. Actual data and simulated data from Garin et al. (2018) and Galí and van Rens (2017) are HP filtered. The black dashed bands represent one standard deviation confidence bands computed using GMM. For more information on computing standard errors, see Section 2 in the Online Appendix.

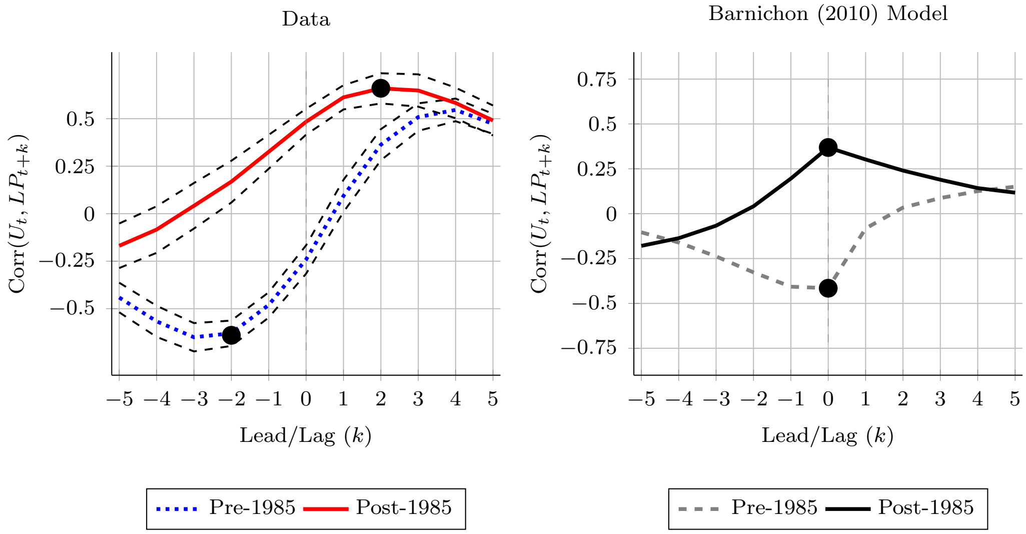
correlations, but does not match the sign switch in the contemporaneous correlation and the lead-lag pattern is counterfactual. Panel (d) shows the cross-correlations based on the simulated data from Garin, Pries and Sims (2018). Unlike, Galí and van Rens (2017), their model does generate a negative contemporaneous correlation, but does not match the sign switch from positive to negative. From the perspective of our paper, it is important to note that the model produces a lead-lag pattern between labour productivity and employment which is counterfactual.

### 2.5 Unemployment Rate Positively Leads Labour Productivity

The relationship between labour productivity and the unemployment rate is a key component in models of search and matching (see, for example, Mortensen and Pissarides (1994), Mertz (1995), Andolfatto (1996), Shimer (2005), Hall (2005), among many other contributions). Recently, Barnichon (2010) noted that the contemporaneous correlation between cyclical unemployment and labour productivity over the post-WWII period switched sign in the mid-1980s: from significantly negative the correlation became significantly positive.

Panel (a) in Figure 7 shows that in the pre-1985 data the largest cross-correlation between the unemployment rate, $U_t$ and output per hour is $\mathrm{Corr}(U_t, LP_{t-2}) = -0.64$, indicating that unemployment lagged output per hour by two quarters with a negative sign. Increases in productivity were associated with declines in unemployment two quarters ahead. This relationship switched in the post-1985 data to $\mathrm{Corr}(U_t, LP_{t+2}) = 0.66$. Thus, increases in the unemployment rate are associated with an increase in productivity two quarters ahead.

Barnichon (2010) also notes in passing that the cross-correlogram between unemployment and productivity look 'dramatically different' (p. 1015). His focus, however, is on the shift in the contemporaneous correlation between unemployment and productivity and he, therefore, does not examine if the model produces the shift in cross-correlations which is the main focus




**(a)** **(b)**

Figure 7: Cross-correlations between the unemployment rate and labour productivity

*Note*: $k$ denotes the number of leads (negative values) or lags (positive values) between the unemployment rate and labour productivity. Black solid circles denote the largest cross- or contemporaneous correlation that occurs at the $k$th lead/lag, $\max |\{\text{Corr}(U_t, LP_{t+k}), k = -5, ...0, ..., 5\}|$. Both actual and model-simulated data are HP filtered. The black dashed bands represent one standard deviation confidence bands computed using GMM. For more information on computing standard errors, see Section 2 in the Online Appendix.

of our paper. Interestingly, the absolute magnitude of the contemporaneous correlations in both pre-1984 and post-1984 periods that Barnichon (2010) considers are smaller than the cross-correlations. This observation reinforces our point that the focus in many recent papers has been on contemporaneous correlations, and the shifts in the lead-lag patterns (the largest absolute magnitude of cross-correlations) capturing important business cycle comovement relationships have either remained unnoticed or have received very little attention.

We simulate data from Barnichon (2010)'s model for pre-and post-1985 periods and compute the cross-correlations between unemployment and labour productivity.[19] Panel (b) in Figure 7 shows the model-based cross-correlations. We find that the model does not produce any lead-lag pattern for the post-1985 period.[20] For the pre-1985 period, the model

[19]We thank Regis Barnichon for providing us with the replication codes.

[20]In Barnichon (2010)'s model, employment is a state variable and does not respond on impact to shocks.

produces a lead of labour productivity over unemployment. Both of these properties are counterfactual relative to the stylized facts for the two sub-samples.

# 3 Robustness

In this section we present a variety of robustness checks to establish that the shifts in lead-lag properties are indeed robust stylized facts across the two sample periods in the US data.

## 3.1 Alternative filters

Our choice of using the HP filtered data as the baseline to present the lead-lag properties is advantageous for two reasons: first, the HP filter is arguably the most common method for obtaining the cyclical component from aggregate data, and second, it allows us to contrast the new stylized facts with those in the previous literature. All the lead-lag shifts that we have documented remain robust to Baxter and King (1999) (BK) and Christiano and Fitzgerald (2003) (CF) band-pass filters.[21] These filters have been used in the literature as an alternative to the HP filter. Tables 3 and 4 in the Online Appendix present the results for the BK and CF filters, respectively. As is evident, the magnitude and signs of the cross-correlations are similar to the HP filter.

Recently, Hamilton (2018) has proposed an alternative to the HP filter.[22] This new filtering method requires obtaining residuals from a regression of a variable $h$-periods ahead on its $p$ most recent values as of date $t$. We refer to this regression-based procedure as

We compute the contemporaneous correlation as Corr$(U_{t+1}, LP)$, and all leads and lags based on this vertical translation, consistent with the approach applied in the paper.

[21]Previously, Burnside (1998), in his comment on Canova (1998), has noted that that business cycle stylized facts obtained from different filters do not necessarily have to agree. Specifically, Burnside (1998) (on page 514) states *I will argue that when the facts differ according to the filter, this simply means there are many facts to be explained.*

[22]Schüler (2018) presents a detailed assessment of the Hamilton (2018) filter and discusses some of its shortcomings.

the *hp* filter. To implement the *hp* filter, we use $h = 8$ and $p = 4$, which are Hamilton (2018)'s suggested parametric specification for detrending quarterly data.[23] The *hp* results are summarized in Table 2 in the Online Appendix. All the four headline stylized facts are consistent with the *hp* filter. There is, however, one measure of labour productivity, output per worker, which does not exhibit a shift in its lead over total employment or output. But the shift in the lead-lag properties of labour productivity measured as output per hour remains consistent across HP, BK, CF, and *hp* filters.

### 3.2 Broader business cycle phase of 8-50 quarters

Recently Beaudry, Galizia and Portier (2017) have documented that many macroeconomic aggregates appear to exhibit a peak in their spectral densities at periodicities between 32 and 50 quarters. Their work suggests that broadening the definition of the business cycle to include up to 50 quarters to may be the more appropriate view of business cycles. With this background, it is of interest to determine if the lead-lag shifts that we document occur when we expand the conventional view of the business cycles (fluctuations occuring between 8 and 32 quarters) to include the lower frequencies. Using the BK and CF filter we confirm that all the lead-lag shifts that we have documented occur across this broader definition of the business cycle (See Tables 10 and 11 in the Online Appendix).

### 3.3 Demographic adjusted hours

Are the lead-lag shifts in labour productivity related to demographic changes that have occurred over time? Using demographically adjusted hours from Wolters (2018) we recompute the cross-correlations containing output per hour.[24] These results are reported in Table 15

[23]Specially, for a series $y_t$, we run the regression $y_{t+h} = \beta_0 + \sum_{j=0}^{p} \beta_{j+1} y_{t-j} + v_{t+h}$ and construct the cyclical component as the residuals $\hat{v}_{t+h} = y_{t+h} - \left(\hat{\beta}_0 + \sum_{j=0}^{p} \hat{\beta}_{j+1} y_{t-j}\right)$.

[24]We thank Maik Wolters for providing us with the adjusted hours data.

in the Appendix. As it turns out, the results reflect the same pattern as the baseline case. These finding suggests that the labour productivity shifts are not related to demographic changes.

### 3.4 Standardized variables

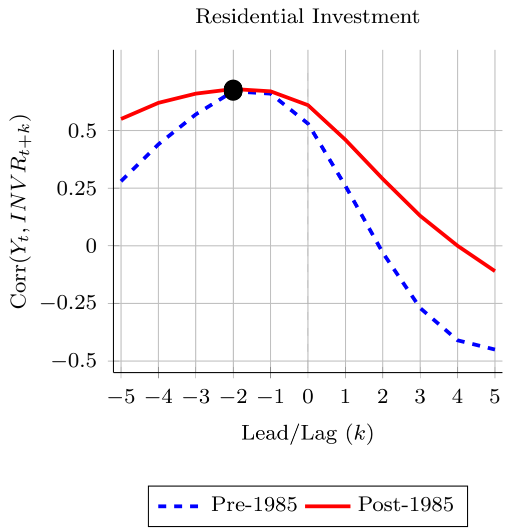
Sharp increases in volatility, as in the stock market data, across sub-samples may introduce a bias in unconditional correlation (Forbes and Rigobon (2002), Stock and Watson (2002)). While this is less of a concern in aggregate US macroeconomic data, we recompute the cross-correlations after standardizing the cyclical components to have variance equal to one in the entire sample, and then variance equal to one in each subsample. These results are reported in Tables 12 and 13 in the Appendix. The cross-correlations are nearly identical in both cases, suggesting that the changes in cross-correlations are not driven by changes in volatility after the Great Moderation.

### 3.5 Filtering on subsamples

The baseline cross-correlations presented in the paper are computed by first filtering the entire data, proceeded by splitting the data at 1984:4. Since the HP filter used in the paper is a two-sided filter, we investigate if the filter leads to any unintended spillovers between the cyclical data in each sample. Table 14 highlights that the changes in lead-lag properties are robust to whether one filters on the entire sample or the pre- and post-1985 data independently.

### 3.6 Alternative samples

The baseline samples used in the paper are 1948:I-1984:IV. As highlighted earlier, the changes in post-1985 data are robust to the exclusion of the Great Recession (ending the sample in




**(a)**

Figure 8: Cross-correlations between output and residential investment

*Note*: $k$ denotes the number of leads (negative values) or lags (positive values) between output and residential investment. Black solid circles denote the largest cross- or contemporaneous correlation that occurs at the $k$th lead/lag, $\max|\{\mathrm{Corr}(Y_t, INVR_{t+k}), k = -5, ...0, ..., 5\}|$.

2007:IV). These results are reported in Table 8 in the Appendix. In addition, we report results for an alternative onset of the Great Moderation (1983:I). All changes in the lead-lag properties discussed are robust to this alternative sample. These results are presented in Table 9 in the Appendix.

### 3.7 Measurement error: an informative check

A well known fact is that residential investment ($INVR$) leads the cycle. We find that this fact is robust across pre-1985 and post-1985 data, and therefore, did not experience the type of shifts we have highlighted in the previous sections. In the post-1985 data, $INVR$ leads output by two quarters over the business cycle, the same as in the pre-1985 data. As shown in Figure 8, the largest cross-correlations are $\mathrm{Corr}(Y_t, INVR_{t-2}) = 0.67$ and $\mathrm{Corr}(Y_t, INVR_{t-2}) = 0.68$, respectively. This finding is also robust to using the BK, CF, and the *hp* filters. The evidence for the robust leading property of residential investment across the two periods is quite informative for at least two reasons. First, it suggests that the potential sources underlying the shifts in the lead-lag properties have likely occured outside the investment sector. Second, it helps to allay any concern about measurement errors in aggregate data being the source of the shifts in the lead-lag properties.

### 3.8 Parameterization versus model structure

An open question is whether an alternative parameterization of the models presented herein could generate cross-correlations inline with the post-1985 data. As an inquiry into this point we take the model of Smets and Wouters (2007) estimated on post-1985 data and generate 5000 draws from the posterior (parameters are drawn randomly from the estimated posterior distributions). Figure X in the Online Appendix presents the distribution of cross-correlations generated and the empirical cross-correlation in the post-1985 data. The empirical cross-correlation lays outside the bounds of the cross-correlations generated from the alternative parameterizations suggesting that model structure is key to understanding the changes in cross-correlations.

## 4 Conclusion

In this paper, we document shifts in the lead-lag properties of the US business cycle since the onset of the Great Moderation period of the mid-1980s. We characterize four new stylized facts in terms of cross-correlations based on cyclical data. First, real interest rates positively lag output. Second, labour productivity negatively lags output. Third, labour inputs negatively lead labour productivity, and fourth, the unemployment rate positively leads labour productivity. The large absolute magnitude of these cross-correlations relative to contemporaneous correlations suggest important empirically relevant business cycle forces at work that are not reflected in contemporaneous correlations alone. We show that many contemporary DSGE models produce counterfactual lead-lag patterns, with incorrect signs. Our empirical findings suggest that explaining why the shifts in US business cycle comovement have occurred since the mid-1980s in both types comovement—contemporaneous correlations and lead-lag properties—is a promising area for future research and for improving DSGE models.

# Bibliography


Andolfatto, D.: 1996, Business Cycles and Labour-Market Search, *American Economic Review* **86**(1), 112–132.

Angeletos, G.-M.: 2017, Frictional Coordination, *Working Paper 24178*, NBER.

Backus, D. K., Kehoe, P. J. and Kydland, F. E.: 1992, International Real Business Cycles, *American Economic Review* **100**(4), 745–775.

Backus, D. K., Kehoe, P. J. and Kydland, F. E.: 1994, Dynamics of the Trade Balance and the Terms of Trade: The J-Curve?, *American Economic Review* **84**(1), 84–103.

Barnichon, R.: 2010, Productivity and unemployment over the business cycle, *Journal of Monetary Economics* (57), 1013–1025.

Basu, S. and Bundick, B.: 2017, Uncertainty Shocks in a Model of Effective Demand, *Econometrica* **85**(3), 937–958.

Baxter, M. and King, R. G.: 1999, Measuring Business Cycles: Approximate Band-Pass Filters For Economic Time Series, *The Review of Economics and Statistics* **81**(4), 575–593.

Beaudry, P., Galizia, D. and Portier, F.: 2017, Putting the Cycle Back into Business Cycle Analysis, *Manuscript*, Carleton University.

Beaudry, P. and Guay, A.: 1996, What do interest rates reveal about the functioning of real business cycle models?, *Journal of Economic Dynamics and Control* **20**, 1661–1682.

Benhabib, J., Rogerson, R. and Wright, R.: 1991, Homework in Macroeconomics: household production and aggregate fluctuations, *Journal of Political Economy* **99**(6), 666–689.

Blanchard, O. J. and Watson, M. W.: 1986, Are Business Cycles All Alike?, University of Chicago Press, pp. 123–180.

Boldrin, M., Christiano, L. J. and Fisher, J. D. M.: 2001, Habit Persistence, Asset Returns, and the Business Cycle, *American Economic Review* **91**(1), 149–166.

Burnside, C.: 1998, Detrending and business cycle facts: A comment, *Journal of Monetary Economics* **41**, 513–532.

Burnside, C. and Eichenbaum, M. S.: 1993, Factor Hoarding and the Propagation of Business Cycle Shocks, *Working Paper 4675*, NBER.

Burnside, C. and Eichenbaum, M. S.: 1996, Factor Hoarding and the Propagation of Business-Cycle Shocks, *American Economic Review* **86**(5), 1154–1174.

Canova, F.: 1998, Detrending and business cycle facts, *Journal of Monetary Economics* **41**(3), 475–512.

Chari, V. V., Christiano, L. J. and Eichenbaum, M.: 1995, Inside Money, Outside Money, and Short-Term Interest Rates, *Journal of Money, Credit and Banking* **27**(4), 1354–1386.

Christiano, L. J. and Eichenbaum, M. S.: 1992, Current Real-Business-Cycle Theories and Aggregate Labor-Market Fluctuations, *American Economic Review* **82**(3), 430–450.

Christiano, L. J. and Fitzgerald, T. J.: 2003, The band pass filter, *International Economic Review* **44**(2), 435–465.

Cooley, T. F. and Hansen, G. D.: 1995, *Money and the Business Cycle*, Princeton University Press, chapter Chapter 7, pp. 175–216.

Daly, M. C., Fernald, J. G., Óscar Jordà and Nechio, F.: 2017, Shocks and Adjustments, *Working Paper 2013-32*, Federal Reserve Bank of San Francisco.

Dotsey, M., Lantz, C. and Scholl, B.: 2003, The Behavior of the Real Rate of Interest, *Journal of Money, Credit and Banking* **35**(1), 91–110.

Fernald, J. G.: 2014, A quarterly, utilization-adjusted series on total factor productivity, *Working Paper 2012-19*, Federal Reserve Bank of San Francisco.

Fernald, J. G. and Wang, J. C.: 2016, Why Has the Cyclicality of Productivity Changed? What Does it Mean?, *Annual Review of Economics* **8**, 465–96.

Fiorito, R. and Kollintzas, T.: 1994, Stylized Facts of Business Cycles in the G7 from a Real Business Cycle Perspective, *European Economic Review* **38**(2), 235–269.

Forbes, K. and Rigobon, R.: 2002, No Contagion, Only Interdependence: Measuring Stock Market Comovements, *Journal of Finance* **57**(5), 2223–2261.

Galí, J.: 1999, Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?, *American Economic Review* **89**(1), 249–271.

Galí, J. and Gambetti, L.: 2009, On the Sources of the Great Moderation, *American Economic Journal: Macroeconomics* **1**(1), 26–57.

Galí, J. and van Rens, T.: 2017, The Vanishing Procyclicality of Labor Productivity, *Technical report*, University of Pompeu Fabra and University of Warwick.

Garin, J., Pries, M. J. and Sims, E. R.: 2018, The Relative Importance of Aggregate and Sectoral Shocks and the Changing Nature of Economic Fluctuations, *American Economic Journal: Macroeconomics* **10**(1), 119–148.

Gavin, W. T. and Kydland, F. E.: 2000, The nominal facts and the October 1979 policy change, *Federal Reserve Bank of St. Louis Review* pp. 39–61.

Hall, R.: 2005, Employment Fluctuations with equilibrium wage stickiness, *American Economic Review* **95**(1), 50–65.

Hall, R.: 2007, How Much Do We Understand About the Modern Recession?, *Brookings Papers on Economic Activity* pp. 13–30.

Hamilton, J. D.: 2018, Why You Should Never Use the Hodrick-Prescott Filter, *The Review of Economics and Statistics* **100**(5), 831–843.

Hodrick, R. J. and Prescott, E. C.: 1980, Postwar U.S. Business Cycles: An Empirical Investigation, *Technical report*, Carnegie Mellon University.

Hodrick, R. J. and Prescott, E. C.: 1997, Postwar U.S. Business Cycles: An Empirical Investigation, *Journal of Money, Credit and Banking* **29**(1), 1–16.

Iacoviello, M.: 2005, House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle, *American Economic Review* **95**(3), 739–764.

Jordà, O., Schularick, M. and Taylor, A. M.: 2016, Macrofinancial History and the New Business Cycle Facts, *NBER Macroeconomics Annual*.

King, R. G. and Watson, M. W.: 1996, Money, Prices, Interest Rates, and the Business Cycle, *Review of Economics and Statistics* pp. 35–53.

Kiyotaki, N. and Moore, J.: 1997, Credit cycles, *Journal of Political Economy* **105**(2), 211–248.

Kydland, F. E. and Prescott, E. C.: 1990, Business Cycles: Real Facts and a Monetary Myth, *Federal Reserve Bank of Minneapolis Quarterly Review* pp. 3–18.

Mertens, E.: 2010, Structural shocks and the comovements between output and interest rates, *Journal of Economic Dynamics and Control* **34**, 1171–1186.

Mertz, M.: 1995, Search in the labor market and the real business cycle, *Journal of Monetary Economics* **36**(2), 269–300.

Mortensen, D. and Pissarides, C.: 1994, Job Creation and Job Destruction in the Theory of Unemployment, *Review of Economic Studies* **61**, 397–415.

Pintus, P. A., Wen, Y. and Xing, X.: 2017, The Inverted Leading Indicator Property and Redistribution Effect of the Interest Rate, *Working paper*, Yale University.

Pintus, P. A., Wen, Y. and Xing, X.: 2018, International Credit Markets and Global Business Cycles, *Working Paper WP 2018-Nr 14*, Aix-Marseille School of Economics.

Schüler, Y. S.: 2018, On the cyclical properties of Hamilton's regression filter, *Working paper*, Deutsche Bundesbank.

Shimer, R.: 2005, The cyclical behaviour of equilibrium unemployment and vacancies, *American Economic Review* **95**(1), 25–49.

Smets, F. and Wouters, R.: 2007, Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach, *American Economic Review* **97**(3), 586–606.

Stiroh, K. J.: 2009, Volatility accounting: A production perspective on increased economic stability, *Journal of the European Economic Association* **7**(4), 671–696.

Stock, J. H. and Watson, M. W.: 1999, Business Cycle Fluctuations in US Macroeconomic Time Series, *in* J. B. Taylor and M. Woodford (eds), *Handbook of Macroeconomics*, Vol. 1 of *Handbook of Macroeconomics*, Elsevier, chapter 1, pp. 3–64.

Stock, J. H. and Watson, M. W.: 2002, Macroeconomic Forecast Using Diffusion Indexes, *Journal of Business & Economic Statistics* **20**(2).

Wolters, M. H.: 2018, How the baby boomers' retirement wave distorts model-based output gap estimates, *Journal of Applied Econometrics* **33**(5), 680–689.

Wu, J. C. and Xia, F. D.: 2016, Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound, *Journal of Money, Credit and Banking* **48**(2-3), 253–291.