

Cauvel, Michael

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# Research Article

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## The neo-Goodwinian model reconsidered

Michael Cauvel\*

Assistant Professor of Economics, University of Southern Maine, Portland, ME, USA

*This paper examines the relationship between aggregate demand and the wage share in the US using a vector autoregression methodology. It finds evidence of Goodwin-cycle effects – that is, profit-led demand and a profit-squeeze effect – in baseline estimates using assumptions traditionally used in the aggregative literature. However, estimates that examine the relationship between demand and the two components of the wage share (the real wage rate and labor productivity) indicate that these results are highly sensitive to ordering restrictions relating demand and labor productivity and that different types of shocks to the wage share may have differing effects on demand. The results suggest two possible interpretations of the initial Goodwin-cycle finding, depending on the assumptions used to identify the demand–productivity relationship. One suggests that the initial estimates reflect a causal relationship in which the effects are driven by a positive effect of productivity on demand and a negative effect of demand on productivity. The other suggests that the initial Goodwin-cycle finding may be spurious, as it interprets contemporaneous pro-cyclical variation in labor productivity as a profit-led demand effect, thereby obscuring an underlying wage-led relationship.*

**Keywords:** *functional distribution of income, neo-Kaleckian model, wage-led and profit-led demand regimes*

**JEL codes:** *E25, E11, E12, E32*

### 1 INTRODUCTION

A vast empirical literature exists examining the relationship between demand and the functional distribution of income – that is, the share of total income going to wage earners vs the share that is earned as profits. Previous studies have generally fallen into two broad groups: ‘aggregative’ studies that examine the bi-directional relationship between the wage share and a single measure of aggregate demand and ‘structural’ studies that treat the wage share as exogenous and separately estimate its relationship with the individual components of aggregate demand.<sup>1</sup> There is a clear pattern in the results found using these two different methodologies. Studies in the latter group typically find evidence of wage-led demand (with a higher wage share increasing demand), except in cases of small, open economies, whereas the former generally find evidence of a cyclical relationship, often called a

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1. Although the empirical measure of the wage share often includes multiple forms of labor compensation, including bonus pay and benefits – and not just wages – the term ‘wage share’ will be used in order to maintain consistency with the theoretical literature.

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‘Goodwin cycle,’ of profit-led demand and a profit squeeze (with a higher profit share increasing demand and higher demand reducing the profit share) (Blecker 2016).<sup>2</sup>

This paper focuses on the aggregative approach, investigating a critique of this methodology that has been highlighted by Lavoie (2017). Lavoie’s critique centers on the treatment of cyclical variation in labor productivity, which is of particular importance given that it is one of the components of the wage share ( $\psi$ ), as shown in equation (1).

$$\begin{aligned}\psi &= \frac{\textit{labour compensation}}{\textit{output}} = \frac{\textit{labour compensation/hours}}{\textit{output/hours}} \\ &= \frac{\textit{real hourly wage rate}}{\textit{labour productivity}}\end{aligned}\quad (1)$$

He argues that labor productivity is likely to vary pro-cyclically with the business cycle, and that if the model is not correctly identified, these positive effects of demand on productivity may be mistakenly interpreted as positive effects of productivity on demand – that is, a profit-led demand effect. Therefore, previous aggregative studies may be biased towards profit-led findings if they do not properly account for these pro-cyclical productivity effects.

This paper explores this issue empirically in the context of the US economy by estimating various vector autoregressions (VARs) including demand and the two components of the wage share – the real wage rate and labor productivity – to test the extent to which estimates are sensitive to identifying assumptions relating demand and productivity. The results suggest that estimates of this relationship are highly sensitive to the assumptions that are used. Models maintaining the common assumption in the aggregative literature that demand has only a lagged effect on productivity find evidence of Goodwin-cycle effects. However, the results suggest that the source of the distributional shock matters, as productivity shocks are profit-led and wage shocks are wage-led, albeit relatively smaller. Moreover, when demand is allowed to affect productivity contemporaneously estimates are suggestive of wage-led demand effects and an initial wage squeeze that results from contemporaneous pro-cyclical variation in productivity. To the extent that the assumption of productivity responding quickly to changes in demand is accurate, these results suggest that estimates maintaining the traditional assumptions will be biased, as some of the estimated Goodwin-cycle effects will be spurious.

It should be noted that all of the results in this paper are limited to the short run, or at most the medium run. The use of quarterly data, data differencing for many variables, and a VAR model make it likely that the estimates pertain only to business-cycle fluctuations. Furthermore, the estimates only capture the relationship between demand and the functional distribution of income in the US economy. Results may differ for other countries.

The rest of the paper proceeds as follows. Section 2 presents the general theoretical foundations and provides a brief overview of the literature. Section 3 discusses the empirical strategy, while Section 4 discusses the results. Section 5 provides some concluding thoughts.

2. Stockhammer (2017) calls those who follow the aggregative approach ‘neo-Goodwinian’ because the cyclical relationship between demand and distribution in these models is different from the theoretical relationship between the wage share and the employment rate originally found in Goodwin’s (1967) model. Stockhammer calls those who follow the structural approach ‘neo-Kaleckians’ because they examine the relationship between distribution and the individual components of aggregate demand and treat the wage share as exogenous, as some neo-Kaleckian theoretical models do.

## 2 THEORETICAL FRAMEWORK AND LITERATURE REVIEW

### 2.1 Theoretical framework

Empirical literature exploring the relationship between demand and the functional distribution of income is primarily inspired by neo-Kaleckian models of distribution and growth, sometimes referred to as ‘structuralist’ or ‘post-Keynesian’ models, which link the functional distribution of income to the components of aggregate demand. These models stem from the work of Kalecki (1954) and Steindl (1952), and have been built upon by many others (for example, Rowthorn 1982; Taylor 1983; 1985; Dutt 1984; 1987; Blecker 1989; 2002; Bhaduri/Marglin 1990; Marglin/Bhaduri 1990).

A basic version of the neo-Kaleckian model is presented below.<sup>3</sup>

$$Y = AD = C + I + G + NX \quad (2)$$

Equation (2) represents the accounting identity that aggregate demand ( $AD$ ) is equal to the sum of consumption ( $C$ ), investment ( $I$ ), government spending ( $G$ ), and net exports ( $NX$ ), which are defined as exports ( $X$ ) minus imports ( $M$ ). In equilibrium, aggregate demand is also equal to total output ( $Y$ ). The various components of aggregate demand can be specified in general terms as:

$$C = C(Y, \psi, Z_c) \quad (3)$$

$$I = I(Y, \psi, Z_I) \quad (4)$$

$$NX = NX(Y, P, Z_X, Z_M); P = P(\psi, Z_P). \quad (5)$$

Each of these components, with the exception of government spending, is a function of  $Y$ ,  $\psi$ , and a vector of exogenous control variables, denoted  $Z_j$ , where  $j = C, I, X, M, P$  indexes the component that the control variables determine. The wage share affects net exports indirectly through the domestic price level ( $P$ ), which is itself a function of the wage share and a vector of control variables affecting the domestic price level, such as import prices. Government spending is assumed to be exogenous, as it is not clear *a priori* how output or the wage share would affect it. The resulting equation is thus:

$$Y = AD = C(Y, \psi, Z_C) + I(Y, \psi, Z_I) + G + NX(Y, P, Z_X, Z_M). \quad (6)$$

In the neo-Kaleckian literature (for example, Stockhammer et al. 2009; 2011; Onaran et al. 2011; Stockhammer/Wildauer 2016), it is typically assumed that the partial derivatives of the components of aggregate demand have the following signs:  $C_Y > 0$ ,  $C_\psi > 0$ ,  $I_Y > 0$ ,  $I_\psi < 0$ ,  $NX_Y < 0$ ,  $P_\psi > 0$ ,  $NX_P < 0$ .<sup>4</sup> The effect of a change in the wage share on aggregate demand and output is found by taking the derivative of  $Y$  with respect to  $\psi$ .

3. This discussion is primarily based on Blecker (2016), which introduces a simplified version of the model from Stockhammer et al. (2011) and explains how the aggregative and structural methodological approaches relate to the theoretical model. The model and Blecker’s explanation are summarized here, and this discussion is not intended to be presented as the author’s independent work.

4. In some cases, it is noted that  $I_\psi$  may be positive or negative because the wage share is likely to have a positive effect on residential investment, even though it is expected to impact non-residential investment negatively (Stockhammer/Wildauer 2016; Stockhammer et al. 2021; Blecker et al. 2022). The sign of  $P_\psi$  may also be theoretically ambiguous, as different types of distributional shocks may have different effects on prices. As Blecker et al. (2022) argue, increases in unit labor

$$\frac{\partial Y}{\partial \psi} = \frac{\partial AD / \partial \psi}{1 - \partial AD / \partial Y} \quad (7)$$

Due to varying effects of distribution on consumption, investment, and net exports, the sign of the relationship between distribution and demand in these models depends upon assumptions made regarding exogenous model parameters and functional forms. Note that assuming stability in the goods market requires condition (8) to be satisfied:

$$\frac{\partial AD}{\partial Y} = \frac{\partial AD}{\partial C} + \frac{\partial AD}{\partial I} + \frac{\partial AD}{\partial NX} < 1. \quad (8)$$

Therefore, in a stable system, the denominator of equation (7) must be positive. As a result, the sign of  $\partial Y / \partial \psi$  depends upon the sign of  $\partial AD / \partial \psi$ . Researchers following the structural approach exploit this fact to sign  $\partial Y / \partial \psi$ . They seek to calculate  $\partial AD / \partial \psi$  by separately estimating and then adding the partial derivatives of consumption, investment, and net exports with respect to the wage share (with the wage share affecting net exports through the price level). Blecker (2016) and Stockhammer (2017) note that studies following this approach usually find evidence that  $\partial AD / \partial \psi > 0$ , that is, demand is wage-led (see, for example, Onaran et al. 2011; Stockhammer et al. 2011; Onaran/Galanis 2012; Onaran/Obst 2016; Stockhammer/Wildauer 2016).

On the other hand, those following the aggregative approach seek to estimate  $\partial Y / \partial \psi$  directly. By estimating the relationship between the wage share and a single measure of output, they arrive at a solution like the following:

$$Y = Y(\psi, Z_C, Z_I, Z_X, Z_M, Z_P). \quad (9)$$

Aggregative models typically combine this with an equation for the wage share, like equation (10), to make distribution endogenous.

$$\psi = \psi(Y, Z_\psi) \quad (10)$$

Those following the aggregative approach typically try to estimate difference equation versions of equations (11) and (12) in discrete time as a system, where output is measured by the utilization rate ( $u$ ), or the ratio of output or the output gap to potential output.

$$\dot{u} = f(u, \psi) \quad (11)$$

$$\dot{\psi} = g(\psi, u) \quad (12)$$

This specification is similar to Goodwin's (1967) theoretical model, which illustrates the relationship between the wage share and the employment rate as a system of two differential equations. While Goodwin's measure of economic activity was the rate of employment, most studies following Barbosa-Filho/Taylor (2006) have used the utilization rate (see Niki-foros/Foley 2012; Kiefer/Rada 2015; Carvalho/Rezai 2016; Barrales/von Arnim 2017).<sup>5</sup>

costs and reductions in firms' monopoly power will both increase the wage share, but the former will raise the price level and the latter will lower it. However, most studies in the literature have focused only on the unit labor cost channel.

5. Goodwin's (1967) model did not examine demand at all, as he followed a Marxian approach in which employment was determined by capital accumulation. There is also a related literature that estimates models that are closer to Goodwin's original model (see, for example, Desai 1984; Harvie 2000; Grasselli/Maheshwari 2017).

These studies mainly use lags of  $u$  and  $\psi$  as right-hand-side variables and often include few or no control variables.

Estimating discrete-time versions of equations (10) and (11) yields estimates of the slopes of the *nullclines*, alternatively called the ‘effective demand’ (for  $\dot{u} = 0$ ) and ‘distributive’ (for  $\dot{\psi} = 0$ ) schedules (see Barbosa-Filho/Taylor 2006). The slopes of the nullclines,  $-f_u/f_\psi$  for the effective demand schedule and  $-g_\psi/g_u$  for the distributive schedule, dictate the dynamics of the model. While there are numerous possible combinations, some stable and some unstable, aggregative studies typically indicate a downward-sloping effective demand schedule and an upward-sloping distributive schedule. In other words, demand is profit-led, such that demand rises as the profit share  $(1 - \psi)$  rises, but there is also a profit squeeze, wherein the profit share falls as demand ( $u$ ) rises. This case is illustrated in Figure 1, which is based on a similar illustration in Barbosa-Filho/Taylor (2006). Here, these dynamics are driven by a negative derivative of  $u$  with respect to  $\psi$  and a positive derivative of  $\psi$  with respect to  $u$ . The presence of cyclical dynamics depends on the functional form used by Barbosa-Filho/Taylor (2006).

There are a few important caveats. First, it is possible that counter-clockwise cycles like those shown in Figure 1 may exist even in the absence of profit-led demand and profit-squeeze effects. For example, Stockhammer/Michell (2017) argue that there is a possibility of a ‘pseudo-Goodwin cycle’ in which counter-clockwise cycles occur due to entirely different dynamics related to Minskyan fragility, and that these pseudo-Goodwin dynamics could be consistent with wage-led demand. Therefore, although this paper estimates the slopes of the nullclines, these slopes may not entirely dictate the direction of the dynamics in  $u, \psi$  space. Furthermore, this two-dimensional representation of the dynamics may be an oversimplification of the underlying relationships. For example, it would not be able to capture differing responses of the utilization rate to changes in the wage share depending on which component of the wage share is driving the changes.

### 2.2 Literature review

Following these theoretical models, many empirical studies have sought to characterize demand regimes as either wage-led or profit-led. However, despite much empirical work in this area, considerable debate remains because results vary drastically. Although the idiosyncrasies of individual studies contribute to the disagreement among results,

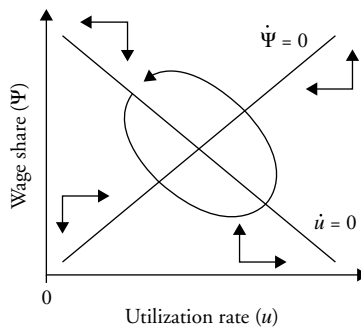


Figure 1 System with profit-led demand and profit-squeeze effects adapted from Barbosa-Filho/Taylor (2006)

Blecker (2016) notes in a survey of the wide literature that results tend to depend on whether researchers follow the aggregative or structural approach.

Aggregative studies typically find evidence of Goodwin-cycle effects. For example, Barbosa-Filho/Taylor (2006) find this pattern when estimating a difference equation version of the system in equations (11) and (12) for the US from 1948 to 2002 using a reduced form VAR with two lags.<sup>6</sup> Using data for 1967–2010 and a threshold vector autoregression model in which the sample is broken up into different regimes based on the value of the Gini coefficient, Carvalho/Rezai (2016) find that both profit-led demand and profit-squeeze effects have become stronger in the regime of higher personal inequality, beginning around 1980.<sup>7</sup> Araujo et al. (2019) find a profit-squeeze effect but no significant effect of the wage share on the utilization rate.<sup>8</sup> This difference in their findings relative to other studies could stem from the use of an alternate ordering restriction in which the wage share is assumed to have no contemporaneous effect on demand, whereas others like Carvalho/Rezai (2016) instead assume no contemporaneous effect of demand on the wage share. Basu/Gautham (2019) estimate a baseline VAR with the same ordering restriction used by Carvalho/Rezai (2016) – albeit with the real exchange rate added as an additional variable<sup>9</sup> – and similarly find profit-led demand and profit-squeeze effects. They also estimate an expanded VAR with three additional variables (the rate of capital accumulation, the unemployment rate, and the rate of productivity growth),<sup>10</sup> maintaining the same ordering restriction relating the wage share and utilization rate. Their identification strategy does not allow them to examine the effects of demand on the wage share, but they find evidence of profit-led demand in this expanded model. They use an identification strategy, developed by Christiano et al. (1999) (hereafter referred to as CEE identification) that requires that each variable only be ordered relative to a key variable of interest – the wage share in this case. However, it is only able to illustrate the effects of shocks to the key variable of interest; it does not capture how the variable of interest changes in response to shocks to the other variables.

Other aggregative studies have found evidence of Goodwin-cycle dynamics using different techniques or country samples.<sup>11</sup> Kiefer/Rada (2015) estimate a system of equations for the wage share and utilization rate for a panel of 13 OECD countries using

6. The model that they estimate is not a standard VAR, because they estimate the equations for the utilization rate and the wage share separately, using data in levels for one and data in log levels for the other. Stockhammer/Stehrer (2011) argue that these results are biased due to autocorrelation problems, and likely sensitive to lag length.

7. Silva de Jesus et al. (2018) also find profit-led demand effects in the impulse response functions from their VAR for Brazil. However, their Granger causality tests suggest that causality does not run from the profit share to utilization or economic growth.

8. They also use the VAR methodology to examine the relationship between the wage share and the employment rate, and estimate an autoregressive distributive lag model with equations for these two variables and the utilization rate.

9. They find no significant relationship between the real exchange rate and either of the other two variables.

10. Although labor productivity growth is included in the model, the authors do not address the inherent link between productivity and the wage share. Although they assume that labor productivity growth has only a lagged effect on the wage share, shocks to labor productivity growth are likely to lead to simultaneous changes in the wage share unless they are fully offset by changes in the real wage rate within the same period.

11. An early study by Stockhammer/Onaran (2004) is an outlier. Estimating a larger model in which the profit share and the utilization rate are only two of several variables included, they find wage-squeeze effects and no significant effect of distribution on demand. It is possible that these findings are the result of accounting for cyclical productivity effects, as they include productivity in the model and find a positive effect of demand on productivity. While controlling for

generalized least squares. Their results indicate Goodwin-cycle effects in the short run, although they also find evidence that the equilibrium is shifting in the direction of a lower wage share and lower utilization in the long run. Diallo et al. (2011) estimate a system of equations using an instrumental variable approach with the generalized method of moments and US data from 1973 to 2008, and find evidence of both profit-led demand and a profit squeeze. Barrales/von Arnim (2017) use a wavelet decomposition to estimate cyclical dynamics of the US economy at different periodicities. They find evidence of Goodwin-cycle dynamics for all periodicities, although they do not find a clear cyclical pattern in the medium run after 1980. Using longer data series and similar wavelet analysis, along with regression analysis including control variables from the endogenous growth literature, Charpe et al. (2019) examine the relationship between the wage share and growth for the US, UK, and France. They find evidence of profit-led growth in the short run and wage-led growth in the longer run, with stronger correlations in the long run. Further complicating matters, Nikiforos/Foley (2012) find evidence that the distributive schedule is non-linear, suggesting the existence of multiple equilibria. Their model is estimated for different sub-samples using two-stage least squares applied to US data. However, their full sample estimates are indicative of Goodwin-cycle effects.

The US case provides a striking illustration of the differing conclusions of aggregative and structural studies. Although most aggregative studies find evidence of profit-led demand, recent structural estimates of this relationship for the US are usually indicative of wage-led demand (see, for example, Onaran et al. 2011; Stockhammer et al. 2011; Onaran/Galanis 2012; Onaran/Obst 2016; Stockhammer/Wildauer 2016). These differences suggest that the disagreement between the results of these two approaches cannot be explained by differing objects of analysis, and must be the results of methodological differences. Proponents of the aggregative approach argue that methodological issues with the structural approach likely explain the generally differing results of the two types of studies (see, for example, Kiefer/Rada 2015; Barrales/von Arnim 2017).

Critics have pointed out several methodological flaws with the structural approach. For example, this methodology has been strongly criticized for not considering the effects of demand on distribution. This methodological decision could lead to simultaneity bias, as Stockhammer/Stehrer (2011) and Barrales/von Arnim (2017) find evidence suggesting that various measures of aggregate demand or its components Granger-cause the wage share. Others argue that simply adding up the coefficients from independently estimated equations will not fully capture the systemic dimensions of the relationships (see, for example, Blecker 2016), and that these estimates should not be interpreted as an aggregate demand equation (Kiefer/Rada 2015).

Although the aggregative approach does not suffer from the same shortcomings as the structural approach, previous aggregative studies have been criticized for other reasons. In particular, Lavoie (2017) argues that models that do not properly account for potential pro-cyclical variation in productivity may bias estimates towards findings of greater profit-led demand.<sup>12</sup> Lavoie (2014: 323–325) shows that the presence of overhead or managerial labor can theoretically cause labor productivity to vary pro-cyclically with

productivity will eliminate any bias caused by the cyclical effects of demand on productivity, this approach will lead to productivity shocks being counted twice, as they will affect both productivity itself and the profit share.

12. It is possible that these issues also affect structural studies, which typically do not consider them either.



the utilization rate.<sup>13</sup> Because the wage share is equal to the hourly wage divided by labor productivity,<sup>14</sup> as shown above in equation (1), pro-cyclical labor productivity effects would make the wage share counter-cyclical (all else being equal), as an increase in the utilization rate would lead to a decrease in the wage share, via an increase in labor productivity. Therefore, empirical estimates may incorrectly capture the increase in utilization as the effect of the decrease in the wage share, when in reality the wage share is decreasing as a result of increased utilization, through these pro-cyclical effects on productivity. As Lavoie (2017: 212) explains:

[I]n an economy with overhead labour, all else being equal, that is, with no change whatsoever in the mark-up over unit direct labour costs, an increase in the rate of utilization leads to an increase in the share of profits. Thus, unless the measures of the profit share are corrected for this effect, statistical enquiries will be biased towards finding that aggregate demand is profit-led.

Although Lavoie's model suggests that the presence of managerial labor makes productivity pro-cyclical, this is not the only theory suggesting that productivity will vary cyclically. These explanations, which are not mutually exclusive, include variable effort and capital utilization over the course of the business cycle, labor hoarding, cyclical changes in technology, and cyclical resource reallocations (Basu/Fernald 2001; Gordon/Solow 2003; Lewis/Van Dijke 2019). However, not all theory suggests that productivity will be pro-cyclical. For example, pro-cyclical effort consistent with labor hoarding would make productivity pro-cyclical, but productivity may be counter-cyclical if effort increases when unemployment is high (Lewis/Van Dijke 2019). This labor discipline channel suggests that worker effort is likely to fall when demand is high and rise during recessions, when workers face both higher costs associated with unemployment and a greater probability of being fired or laid off (see, for example, Pacitti 2011).

Empirically, the pro-cyclical of productivity was long considered to be a 'stylized fact' and 'an essential feature of business cycles' (Basu/Fernald 2001: 225), with data supporting this conclusion (for example, Stock/Watson 1999). However, more recent evidence seems to suggest that this relationship has changed in the US, with productivity becoming a counter-cyclical variable (see, for example, Burda 2018; Brault/Khan 2019). Burda (2018) suggests that this may be the result of increased exit of inefficient firms during downturns (as the result of globalization) and the erosion of labor market protections, which may have reduced labor hoarding and incentivized greater effort from workers during downturns. Similarly, Fernald/Wang (2016) argue that effort has

13. In his model, the quantity of production workers employed is variable and depends on the level of output, while the quantity of overhead managerial labor employed depends on the full capacity level of output, and therefore does not vary cyclically. As capacity utilization increases, the ratio of production workers to total workers increases, causing total labor productivity to increase. Lavoie (2017) notes that the argument that overhead labor will cause productivity and therefore the profit share to vary pro-cyclically had previously been made by others, such as Hahnel/Sherman (1982) and Sherman/Evans (1984) in their critiques of Weisskopf (1979). Giovannoni (2010) makes a similar point, arguing that counter-cyclical variation in the labor share can be explained by a combination of pro-cyclical productivity and sticky wages. Although they focus on the long run rather than the business cycle, Böckerman/Maliranta (2012) similarly argue that the behavior of the labor share can be explained by greater responsiveness of productivity than wages (in this case in response to globalization).

14. If the wage rate and labor productivity are deflated using the same price index, these two variables are the two components of the wage share. However, if the wage rate and labor productivity are deflated using different price indexes, then the wage share has three components: the real wage rate, real labor productivity, and the ratio of the price indexes used to deflate the two other components.

become less pro-cyclical and suggest changes in labor markets as one contributing factor, along with changes in the composition of shocks affecting the economy.

Although this literature can offer important insights about the overall relationship between productivity and the business cycle, the salient question for the purposes of this study is a slightly narrower one: how to interpret the contemporaneous correlation between productivity and demand. This question matters a great deal in this context because researchers using a VAR methodology with short-run restrictions must make assumptions about contemporaneous effects in order to identify models, as discussed in more detail below. Following Lavoie's (2017) argument, results would be biased towards more profit-led findings if there are contemporaneous pro-cyclical productivity effects and empirical models interpret them as an effect of the labor share on demand. On the other hand, it is also possible that estimates could be biased in the other direction – underestimating profit-led demand effects – if there are contemporaneous counter-cyclical productivity effects that models interpret as a positive effect of a higher wage share on demand.

Most previous studies following the aggregative approach have not controlled for potential cyclical variation in labor productivity when estimating the relationship between the utilization rate and the wage share. One notable exception is the concurrent work of Mendieta-Muñoz et al. (2020). They estimate a structural VAR including the two components of the wage share, real GDP, and the unemployment rate. They find significant Goodwin-cycle effects even though they allow for a bi-directional contemporaneous relationship between demand and productivity (by including additional restrictions relating the unemployment rate to other variables). Whereas they explore the relationships between demand, distribution, and unemployment, the model in this paper is designed to maximize comparability with the bulk of the aggregative literature that focuses exclusively on the demand–distribution relationship in order to test the importance of accounting for contemporaneous effects of productivity on demand. Nevertheless, their estimates represent an interesting point of comparison with those presented below. Although a full exploration of the sources of similarities and differences between these two sets of estimates is beyond the scope of this paper, Section 4.2 briefly discusses the results in relation to those in Mendieta-Muñoz et al. (2020).

### 3 EMPIRICAL STRATEGY

#### 3.1 Methodology

To examine how productivity effects impact the relationship between demand and distribution, a baseline set of estimates, found using a model including only the wage share and utilization rate, is compared to estimates that replace the wage share with its two components to allow for more precise ordering restrictions. The VAR methodology is used for comparability with many previous aggregative studies that have used this estimation method. The baseline model is a VAR that combines elements of the models used by Barbosa-Filho/Taylor (2006) and Carvalho/Rezai (2016). Barbosa-Filho/Taylor (2006) estimated a VAR of the following form:

$$\mathbf{y}_t = \boldsymbol{\mu} + \sum_{j=1}^L \mathbf{F}_j \mathbf{y}_{t-j} + \mathbf{e}_t, \quad (13)$$

where  $t$  is the time period,  $\mathbf{y}_t$  is a vector of dependent variables, and  $\mathbf{F}_j$  represents the coefficient matrices to be estimated,  $\boldsymbol{\mu}$  is the constant,  $\mathbf{e}_t$  is the error term,  $j = 1, \dots, L$  indexes time period, and  $L$  is the number of lags.

This model is very similar to the one used by Carvalho/Rezai (2016). However, whereas their model computes separate estimates for different regimes, depending on

the value of the Gini coefficient, this model does not feature any regime-switching elements. Furthermore, whereas they measure both the wage share and utilization in natural logarithm transformed levels, the baseline model includes the log level of the utilization rate and the log difference of the wage share. The logged wage share is differenced in this case because unit-root tests, which will be discussed in more detail below, suggest that it is non-stationary. In this way, the baseline model also diverges from the methodology of Barbosa-Filho/Taylor (2006), who estimate one model with the dependent variables in levels and another with the variables in natural logarithms to facilitate the decomposition of each variable into its component parts. As this paper will not conduct such a variable decomposition, it will simply use the log transformation.<sup>15</sup> Another difference from the Barbosa-Filho/Taylor (2006) model is that they include an exogenous trend. No trend is included in the baseline model here because neither the log utilization rate nor the first difference of the log wage share exhibits a trend.

Following this estimation, modified versions of the model are estimated and compared to the results of the baseline model. These additional specifications are used to examine how ordering restrictions impact the results. In all specifications, the lag length is determined by using the Hannan–Quinn information criterion (HQIC) – the recommended information criterion when using quarterly data and a sample size above 120 (see Ivanov/Kilian 2005) – as a starting point. Models are then tested for serial correlation using the Breusch–Godfrey test. Additional lags are added one at a time if any of the following null hypotheses are rejected at the 10 percent level: no serial correlation at lag 1, lag 2, lag 3, or lag 4. The White test (with no cross terms included) is used to test each model for heteroskedasticity.<sup>16</sup> In some cases where evidence of heteroskedasticity is found, an additional lag is added to the model if doing so leads to a failure to reject the null hypothesis of homoskedastic errors at the 10 percent level.<sup>17</sup>

As in Carvalho/Rezai (2016), Cholesky decomposition is used to obtain error terms that are not correlated across equations, as reduced form errors will be correlated with one another if the variables in the VAR are correlated. This is a necessary step if impulse response functions (IRFs) are to be used for causal interpretation, because IRFs require keeping all errors but one constant, and this is not possible if the errors are correlated (Stock/Watson 2001). This technique also allows for some contemporaneous effects between variables. Following this method, the order of the VAR imposes the restriction that variables have no contemporaneous effect on those that come before them in the ordering. However, variables do have contemporaneous effects on those that come after them in the order. As Barbosa-Filho/Taylor (2006) do not use Cholesky decomposition, the ordering used in Carvalho/Rezai (2016) and Basu/Gautham (2019) is used for the baseline model.<sup>18</sup>

15. The components of the wage share, which are used in other specifications, are logged as well.

16. Unless otherwise noted, there is no evidence of serial correlation in any of the models discussed in this paper. Serial correlation test results are available from the author upon request. Heteroskedasticity test results are presented along with the results of each model. Heteroskedasticity does appear to be an issue for some models. Hypothesis tests are unreliable in the presence of heteroskedasticity, although it does not impact the estimation of the impulse response functions themselves. The significance tests of the results of these models should therefore be viewed with caution.

17. The inverse roots of the characteristic autoregressive polynomial are also examined for each model. For every model discussed in this paper, the modulus for each root falls within the unit circle, suggesting that each model is dynamically stable.

18. In a study of the Brazilian economy Silva de Jesus et al. (2018) use a VAR model with generalized impulse response functions (GIRFs). GIRFs are insensitive to variable ordering, but only because they impose assumptions of their own, rather than leaving this task to researchers. GIRFs essentially

$$\mathbf{y}_t = [\Delta \ln wage\ share_t, \ln utilization_t]. \quad (14)$$

This ordering imposes the restriction that the log utilization rate does not affect the first difference of the log wage share contemporaneously. Models with this ordering use a less restrictive version of the assumption in structural studies that demand has no effect on the wage share at all. Although this assumption is commonly used in the literature, it is not necessarily accurate. If productivity varies contemporaneously with demand, this assumption will bias estimates of the effect of the wage share on demand. Following Lavoie's (2017) argument, positive contemporaneous effects of demand on productivity would improperly be interpreted as profit-led demand effects. Therefore, although this restriction is used in the baseline model, other specifications are also used to test the sensitivity of the results to this assumption. In order to differentiate between changes in the real wage rate and labor productivity, and to allow for more precise ordering assumptions, another version of the model includes these two components of the wage share in a VAR with the utilization rate.<sup>19</sup> Different variable orderings are used to test the sensitivity of the results to the assumptions regarding productivity and demand.<sup>20</sup>

combine IRFs from various orderings – taking responses for each type of shock from a specification where the variable being shocked comes first in the ordering. As such, the ordering restrictions used for GIRFs are neither theoretically motivated, nor internally consistent. As Kim (2013) notes, GIRFs can be misleading because they impose assumptions that are more extreme than those used in Cholesky decomposition, and these assumptions can be contradictory. Although this paper presents results found using Cholesky decomposition with various orderings in order to emphasize the assumptions influencing the results, a complete set of GIRFs can be constructed from various results that are presented in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>). Those for the model including the wage share and the utilization rate would combine the first column of IRFs from Figure A1 (the responses to a wage share shock in the specification where the wage share comes first in the ordering) and the second column of Figure A9 (the responses to a utilization shock in the specification where the utilization rate comes first). Similarly, those for the three-variable model would combine the first column from either Figure A14 or A15, the second column from either Figure A12 or A13, and the third column from either A10 or A11.

19. The CEE identification strategy used by Basu/Gautham (2019) does not offer a way to sidestep the issue of variable ordering, as it would still require the wage share and demand to be ordered in relation to one another, as is the case using Cholesky decomposition. In the model with the real wage rate and labor productivity, CEE identification could eliminate the need for one ordering restriction (for example, between productivity and demand, if the wage rate were treated as the key variable of interest). However, this would only show the effects of wage-rate shocks on the other two variables. Because it would not allow for a full examination of all the relationships of interest, this method is not used.

20. While Mendieta-Muñoz et al. (2020) simultaneously allow for contemporaneous effects of productivity and demand on one another by including additional restrictions on the relationship between unemployment and the other variables, that approach is not possible in this case because no other variables are included. Including other variables is not desirable in this case because doing so would reduce comparability with most previous aggregative models, which include only the wage share and demand. Moreover, this methodology requires additional ordering assumptions that would increase the complexity of the model, making it more difficult to isolate the effect of changing the restrictions relating productivity and demand. Furthermore, it could potentially introduce other avenues for bias if these additional assumptions are not accurate. In other words, this method does not eliminate the need to examine the sensitivity of results to ordering restrictions; it only adds more assumptions to which the results could be sensitive.

### 3.2 Data

All models are estimated using quarterly US data from 1947 to 2016.<sup>21</sup> For comparison to the previous literature, the baseline measure of demand that is used is constructed using the same techniques as Barbosa-Filho/Taylor (2006) and Carvalho/Rezai (2016). Following their methodology, the utilization rate is measured as the ratio of output to potential output, where the potential output series is constructed by taking the trend component of output obtained by applying a Hodrick–Prescott (1997) (HP) filter to the output series.<sup>22</sup> The output series is the Bureau of Labor Statistics (BLS) index of real business-sector output. The resulting series is multiplied by 100.

There are reasons to question whether this is an accurate measure of capacity utilization, due to several well-documented issues with the HP filter. Cogley/Nason (1995) show that the application of an HP filter to persistent time series can generate cyclical variation that is not present in the original data. Gordon/Krenn (2010) argue that filtering techniques lead to implausible estimates of trend capacity. Barrales/von Arnim (2017) note two additional problems: the filter generally puts too much of a bend in the trend near the end of the sample, and filtering removes any medium-term trends, allowing only examinations of short-run effects. Blecker (2016) argues that measuring demand in this way may make studies more likely to find profit-led demand, as demand is more likely to be profit-led in the short run. Expanding on previous criticisms of the HP filter, Hamilton (2018: 831) argues that the HP filter should not be used:

... (a) HP introduces spurious dynamic relations that have no basis in the underlying data-generating process. (b) Filtered values at the end of the sample are very different from those in the middle, and are also characterized by spurious dynamics. (c) A statistical formalization of the problem typically produces values for the smoothing parameter vastly at odds with common practice.<sup>23</sup>

This may not be a sensible way to measure demand, even if potential output were not calculated using an HP filter. Cerra/Saxena (2017) argue that measures of the deviation between output and potential output, such as the output gap and the utilization rate, will be difficult to accurately measure and to interpret. These variables are difficult to accurately measure because estimates of potential output, either obtained using a filter or estimated with a production function, will change when new data is included in the sample (Borio et al. 2013; Cerra/Saxena 2017). Moreover, it is not clear how these measures should be interpreted. As Cerra/Saxena (2017) argue, the view of the output gap (and by implication the utilization rate) as the temporary deviations of output from an exogenously given trend is flawed, because changes in output can lead to permanent changes in potential output. For this reason, the utilization rate may not be an appropriate measure of demand, even if the methods used to construct it do not introduce any bias.

Therefore, this measure of the utilization rate could generate bias. For this reason, other measures of demand are used as sensitivity tests. One of these measures is a utilization rate constructed by applying Hamilton's filtering technique to the BLS output index. Hamilton (2018) argues that this technique accomplishes the same goal as an HP filter – that is, separating a stationary cyclical component from a non-stationary series – without many of the drawbacks. Following his methodology, the cyclical component of the output series is found by simply

21. However, data transformations and lags lead to shorter sample periods.

22. The standard value of the smoothing parameter for quarterly data, 1600, is used for filtering.

23. Franke/Kukacka (2020) argue that the criticism regarding spurious dynamics is overstated and note that it relies on the assumption that trends follow a random walk.

taking the residuals of an ordinary least squares regression of equation (15), while the predicted values from this regression represent the trend component.

$$\ln output_t = \alpha + \sum_{i=8}^{11} \beta_i \ln output_{t-i} + \epsilon_t \tag{15}$$

The Hamilton utilization rate is therefore measured as the cyclical component of the output series, that is, the estimated residuals from this regression:  $\hat{o}_t$ . In other words, it is calculated as the deviation of output from the trend of output, where this trend is found by taking the two-years-ahead forecast based on observations for the preceding year, as Hamilton (2018) recommends for analysis of business-cycle effects. Because the cycle and trend components are calculated using only past data, this technique is not subject to Cerra/Saxena’s (2017) criticism for measures calculated using an HP filter or a production function approach that estimates of potential output based on future information not available at time  $t$ . Araujo et al. (2019) previously examined differences between the Hamilton and HP techniques in the context of an aggregative model. However, they only used these filters to detrend the wage share, the Federal Reserve utilization rate, and the employment share; they did not use the Hamilton technique to construct a separate measure of the utilization rate.

Figure 2 compares utilization-rate measures constructed using the HP and Hamilton techniques. The two series described above are not directly comparable because the Hamilton utilization rate captures the cyclical component of the  $\ln output$  series, whereas the log-transformed HP utilization rate consistent with the methodology of Barbosa-Filho/Taylor (2006) and Carvalho/Rezai (2016) measures the natural log of the cyclical component of the output series. In other words, they differ in whether the series is log-transformed before or after the filter is applied. Therefore, a third series – the HP cyclical component of  $\ln output$  – is included in Figure 2 to illustrate the degree to which the differences between the other two series can be explained by the differences in the filtering

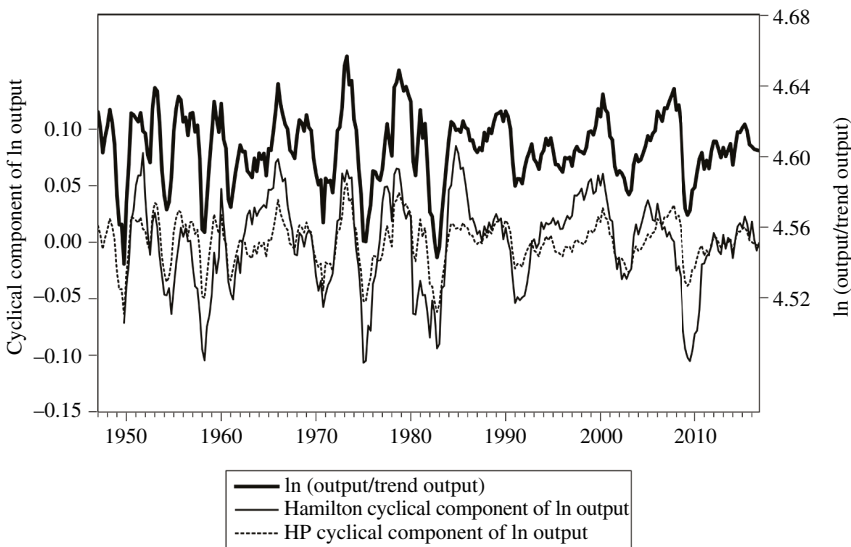


Figure 2 Comparison of HP and Hamilton utilization rates, 1947–2016

technique alone.<sup>24</sup> As Figure 2 shows, the resulting series can differ substantially when a different filtering technique is used.

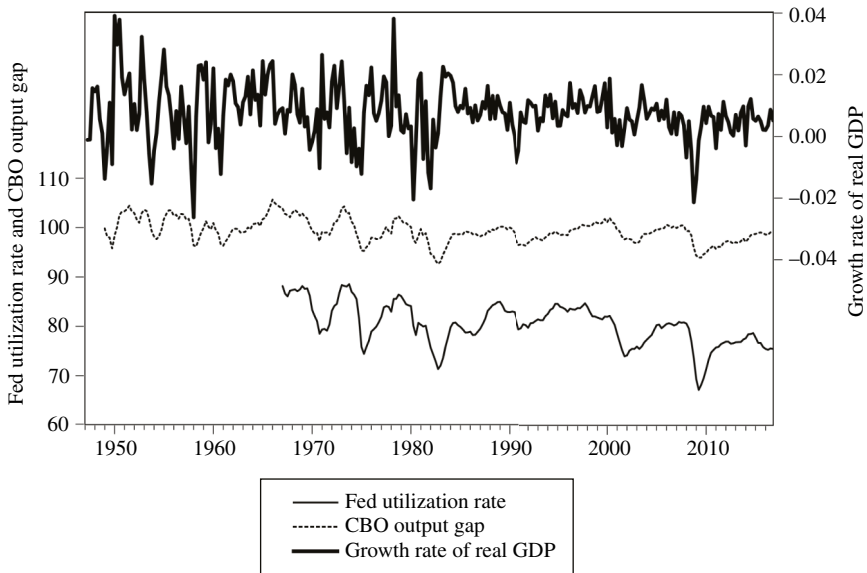
When using the Hamilton technique, the estimated potential output series tends to vary cyclically, lagging behind the cyclical changes in output. This is a desirable feature of a potential output series, based on Cerra/Saxena's (2017) argument that persistent changes in actual output lead to permanent changes in its trend. However, the timing of the changes in potential output may not be plausible. By construction, changes in output generate changes in potential output beginning two years later. As a result, potential output often continues rising during contractions, and drops two years later, often when the economy has begun expanding. Because of this, the resulting utilization-rate series would indicate recoveries beginning (or contractions occurring) two years after a recession (expansion) begins, even if output did not change. Consequently, the initial size and speed of recoveries and contractions may be overestimated. Moreover, Franke/Kukacka (2020) argue that the Hamilton filter is actually not appropriate if trends are deterministic and highlight other flaws with this procedure as well. Therefore, the Hamilton utilization rate is not an ideal measure, although results found using this measure can still represent an interesting sensitivity test.

Given these potential shortcomings of the HP and Hamilton utilization rates, other measures of output are used as sensitivity tests as well. These include the growth rate of the Bureau of Economic Analysis's (BEA) real GDP series, and two alternative measures of utilization that are not constructed with filters. Both of these measures – the Federal Reserve's (Fed) capacity utilization index and a measure of the output gap – were previously used by Barrales/von Arnim (2017). The output gap measure is the ratio of the real GDP series to the US Congressional Budget Office's (CBO) estimate of potential output, which is estimated within a growth accounting framework. Although this measure does not rely on filtering techniques, it is still subject to the critique of Cerra/Saxena (2017) that the utilization rate (or output gap) is not well conceived, because the business cycle is not simply a temporary deviation of output from a steady trend. The Fed index estimates capacity based upon plant-level survey data. However, it covers only industrial production, and not the entire economy. The growth rate of real GDP covers the entire economy and does not depend on the same conception of the business cycle as the HP utilization rate and the CBO output gap. The downside of using this series is that it is less comparable to the previous aggregative literature, although it is used by Charpe et al. (2019). Figure 3 provides a graph of the three alternative measures of demand used as sensitivity tests.

The wage share is measured using the BLS business-sector labor share index. This is an index of the ratio of total labor compensation paid to total output with 2012 as the base year (Bureau of Labor Statistics 2008). Total labor compensation includes all forms of pay and benefits, as explained in Bureau of Labor Statistics (2017). For consistency with the output and utilization measures, the business-sector series is also used for the wage share.<sup>25</sup> Other specifications replace the wage share with its two components: labor productivity and the real

24. Although the HP cyclical component of *ln output* is more comparable with the Hamilton utilization rate, the natural log of the HP cyclical component of the output series is more consistent with the methodology used by Barbosa-Filho/Taylor (2006) and Carvalho/Rezai (2016). Because the HP utilization rate is primarily used for the purpose of comparison to the previous literature, the latter measure is preferred. Differences stemming from the decision to log-transform the series *before* the filter is applied, rather than *after*, are negligible, as these two series have a correlation coefficient of 0.998.

25. It should be noted that this wage-share measure is slightly different from the one used by Barbosa-Filho/Taylor (2006), who construct their wage-share series by dividing the BEA measure of labor compensation by the BEA measure of national income. However, the BLS measure has been used in more recent work that has built on Barbosa-Filho/Taylor (see Carvalho/Rezai 2016).



Source: Refer to Table A1 in Appendix 1.

Figure 3 *Alternative measures of demand, 1947–2016*

wage rate. Productivity is measured as the BLS index of business-sector labor productivity, calculated as output divided by hours. The real wage rate is measured as the BLS index of nominal hourly compensation for the business sector deflated by the BLS implicit price deflator for business-sector output. Because the real wage rate is measured in this way, labor productivity and the real wage rate contain all of the information in the wage-share series.<sup>26</sup> Variable measurement and data sources are summarized in Table A1 in Appendix 1.

In order for the empirical models to have valid results, the data series used to estimate them must be stationary. Three unit-root tests are used to test for stationarity: the augmented Dickey–Fuller (ADF) test with lag length selected using the modified Akaike information criterion (see Ng/Perron 2001), the Phillips–Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Unit-root tests are conducted over the largest sample possible for each variable given the available data. The first difference of each variable is taken unless two of the following three criteria are met for the given sample period: the ADF test rejects the null hypothesis of a unit root at the 5 percent level, the PP test rejects the null hypothesis of a unit root at the 5 percent level, and the KPSS test fails to reject the null hypothesis of stationarity at the 5 percent level. Using this decision rule, only the utilization-rate measures were found to be stationary, while the first difference of all other variables – with the exception of the CPI-deflated real wage series used as a sensitivity test – were found to be

26. The real wage-rate index for the business sector constructed by the BLS, which is deflated using the consumer price index (CPI) and the BLS Consumer Price Index research series, is used as a sensitivity test. However, when using this measure the real wage and productivity series do not contain all of the information in the wage share, because a relative price ratio (of the price index used to deflate the real wage series to the output price deflator used in deflating real output in the productivity calculations) is not included.



stationary.<sup>27</sup> Selected unit-root test results are shown in Table A2 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>). Models were estimated using the log levels of stationary variables and the log difference of variables with unit roots.<sup>28</sup>

## 4 ECONOMETRIC RESULTS

### 4.1 Baseline estimates

The baseline model maintains the assumptions traditionally used in the previous aggregative literature, and therefore uses the variable ordering shown in equation (14), in which the log-differenced wage share is placed before the log of the HP utilization rate. This model is estimated for the sample period of 1948Q1–2016Q4 and includes a constant term and 3 lags.<sup>29</sup> Selected IRFs for this specification are shown in Figure 4.<sup>30</sup> These represent accumulated responses to a one standard deviation positive shock, along with confidence bands of  $\pm$  two standard errors that correspond roughly to a 5 percent significance level.

The accumulated response of utilization to a positive wage-share shock, shown in panel (a) of Figure 4, is significantly negative in the first seven quarters and insignificantly negative afterwards. The negative sign here is indicative of profit-led demand. The accumulated response of the wage share to a utilization shock, shown in panel (b), is positive and statistically significant, suggesting a profit-squeeze effect. These results match the Goodwin-cycle dynamics that have been found in many aggregative studies.

These effects are found to be economically meaningful. A one standard deviation shock to  $\Delta \ln$  wage share (an increase of 0.94 percentage points in the growth rate of the wage share) leads to a decrease of 0.0395 in the HP utilization rate (roughly 1.96 standard deviations). Similarly, a one standard deviation shock to the HP utilization rate (an increase of 0.0202) leads to an increase of 0.0063 in  $\Delta \ln$  wage share (approximately 67 percent of a standard deviation).<sup>31</sup> Unreported results show that the qualitative findings of the baseline model are not driven by the decision to difference the wage share and leave the utilization rate in levels.<sup>32</sup>

27. The choice of whether to take the second difference of the CPI-deflated real wage series depends on the significance threshold that is used, as the ADF test rejects the null hypothesis of a unit root at the 10 percent significance level. Although the decision rule used here suggests that the second difference should be taken, preliminary estimates of models using a twice-differenced series are found to have persistent issues with serial correlation. Therefore, the first-differenced series is used.

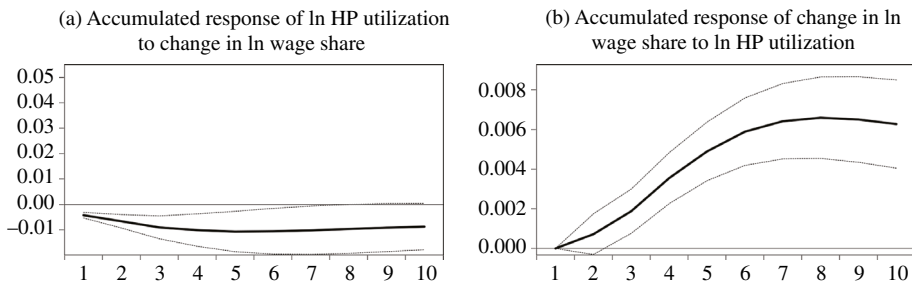
28. Note that no models were estimated as vector error correction models because there was no evidence of cointegration between the wage share and real GDP – the only non-stationary measure of demand used in this analysis.

29. Although the HQIC suggests a lag length of 2, some evidence of serial correlation is found using only 2 lags. There is no evidence of serial correlation when the lag length is 3. Unreported results show that the results do not qualitatively differ when using 2 lags instead of 3.

30. The heteroskedasticity test results reported in the caption of this figure and the others below and in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>) represent the chi-squared statistic for a White heteroskedasticity test with no cross terms included. The null hypothesis is that errors are homoskedastic.

31. These descriptions are based on the cumulative effects over ten periods.

32. Results for specifications with both variables in either differences or levels are available from the author upon request. Although the IRFs differ somewhat in these specifications, both generally show significant profit-led demand and profit-squeeze effects. However, because the White tests



*Notes:* Sample period: 1948Q1–2016Q4.

Model specification: 3 lags and constant term.

Variable ordering:  $\Delta$  ln wage share, ln HP utilization.

White heteroskedasticity test statistic ( $p$ -value): 41.38 (0.247).

Complete results shown in Figure A1 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>).

*Figure 4 Selected IRFs for the baseline model with HP utilization rate*

Although there was concern that the use of the HP filter could bias the estimates, sensitivity tests show that the results are qualitatively robust to using several other measures of demand. The same general Goodwin-cycle pattern is found using the Hamilton utilization rate,<sup>33</sup> the Federal Reserve utilization rate, the CBO output gap, or the growth rate of real GDP in place of the HP utilization rate. While some caution should be applied in interpreting the significance of the effects in the case of the CBO output gap and GDP growth rate models, given that there is evidence of heteroskedasticity for those specifications, both the profit-led demand and profit-squeeze effects appear to be significant in all four of these specifications. IRFs for these specifications can be found in Figures A2–A5 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>).

Unreported results also show that the results found using the HP utilization rate are qualitatively robust to changes in the sample period. Although a full exploration of how and why the relationship between the wage share and demand may have changed over time is beyond the scope of this paper, the model is estimated for different sub-samples in order to check whether the relationship is stable over time. For these estimates, the sample period is divided into three roughly equal sub-periods: 1947Q1–1970Q4,

suggest that there is heteroskedasticity in both of these models, the significance levels should be viewed with a grain of salt. Other unreported results show that the findings are similarly robust to using data series without log transformation, and to including an exogenous trend. Heteroskedasticity also appears to be an issue in the latter specification.

33. The number of lags used for the Hamilton utilization rate model – 13 – is high in comparison to specifications using other measures of demand and relative to many previous aggregative studies. The HQIC suggested a lag length of 9, but evidence of serial correlation was found when using 9, 10, 11, or 12 lags. It is possible that the large number of lags suggested by the HQIC and required to eliminate serial correlation stems from the construction of the Hamilton utilization rate, wherein observations will be correlated with those 8 to 11 quarters in the past. Another possibility, given the large estimation period, is that there is some underlying parameter instability. However, the results do not appear to be very sensitive to lag selection, as qualitatively similar results are found using either 2 lags or 9 lags.

1971Q1–1993Q4, and 1994Q1–2016Q4. Although the IRFs differ slightly from period to period, the results for each sub-period are qualitatively similar to those for the whole sample period. Significant profit-led demand and profit-squeeze effects are found in all periods. These results are presented in Figures A6–A8 in Appendix 2 (available online at <https://doi.org/10.4337/ejep.2022.0085>).

## 4.2 Alternative ordering restrictions

The specifications discussed above have maintained the restriction that the utilization rate does not have a contemporaneous effect on the wage share. Although the ordering assumptions used in the baseline model, and shown in equation (14), are consistent with the existing empirical literature, they may not be accurate. Evidence from Granger causality tests, presented by Barrales/von Arnim (2017), suggest that both the utilization rate and the wage share affect one another – at least in the case of the US. However, the timing of these effects is not fully clear. If output has a contemporaneous effect (that is, within a quarter) on productivity, it would not be appropriate to assume that the wage share is only affected by changes in the utilization rate after a lag of at least one quarter. In cases where productivity changes cyclically and reacts quickly to changes in demand, imposing the restriction that the utilization rate has no contemporaneous effect on the wage share will bias estimates. In these cases, changes in the utilization rate will appear to be the result of cyclical changes in the wage share that are driven by those very changes in the utilization rate (through its effects on labor productivity).

The results of the model are highly sensitive to the ordering that is used. Figure A9 in Appendix 2 (available online at <https://doi.org/10.4337/ejep.2022.0085>) shows the results of specifications that reverse the ordering assumption in the model using the HP utilization rate. This model imposes the restriction that the wage share does not have a contemporaneous effect on the utilization rate, but allows the wage share to vary contemporaneously with demand. This ordering was previously used by Araujo et al. (2019). The results still ultimately show a profit-squeeze effect, but only with a lag following an initial negative effect of distribution on demand. There is no longer evidence of profit-led demand effects, and in fact there is a positive and significant effect of the wage share on demand.

Although these specifications illustrate the importance of the variable ordering, the assumptions that they impose are too restrictive. Although it would be appropriate to allow demand to impact productivity contemporaneously if there are contemporaneous effects of demand on productivity, there is not a strong theoretical reason for imposing the restriction that the real wage rate responds quickly to demand but has only a lagged effect on the utilization rate. On the contrary, the theory of sticky wages suggests that wages are likely to adjust slowly in response to changes in demand.<sup>34</sup> On the other hand, demand should adjust quickly to changes in wages because wage increases

34. This theory is supported by some empirical evidence. For example, Barattieri et al. (2014) find, using US microdata, that the probability of a nominal wage change within a quarter for a given worker is 21.1–26.6 percent, with higher probabilities for those who change jobs and lower probabilities for those who do not. Moreover, their estimates suggest that nominal wages are typically unchanged for a period of 3.8–4.7 quarters, on average. To the extent that nominal wage changes do occur in a given quarter, it is unlikely that they reflect contemporaneous changes in aggregate demand given lags in measurement and recognition. Even if nominal wages change infrequently, changes in demand could still impact real wages if they lead to changes in the price level. However, there are likely to be some lags in the adjustment of the price level as well.

immediately give workers more income, which they can spend. Therefore, theory suggests that the real wage rate should come before demand in the variable ordering.

This illustrates a shortcoming of a two-dimensional model including the wage share and a measure of demand: it requires that the same restrictions regarding the timing of effects with demand be imposed on both the wage rate and productivity. Models that replace the wage share with its two components – the real wage rate and labor productivity – can be used to impose more precise ordering restrictions and further test Lavoie's (2017) hypothesis.

The six possible orderings of this three-variable VAR are shown in Table 1. Four of these orderings align with different orderings of the two variable models, because the restrictions related to the utilization rate are the same for both of the main components of the wage share. However, the other two orderings present new cases, in which the two components of the wage share have different orderings relative to the utilization rate.

Orders 3, 5, and 6 are theoretically implausible, as they assume that the wages respond contemporaneously to demand, while demand is only affected by wages with a lag. Similarly, Order 4 does not present a theoretically appealing set of assumptions, because the same factors that make wages slow to adjust to changes in demand are also likely to make them slow to adjust to changes in productivity. Conversely, efficiency wage effects provide a channel through which the wage rate may have an immediate effect on productivity.<sup>35</sup> That leaves two variable orderings that are of particular interest: Orders 1 and 2. Order 1 reflects the same assumptions used in the baseline model – as both components of the wage share are affected by demand only with a lag – without maintaining the implausible assumptions relating productivity and the wage rate found in Order 4. Order 2 similarly assumes that wages will react the least quickly to changes in the other two variables, but allows labor productivity to vary contemporaneously with the business cycle.

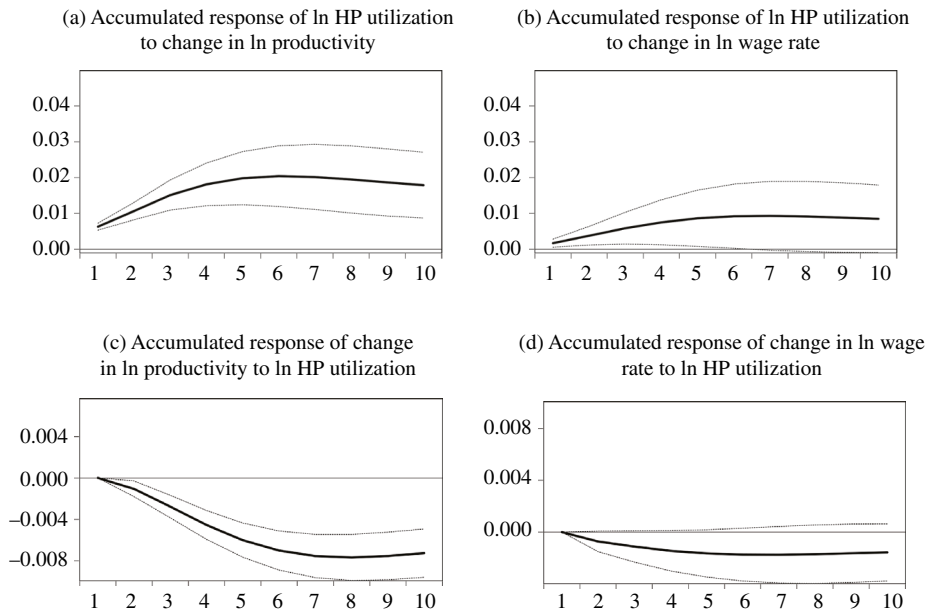
Figures 5 and 6 show selected IRFs – which capture both direct and indirect effects of the shock on the response variable – for Orders 1 and 2 using the HP utilization rate. The

*Table 1 Possible orderings in wage-share decomposition model*

Order number	Variable order	Corresponding order in two variable model
Order 1	Wage rate, productivity, utilization	Wage share, utilization
Order 2	Wage rate, utilization, productivity	n.a.
Order 3	Productivity, utilization, wage rate	n.a.
Order 4	Productivity, wage rate, utilization	Wage share, utilization
Order 5	Utilization, productivity, wage rate	Utilization, wage share
Order 6	Utilization, wage rate, productivity	Utilization, wage share

*Note:* n.a. = not applicable.

35. This theory suggests that higher wages will improve productivity, as workers will work harder and provide higher-quality work because they have more to lose if they get fired (see, for example, Pacitti 2011).



*Notes:* Sample period: 1947Q4–2016Q4.

Model specification: 2 lags and constant term.

Variable ordering:  $\Delta \ln$  real wage rate,  $\Delta \ln$  productivity,  $\ln$  HP utilization.

White heteroskedasticity test statistic ( $p$ -value): 91.80 (0.058).

Complete results shown in Figure A10 in Appendix 2 (available online at <https://doi.org/10.4337/ejep.2022.0085>).

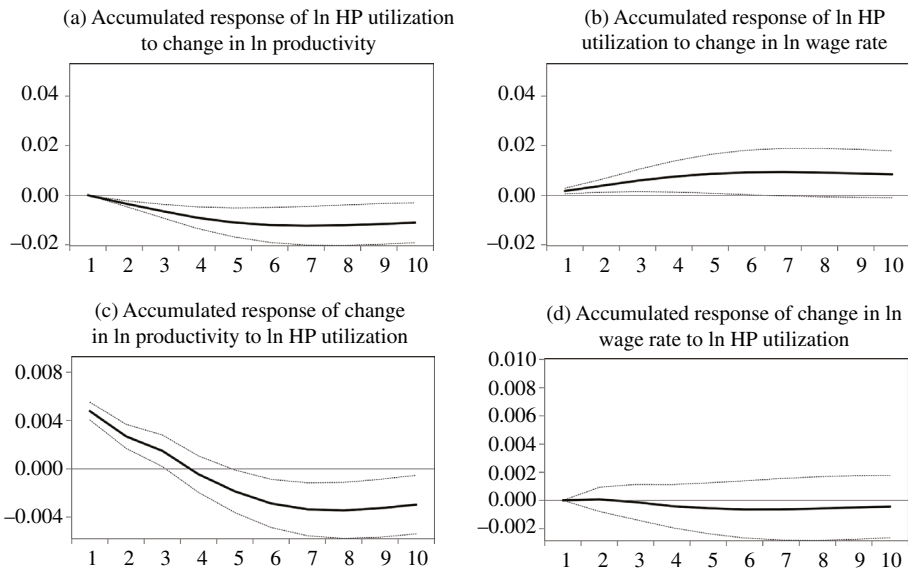
*Figure 5 Selected IRFs for Order 1 with HP utilization*

significance levels for these results should be viewed with caution because there is some evidence of heteroskedasticity in this specification: the null hypothesis of homoskedasticity is rejected at the 10 percent level.<sup>36</sup> Because this heteroskedasticity may reflect changing relationships over the course of the long estimation period, sub-sample estimation is conducted as a sensitivity test. These results are discussed following those for the full sample period.

Order 1 maintains the assumptions that are implicit in the baseline model – that is, that demand has no contemporaneous effect on either component of the wage share. It also assumes that productivity has no contemporaneous effect on the real wage rate. Examining the response of demand to wage and productivity shocks can provide new insights into the finding of profit-led demand in the baseline model. Each type of shock can be wage-led (if a shock that increases the wage share leads to an increase in demand) or profit-led (if a shock that increases the wage share leads to a decrease in demand).<sup>37</sup>

36. Using 3 lags instead of 2, the null hypothesis of heteroskedasticity cannot be rejected. However, there is some evidence of serial correlation in the specification with 3 lags. For this reason, the model with 2 lags is used. Most results are qualitatively robust to the use of 3 lags instead of 2. The exceptions are noted in footnotes below. These results are available from the author upon request.

37. Interpreting whether a wage-rate or productivity shock increases or decreases  $\Delta \ln$  wage share is not completely straightforward, because a shock to one component could be offset by its effects on



Notes: Sample period: 1947Q4–2016Q4.

Model specification: 2 lags and constant term.

Variable ordering:  $\Delta \ln$  real wage rate,  $\ln$  HP utilization,  $\Delta \ln$  productivity.

White heteroskedasticity test statistic ( $p$ -value): 91.80 (0.058).

Complete results shown in Figure A11 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>).

Figure 6 Selected IRFs for Order 2 with HP utilization

The results found using Order 1 indicate that the source of the shock matters for whether a demand regime is wage-led or profit-led. As panels (a) and (b) in Figure 5 show, both components of the wage share have a positive effect on demand (though they have different effects on the wage share). Increases in the wage rate increase both the wage share and demand (a wage-led demand effect), while increases in productivity decrease the wage share and increase demand (a profit-led demand effect). Both of these effects are found to be statistically significant, although the need for caution in interpreting significance remains given the evidence of heteroskedasticity. Shocks to the wage

the other. For example, an increase in  $\Delta \ln$  wage rate could potentially decrease  $\Delta \ln$  wage share if the wage-rate shock led to a sufficiently large increase in  $\Delta \ln$  productivity. However, in all reported specifications such secondary effects are smaller than the direct effects. As such, all positive wage-rate shocks can be interpreted as increasing  $\Delta \ln$  wage share and all positive productivity shocks can be interpreted as decreasing  $\Delta \ln$  wage share. In two cases – the specifications using Orders 3 and 4 with the HP utilization rate – the cumulative response through 10 quarters of a productivity shock on  $\Delta \ln$  wage share nearly equals the response of  $\Delta \ln$  productivity to its own shock. In these two cases,  $\Delta \ln$  wage share would return close to its initial level after initially decreasing. In all other cases, the cumulative response of one component to its own shock are sizable relative to the indirect effects on the other component, allowing for straightforward interpretation.

rate are found to be wage-led because a shock that increases the wage share – that is, an increase in the wage rate – has a positive effect on demand. On the other hand, shocks to productivity are found to be profit-led because a shock that increases the wage share – that is, a negative productivity shock – leads to a reduction in demand (due to the positive relationship between productivity and demand). Although these two types of shocks that would increase the wage share have opposite effects on demand, the response of demand to productivity shocks is larger in magnitude than the response of demand to wage shocks. Therefore, the average shock to the wage share will have a profit-led effect, as long as shocks to wages and productivity occur with similar frequency. This likely explains the finding of profit-led demand in the two-variable model.

The response of productivity and the wage rate to demand shocks can be seen in panels (c) and (d) in Figure 5. They indicate that an increase in demand leads to a decrease in productivity but has no significant effect on wages.<sup>38</sup> The negative response of productivity to an increase in demand suggests that productivity is counter-cyclical, rather than procyclical as Lavoie (2014: 323–325) argues. This could reflect the labor discipline effect of the business cycle on worker effort. However, these estimates may be missing important effects because they are based on the assumption that demand has no contemporaneous effect on productivity. The effects that Lavoie (2014: 323–325) discusses are likely to materialize quickly, as changes in utilization will necessarily affect productivity as soon as firms change production workers' hours or employment. As such, the model with this variable ordering may be unlikely to capture them. These effects of demand on productivity drive the overall profit-squeeze effect found in the baseline model, as a decrease in productivity resulting from an increase in demand would lead to an increase in the wage share. The negative effect of demand on the wage rate would be indicative of a wage squeeze, rather than a profit squeeze, but these effects are insignificant and small in comparison to the effects on productivity.<sup>39</sup>

Order 2 maintains the same ordering restrictions relating demand and wages, as well as those relating productivity and wages, that were used in Order 1. However, it reverses the order of productivity and demand. Therefore, this specification allows productivity to vary contemporaneously with demand, but assumes that productivity has only a lagged effect on demand. The IRFs relating the wage rate and demand (shown in panels (b) and (d) in Figure 6) are qualitatively similar to those found using Order 1, in that they show a positive and significant effect of wages on demand and no significant effect of demand on wages.<sup>40</sup> However, there are important differences relative to Order 1 in the IRFs relating productivity and demand, shown in panels (a) and (c) in Figure 6. Whereas no evidence of pro-cyclical variation in labor productivity was found in Order 1, here an increase in demand initially leads to an increase in productivity. The positive contemporaneous effect of demand on productivity found in these estimates matches the theoretical expectation of

38. The other off-diagonal IRFs show positive effects in both directions of the wage–productivity relationship. However, the effects of productivity on wages are not found to be significant. These results can be seen in Figure A10 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>).

39. These negative effects of demand on the wage rate are found to be statistically significant in the model using 3 lags instead of 2. The only other qualitative difference in that specification using Order 1 is that the positive effect of productivity on the wage rate becomes significant when adding a third lag.

40. The relationship between wages and productivity is also similar, as it shows positive effects in both directions. The only qualitative difference from Order 1 concerning this relationship is that the effect of productivity on wages is found to be significant.

pro-cyclical productivity based on the model in Lavoie (2014: 323–325). These initial positive effects are followed by larger negative lagged effects that ultimately make the cumulative effect negative. This pattern likely reflects a longer adjustment time for counter-cyclical productivity effects, such as reduced effort from workers when they recognize that the probability and cost of job loss has fallen, than for the pro-cyclical effects, which are likely to be realized only once when the share of production-worker hours to total hours changes along with utilization. Although the cumulative effect is ultimately negative, the contemporaneous pro-cyclical productivity effects support Lavoie's (2017) argument. Using the ordering assumptions of the baseline model, these effects would be interpreted as a profit-led demand effect. These estimated effects of demand on productivity largely determine the response of the wage share to a positive demand shock, given the very small and insignificant response of the wage rate to demand. The overall relationship shows a delayed profit-squeeze effect following an initial increase in the wage share.

The response of demand to a productivity shock is also sensitive to changing the order of productivity and demand. In contrast to Order 1, wherein productivity has a positive and significant effect on demand, the results for Order 2 show a negative and significant effect. In other words, positive productivity shocks are found to increase demand when it is assumed that demand has only a lagged effect on productivity, but the same shock is found to decrease demand when productivity is allowed to vary contemporaneously with demand.<sup>41</sup> Whereas wage-rate shocks were wage-led and productivity shocks were profit-led using Order 1, both types of shocks to the wage share produce wage-led demand effects using Order 2.

The estimated effect of productivity on demand has a dramatic impact on the interpretation of the overall relationship between the wage share and demand. Whereas the results for Order 1 reflect profit-led demand (assuming a similar frequency of productivity and wage shocks) because the profit-led productivity shocks are larger in magnitude than the wage-led wage-rate shocks, all of the estimated effects found using Order 2 are wage-led. When productivity is allowed to vary contemporaneously with demand, either type of shock that increases the wage share (that is, an increase in the wage rate or a decrease in productivity) is found to have a positive and statistically significant effect on demand.<sup>42</sup>

41. Given that the methodology used to arrive at these estimates is likely to capture only short-run relationships, the finding of a negative effect of productivity on demand is not necessarily surprising. Although a positive effect of productivity on output is expected in the long run, there are multiple plausible theoretical explanations for a negative effect of productivity on the utilization rate in the short run. For example, Walsh (2004) argues that productivity growth increases potential output, which improves growth in the long run but can create a negative output gap (or in this case a lower utilization rate) in the short run if output rises by less than potential output. Moreover, as Basu et al. (2006) explain, business-cycle models with sticky prices or imperfect information suggest that improvements in technology – which would increase labor productivity – may lead to lower output in the short run as firms reduce investment and input use. Although they find little initial effect of a positive technology shock on output, their estimates indicate that such a shock initially has a negative effect on utilization, total inputs, and non-residential investment. A related explanation is that lower demand in the short run results from increased unemployment as firms initially reduce labor demand. Empirical studies suggest that productivity growth tends to reduce unemployment in the long run but increase it in the short and medium run (see, for example, Chen et al. 2008; Gallegati et al. 2015). Further exploration of the short-run relationship between demand and productivity in this context remains an important area for future research.

42. All of the results found using Order 2 are qualitatively similar in the specification using 3 lags instead of 2.



Most results found with the HP utilization rate are also qualitatively similar when using the Hamilton utilization rate, CBO output gap, the growth rate of GDP, or the Fed utilization rate as the measure of demand. There are three exceptions: for Order 2 using the Hamilton utilization rate, CBO output gap, or the growth rate of GDP the lagged negative cumulative effect of demand on productivity is insignificant (though the cumulative IRF maintains a similar shape), for Order 2 using the CBO output gap or growth rate of GDP there is a positive and significant effect of demand on wages, using the Hamilton utilization rate the effect of productivity on demand is positive, but small and insignificant in Order 2, and using the Fed utilization rate the positive effect of wages on demand is insignificant for both Order 1 and Order 2.<sup>43</sup> However, it should also be noted that there is evidence of heteroskedasticity in the specifications using the Hamilton utilization rate, the growth rate of GDP, and the Fed utilization rate. Results for these specifications are shown in Figures A16–A23 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>).<sup>44</sup>

Most results found using the HP utilization rate with Order 1 or Order 2 are also qualitatively robust to using the CPI-deflated real wage rate in place of the wage rate deflated with the output price deflator. There is one exception: for Order 1 using the HP utilization rate, the negative effect of demand on wages becomes significant. However, heteroskedasticity remains a potential issue in this specification. These results are shown in Figures A24–A25 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>).

Results found using the HP utilization rate with Orders 1 and 2 are somewhat sensitive to changes in the ordering of the real wage rate relative to the other two variables.<sup>45</sup> However, results relating productivity and demand in Orders 5 and 6 follow the same pattern as those found using Order 2 (which maintains the same ordering of productivity relative to demand), while those for Orders 3 and 4 are qualitatively similar to those found using Order 1. While these results highlight the importance of the ordering assumptions relating productivity and demand, there is not a clear theoretical justification for using any of these orderings in which the wage rate responds more quickly than productivity or demand. Results for these specifications can be found in Figures A12–A15 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>).

Given the large sample period for the estimation of these models, it is possible that the heteroskedasticity found in many specifications reflects changes in the underlying relationships over time. For this reason, the models using the HP utilization rate with Orders 1 and 2 are estimated for the same sub-periods used to analyse the stability of the

43. Although a positive wage shock is found to have a positive and significant effect on demand for Orders 1 and 2 using the Hamilton utilization rate, this finding is sensitive to lag length. For example, it remains significant using a lag length of 4, but not a lag length of 2. No other relationships have a change in sign or significance when using a lag length of 2 instead of 9.

44. There is also some evidence of mild serial correlation in the case of the Hamilton utilization rate, as the null hypothesis of no serial correlation of the residuals at the fourth lag is rejected at the 10 percent level (the null hypothesis cannot be rejected for lags 1 through 3). However, the specification with 9 lags, as suggested by the HQIC, is used because adding a few more lags did not improve the results of the serial correlation or heteroskedasticity tests. Unreported results show that all of the estimated relationships are qualitatively robust to a model specification with 17 lags, for which there is no evidence of serial correlation or heteroskedasticity.

45. Some of the results relating demand and the real wage rate differ. There is a positive and significant effect of demand on wages in Orders 5 and 6, and the positive effect of wages on demand becomes insignificant in Order 6. Using Order 3, there is a negative and significant effect of demand on wages, and Order 4 shows a negative and significant effect of wages on demand. There is also a positive and significant effect of productivity on wages in Orders 3 and 4.

relationship in the baseline model. No evidence of heteroskedasticity is found for any of these specifications. Although there are some differences in significance in various sub-periods, the directions of the relationships appear to remain stable.<sup>46</sup> These results, shown in Figures A26–A31 in Appendix 2 (available online at <https://doi.org/10.4337/ejeep.2022.0085>), indicate that the key results in the full-sample estimates are largely confirmed by the sub-sample specifications that do not suffer from heteroskedasticity.

Overall, these results clearly indicate that the interpretation of the relationship between the wage share and demand is highly dependent on the model's assumptions about the timing of the effects relating demand and productivity. In other words, the way that the model assigns causality to the contemporaneous correlation between demand and productivity largely dictates whether the estimates ultimately suggest wage-led or profit-led demand, as well as the response of distribution to demand shocks. Observed profit-led demand and profit-squeeze effects will be much larger when imposing ordering restrictions that assume that utilization has only a lagged effect on productivity. When this assumption is maintained, the contemporaneous correlation between utilization and productivity – which may reflect cyclical variation in productivity – is viewed as an effect of productivity on utilization. As a result, the estimated response of utilization to a productivity shock will be more positive, and the estimated response of productivity to a utilization shock will be less positive. Because there is an inverse relationship between productivity and the wage share by definition, this will lead to estimates that suggest a more negative response of utilization to an increase in the wage share (that is, more profit-led demand) and a more positive response of the wage share to an increase in utilization (that is, more of a profit squeeze). In other words, observed Goodwin-cycle effects will be larger when it is implicitly assumed that productivity drives utilization contemporaneously; when the model treats the contemporaneous causality between the two as an effect of demand on productivity, estimates will be less likely to indicate profit-led demand and profit-squeeze effects. Although some specific results (for example, the significance of some individual IRFs) are sensitive to measurement, the chosen sample period, and other methodological choices, this pattern is generally consistent across all specifications.

The results presented here suggest that there are (at least) two possible interpretations of the Goodwin-cycle relationship found by the baseline model. One possible interpretation, following the findings of models using Order 1, suggests that demand is profit-led because productivity shocks that increase the wage share and decrease demand have a bigger impact on demand than wage shocks, which increase demand (and the wage share). In other words, demand is primarily driven by large productivity shocks that have an immediate impact (that is, within a quarter). Following this interpretation, there is a profit-squeeze effect because productivity decreases as demand increases (that is, there are counter-cyclical productivity effects). This interpretation relies on the assumption that demand has no contemporaneous effect on productivity.

46. The only qualitative change regarding the relationship between productivity and demand is that the lagged negative cumulative effects of demand on productivity are insignificant for the second and third sub-periods when using Order 2 (though they still show the same general pattern of positive effects followed by negative lagged effects). For both Orders 1 and 2, the effect of wages on demand becomes insignificant in the second and third sub-periods. There is also a positive and significant effect of demand on wages in the third sub-period using Order 2. Some specifications also show changes in the significance of the effect of productivity on wages. It should be noted that some differences between these estimates and those using the entire sample period could reflect differences in lag length, as 3 lags were used for the first two sub-periods and 6 lags were used for the last sub-period, in contrast to 2 lags for the full sample estimates.

An alternate interpretation, following the findings of models using Order 2, suggests that the Goodwin cycle found in the baseline model is driven by the model's misinterpretation of productivity effects. In this narrative, demand has a strong and positive contemporaneous effect on productivity. However, the baseline model captures this positive effect of demand on productivity as a negative effect of the wage share on demand because it assumes that any contemporaneous correlation between productivity and demand represents an effect of productivity on demand, rather than the reverse. According to this interpretation, contemporaneous pro-cyclical variation in productivity followed by a negative lagged effect of demand on productivity (that makes the cumulative effect significantly negative in some cases, but not in others) generates an initial wage-squeeze effect (that may or may not be followed by a delayed profit squeeze).<sup>47</sup> Following this narrative, the baseline model's misinterpretation of contemporaneous pro-cyclical productivity effects obscures an underlying relationship of wage-led demand. This is driven by a positive effect of wages on demand, a negative effect of productivity on demand, or both (depending on the exact specification). Although some of these findings are sensitive to various aspects of variable measurement and model specification, no evidence of significant profit-led demand effects are found using a variable ordering in which demand has a contemporaneous effect on productivity (an assumption that this interpretation depends on).

If there are, in fact, pro-cyclical productivity effects, as Lavoie (2017) suggests – and particularly if demand affects productivity contemporaneously – then the latter interpretation may be more accurate and Order 2 would be the appropriate way to model this relationship. However, one shortcoming of the methodological approach of using VARs with Cholesky decomposition to identify IRFs is that all of the contemporaneous correlation between two variables must be interpreted as the effect of one variable on the other. Therefore, if both productivity and demand affect one another contemporaneously, neither set of results would be a fully accurate interpretation of the underlying data. In such a case, the true relationships would likely fall somewhere between the results found for Order 1 and Order 2. Therefore, in order to fully understand the relationship between the wage share and demand, further investigation of the timing of the underlying effects is needed – especially for the productivity-demand dynamics. Future studies should give careful consideration to these dynamics.

It is interesting to compare these results to those of Mendieta-Muñoz et al. (2020), who find evidence of a Goodwin cycle even when allowing demand to affect productivity contemporaneously. Although fully reconciling these two sets of results is beyond the scope of this paper and any explanation of their differences remains speculative, it seems likely that estimates of the relationship between demand and the wage share are sensitive to other identifying assumptions in addition to those concerning whether demand impacts productivity contemporaneously or only with a lag. For example, the results may differ because the model in Mendieta-Muñoz et al. (2020) allows productivity to affect demand contemporaneously, while this isn't possible in the model presented above using Order 2. Another possibility is that the results are sensitive to the treatment of unemployment. Estimates that do not include unemployment could potentially suffer from omitted variable bias, whereas estimates that do include unemployment could be

47. It is not immediately clear how to interpret these cyclical dynamics in the context of the effective demand and distributive nullclines. While wage-led demand and wage-squeeze effects would typically be viewed as evidence of a clockwise cycle, this is complicated by the finding of a delayed profit-squeeze effect in some specifications. Further exploration is needed in future research to unpack the cyclical dynamics of productivity, the wage rate, and demand.

sensitive to assumptions relating it to the other variables. Further untangling these issues remains an important area for future research.

## 5 CONCLUDING REMARKS

Aggregative estimates of the relationship between demand and the functional distribution of income have typically found evidence of Goodwin-cycle effects, wherein demand is profit-led and the wage share varies pro-cyclically with utilization. However, Lavoie (2017) argues that these findings could be driven in part by bias that results from models capturing pro-cyclical variation in labor productivity – one of the components of the wage share – as a negative effect of the wage share on demand.

Like most previous aggregative estimates, the baseline model in this paper finds evidence of profit-led demand and profit-squeeze effects. However, these estimates, found using model specifications that follow assumptions traditionally used in the literature, may not properly account for cyclical productivity effects. Other specifications replace the wage share with its two components – the real wage rate and labor productivity – in order to observe the underlying dynamics and allow for more precise ordering restrictions. The results suggest that the effect of the wage share on demand may differ for wage shocks and productivity shocks. They also indicate that stronger Goodwin-cycle effects will likely be found when assuming that demand has only a lagged effect on productivity, offering support for Lavoie's (2017) hypothesis. When maintaining this assumption, which is implicit in the baseline model, Goodwin-cycle effects are still found. However, when productivity is allowed to vary contemporaneously with demand, the evidence is indicative of wage-led demand and an initial wage squeeze.

These findings provide two very different interpretations of observed Goodwin cycles. One interpretation, reflected in results based on the assumption that demand affects productivity only with a lag, suggest that the Goodwin cycle represents a causal relationship that is primarily driven by the relationship between productivity and demand. In this case, the profit squeeze reflects counter-cyclical variation in productivity, while demand is profit-led on average because positive productivity shocks (that decrease the wage share) lead to immediate increases in demand. These effects of productivity on demand outweigh the positive effects of real-wage-rate increases on demand.

Results found using the alternate assumption that productivity varies contemporaneously with demand, but has only a lagged effect on demand, suggest a very different interpretation. Following this interpretation, the observed Goodwin-cycle effects are spurious, reflecting the model's misinterpretation of contemporaneous pro-cyclical variation in productivity as a negative effect of the wage share on demand. There is an initial wage squeeze driven by a positive contemporaneous response of productivity to increases in demand, although there may be some delayed profit-squeeze effects. In the other direction, results indicate that demand is wage-led, as shocks to either productivity or the wage rate that increase the wage share lead to increases in demand – although the significance of some of these wage-led demand effects is somewhat sensitive to various aspects of model specification. These results suggest that the relationship between the wage share and demand over the course of the business cycle may be better characterized as one of initially pro-cyclical productivity effects and wage-led demand.

Future research examining the relationship between the wage share and demand should pay careful consideration to the underlying dynamics in the components of the wage share. Although Lavoie's (2017) argument regarding pro-cyclical variation in labor productivity suggests that the latter interpretation is more accurate (especially if these effects occur quickly), further work examining the timing of effects between productivity and demand is needed to arrive at a more definitive understanding of the relationship of interest.

Moreover, further exploration of the differing results in this paper and those in Mendieta-Muñoz et al. (2020) is needed to move the debate forward. Additional theoretical research exploring the three-dimensional dynamics implied by the findings of this paper would also be a valuable contribution to the literature.

## REFERENCES

- Araujo, R.A., Dávila-Fernández, M.J., Nunes Moreira, H. (2019): Some new insights on the empirics of Goodwin's growth-cycle model, in: *Structural Change and Economic Dynamics*, 51, 42–54.
- Barattieri, A., Basu, S., Gottschalk, P. (2014): Some evidence on the importance of sticky wages, in: *American Economic Journal: Macroeconomics*, 6(1), 70–101.
- Barbosa-Filho, N.H., Taylor, L. (2006): Distributive and demand cycles in the US economy: a structuralist Goodwin model, in: *Metroeconomica*, 57(3), 389–411.
- Barrales, J., von Arnim, R. (2017): Longer run distributive cycles: wavelet decompositions for the US, 1948–2011, in: *Review of Keynesian Economics*, 5(2), 196–217.
- Basu, S., Fernald, J. (2001): Why is productivity procyclical? Why do we care?, in: Hulten, C.R., Dean, E.R., Harper, M.J. (eds), *New Developments in Productivity Analysis*, Chicago: University of Chicago Press, 225–302.
- Basu, D., Gautham, L. (2019): What is the impact of an exogenous shock to the wage share? VAR results for the US economy, 1973–2018, Working Paper 2019-08, University of Massachusetts Amherst, URL: <http://www.umass.edu/economics/publications/2019-08.pdf>.
- Basu, S., Fernald, J.G., Kimball, M.S. (2006): Are technology improvements contractionary?, in: *American Economic Review*, 96(5), 1418–1448.
- Bhaduri, A., Marglin, S. (1990): Unemployment and the real wage: the economic basis for contesting political ideologies, in: *Cambridge Journal of Economics*, 14(4), 375–393.
- Blecker, R.A. (1989): International competition, income distribution and economic growth, in: *Cambridge Journal of Economics*, 13(3), 395–412.
- Blecker, R.A. (2002): Demand, distribution, and growth in neo-Kaleckian macro models, in: Setterfield, M. (ed.), *The Economics of Demand-Led Growth: Challenging the Supply-Side Vision of the Long Run*, Cheltenham, UK and Northampton, MA: Edward Elgar Publishing, 129–152.
- Blecker, R.A. (2016): Wage-led versus profit-led demand regimes: the long and the short of it, in: *Review of Keynesian Economics*, 4(4), 373–390.
- Blecker, R.A., Cauvel, M., Kim, Y.K. (2022): Systems estimation of a structural model of distribution and demand in the US economy, in: *Cambridge Journal of Economics*, 46(2), 391–420.
- Böckerman, P., Maliranta, M. (2012): Globalization, creative destruction, and labour share change: evidence on the determinants and mechanisms from longitudinal plant-level data, in: *Oxford Economic Papers*, 64, 259–280.
- Borio, C., Disyatat, P., Juselius, M. (2013): Rethinking potential output: embedding information about the financial cycle, Technical Report Working Paper No 404, Bank for International Settlements.
- Braut, J., Khan, H. (2019): The shifts in lead-lag properties of the U.S. business cycle, in: *Economic Inquiry*, 58(1), 319–334.
- Burda, M.C. (2018): Aggregate labor productivity, in: *IZA World of Labor*, 435, doi: 10.15185/izawol.435.
- Bureau of Labor Statistics (2008): Major sector productivity and costs, URL: <http://www.bls.gov/lpc/lpcmethods.pdf> (accessed 5 September 2017).
- Bureau of Labor Statistics (2017): Estimating the U.S. labor share, Technical Report, February, Monthly Labor Review, URL: <https://www.bls.gov/opub/mlr/2017/article/estimating-the-us-labor-share.htm>.
- Carvalho, L., Rezai, A. (2016): Personal income inequality and aggregate demand, in: *Cambridge Journal of Economics*, 40(2), 491–505.

- Cerra, V., Saxena, S.C. (2017): Booms, crises, and recoveries: a new paradigm of the business cycle and its policy implications, Technical Report WP/17/250, International Monetary Fund Working Paper.
- Charpe, M., Bridji, S., McAdam, P. (2019): Labor share and growth in the long run, Working Paper 2251, European Central Bank, URL: <https://ssrn.com/abstract=3359498>.
- Chen, P., Gong, G., Rezai, A., Semmler, W. (2008): Productivity shocks in the short and long-run: an intertemporal model and estimation, in: *Investigación Económica*, 67(264), 39–61.
- Christiano, L.J., Eichenbaum, M., Evans, C.L. (1999): Monetary policy shocks: what have we learned and to what end?, in: *Handbook of Macroeconomics*, 1, 65–148.
- Cogley, T., Nason, J.N. (1995): Effects of the Hodrick–Prescott filter on trend and difference stationary time series: implications for business cycle research, in: *Journal of Economic Dynamics and Control*, 19(1–2), 253–278.
- Desai, M. (1984): An econometric model of the share of wages in national income: UK 1855–1965, in: Goodwin, R.M., Krüger, M., Vercelli, A. (eds), *Nonlinear Models of Fluctuating Growth: An International Symposium, Siena, Italy, March 24–27, 1983*, Berlin and Heidelberg: Springer, 253–277.
- Diallo, M.B., Flaschel, P., Krolzig, H.-M., Proaño, C.R. (2011): Reconsidering the dynamic interaction between real wages and macroeconomic activity, in: *Research in World Economy*, 2(1), 77–93.
- Dutt, A.K. (1984): Stagnation, income distribution and monopoly power, in: *Cambridge Journal of Economics*, 8(1), 25–40.
- Dutt, A.K. (1987): Alternative closures again: a comment on ‘Growth, distribution and inflation,’ in: *Cambridge Journal of Economics*, 11(1), 75–82.
- Fernald, J.G., Wang, C. (2016): Why has the cyclical productivity changed? What does it mean?, in: *Annual Review of Economics*, 8, 465–496.
- Franke, R., Kukacka, J. (2020): Notes on the neglected premisses of the Hodrick–Prescott detrending and the Hamilton regression filter, Working Paper, Universities of Kiel and Prague, URL: <https://dx.doi.org/10.2139/ssrn.3747794>.
- Gallegati, M., Gallegati, M., Ramsey, J.B., Semmler, W. (2015): Productivity and unemployment: a scale-by-scale panel data analysis for the G7 countries, in: *Studies in Nonlinear Dynamics and Econometrics*, 20(4), 477–493.
- Giovannoni, O. (2010): Functional distribution of income, inequality and the incidence of poverty: stylized facts and the role of macroeconomic policy, University of Texas Inequality Working Paper No 58, URL: [https://utip.gov.utexas.edu/papers/utip\\_58.pdf](https://utip.gov.utexas.edu/papers/utip_58.pdf).
- Goodwin, R.M. (1967): A growth cycle, in: Feinstein, C.H. (ed.), *Socialism, Capitalism, and Economic Growth*, Cambridge, UK: Cambridge University Press, 54–58.
- Gordon, R.J., Krenn, R. (2010): The end of the Great Depression 1939–41: policy contributions and fiscal multipliers, Working Paper 16380, National Bureau of Economic Research, URL: <http://www.nber.org/papers/w16380>.
- Gordon, R.J., Solow, R.M. (2003): Are procyclical productivity fluctuations a figment of measurement error?, in: *Productivity Growth, Inflation, and Unemployment: The Collected Essays of Robert J. Gordon*, Cambridge, UK: Cambridge University Press and Cambridge Books Online, 239–272.
- Grasselli, M.R., Maheshwari, A. (2017): A comment on ‘Testing Goodwin: growth cycles in ten OECD countries,’ in: *Cambridge Journal of Economics*, 41(6), 1761–1766, doi: 10.1093/cjel/bex018.
- Hahnel, R., Sherman, H. (1982): The rate of profit over the business cycle, in: *Cambridge Journal of Economics*, 6(2), 185–194.
- Hamilton, J.D. (2018): Why you should never use the Hodrick–Prescott filter, in: *Review of Economics and Statistics*, 100(5), 831–843.
- Harvie, D. (2000): Testing Goodwin: growth cycles in ten OECD countries, in: *Cambridge Journal of Economics*, 24(3), 349–376.
- Hodrick, R.J., Prescott, E.C. (1997): Postwar U.S. business cycles: an empirical investigation, in: *Journal of Money, Credit and Banking*, 29(1), 1–16.
- Ivanov, V., Kilian, L. (2005): A practitioner’s guide to lag order selection for VAR impulse response analysis, in: *Studies in Nonlinear Dynamics and Econometrics*, 9(1), article 2.

- Kalecki, M. (1954): *Theory of Economic Dynamics*, London: Unwin.
- Kiefer, D., Rada, C. (2015): Profit maximising goes global: the race to the bottom, in: *Cambridge Journal of Economics*, 39(5), 1333–1350.
- Kim, H. (2013): Generalized impulse response analysis: general or extreme?, in: *EconoQuantum*, 10(2), 135–141.
- Lavoie, M. (2014): *Post-Keynesian Economics: New Foundations*, Cheltenham, UK and Northampton, MA: Edward Elgar Publishing.
- Lavoie, M. (2017): The origins and evolution of the debate on wage-led and profit-led regimes, in: *European Journal of Economics and Economic Policies: Intervention*, 14(2), 200–221.
- Lewis, V., Van Dijke, D. (2019): Work effort and the cycle: evidence from survey data, Unpublished Working Paper, doi: 10.13140/RG.2.2.24098.17609.
- Marglin, S.A., Bhaduri, A. (1990): Profit squeeze and Keynesian theory, in: Marglin, S.A., Schor, J.B. (eds), *The Golden Age of Capitalism*, Oxford: Oxford University Press, 153–186.
- Mendieta-Muñoz, I., Rada, C., Santetti, M., von Arnim, R. (2020): The US labour share of income: what shocks matter?, in: *Review of Social Economics*, advance access, doi: 10.1080/00346764.2020.1821907.
- Ng, S., Perron, P. (2001): Lag length selection and the construction of unit root tests with good size and power, in: *Econometrica*, 69(6), 1519–1554.
- Nikiforos, M., Foley, D.K. (2012): Distribution and capacity utilization: conceptual issues and empirical evidence, in: *Metroeconomica*, 63(1), 200–229.
- Onaran, Ö., Galanis, G. (2012): Is aggregate demand wage-led or profit-led? National and global effects, Working Paper, International Labour Organization, URL: <http://econpapers.repec.org/paper/iloilowps/994786233402676.htm>.
- Onaran, Ö., Obst, T. (2016): Wage-led growth in the EU15 member-states: the effects of income distribution on growth, investment, trade balance and inflation, in: *Cambridge Journal of Economics*, 40(6), 1517–1551.
- Onaran, Ö., Stockhammer, E., Grafl, L. (2011): Financialisation, income distribution and aggregate demand in the USA, in: *Cambridge Journal of Economics*, 35(4), 637–661.
- Pacitti, A. (2011): Efficiency wages, unemployment, and labor discipline, in: *Journal of Business and Economics Research*, 9(3), 1–10.
- Rowthorn, B. (1982): Demand, real wages and economic growth, in: *Studi Economici*, 18, 3–53.
- Sherman, H.J., Evans, G.R. (1984): *Macro-Economics: Keynesian, Monetarist and Marxist Views*, New York: Harper & Row.
- Silva de Jesus, C., Araujo, R.A., Drumond, C.E. (2018): An empirical test of the Post-Keynesian growth model applied to functional income distribution and the growth regime in Brazil, in: *International Review of Applied Economics*, 32(4), 428–449.
- Steindl, J. (1952): *Maturity and Stagnation in American Capitalism*, Oxford: Blackwell. (Reprinted New York: Monthly Review Press, 1976.)
- Stock, J.H., Watson, M.W. (1999): Business cycle fluctuations in US macroeconomic time series, in: Taylor, J.B., Woodford, M. (ed.), *Handbook of Macroeconomics, Volume 1*, Amsterdam: Elsevier, 3–64.
- Stock, J.H., Watson, M.W. (2001): Vector autoregressions, in: *The Journal of Economic Perspectives*, 15(4), 101–115.
- Stockhammer, E. (2017): Wage-led versus profit-led demand: what have we learned? A Kaleckian–Minskyan view, in: *Review of Keynesian Economics*, 5(1), 25–42.
- Stockhammer, E., Michell, J. (2017): Pseudo-Goodwin cycles in a Minsky model, in: *Cambridge Journal of Economics*, 41(1), 105–125.
- Stockhammer, E., Onaran, Ö. (2004): Accumulation, distribution and employment: a structural VAR approach to a Kaleckian macro model, in: *Structural Change and Economic Dynamics*, 15(4), 421–447.
- Stockhammer, E., Stehrer, R. (2011): Goodwin or Kalecki in demand? Functional income distribution and aggregate demand in the short run, in: *Review of Radical Political Economics*, 43(4), 506–522.
- Stockhammer, E., Wildauer, R. (2016): Debt-driven growth? Wealth, distribution and demand in OECD countries, in: *Cambridge Journal of Economics*, 40(6), 1609–1634.

- Stockhammer, E., Onaran, Ö., Ederer, S. (2009): Functional income distribution and aggregate demand in the Euro area, in: *Cambridge Journal of Economics*, 33(1), 139–159.
- Stockhammer, E., Hein, E., Grafl, L. (2011): Globalization and the effects of changes in functional income distribution on aggregate demand in Germany, in: *International Review of Applied Economics*, 25(1), 1–23.
- Stockhammer, E., Rabinovich, J., Reddy, N. (2021): Distribution, wealth and demand regimes in historical perspective: the USA, the UK, France and Germany, 1855–2010, in: *Review of Keynesian Economics*, 9(3), 337–367.
- Taylor, L. (1983): *Structuralist Macroeconomics: Applicable Models for the Third World*, New York: Basic Books.
- Taylor, L. (1985): A stagnationist model of economic growth, in: *Cambridge Journal of Economics*, 9(4), 383–403.
- Walsh, C.E. (2004): The productivity and jobs connection: the long and the short run of it, Economic Letter 2004-18, Federal Reserve Bank of San Francisco, URL: <https://www.frbsf.org/economic-research/publications/economic-letter/2004/july/the-productivity-and-jobs-connection-the-long-and-the-short-run-of-it/>.
- Weisskopf, T.E. (1979): Marxian crisis theory and the rate of profit in the postwar U.S. economy, in: *Cambridge Journal of Economics*, 3(4), 341–378.



## APPENDIX 1

*Table A1 Variable definitions and data sources*

Variable	Definition	Units	Source
Wage share	Wage-share index for the business sector	Index, 2012 = 100	BLS
HP utilization rate	100 * output / HP filtered trend in output for the business sector	Percentage *100	BLS, author's calculations
Federal Reserve utilization rate	Capacity utilization, total index	Percentage *100	Federal Reserve <sup>a</sup>
Real GDP	Real gross domestic product, seasonally adjusted	Billions of chained 2009 dollars	BEA <sup>a</sup>
Business-sector output	Business-sector current dollar output index	Index, 2012 = 100	BLS
CBO potential output	Real potential gross domestic product	Billions of chained 2009 dollars	CBO <sup>a</sup>
CBO output gap	100 * real GDP / CBO potential output	Percentage *100	Author's calculations
Nominal GDP	Nominal gross domestic product	Billions of dollars	BEA <sup>a</sup>
Labor productivity	Business-sector labor productivity index, output per hour	Index, 2012 = 100	BLS
Real hourly wage rate	100 * BLS business-sector nominal hour compensation index / BLS business-sector implicit price deflator index	Index, 2012 = 100	BLS, Author's calculations
CPI-deflated real hourly wage rate	Ratio of labor compensation to hours worked for the business sector, adjusted for inflation using the CPI and the BLS Consumer Price Index research series	Index, 2012 = 100	BLS

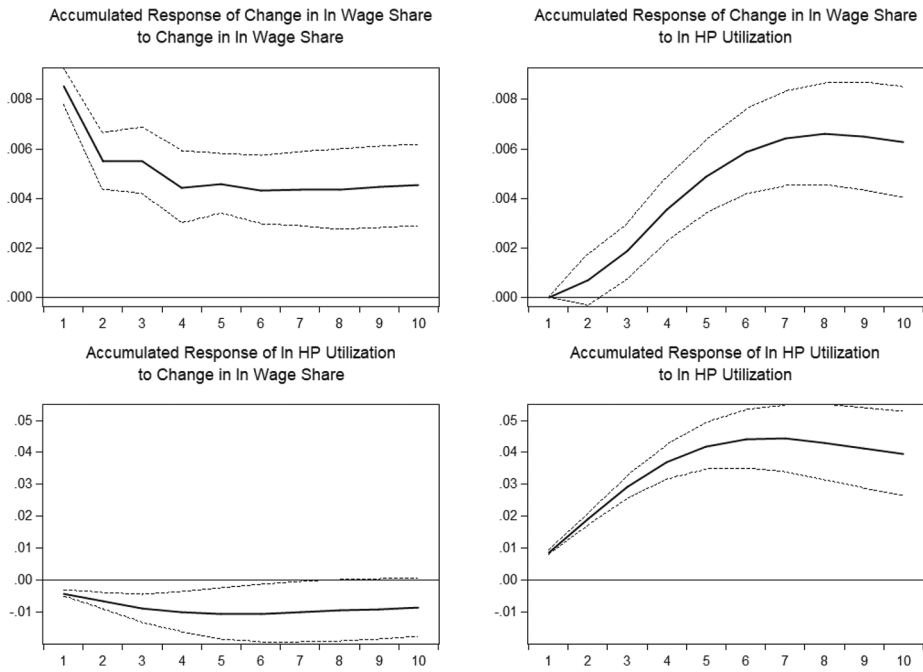
*Note:* a. Indicates series downloaded from the Federal Reserve Bank of St. Louis FRED Database. Details regarding construction of the Hamilton utilization rate are discussed in Section 3.2.

APPENDIX 2

Table A2 Selected unit root test results

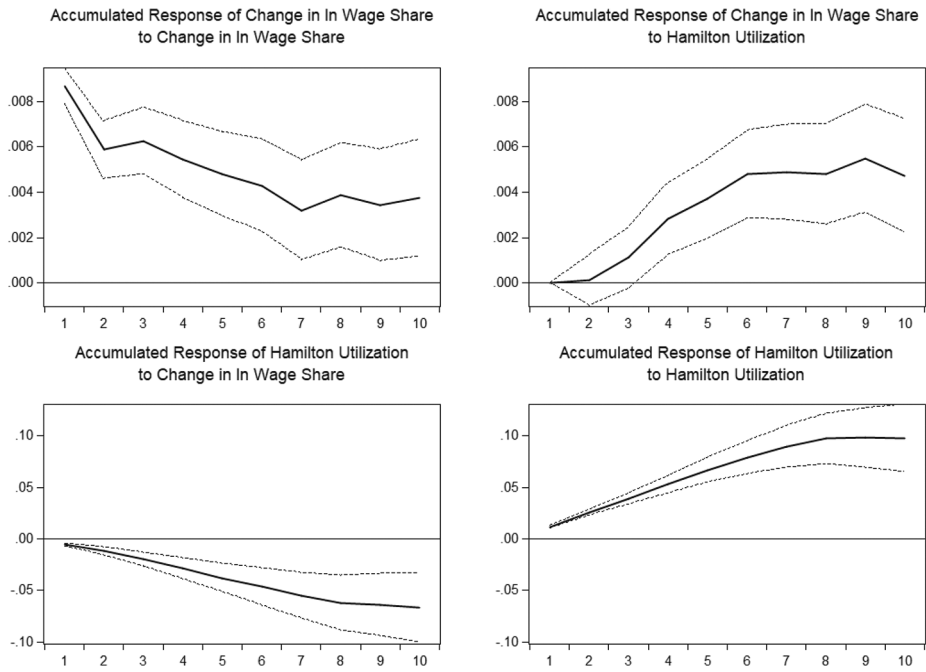
Variables	Sample	Trend	ADF	PP	KPSS	Result
ln HP utilization	1947 Q1-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
ln wage share	1947 Q1-2016 Q4	Y	Fail	Fail	Reject 1%	Difference
$\Delta$ ln wage share	1947 Q2-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
ln GDP	1947 Q1-2016 Q4	Y	Fail	Fail	Reject 1%	Difference
$\Delta$ ln GDP	1947 Q2-2016 Q4	N	Reject 1%	Reject 1%	Reject 5%	Stationary
Hamilton utilization	1949 Q4-2016 Q4	N	Reject 5%	Reject 1%	Fail	Stationary
ln CBO output gap	1949 Q1-2016 Q4	Y	Reject 1%	Reject 1%	Fail	Stationary
ln CBO output gap	1949 Q1-2016 Q4	N	Reject 10%	Reject 1%	Reject 1%	Difference
ln fed utilization	1967 Q1-2016 Q4	Y	Fail	Reject 5%	Fail	Stationary
ln real wage rate	1947 Q1-2016 Q4	Y	Fail	Fail	Reject 1%	Difference
$\Delta$ ln real wage rate	1947 Q2-2016 Q4	N	Reject 1%	Reject 1%	Reject 1%	Stationary
ln CPI-deflated real wage rate	1947 Q1-2016 Q4	Y	Fail	Fail	Reject 1%	Difference
$\Delta$ ln CPI-deflated real wage rate	1947 Q2-2016 Q4	N	Reject 10%	Reject 1%	Reject 1%	Difference
ln productivity	1947 Q1-2016 Q4	Y	Fail	Fail	Reject 1%	Difference
$\Delta$ ln productivity	1947 Q2-2016 Q4	N	Reject 1%	Reject 1%	Reject 5%	Stationary

Note: Null hypotheses: ADF Test – Unit Root, PP Test – Unit Root, KPSS Test – Stationarity



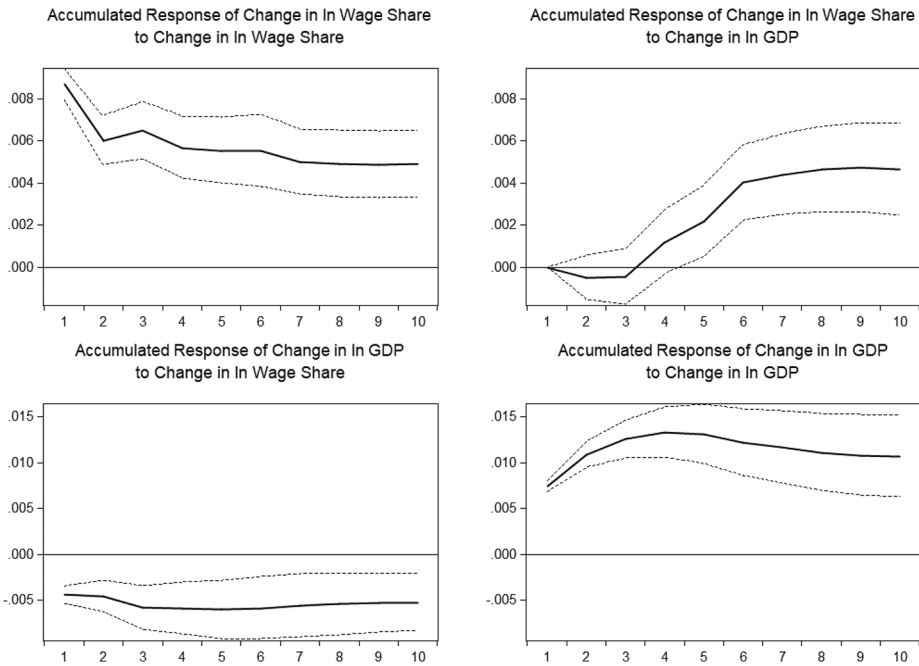
Notes: Sample period: 1948 Q1–2016 Q4.  
 Model specification: 3 lags and constant term.  
 Variable ordering:  $\Delta$  In wage share, In HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 41.38 (0.247).

Figure A1 Complete IRFs for the Baseline Model with HP Utilization Rate



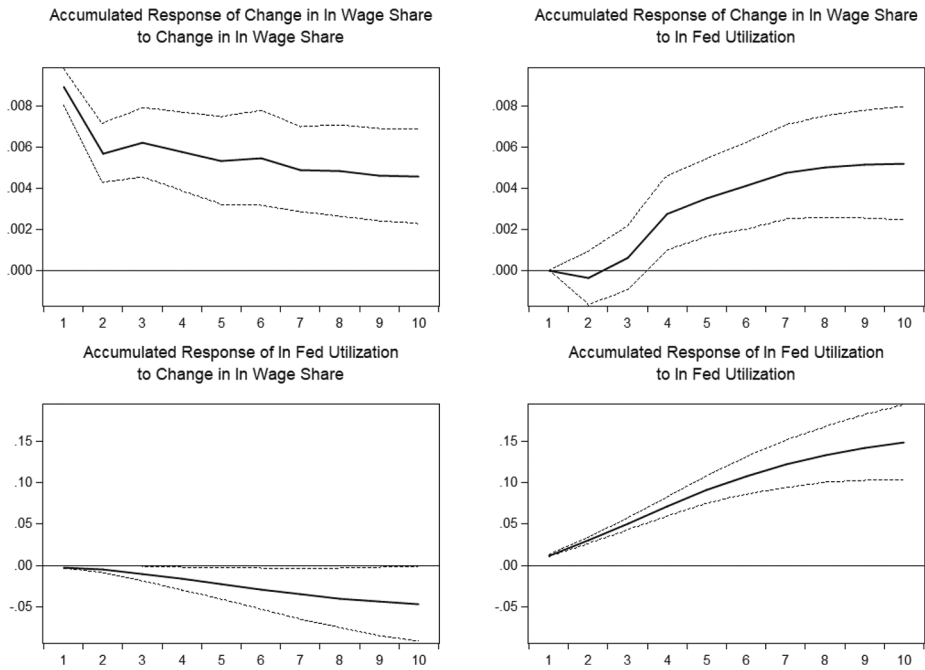
Notes: Sample period: 1953 Q1–2016 Q4.  
 Model specification: 13 lags and constant term.  
 Variable ordering:  $\Delta$  ln wage share, Hamilton utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 161.40 (0.367).

Figure A2 Complete IRFs for Baseline Model with Hamilton Utilization Rate



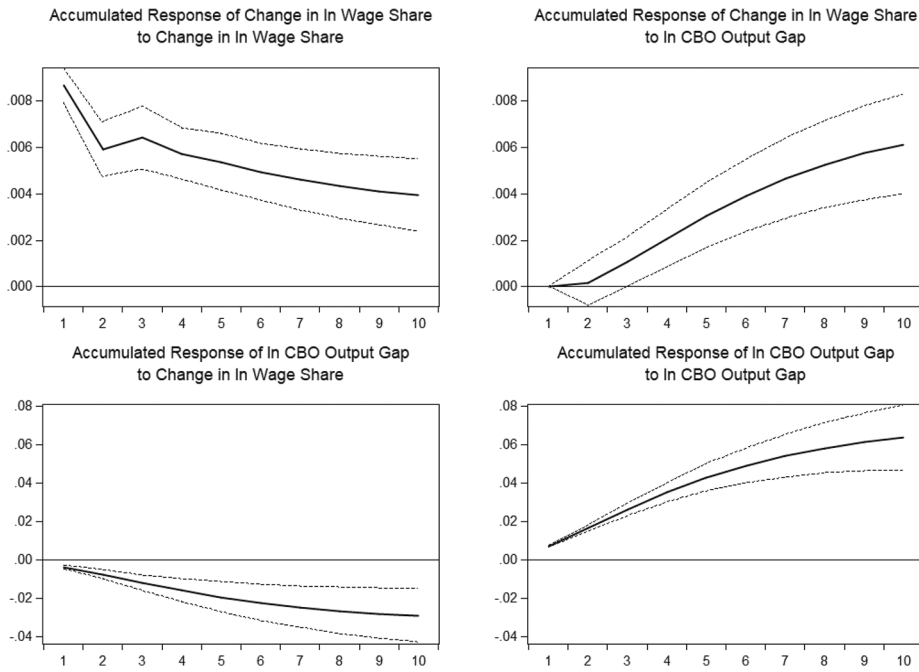
Notes: Sample period: 1948 Q3–2016 Q4.  
 Model specification: 5 lags and constant term.  
 Variable ordering:  $\Delta$  ln wage share, L ln real GDP.  
 White heteroskedasticity test statistic ( $p$ -value): 92.33 (0.005).

Figure A3 Complete IRFs for Baseline Model with Real GDP



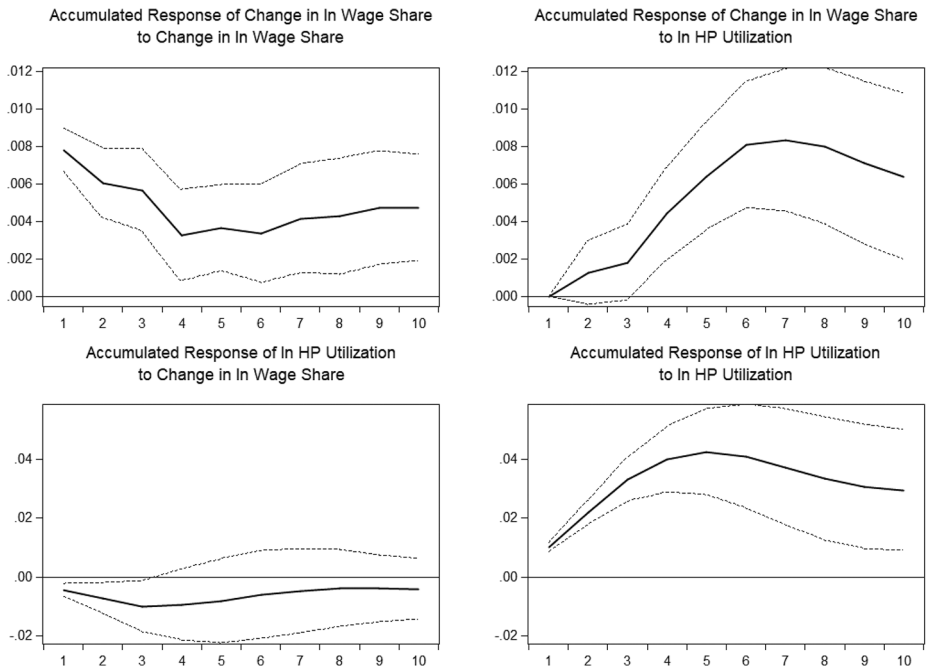
Notes: Sample period: 1968 Q2–2016 Q4.  
 Model specification: 5 lags and constant term.  
 Variable ordering:  $\Delta$  In wage share, In Fed utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 70.86 (0.159).

Figure A4 Complete IRFs for Baseline Model with Federal Reserve Utilization Rate



Notes: Sample period: 1949 Q3–2016 Q4.  
 Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta$  ln wage share, ln CBO output gap.  
 White heteroskedasticity test statistic ( $p$ -value): 38.83 (0.028).

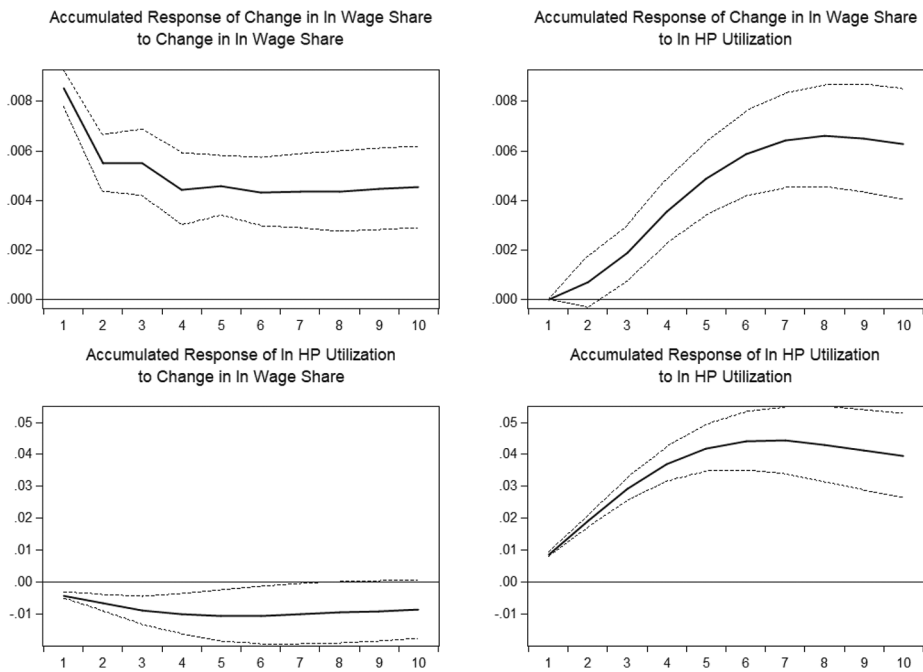
Figure A5 Complete IRFs for Baseline Model with CBO Output Gap



Notes: Sample period: 1948 Q1–1970 Q4.  
 Model specification: 3 lags and constant term.  
 Variable ordering:  $\Delta$  In wage share, In HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 23.17 (0.952).

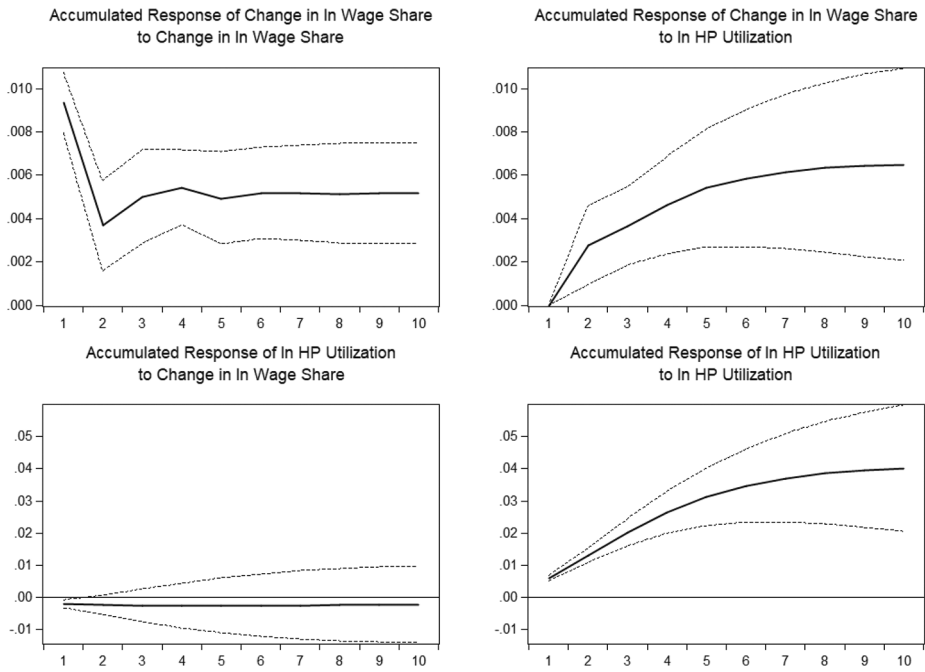
Figure A6 Complete IRFs for the Baseline Model in Period 1





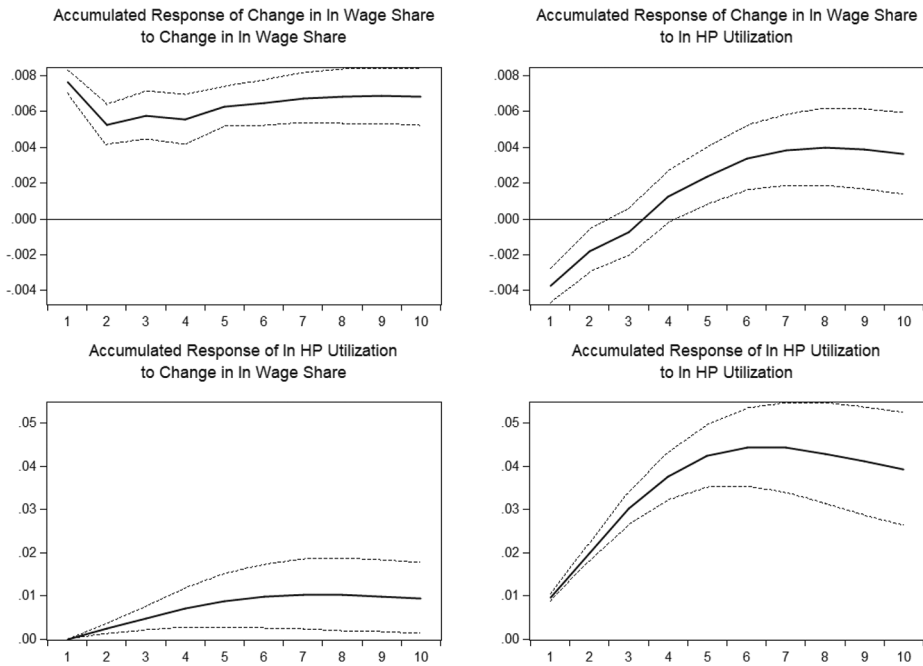
Notes: Sample period: 1971 Q1–1993 Q4.  
 Model specification: 6 lags and constant term.  
 Variable ordering:  $\Delta$  In wage share, In HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 61.64 (0.803).

Figure A7 Complete IRFs for the Baseline Model in Period 2



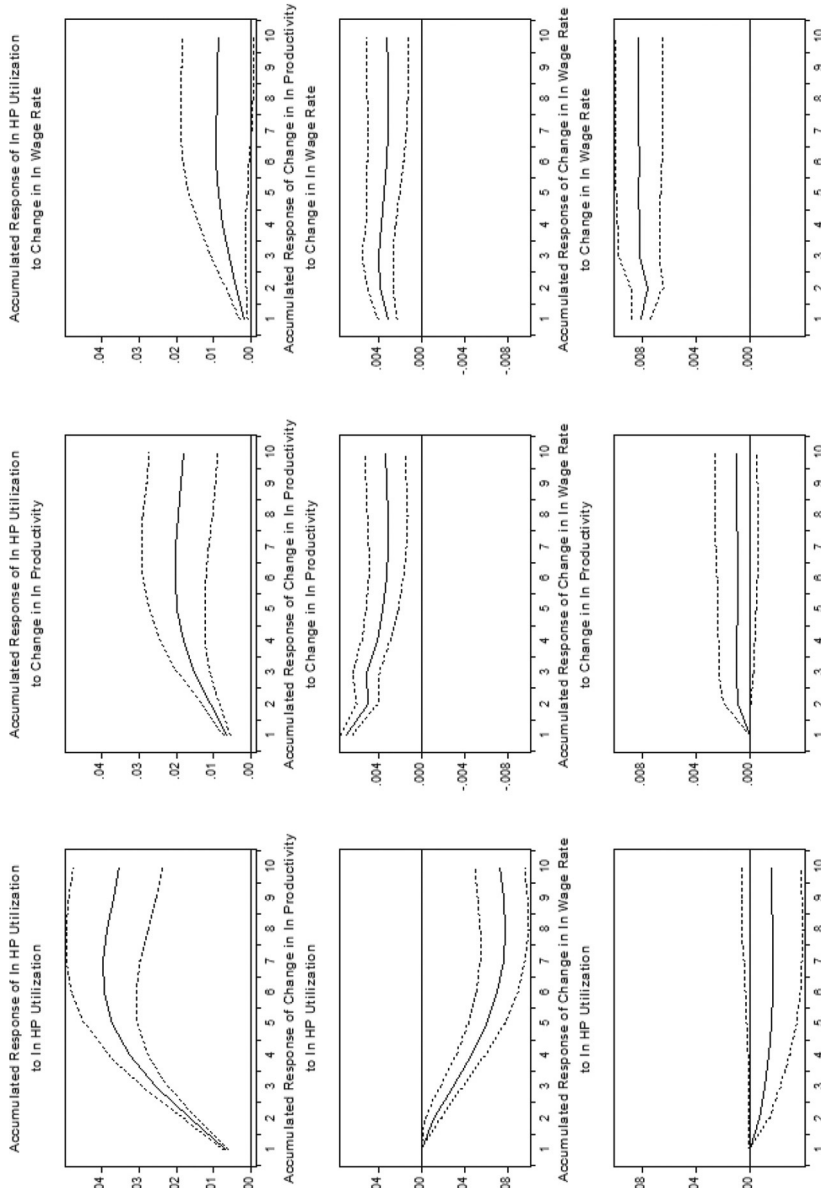
Notes: Sample period: 1994 Q1–2016 Q4.  
 Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta \ln$  wage share,  $\ln$  HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 28.26 (0.249).

Figure A8 Complete IRFs for the Baseline Model in Period 3



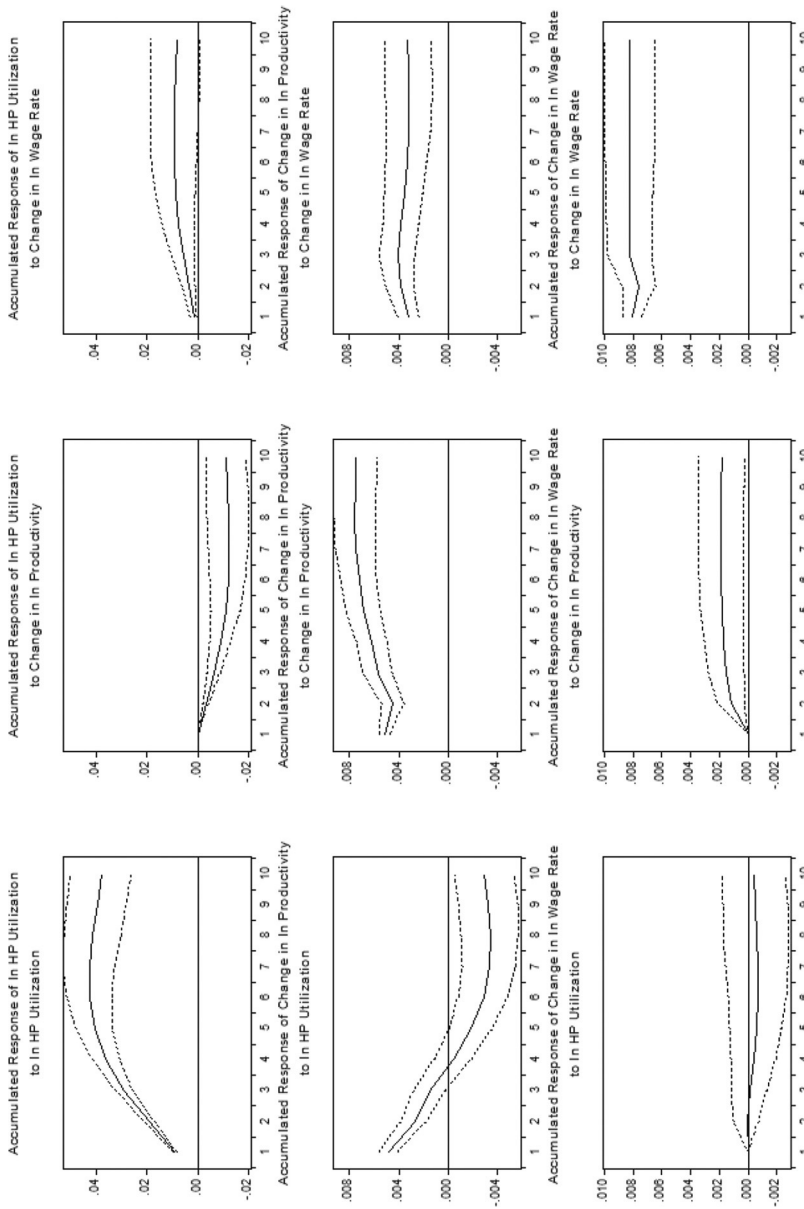
Notes: Sample period: 1948 Q1–2016 Q4.  
 Model specification: 3 lags and constant term.  
 Variable ordering:  $\Delta$  ln wage share, ln HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 41.38 (0.247).

Figure A9 Complete IRFs for Reverse Ordering Model with HP Utilization



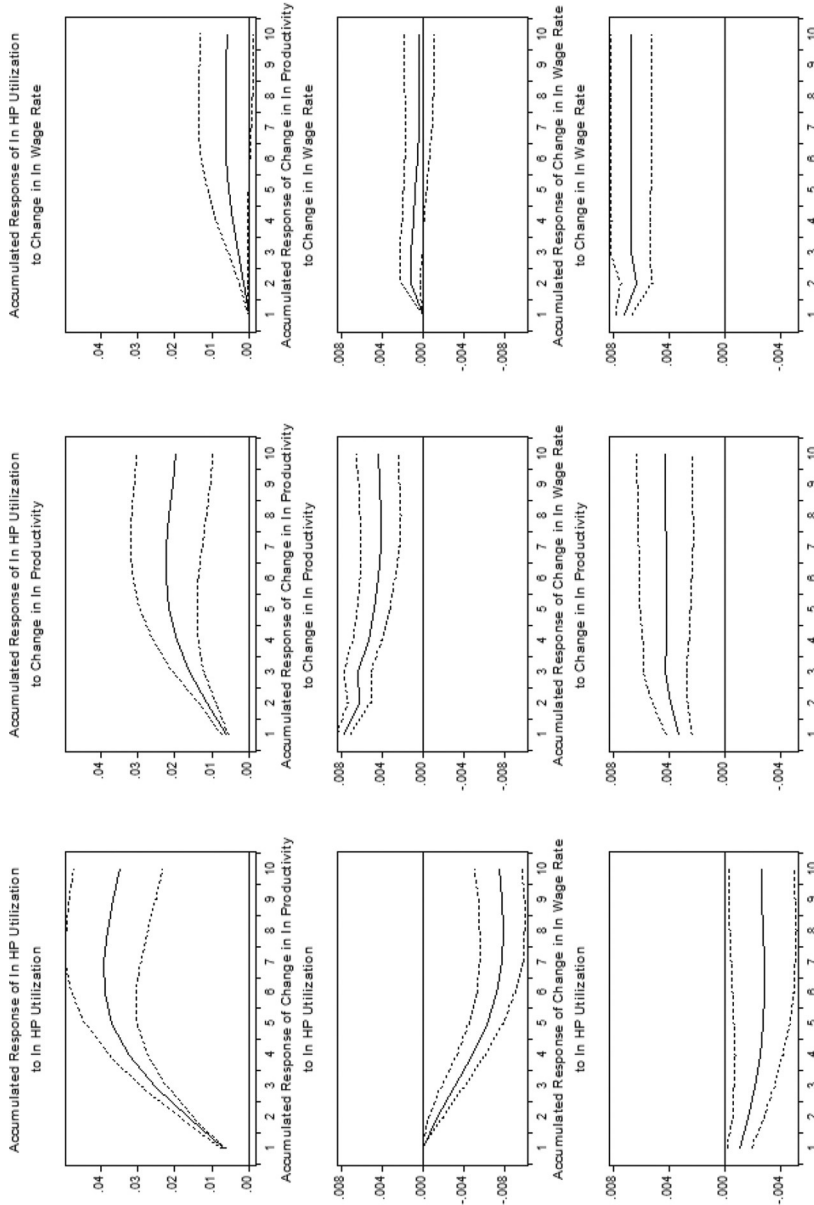
Notes: Sample period: 1947 Q4–2016 Q4; Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\Delta$  In productivity, In HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 91.80 (0.058).

Figure A10 Complete IRFs for Order 1 with HP Utilization



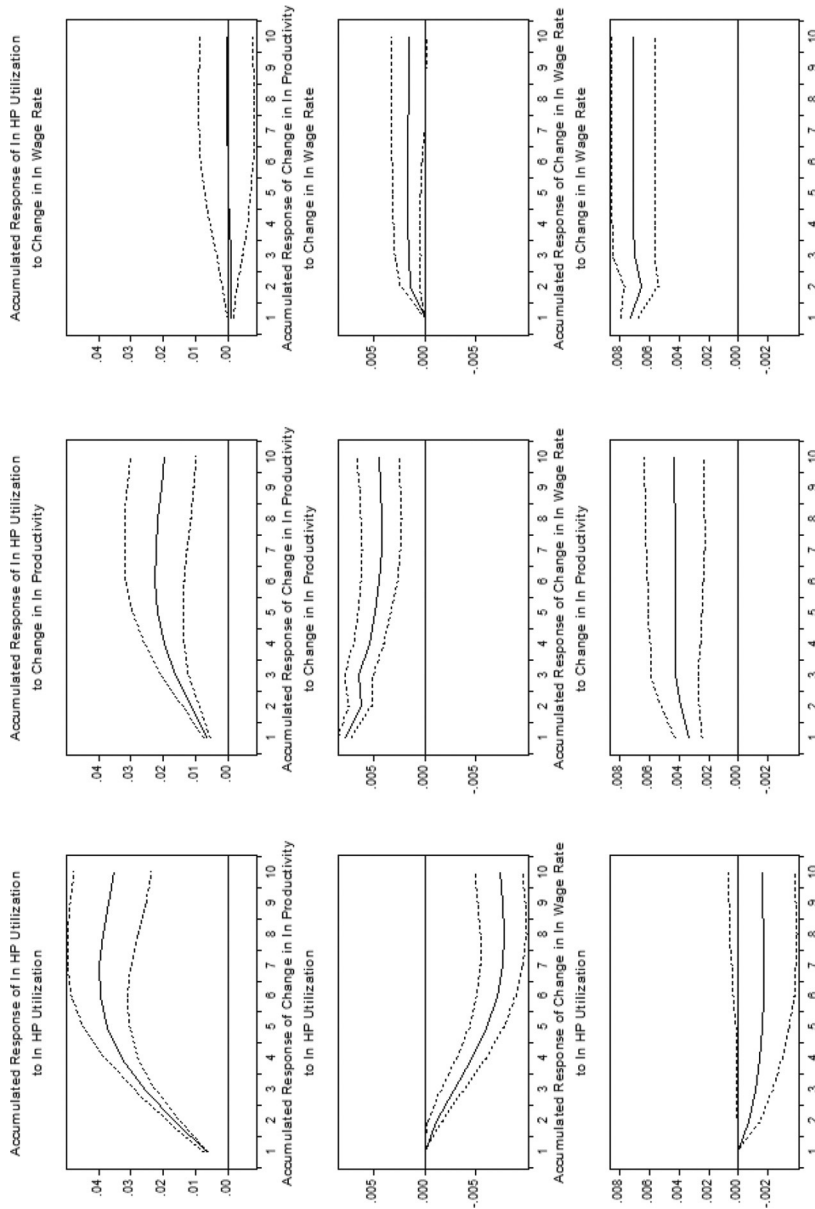
Notes: Sample period: 1947 Q4–2016 Q4; Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate, In HP utilization,  $\Delta$  In productivity.  
 White heteroskedasticity test statistic ( $p$ -value): 91.80 (0.058).

Figure A11 Complete IRFs for Order 2 with HP Utilization



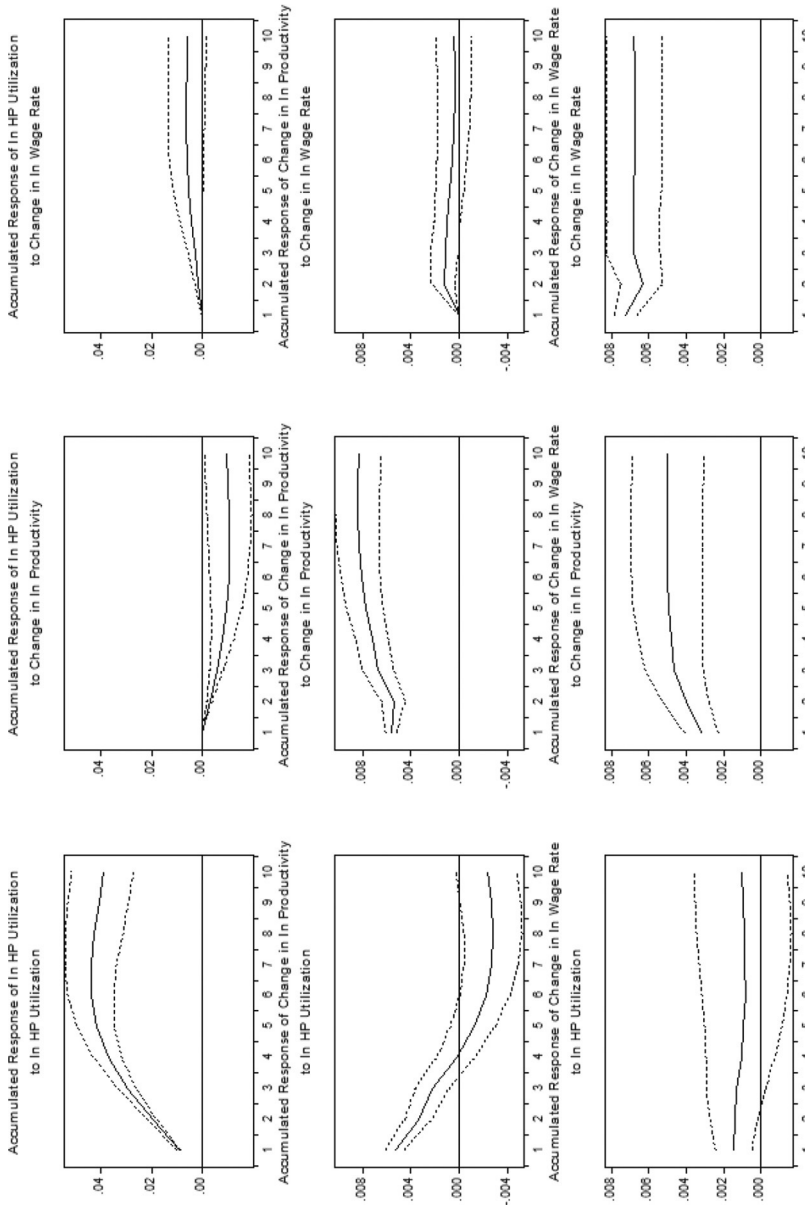
Notes: Sample period: 1947 Q4–2016 Q4; Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta$  In productivity, In HP utilization,  $\Delta$  real wage rate.  
 White heteroskedasticity test statistic ( $p$ -value): 91.80 (0.058).

Figure A12 Complete IRFs for Order 3 with HP Utilization



Notes: Sample period: 1947 Q4–2016 Q4; Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta$  In productivity,  $\Delta$  real wage rate, In HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 91.80 (0.058).

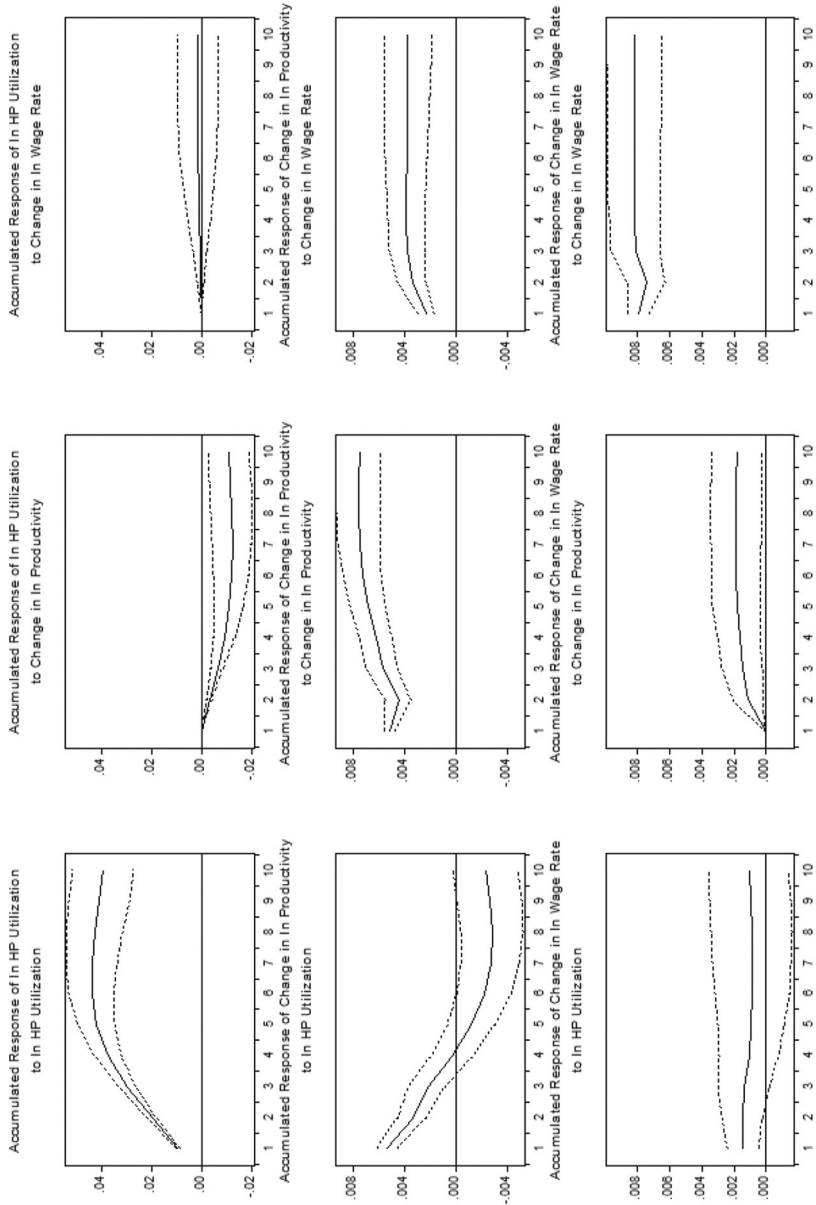
Figure A13 Complete IRFs for Order 4 with HP Utilization



Notes: Sample period: 1947 Q4–2016 Q4; Model specification: 2 lags and constant term. Variable ordering:  $\ln$  HP utilization,  $\Delta \ln$  productivity,  $\Delta$  real wage rate. White heteroskedasticity test statistic ( $p$ -value): 91.80 (0.058).

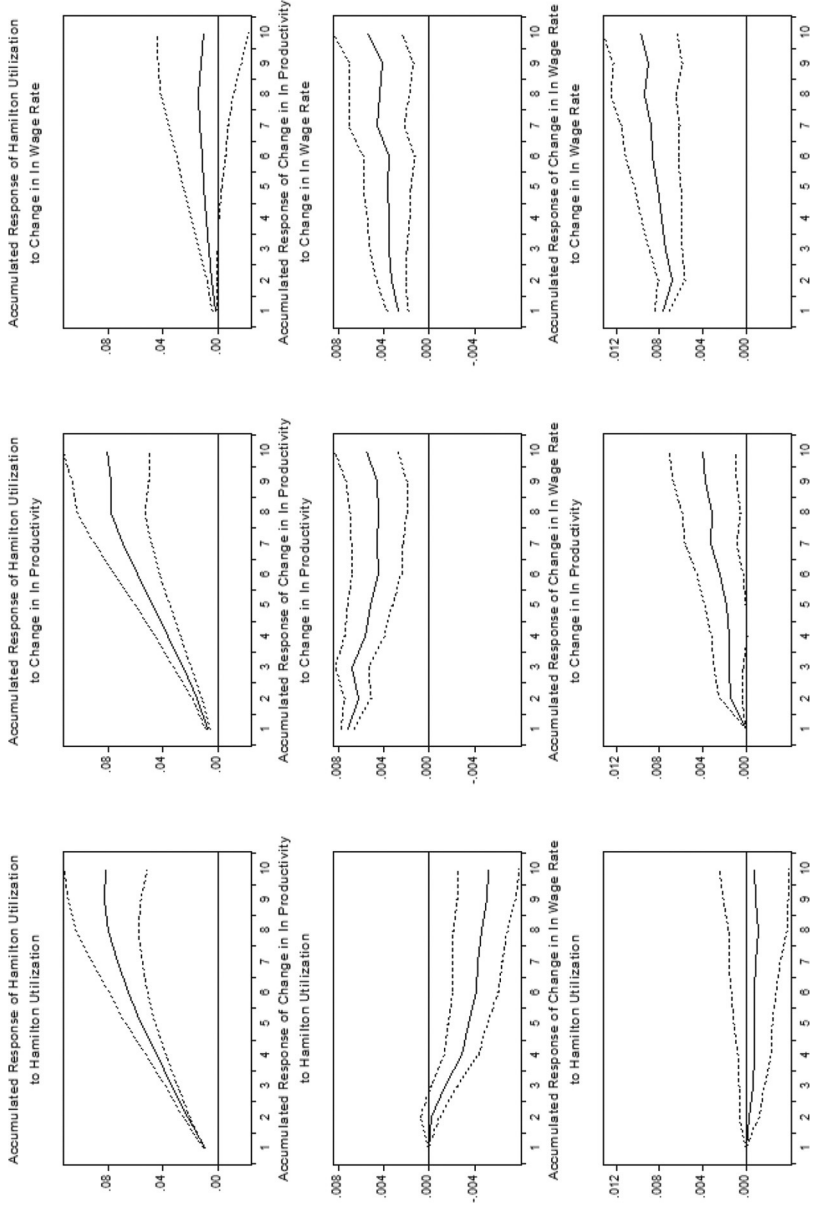
Figure A14 Complete IRFs for Order 5 with HP Utilization





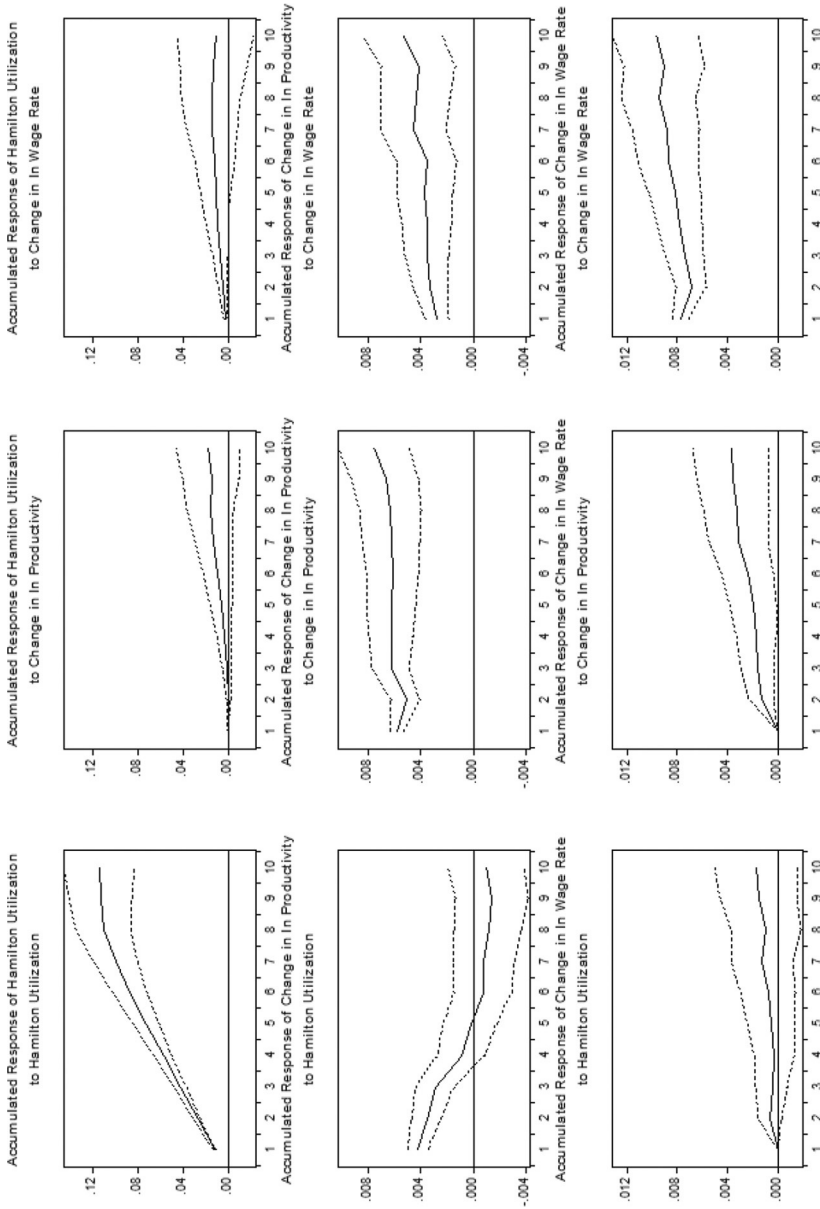
Notes: Sample period: 1947 Q4–2016 Q4; Model specification: 2 lags and constant term. Variable ordering: In HP utilization,  $\Delta$  real wage rate,  $\Delta$  In productivity. White heteroskedasticity test statistic ( $p$ -value): 91.80 (0.058).

Figure A15 Complete IRFs for Order 6 with HP Utilization



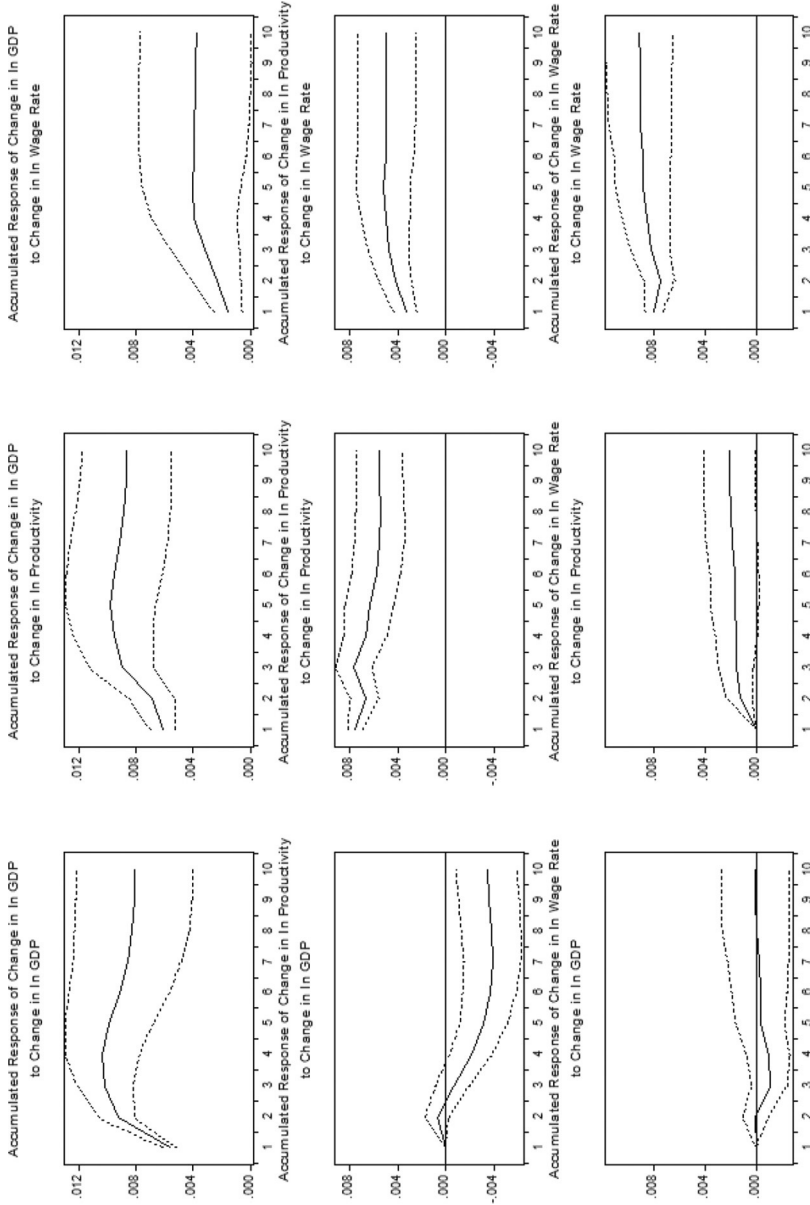
Notes: Sample period: 1952 Q1–2016 Q4; Model specification: 9 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\Delta$  In productivity, Hamilton utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 404.51 (0.002).

Figure A16 Complete IRFs for Order 1 with Hamilton Utilization



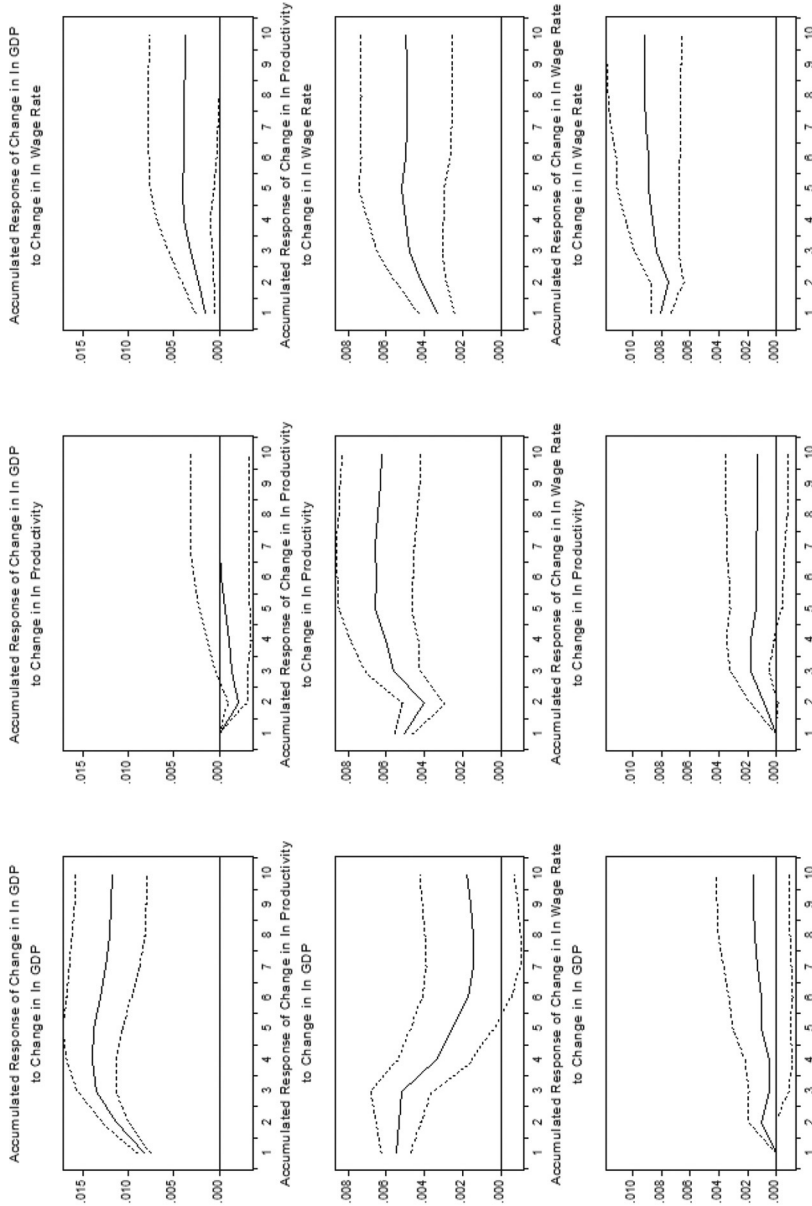
Notes: Sample period: 1952 Q1–2016 Q4; Model specification: 9 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate, Hamilton utilization,  $\Delta$  In productivity.  
 White heteroskedasticity test statistic ( $p$ -value): 404.51 (0.002).

Figure A17 Complete IRFs for Order 2 with Hamilton Utilization



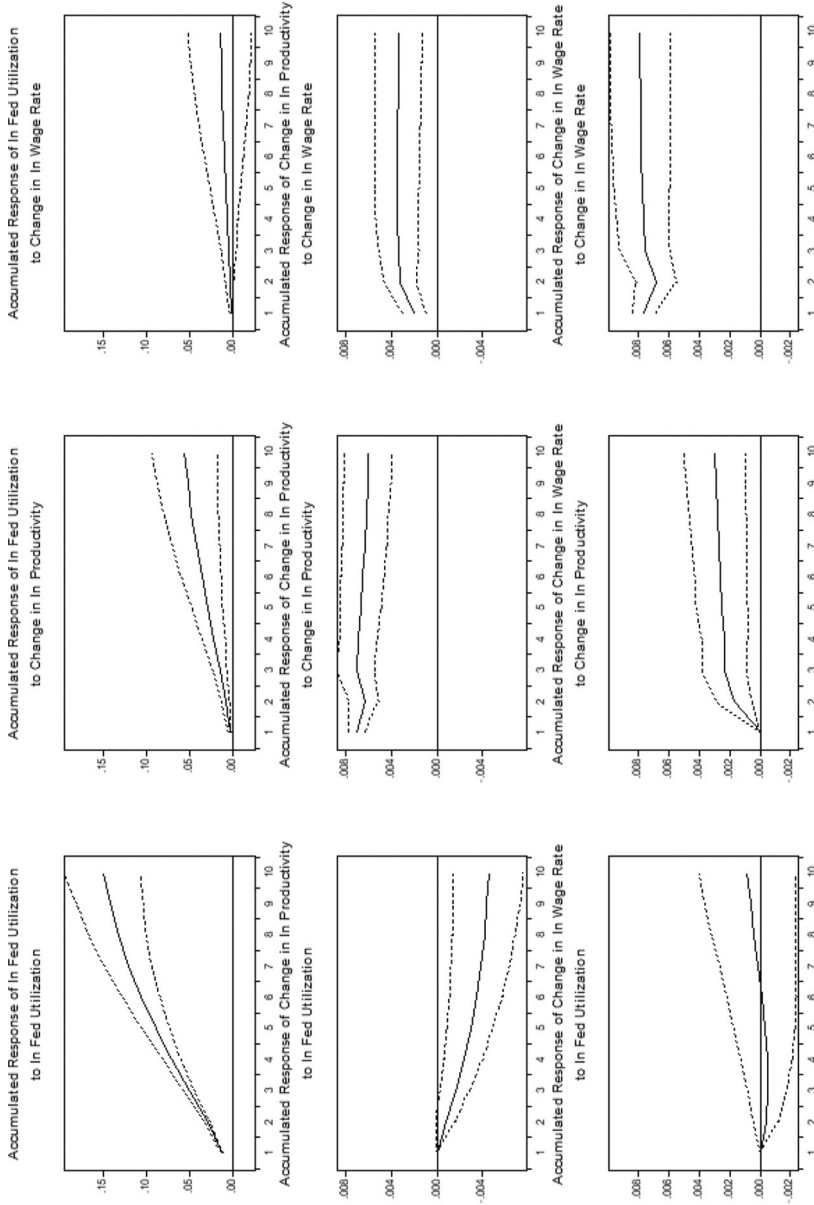
Notes: Sample period: 1948 Q2–2016 Q4; Model specification: 4 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\Delta$  In productivity,  $\Delta$  In real GDP.  
 White heteroskedasticity test statistic (p-value): 193.70 (0.004).

Figure A18 Complete IRFs for Order 1 with Real GDP



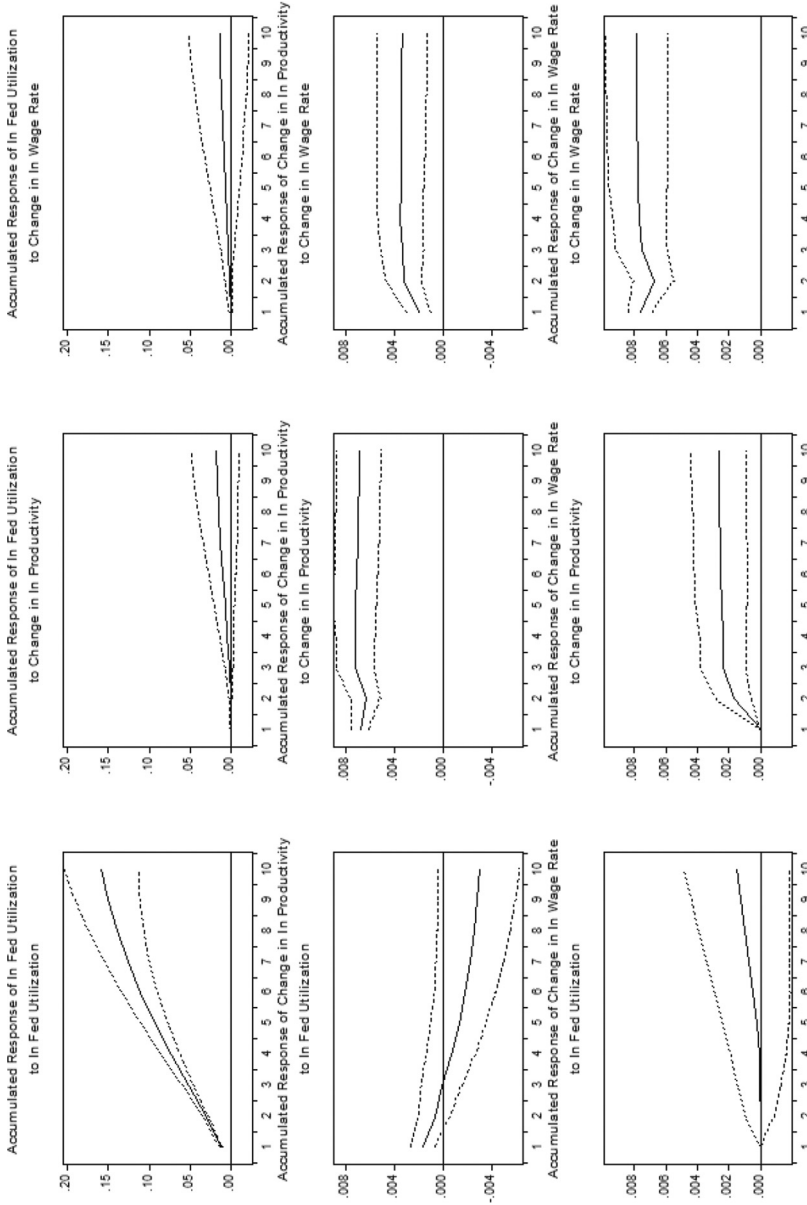
Notes: Sample period: 1948 Q2–2016 Q4; Model specification: 4 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\Delta$  ln real GDP,  $\Delta$  ln productivity.  
 White heteroskedasticity test statistic ( $p$ -value): 193.70 (0.004).

Figure A19 Complete IRFs for Order 2 with Real GDP



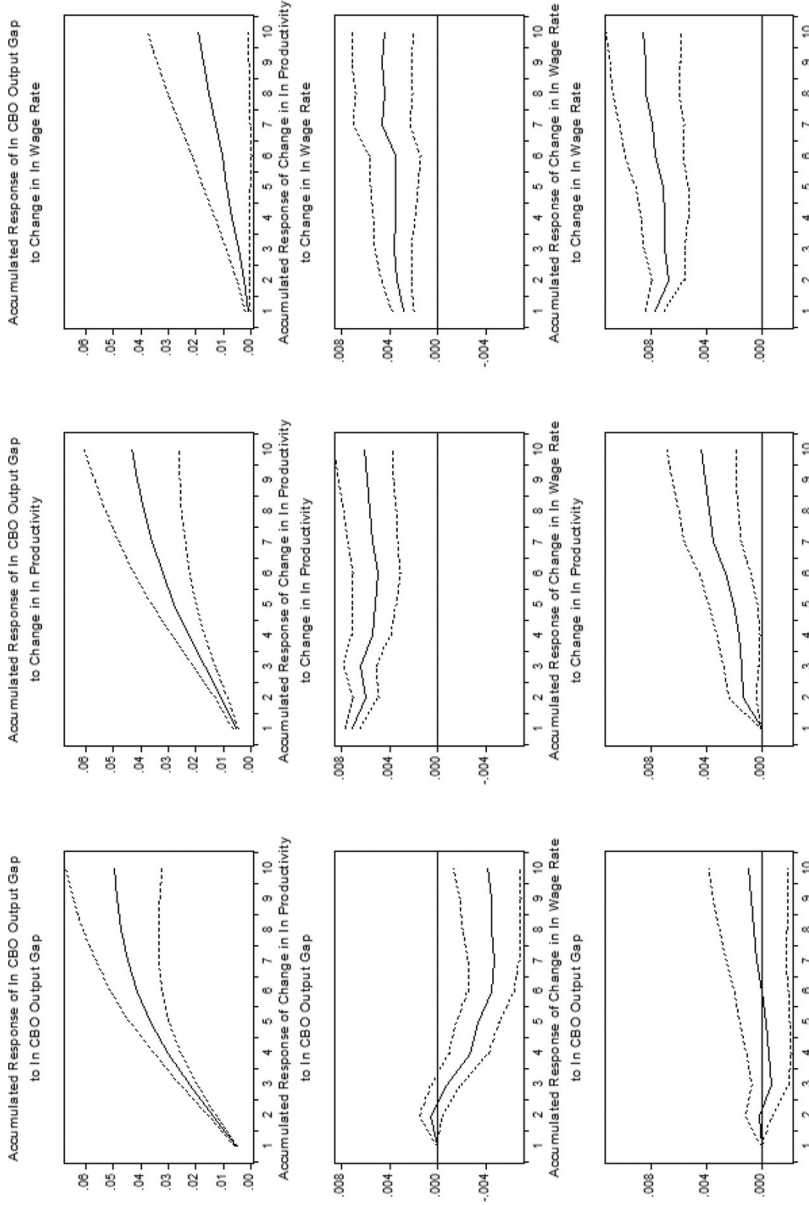
Notes: Sample period: 1967 Q3–2016 Q4; Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\Delta$  In productivity, In Fed utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 99.61 (0.017).

Figure A20 Complete IRFs for Order 1 with Fed Utilization Rate



Notes: Sample period: 1967 Q3–2016 Q4; Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\ln$  Fed utilization,  $\Delta \ln$  productivity.  
 White heteroskedasticity test statistic ( $p$ -value): 99.61 (0.017).

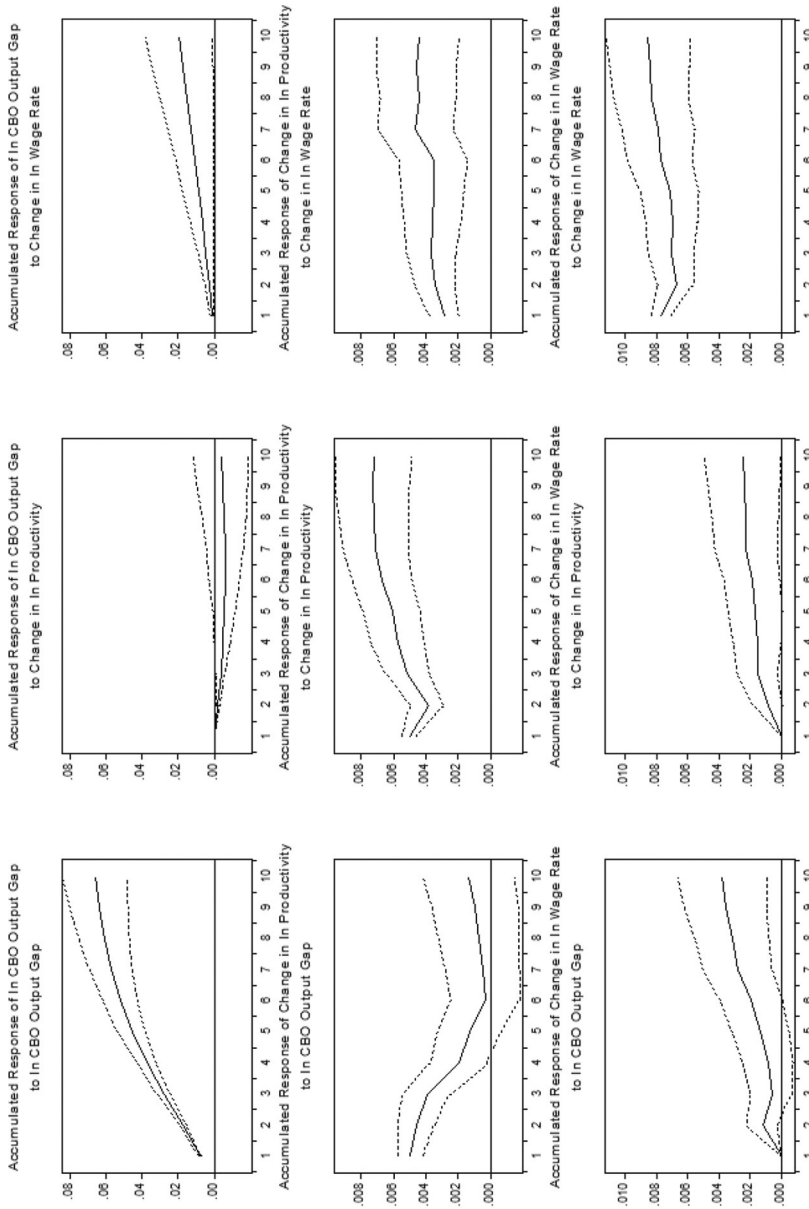
Figure A21 Complete IRFs for Order 2 with Fed Utilization Rate



Notes: Sample period: 1950 Q3–2016 Q4; Model specification: 6 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\Delta$  In productivity, In CBO output gap.  
 White heteroskedasticity test statistic ( $p$ -value): 241.17 (0.115).

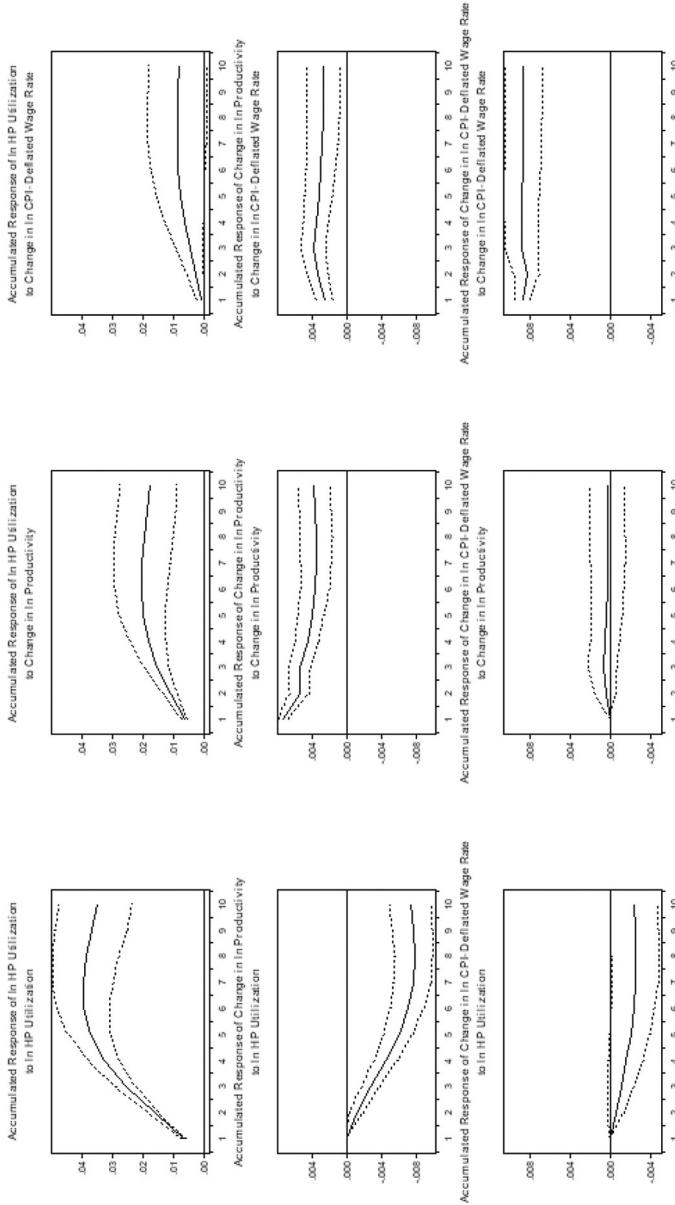
Figure A22 Complete IRFs for Order 1 with CBO Output Gap





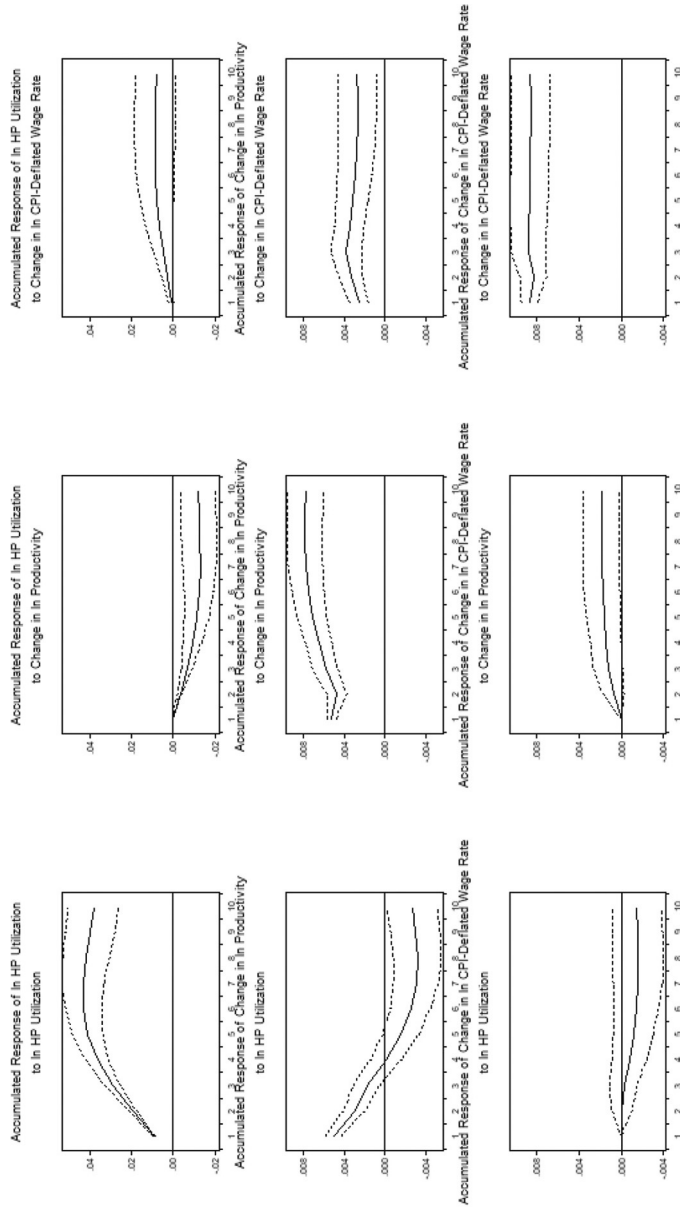
Notes: Sample period: 1950 Q3–2016 Q4; Model specification: 6 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate, In CBO output gap,  $\Delta$  In productivity.  
 White heteroskedasticity test statistic (p-value): 241.17 (0.115).

Figure A23 Complete IRFs for Order 2 with CBO Output Gap



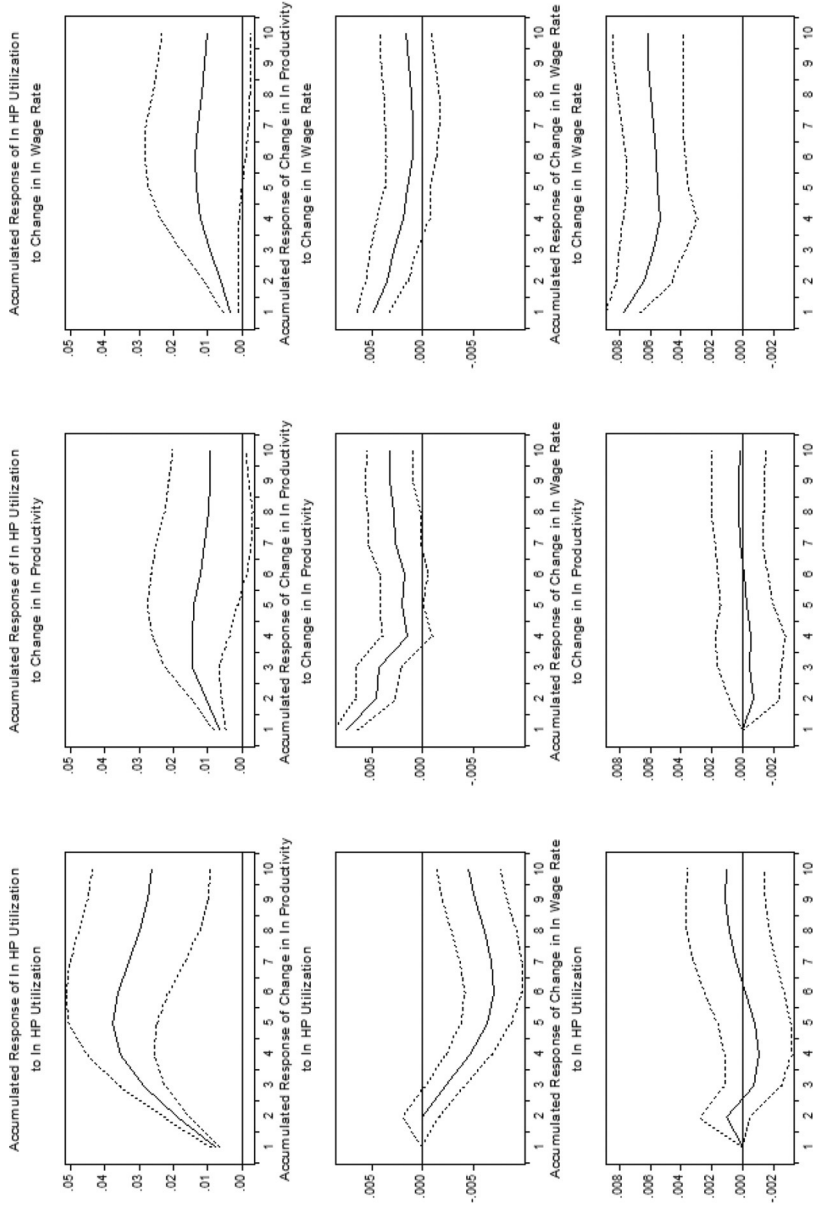
Notes: Sample period: 1947 Q4–2016 Q4; Model specification: 2 lags and constant term. Variable ordering:  $\Delta$  CPI-deflated wage rate,  $\Delta$  In productivity, In HP utilization. White heteroskedasticity test statistic ( $p$ -value): 121.15 (0.000).

Figure A24 Complete IRFs for Order 1 with CPI-deflated Wage Rate



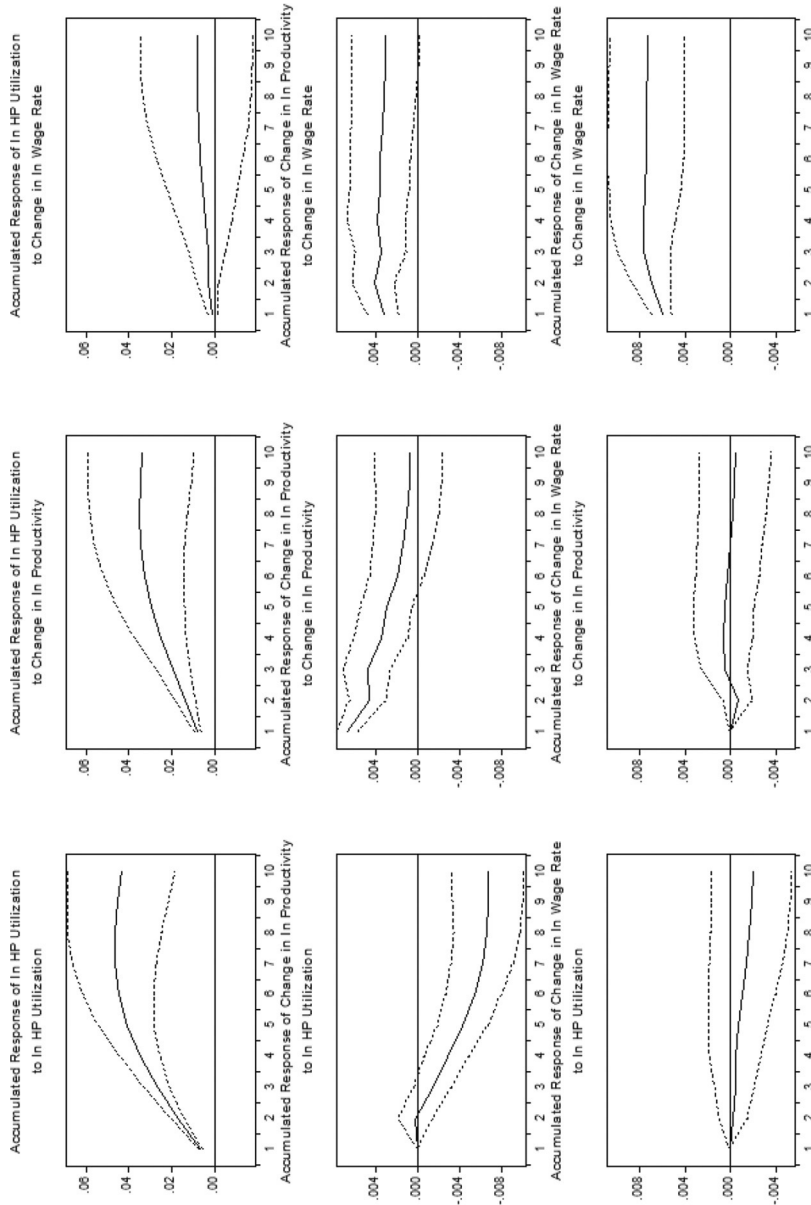
Notes: Sample period: 1947 Q4–2016 Q4; Model specification: 2 lags and constant term.  
 Variable ordering:  $\Delta$  CPI-deflated wage rate,  $\ln$  HP utilization,  $\Delta$  in productivity.  
 White heteroskedasticity test statistic ( $p$ -value): 121.15 (0.000).

Figure A25 Complete IRFs for Order 2 with CPI-deflated Wage rate



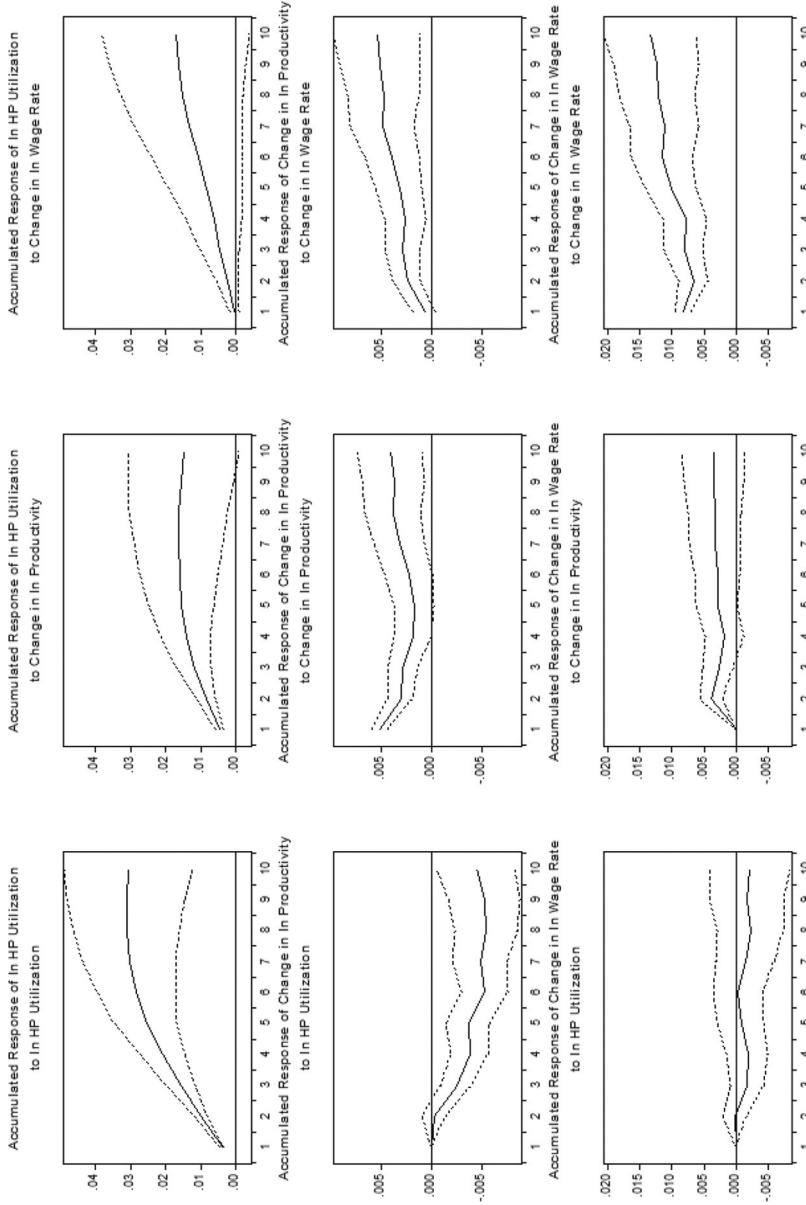
Notes: Sample period: 1948 Q1–1972 Q4; Model specification: 3 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\Delta$  In productivity, In HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 124.00 (0.139).

Figure A26 Complete IRFs for Order 1 in Period 1



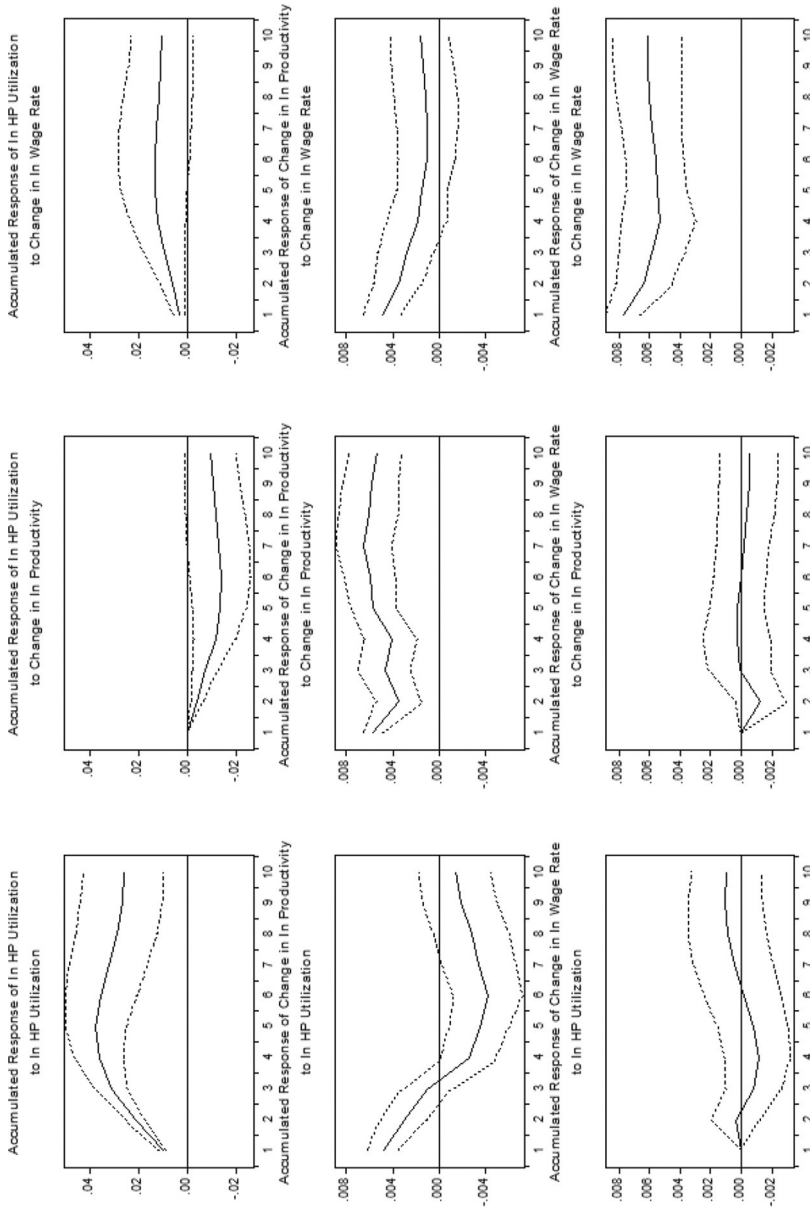
Notes: Sample period: 1971 Q1–1993 Q4; Model specification: 3 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\Delta$  In productivity,  $\Delta$  In HP utilization.  
 White heteroskedasticity test statistic ( $p$ -value): 112.38 (0.367).

Figure A27 Complete IRFs for Order 1 in Period 2



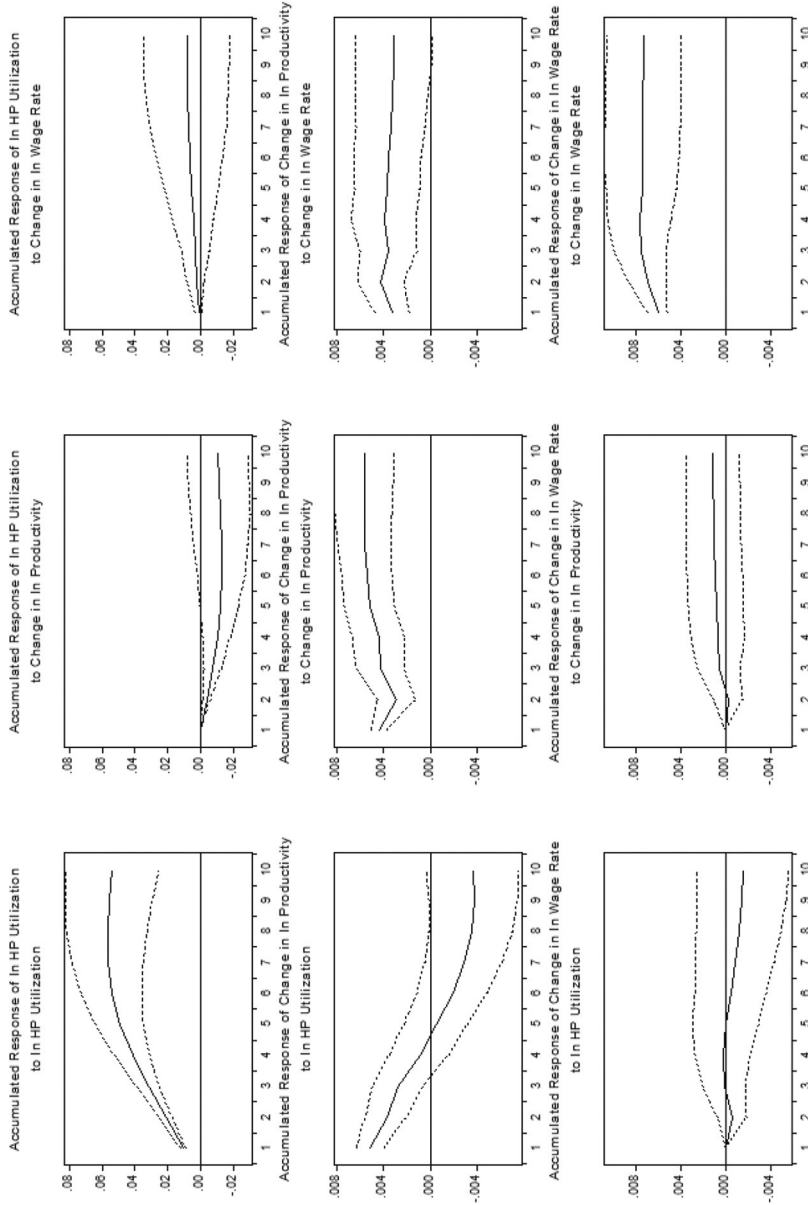
Notes: Sample period: 1994 Q1–2016 Q4; Model specification: 6 lags and constant term. Variable ordering:  $\Delta$  real wage rate,  $\Delta$  In productivity,  $\Delta$  In HP utilization. White heteroskedasticity test statistic ( $p$ -value): 231.22 (0.227).

Figure A28 Complete IRFs for Order 1 in Period 3



Notes: Sample period: 1948 Q1–1972 Q4; Model specification: 3 lags and constant term. Variable ordering:  $\Delta$  real wage rate, ln HP utilization,  $\Delta$  ln productivity. White heteroskedasticity test statistic ( $p$ -value): 124.00 (0.139).

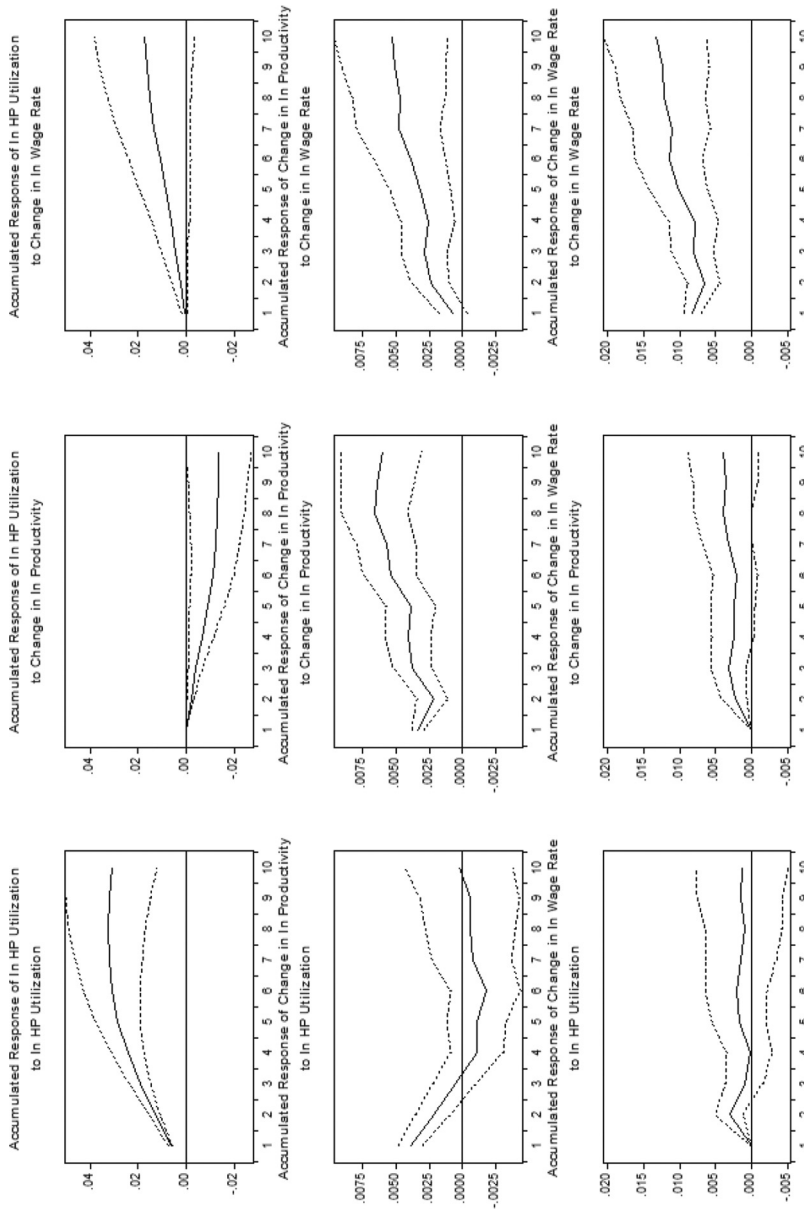
Figure A29 Complete IRFs for Order 2 in Period 1



Notes: Sample period: 1971 Q1–1993 Q4; Model specification: 3 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\ln$  HP utilization,  $\Delta \ln$  productivity.  
 White heteroskedasticity test statistic ( $p$ -value): 112.38 (0.367).

Figure A30 Complete IRFs for Order 2 in Period 2





Notes: Sample period: 1994 Q1–2016 Q4; Model specification: 6 lags and constant term.  
 Variable ordering:  $\Delta$  real wage rate,  $\ln$  HP utilization,  $\Delta \ln$  productivity.  
 White heteroskedasticity test statistic ( $p$ -value): 231.22 (0.227).

Figure A31 Complete IRFs for Order 2 in Period 3