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The neo-Goodwinian model reconsidered

Michael Cauvel

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The Neo-Goodwinian Model Reconsidered

Michael Cauvel*

Abstract

This paper estimates the relationship between aggregate demand and the functional distribution of income in the U.S. economy using a series of aggregative VAR models. Like most previous aggregative studies, it finds evidence of Goodwin cycle effects—i.e. profit-led demand and a profit-squeeze effect—for the U.S. economy in baseline estimates using assumptions traditionally used in the aggregative literature. However, the results of other specifications suggest that these observed Goodwin cycle effects likely reflect a misinterpretation of procyclical variation in labor productivity—one of the main components of the wage share. When correcting for the cyclical effects of demand on productivity, the results differ dramatically; estimates are indicative of wage-led demand, and the effects of demand on distribution are mixed or insignificant. These findings suggest that evidence of Goodwin cycle effects is likely the result of biased estimates. Instead, it appears that the short-run relationship between the wage share and demand should be viewed as a combination of wage-led demand and procyclical productivity effects.

Keywords: Functional distribution of income, neo-Kaleckian model, wage-led and profit-led demand regimes
JEL codes: E25, E11, E12, E32

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*Assistant Professor of Economics at Ithaca College. Correspondence: Department of Economics, 953 Danby Road, Ithaca, NY 14850. Email: mcauvel@ithaca.edu. Tel.: (607)-274-1521.

1 Introduction

The relationship between aggregate demand and the distribution of income is a topic of considerable importance, as research in this area may be able to identify policy options that could simultaneously make economies more equitable and more dynamic. Much of the recent research in this area has focused on the functional distribution of income—i.e., the share of total income going to wage earners vs. the share that is earned as profits. The focus on functional distribution can be explained in part by the strong theoretical framework for examining the relationship between the wage share and aggregate demand that neo-Kaleckian models have provided.

Following these theoretical models, many empirical studies have sought to characterize demand regimes as either "wage-led," with a higher wage share leading to higher aggregate demand, or "profit-led," with a lower wage share leading to higher aggregate demand.[1] However, despite much empirical work in this area, previous attempts to estimate this relationship have not resolved the issue, as results vary drastically across studies. Although the idiosyncrasies of individual studies contribute to the disagreement among results, Blecker (2016) notes that the studies' varying results tend to depend upon the methodological approach that they follow. Structural models, which estimate the relationship between the wage share and the individual components of aggregate demand (see e.g. Stockhammer and Wildauer, 2016; Stockhammer et al., 2011; Onaran and Galanis, 2012; Onaran et al., 2011; Onaran and Obst, 2016), tend to find more evidence of wage-led demand (except in cases of small, open economies), whereas aggregative models (e.g. Barbosa-Filho and Taylor, 2006; Carvalho and Rezai, 2016; Kiefer and Rada, 2015; Silva de Jesus et al., 2018; Diallo et al.,

[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.

2011), which estimate the relationship between the wage share and the capacity utilization rate, tend to find uniformly profit-led results.

Although structural studies generally focus on the effect of the functional distribution of income on demand, aggregative studies often examine this relationship from both directions of causality. In addition to their general finding that demand is profit-led, these studies typically find a "profit-squeeze" result, wherein an increase in utilization leads to a reduction in profits. Together, these two results suggest a cyclical relationship between these two variables, in which an initial increase in the profit share (i.e. a decrease in the wage share) leads to higher demand, which in turn reduces profits. This cyclical pattern is often called a "Goodwin cycle," as it resembles the relationship suggested by Goodwin (1967).[2]

One potential explanation for the differences in the results typically found by aggregative and structural studies is that that the methodology used in many aggregative studies could bias results. Lavoie (2017) argues that models that do not account for the cyclical variation of labor productivity—a component the wage share—will be biased towards findings of profit-led demand. Furthermore, measurement error resulting from the use of a Hodrick and Prescott (HP) (1997) filter to calculate the utilization rate measure in some aggregative studies also has the potential to introduce bias (Blecker, 2016; Barrales and von Arnim, 2017).[3]

Although the literature has theorized that these potential sources of misspecification may bias existing aggregative estimates, little work has yet been done to test these hypothe-

[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.

[3]Others have proposed alternative hypotheses. Critics of the structural approach, such as Barrales and von Arnim (2017) and Kiefer and Rada (2015), argue that the wage-led findings of structural studies are driven by improperly treating the wage share as exogenous. Blecker (2016) suggests that there may be differing effects in the short run and the long run, and that the two types of studies could be capturing effects at different time horizons due to differences in the methodologies that they generally employ.

ses. This paper explores these issues empirically in the context of the U.S economy. It examines how cyclical variation in labor productivity affects aggregative estimates of the bi-directional demand-distribution relationship and introduces a method to adjust estimates for these effects. It also constructs a measure of the utilization rate using an alternative filtering technique, proposed by Hamilton (2018), that avoids some of the potential measurement error caused by the use of an HP filter.

Initial estimates, found using a model specification that maintains the assumptions of previous aggregative studies, find evidence of Goodwin cycle effects. However, further investigation reveals that these results likely reflect a misinterpretation of the cyclical effects of demand on labor productivity. VAR models that separate the real wage rate and labor productivity—the two primary components of the wage share—reveal that estimates are highly sensitive to the ordering restrictions relating productivity and demand. The findings indicate that stronger estimates of profit-led demand and profit-squeeze effects will be found when using restrictions that enforce the assumption, implicit in previous aggregative studies, that demand has only a lagged effect on labor productivity. When such restrictions are imposed, the contemporaneous correlation between demand and productivity will be interpreted as an effect of productivity (and therefore the wage share) on demand, even though it likely reflects procyclical variation in productivity. These findings suggest that Lavoie's (2017) critique of previous aggregative studies is valid and some previous aggregative estimates are likely biased.

Moreover, when using filters to separate the cyclical variation in productivity from the wage share, the Goodwin cycle pattern is not found. The results instead suggest that demand is wage-led, and the effects of demand on distribution are mixed or insignificant. These results are found regardless of whether the utilization rate is constructed using the conventional HP filtering technique or the preferred method introduced by Hamilton (2018). These findings suggest that previous estimates of Goodwin cycle effects are spurious, capturing a positive effect of demand on productivity, rather than a negative effect of the wage share on demand.

Therefore, it appears that the short-run relationship between the wage share and demand should be viewed as a combination of wage-led demand and procyclical productivity effects, rather than profit-led demand and profit-squeeze effects, at least in the case of the U.S.

To the author's knowledge, this is the first study to examine how the relationship between demand and labor productivity impacts estimates of the relationship between the wage share and the utilization rate. It introduces two methods for treating these productivity effects: separate exploration of the relationship between utilization and the two main components of the wage share, and the use of an cyclically adjusted wage share measure from which the cyclical variation in labor productivity has been separated. It is also the first study to use the Hamilton (2018) filter to examine the relationship between the wage share and capacity utilization.

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 vector autoregression (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 U.S. 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 Theoretical Framework and Literature Review

2.1 Theoretical Framework

A sizable literature exists on the empirical relationship between demand and the function distribution of income.[4] This literature 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 (e.g. Rowthorn, 1982; Taylor, 1983; Dutt, 1984; Taylor, 1985; Dutt, 1987; Blecker, 1989; Bhaduri and Marglin, 1990; Marglin and Bhaduri, 1990; Blecker, 2002).

A basic version of the neo-Kaleckian model is presented below.[5]

$$Y = AD = C + I + G + NX \tag{1}$$

Equation (1) 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:

$$C = C(Y, \psi, Z_c) \tag{2}$$

$$I = I(Y, \psi, Z_I) \tag{3}$$

[4]Stockhammer (2017) estimates that there are approximately two dozen empirical studies on the subject.

[5]This discussion of the model and how it relates to different approaches to estimating the relationship between demand and the functional distribution of income is largely based on the presentation in Blecker (2016). The model in Blecker (2016) is a simplified version of the one presented by presented by Stockhammer et al. (2011).

$$NX = NX(Y, P, Z_X, Z_M); P = P(\psi, Z_P) \tag{4}$$

Each of these components, with the exception of government spending, is a function of output (Y), the wage share (ψ), 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 a function of the wage share and a vector of control variables, such as the real exchange rate and the foreign price level. 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:

$$Y = AD = C(Y, \psi, Z_C) + I(Y, \psi, Z_I) + G + NX(Y, P, Z_X, Z_M) \tag{5}$$

The following assumptions are commonly made regarding the signs of the partial derivatives of the components of aggregate demand: $C_Y > 0$, $C_\psi > 0$, $I_Y > 0$, $I_\psi < 0$, $NX_Y < 0$, $P_\psi > 0$, $NX_P < 0$. Following these assumptions, 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 ψ.

$$\frac{\partial Y}{\partial \psi} = \frac{\partial AD/\partial \psi}{1 - \partial AD/\partial Y} \tag{6}$$

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 the condition (7) to be satisfied:

$$\frac{\partial AD}{\partial Y} = \frac{\partial AD}{\partial C} + \frac{\partial AD}{\partial I} + \frac{\partial AD}{\partial NX} < 1 \tag{7}$$

Therefore, in a stable system, the denominator of equation (6) 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 $\partial AD/\partial\psi > 0$, i.e., demand is wage-led (see e.g. Stockhammer and Wildauer, 2016; Stockhammer et al., 2011; Onaran and Galanis, 2012; Onaran et al., 2011; Onaran and Obst, 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:

$$Y = Y(\psi, Z_C, Z_I, Z_X, Z_M, Z_P) \tag{8}$$

Aggregative models typically combine this with an equation for the wage share, like equation (9) to make distribution endogenous.

$$\psi = \psi(Y, Z_\psi) \tag{9}$$

Those following the aggregative approach typically try to estimate difference equation versions of equations (10) and (11) 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.

$$\dot{u} = f(u, \psi) \tag{10}$$

$$\dot{\psi} = g(\psi, u) \tag{11}$$

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 and Taylor (2006) have used the utilization rate (see Carvalho and Rezai, 2016; Kiefer and Rada, 2015; Barrales and von Arnim, 2017; Nikiforos and Foley, 2012).[6] These studies use mainly lags of u and ψ 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 and Taylor, 2006). The slopes of the nullclines, $-f_u/f_\psi$ for the effective demand scheulde 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 find 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 and Taylor (2006). This outcome requires a negative derivative of u with respect to ψ and a positive derivative of ψ with respect to u. The presence of cyclical dynamics depends on the functional form used by Barbosa-Filho and Taylor (2006). The models used in this paper will estimate the slopes of these nullclines.

[6] 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 e.g. Harvie, 2000; Grasselli and Maheshwari, 2017; Desai, 1984).

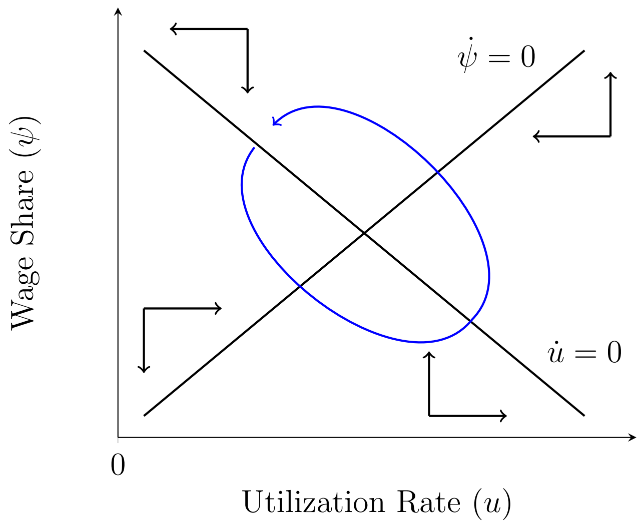

Figure 1: System with Profit-led Demand and Profit-squeeze Effects
Adapted from Barbosa-Filho and Taylor (2006)

2.2 Literature Review

Barbosa-Filho and Taylor (2006) estimated a difference equation version of the system in equations (10) and (11) for the U.S. from 1948-2002 using a reduced form VAR with two lags.[7] They found evidence of a Goodwin cycle, i.e. profit-led demand and a profit squeeze.[8] Using data for 1967-2010 and a TVAR model in which the sample is broken up into different regimes based on the value of the Gini coefficient, Carvalho and 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.[9] Other aggregative studies have found evidence of similar dynamics using different techniques or country samples.[10] Kiefer and Rada (2015)

[7] 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.

[8] Stockhammer and Stehrer (2011) argue that these results are biased due to autocorrelation problems, and likely sensitive to lag length.

[9] 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.

[10] An early study by Stockhammer and 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

estimate a system of equations for the wage share and utilization rate for a panel of 13 OECD countries using 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 instrumental variables GMM applied to U.S. data from 1973-2008 and find evidence of both profit-led demand and a profit-squeeze. Barrales and von Arnim (2017) use a wavelet decomposition to estimate cyclical dynamics of the U.S. 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 U.S., U.K., 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 and Foley (2012) find evidence that the distributive schedule is nonlinear, suggesting the existence of multiple equilibria. Their model is estimated for different subsamples using 2SLS applied to U.S. data. However, their full sample estimates are indicative of Goodwin cycle effects.

The U.S. 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 U.S. are usually indicative of wage-led demand (e.g., Onaran et al., 2011; Onaran and Galanis, 2012). 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.

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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 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.

It is possible that misspecification of aggregative models contributes to these differences. The literature has identified some issues that may bias the results of previous aggregative models. One major issue is that the these studies do not account for the effects of cyclical variation in labor productivity.[11] Lavoie (2014, 323-5) argues that the presence of overhead or managerial labor can cause labor productivity to vary procyclically with the utilization rate.[12] Because the wage share is equal to the hourly wage divided by labor productivity, as shown in equation (12),[13] the procyclicality of labor productivity will make the wage share countercyclical, as an increase in the utilization rate will lead to a decrease in the wage share, via an increase in labor productivity.[14]

$$\begin{aligned} \psi = \frac{worker\ compensation}{output} &= \frac{worker\ compensation/hours}{output/hours} \\ &= \frac{real\ hourly\ wage\ rate}{labor\ productivity} \end{aligned} \tag{12}$$

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 the cyclical effects on productivity. As Lavoie (2017, p. 212) explains:

[11] Although structural studies do not typically consider these effects either, such short-run variation in productivity is most likely to affect estimates of short-run dynamics found using quarterly data (Lavoie, 2017). Blecker (2016) argues that typical methodological decisions make aggregative studies more likely to capture short-run effects, while structural studies are more likely to capture a longer-term effect.

[12] 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 procyclically had previously been made by others, such as Sherman and Evans (1984) and Hahnel and Sherman (1982) in their critiques of Weisskopf (1979).

[13] 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.

[14] Although Lavoie's model suggests that the presence of managerial labor is one reason why productivity is procyclical, there are other potential reasons why productivity may be cyclical. These include variable effort and capital utilization over the course of the business cycle, as well as labor hoarding (see Gordon and Solow (2003) for a full discussion).

> ...in 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.

However, previous studies following the aggregative approach have not controlled for the role of cyclical variation in labor productivity in estimating the relationship between the utilization rate and the wage share.

Some aggregative studies have also been criticized for their measurement choices. A common measure of the utilization rate is the deviation of output from the trend of the output series, found by applying an HP filter (see Barbosa-Filho and Taylor, 2006; Carvalho and Rezai, 2016; Nikiforos and Foley, 2012). There are reasons to doubt whether this is an accurate measure of capacity utilization, due to several well-documented issues with this methodology. Cogley and 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 and Krenn (2010) argue that filtering techniques lead to implausible estimates of trend capacity. Barrales and 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, p. 831) offers this explanation for why this technique should never 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 spuri-

ous dynamics. (c) A statistical formalization of the problem typically produces values for the smoothing parameter vastly at odds with common practice.

Therefore, it is possible that the use of this measurement approach has biased the results of the aggregative studies that have used it.

This may not be a sensible way to measure demand, even if potential output were not calculated using an HP filter. Cerra and 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.[15] 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 (Cerra and Saxena, 2017; Borio et al., 2013). Moreover, it is not clear how these measures should be interpreted. As Cerra and 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.

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 found using alternative specifications. The

[15] Although their analysis mostly focuses on the output gap—or the difference between output and potential output—it applies to the utilization rate as well, as this measure is simply another way of comparing output and potential output.

baseline model is a VAR that combines elements of the models used by Barbosa-Filho and Taylor (2006) and Carvalho and Rezai (2016). Barbosa-Filho and Taylor (2006) estimated a VAR of the following form:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \sum_{j=1}^{L} \boldsymbol{F_j} \boldsymbol{y_{t-j}} + \boldsymbol{e_t} \tag{13}$$

where t is the time period, $\boldsymbol{y_t}$ is a vector of dependent variables, and $\boldsymbol{F_j}$ represents the coefficient matrices to be estimated, $\boldsymbol{\mu}$ is the constant, $\boldsymbol{e_t}$ is the error term, $j = 1, . . ., L$ indexes time period, and L is the number of lags.

This model is very similar to the one used by Carvalho and 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 nonstationary. In this way, the baseline model also diverges from the methodology of Barbosa-Filho and 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.[16] Another difference from the Barbosa-Filho and 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.

[16]The components of the wage share, which are used in some specifications, are logged as well.

Following this estimation, modified versions of the model are estimated and compared to the results of the baseline model. These additional specifications use different methods of treating productivity effects. One uses alternative ordering restrictions, another replaces the wage share with its two primary components—labor productivity and the real hourly wage—and a third separates the cyclical component of labor productivity from the wage share. In all specifications, the lag length is determined by using the Hannan-Quinn Information Criterion (HQIC), which is the recommended information criterion when using quarterly data and a sample size above 120 (see Ivanov and Kilian, 2005).

As in Carvalho and 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 other 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 impulse response functions require keeping all errors but one constant, and this is not possible if the errors are correlated (Stock and 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 and Taylor (2006) do not use Cholesky decomposition, the ordering used in Carvalho and Rezai (2016) is used for the baseline model:[17]

$$\boldsymbol{y_t} = [\Delta\ ln\ wage\ share_t, ln\ utilization_t] \tag{14}$$

[17]In a study of the Brazilian economy Silva de Jesus et al. (2018) use a VAR model with generalized impulse response functions (GIRFs), for which the variable ordering does not matter. While insensitivity to ordering is a benefit of GIRFs, they also have a downside. 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. Furthermore, because results for all possible orderings are reported for all specifications, GIRFs would not provide any additional information, as they simply combine IRFs from estimates with different orderings. For this reason, GIRFs are not used.

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.[18] In fact, if the wage share is countercyclical due to the procyclicality of labor productivity, as argued by Lavoie (2014, 323-5), the reverse ordering may be more appropriate, because it would allow labor productivity to vary contemporaneously with shocks to utilization. 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. The importance of the cyclicality of productivity is also explored with an alternative model separating the cyclical variation in labor productivity from the wage share.

3.2 Data

All models are estimated using quarterly U.S. data from 1947-2016.[19] For comparison to the previous literature, one measure of the utilization rate that is used is constructed using the same techniques as Barbosa-Filho and Taylor (2006) and Carvalho and 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

[18]Stockhammer and Onaran (2004) impose the opposite restrictions in their structural VAR, allowing demand to impact the profit share contemporaneously, but not the reverse. They justify this by arguing that the profit share will fluctuate automatically with demand if markups are constant and labor costs are fixed, while consumption may be slow to adjust to income. However, the assumptions regarding markups and labor costs may not be plausible. Furthermore, as Blecker (2016) points out, investment and net exports may adjust more quickly than consumption, and these components of output will also impact the utilization rate.

[19]However, data transformations and lags lead to shorter sample periods.

component of output obtained by applying an HP filter to the output series.[20] The output series is the BLS index of real business sector output. The resulting series is multiplied by 100.

Due to some of the documented issues with the HP filter, this measure of the utilization rate could be biased. Therefore, a preferred measure of the utilization rate is 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—i.e. separating a stationary cyclical component from a nonstationary series—without many of the drawbacks. Following his methodology, the cyclical component of the output series is found by simply taking the residuals of an OLS regression of equation (15), while the predicted values from this regression represent the trend component.

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

The utilization rate is therefore measured as the cyclical component of the output series, i.e. the estimated residuals from this regression—$\hat{\epsilon}_t$. 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-year-ahead forecast based on observations for the preceding year.[21] Because the cycle and trend components are calculated using only past data, this technique is not subject to Cerra and 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.

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-

[20]The standard value of the smoothing parameter for quarterly data, 1,600, is used for filtering.
[21]This is what Hamilton (2018) recommends for analysis of business cycle effects.

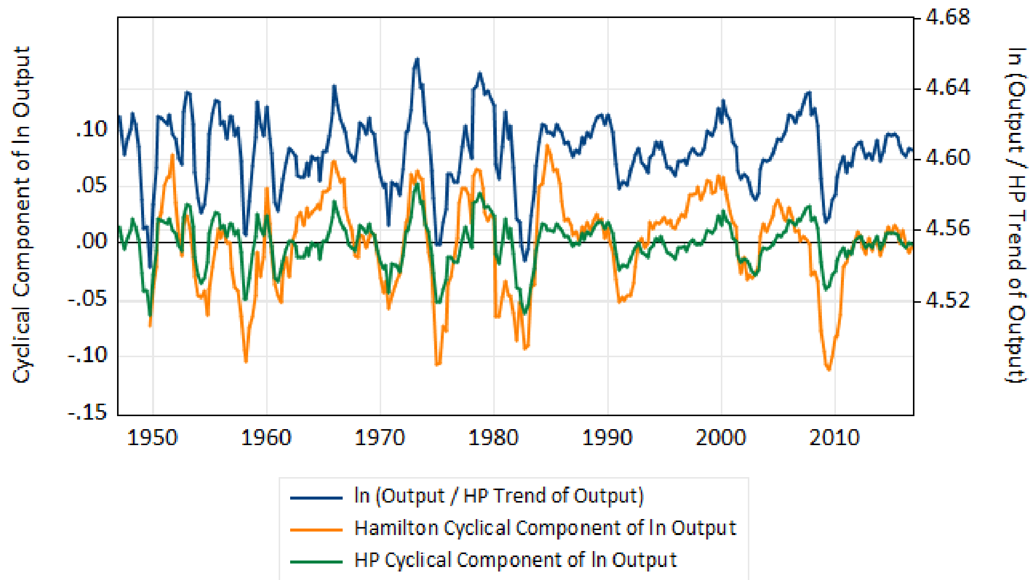


Figure 2: Comparison of HP and Hamilton Utilization Rates, 1947-2016

transformed HP utilization rate consistent with the methodology of Barbosa-Filho and Taylor (2006) and Carvalho and 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 technique alone.[22] 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

[22]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 and Taylor (2006) and Carvalho and 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.

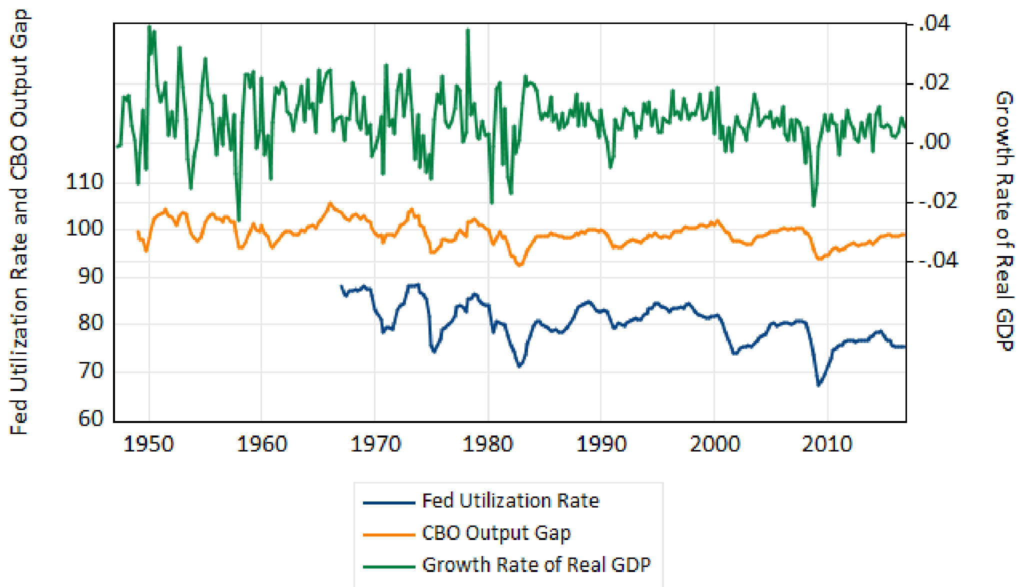


Figure 3: Alternative Measures of Demand, 1947-2016
Sources: Refer to Table A.2 in the Appendix

of a potential output series, based on Cerra and 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. Therefore, even though this technique represents an improvement over the HP filter, it is still not a perfect measure.

For this reason, other measures of output are used as sensitivity tests. These include the growth rate of the Bureau of Economic Analysis' (BEA) real GDP series, and two alternative measures of utilization that are not constructed with filters. Both of these measures—the Federal Reserve's capacity utilization index and a measure of the output gap—were previously used by Barrales and von Arnim (2017).[23] The output gap measure is the ratio of the real GDP series to the U.S. 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 and 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. However, it is less comparable to the previous aggregative literature, although it is used by Charpe et al. (2019). For these reasons, the Hamilton measure is preferred. 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 2009 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.[24] Other specifications replace the wage share with its two main components—labor productivity and the real wage rate. Productivity is measured as the BLS index of business

[23]See Barrales and von Arnim (2017) for a more detailed comparison of these measures with the HP filter utilization rate. They also use a third measure to proxy for the utilization rate—the income-capital ratio. This paper does not make use of this measure because data on net-fixed assets (Barrales and von Arnim's (2017) measure of the capital stock) is only available annually, and because there are some questions about the validity of the income-capital ratio as a proxy for utilization. As Barrales and von Arnim (2017) note, the income-capital ratio is only proportionate to the utilization rate if this ratio is assumed to be fixed at full capacity utilization.

[24]It should be noted that this wage share measure is slightly different from the one used by Barbosa-Filho and 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 and Taylor (see Carvalho and Rezai, 2016).

sector labor productivity, calculated as output divided by hours. The real wage rate is measured using the BLS index of real hourly compensation for the business sector. This measure is the ratio of labor compensation to hours worked, adjusted for inflation using the Consumer Price Index (CPI).

Because the real wage rate is deflated using CPI and the real output measure used to calculate productivity is deflated using the BLS implicit price deflator for business sector output, a full decomposition of the wage share would include these two series as well as the ratio of CPI to the output deflator, as shown in equation (16).

$$\begin{aligned}\psi &= \frac{100 * nominal\ hourly\ compensation/CPI}{100 * nominal\ output\ per\ hour/output\ deflator} \\ &= \frac{real\ hourly\ wage\ rate}{labor\ productivity} * \frac{CPI}{output\ deflator}\end{aligned} \tag{16}$$

However, the relative price variable is excluded from estimates in order to avoid further complicating the model, as there is no strong theoretical explanation for why this variable would affect demand. This variable is not expected to dramatically impact the results, as it exhibits little short-term variation relative to the other two components of the wage share. At 0.205, the variance for *ln productivity* is roughly 8 times larger than the variance for *ln relative price* of 0.025. Similarly, the variance of *ln real hourly wage rate* is about 7 times that of the variance for *ln real hourly wage rate*, at 0.178.

In order to control for the effects of demand on labor productivity over the course of the business cycle, two cyclically adjusted wage measures are constructed. These measures are adjusted by removing the cyclical component of labor productivity—found by applying either the HP filter or the Hamilton method.[25] The HP adjusted wage share is constructed

[25]While the use of filtering techniques is not ideal, for the reasons discussed above, they are employed here because the author knows of no other method for separating the cyclical component of productivity from the rest of the wage share. It is hoped that any bias caused by the use of these filtering techniques is limited by the fact that the adjusted wage share series and the cyclical component of productivity will always appear together in the VAR systems that are estimated. Therefore, the models will contain the same exact

using equation (17), where *ln HP trend productivity* is calculated by taking the natural log of the HP trend component of the labor productivity series.[26]

$$ln\ HP\ adjusted\ wage\ share_t = ln\ real\ wage\ rate_t - ln\ HP\ trend\ productivity_t \tag{17}$$

The Hamilton adjusted wage share is calculated by subtracting the Hamilton trend component of *ln productivity* from *ln real wage rate*. The trend component of *ln productivity* is taken as the series of predicted values from OLS estimates of equation (18), while the residuals from this regression represent the cyclical component of productivity.[27]

$$ln\ productivity_t = \alpha + \sum_{i=8}^{11} \boldsymbol{\beta_i}\ ln\ productivity_{t-i} + \epsilon_t \tag{18}$$

Figure 4 compares the two adjusted wage share series with the unadjusted wage share. Variable measurement and data sources are summarized in Table A.2 in the Appendix.

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 MAIC (see Ng and 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% level, the PP test rejects the null hypothesis of a unit root at the 5% level, and the KPSS test fails to reject the null hypothesis of stationarity at the 5%

information as those using the unadjusted wage share, but this information is separated into two variables to allow for more precise ordering restrictions.

[26] As with the HP utilization rate, a smoothing parameter of 1,600 is used.

[27] Note that because the wage share, real hourly wage, and productivity series are all indexed, the resulting *ln adjusted wage share* series will have a different scale than the natural log of the wage share index. However, because both the wage share and the two cyclically adjusted wage share series are used in log-difference form, the scale does not impact the results.

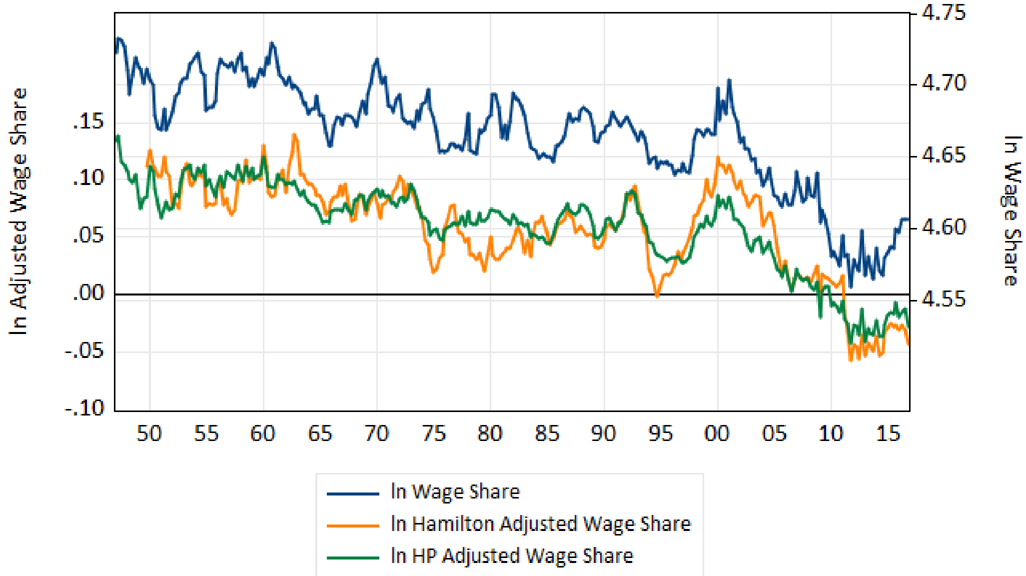


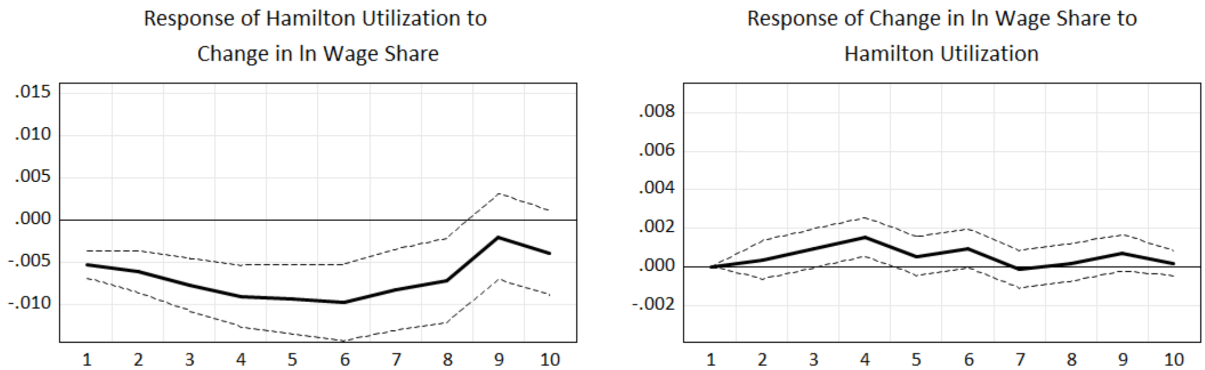
Figure 4: Comparison of Wage Share and Adjusted Wage Shares, 1947-2016
Sources: Refer to Table A.2 in the Appendix

level.[28] Using this decision rule, only the log of the utilization rate measures and the two measures of the cyclical component of labor productivity were found to be stationary. The second difference of the real hourly labor compensation series was taken, because this series was found to be integrated of order two. All other variables were found to be integrated of order one and were first differenced.[29] Selected unit root test results are shown in Table A.1 of the Appendix. Models were estimated using the log levels of stationary variables and the log difference of variables with unit roots.[30]

[28]Nonstationary series are differenced so that the variables will match the data-generating process, as is common practice (see, e.g. Enders, 2014, p. 291).

[29]In cases where the determination of stationarity was sensitive to the use of the 5% threshold of significance instead of the 10% threshold, the results were tested for sensitivity to differencing. Similarly, in cases where the determination of stationary was sensitive to the inclusion or exclusion of a trend in the unit root tests, the results were tested for sensitivity to differencing the series. In no case did the decision to difference a series lead to a major difference in the interpretation of the results.

[30]Note that no models were estimated as vector error correction (VEC) models because there was no evidence of cointegration between the wage share and real GDP—the only nonstationary measure of demand used in this analysis.



(a) **(b)**

Sample period: 1952 Q1 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: Δ ln wage share, Hamilton utilization
Complete results shown in Figure A.1 of the Appendix

Figure 5: Selected IRFs for the Baseline Model with Hamilton Utilization Rate

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 Hamilton utilization rate. This model is estimated for the sample period of 1952 Q1 to 2016 Q4 and includes a constant term and nine lags. Selected impulse response functions for this specification are shown in Figure 5. These represent responses to a one standard deviation positive shock, along with confidence bands of $\pm$ two standard errors that correspond roughly to a 5% significance level.

The response of utilization to a positive wage share shock, shown in panel (a) of Figure 5, is significantly negative in the first eight quarters and insignificantly negative afterwards. The negative sign here is indicative of profit-led demand. The response of the wage share to a utilization shock, shown in panel (b), is positive and statistically significant in quarter four, 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 Δ *ln wage share* (an increase of 0.95 percentage points in the growth rate of the wage share) leads to a decrease of 0.0139 in the Hamilton utilization rate (roughly 1.68 standard deviations). Similarly, a one standard deviation shock to the Hamilton utilization rate (an increase of 0.0411) leads to an increase of 0.0053 in Δ *ln wage share* (approximately 56% of a standard deviation).[31] 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.[32]

Goodwin cycle effects are similarly found when using the HP utilization rate that is more consistent with the previous literature. The IRFs for this model can be found in Figure A.2 of the Appendix. The profit-squeeze effects are similar to those found when using the Hamilton utilization rate, although they are significant for more periods. The profit-led demand effects are smaller and less persistent than those found using the Hamilton utilization rate. These differences in persistence could be explained by the construction of the Hamilton utilization rate. Because the values of the utilization rate will be correlated with values of output 8 to 11 quarters in the past, it is not surprising that larger effects are found at later time horizons for the Hamilton utilization rate.[33]

[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 profit-led demand and profit-squeeze effects. Some significant lagged wage-led demand effects are present in the specification using the first difference of both variables, but the accumulated response of utilization to the wage share shock remains negative and significant in all ten quarters. Other unreported results show that the findings are similarly robust to using data series without log transformation, and to including an exogenous trend.

[33]Unreported results found using the Hamilton utilization rate show that the magnitude of the lagged profit-led demand effects becomes smaller when using 2 lags, as in the HP model, instead of the optimal lag length of 9 for the Hamilton model. However, these effects remain significant, and more persistent in comparison to those found in the HP model.

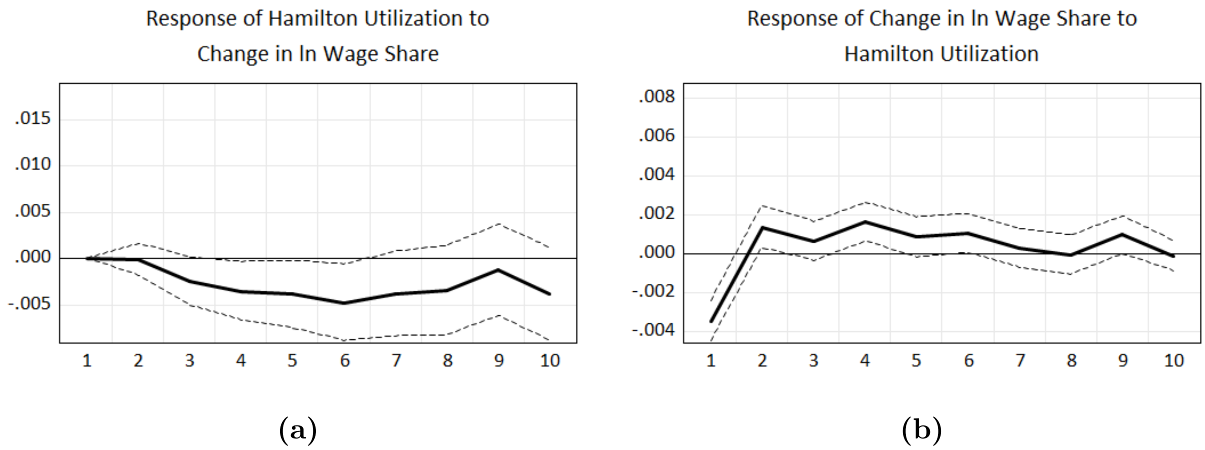
Statistically significant profit-led demand and profit-squeeze effects are also found using the Federal Reserve utilization rate, the CBO output gap, or the growth rate of real GDP in place of the HP utilization rate or Hamilton utilization rate. However, there are some differences when using these other measures. Using the growth rate of real GDP, the effects in both directions are less persistent and significant for fewer quarters. Using the Federal Reserve utilization rate or the CBO output gap, the magnitude of the profit-squeeze effect is smaller than in the HP and Hamilton utilization rate models. As with the Hamilton utilization rate model, the profit-led demand effects are more persistent in the models using the Fed utilization rate or the CBO output gap, relative to the HP utilization rate. IRFs for these specifications can be found in Figures A.3-A.5 in the Appendix.

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. In other words, the wage share has been placed before the utilization rate in all of the orderings. Figure 6 shows how the results change when the ordering is reversed, as in equation (19), and it is instead assumed that the wage share does not have a contemporaneous effect on the utilization rate.

$$\boldsymbol{y_t} = [ln\ utilization_t, \Delta\ ln\ wage\ share_t] \tag{19}$$

The results change substantially when changing the ordering restrictions. The response of utilization to a wage share shock, shown in panel (a) is considerably weaker. The maximum magnitude of the profit-led demand effects is only about half as large as those found using the baseline ordering, and they are statistically significant in only three quarters



Sample period: 1952 Q1 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: Hamilton utilization, Δ ln wage share
Complete results shown in Figure A.6 in the Appendix

Figure 6: Selected IRFs for Reverse Ordering Model with Hamilton Utilization

(4 through 6).[34] The response of the wage share to a utilization shock, shown in panel (b), is initially negative before becoming positive one quarter after the shock. In other words, there is an initial wage squeeze, but ultimately profits are squeezed as utilization rises, as was the case in the baseline model. This initial negative effect of the utilization rate shock on the wage share could be explained by positive effects of utilization on productivity.[35]

Estimates found using the HP utilization rate change even more dramatically when the ordering restrictions are reversed. The response of the HP utilization rate to a wage share shock becomes positive, indicating that demand is wage-led rather than profit-led. However, the magnitude is smaller than the estimated profit-led effects found using the baseline ordering, and the positive effect is only significant for one quarter. Using this ordering, the effects of a utilization rate shock on the wage share are similar to those found

[34] This finding could be driven by correlation between the Hamilton utilization rate and values of output 8 to 12 quarters in the past. When using only 2 lags, instead of 9, insignificant wage-led demand effects are found.

[35] Using the level of *ln wage share* instead of the first difference, the response of utilization to a wage share shock is negative but insignificant, and the response of the wage share to a utilization shock is negative for three quarters before becoming positive.

using the Hamilton utilization rate. IRFs for this specification are shown in Figure A.7 in the Appendix.[36]

Although the ordering assumptions used in the baseline model, and shown in equation (14), are more consistent with the existing empirical literature than the reverse ordering, shown in equation (19), they are not necessarily accurate. Evidence from Granger causality tests, presented by Barrales and von Arnim (2017), suggest that both the utilization rate and the wage share affect one another—at least in the case of the U.S. However, the timing of these effects is not fully clear. If labor productivity varies procyclically, as Lavoie (2017) suggests, 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, 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).

4.3 Models Separating the Main Components of the Wage Share

Models that replace the wage share with its two main 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 model, 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

[36]The results found using this ordering and the other measures of demand are generally qualitatively similar to those found using the HP utilization rate, although the magnitudes vary across specifications and some show lagged profit-led demand. One exception is the specification using the Federal Reserve utilization rate as the measure of demand. When using this measure, the initial wage-led effects are small and insignificant.

Table 1: Possible Orderings in Wage Share Decomposition Model

Order Number	**Variable Order**	**Corresponding Order in Two Variable Model**
Order 1	Wage rate, utilization, productivity	N/A
Order 2	Utilization, productivity, wage rate	Utilization, wage share
Order 3	Utilization, wage rate, productivity	Utilization, wage share
Order 4	Productivity, utilization, wage rate	N/A
Order 5	Productivity, wage rate, utilization	Wage share, utilization
Order 6	Wage rate, productivity, utilization	Wage share, utilization

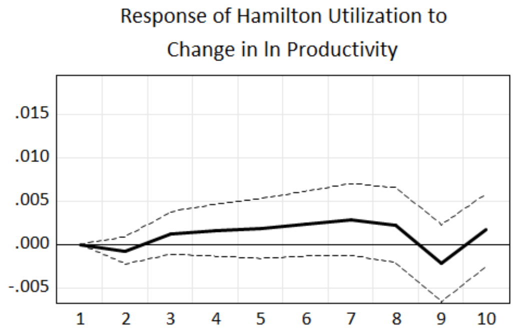
cases, in which the two main components of the wage share have different orderings relative to the utilization rate.

The estimates for these models suggest that differences in the results for the baseline model and the specification using the reverse variable ordering can largely be explained by their differing assumptions regarding the relationship between the utilization rate and labor productivity. In Orders 1-3, the utilization rate has a contemporaneous effect on labor productivity, but productivity has only a lagged effect on utilization. The reverse is true in Orders 4-6, wherein productivity has a contemporaneous effect on utilization, but utilization effects productivity only with a lag. Selected IRFs for Orders 1 and 4, which are generally representative of their respective groups, are shown in Figures 7 and 8. Complete IRFs for every ordering can be found in Figures A.8-A.13 in the Appendix.

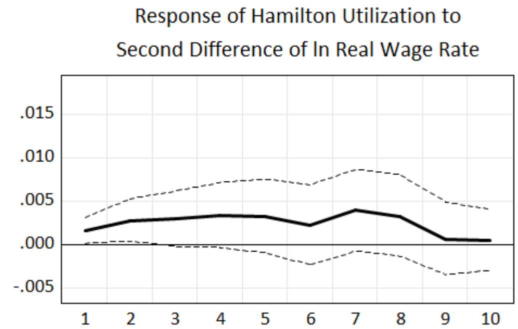
The relationship between the real wage rate and utilization is found to be fairly consistent across all six specifications. An increase in the wage rate is generally found to have a positive effect on the utilization rate,[37] although these effects are only significant for Orders 1 and 6—the two cases in which the wage rate has a contemporaneous effect on both of the other variables. The response of the wage rate to a utilization rate shock is generally small and insignificant in most specifications.[38]

[37] Order 5 is a slight exception, as effects are initially negative before becoming positive, but these effects are small and insignificant.

[38] Using Order 3, a positive and significant response is found in the first quarter.



(a)



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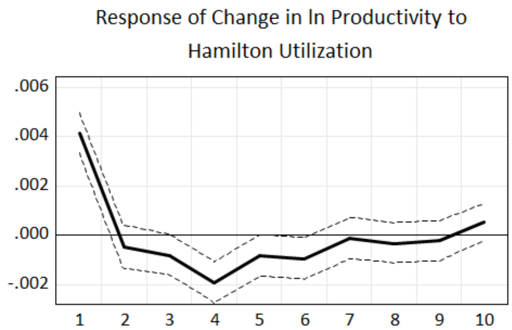
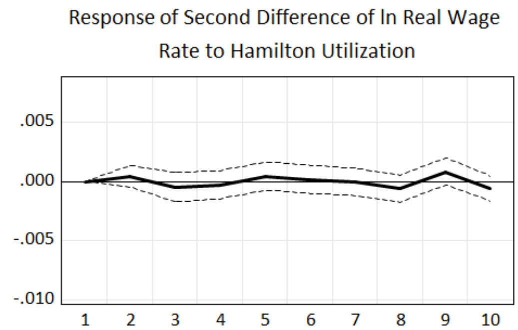


(c)



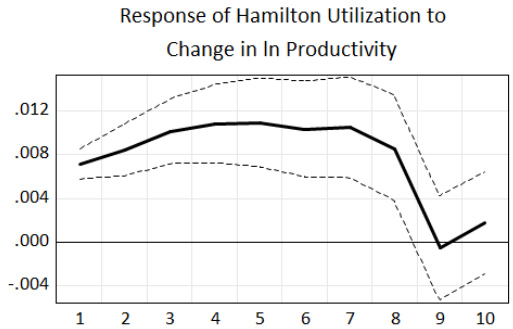
(d)

Sample period: 1952 Q1 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: $\Delta\,\Delta$ real wage rate, Hamilton utilization, Δ ln productivity
Complete results shown in Figure A.8 in the Appendix

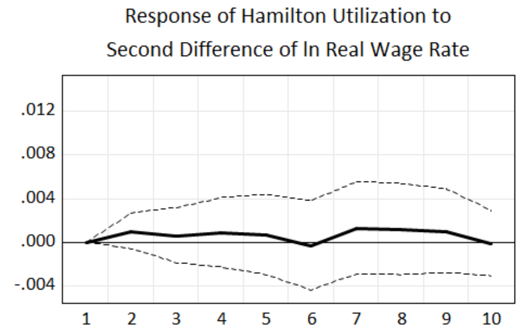
Figure 7: Selected IRFs for Order 1 with Hamilton Utilization

Conversely, the estimated relationship between productivity and utilization is heavily dependent upon the ordering of these two variables. Although the response of utilization to a positive productivity shock is generally positive across all specifications, the magnitude is over three times larger when productivity is assumed to have a contemporaneous effect on utilization (i.e. in Orders 4-6), and these effects are insignificant in the other three cases (i.e. Orders 1-3).[39] Ordering restrictions are also found to impact the response of productivity to a utilization shock. When productivity is assumed to have only a lagged

[39]The relevant IRF reaches a magnitude of at least 0.0104 when using Orders 4-6, while the maximum magnitude for Orders 1-3 is 0.0029.



(a)



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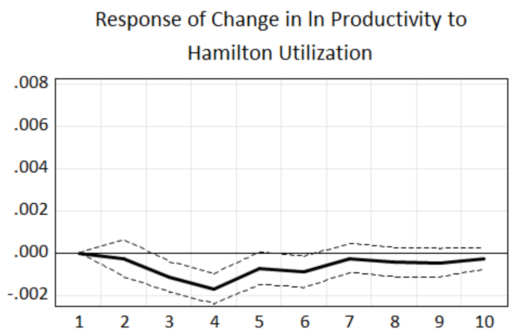

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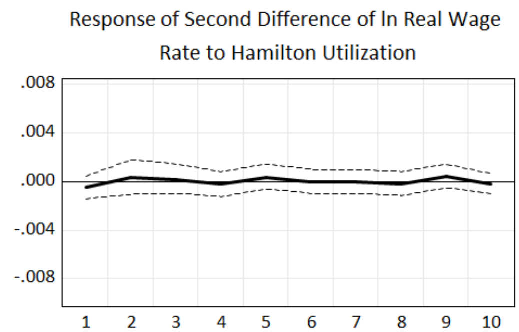


(d)

Sample period: 1952 Q1 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: Δ ln productivity, Hamilton utilization, Δ Δ real wage rate
Complete results shown in Figure A.11 in the Appendix

Figure 8: Selected IRFs for Order 4 with Hamilton Utilization

effect on utilization and the contemporaneous correlation between the two variables is viewed as an effect of utilization on productivity, as in Orders 1-3, an increase in the utilization rate leads to a large and statistically significant increase in productivity. This increase is followed by negative lagged and significant lagged effects.[40] However, the accumulated response is positive and significant for the first three quarters and insignificant afterwards. This suggests that productivity is procyclical, as Lavoie (2017) argues. When using the reverse ordering of these two variables, as in Orders 4-6, these initial effects are assumed away, and the estimated

[40]These negative effects could reflect workers reducing their effort when the economy is booming and they have more bargaining power.

response includes only the negative and significant lagged effects. This result contradicts the theoretical prediction of Lavoie (2014, 323-5) that labor productivity will be procyclical. However, this is unsurprising because contemporaneous effects of utilization on productivity have been ruled out by assumption.

These results indicate that the model's findings are highly dependent upon its treatment of productivity effects.[41] 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 likely reflects 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 (i.e. more profit-led demand) and a more positive response of the wage share to an increase in utilization (i.e. more of a profit squeeze). In other words, observed Goodwin cycle effects will be larger when it is implicitly assumed that productivity drives utilization; when the model accounts for the potential cyclicality of productivity and assumes that productivity has only a lagged effect on utilization, estimates will be less likely to indicate profit-led demand and profit-squeeze effects.

The same general pattern is found when using the HP utilization rate measure that is consistent with the previous aggregative literature in place of the Hamilton utilization rate. IRFs for these specifications can be found Figures A.14-A.19 in the Appendix. As with

[41] This conclusion is not driven by the decision to use the second difference of the real hourly compensation series. Unreported results show that when using the first difference of the wage rate instead of the second, there are no qualitative differences in the IRFs relating utilization and productivity. However, there are some minor differences in the relationship between the real wage rate and utilization, as no significant effects are found in either direction for any variable ordering when using the first difference.

the estimates found using the Hamilton utilization rate, these results show more negative effects of utilization on productivity and more positive effects of productivity on utilization for Orders 4-6 relative to Orders 1-3.[42] In other words, they also indicate that observed Goodwin cycle effects will be stronger when ordering restrictions rule out contemporaneous cyclical variation in productivity and treat productivity as an immediate determinant of utilization. Unreported results show a similar pattern for the CBO output gap, the real GDP growth rate, and the Fed utilization rate.[43]

Therefore, all specifications in which the wage share is replaced by its two primary components—the real wage rate and labor productivity—provide evidence that estimates of both profit-led demand and profit-squeeze effects will be larger if the contemporaneous correlation between productivity and demand—which likely reflects the positive effect of demand on productivity—is instead interpreted as a positive effect of productivity on demand. These findings suggest that the assumption—used in the baseline model and some previous aggregative studies—that demand has no contemporaneous effect on the wage share may be

[42] Productivity is found to have a strong and significantly positive impact on utilization when using Orders 4-6, but a negative and statistically significant effect when using Orders 1-3. The latter finding could be explained by reduced input use and investment following an improvement in technology (Basu et al., 2004). In the other direction, the effects of utilization on productivity follow the same pattern as those found using the Hamilton utilization rate. However, the IRFs for the HP utilization rate differ in that significant positive effects are found in periods 9 and 10 for all specifications (these effects are found to be significant in both of these periods for Orders 1-3, but only in the 10th period for Orders 4-6.). Significant effects of the wage rate on utilization are found for all specifications except for Order 3. These effects are negative in the case of Order 5, and positive in the other cases. For the estimated response of the wage rate to a positive utilization shock, positive and significant effects are found for Orders 2-3, and negative and significant effects are found in Order 4. However, these effects are generally small and significant only for one quarter.

[43] When using the CBO output gap or the growth rate of GDP as the measure of demand, productivity is found to have a negative and significant effect on demand for Orders 1-3, and a positive and significant effect for Orders 4-6. In the case of the Fed utilization rate, productivity is always found to have a positive and significant effect on demand, but these effects are considerably larger for Orders 4-6. When using Orders 1-3 and the Fed utilization rate or GDP growth rate, demand is initially found to have a large and significant positive effect on productivity. These effects are followed by negative and significant lagged effects, except in the case of Order 3 for the GDP growth rate. When using Orders 4-6 and these same measures, the initial positive effects are ruled out by assumption and the negative lagged effects are the only significant effects remaining. The results for the CBO output gap follow the same pattern, but each specification also shows small but statistically significant positive effects in periods 9 and 10 that are similar to those found when using the HP utilization rate. These positive effects in periods 9 and 10 are not found when using the first difference of *ln CBO output gap* instead of the level, but the results are otherwise robust to this change.

problematic. If productivity is in fact positively affected by demand over the course of the business cycle, as Lavoie (2017) suggests, it is likely that some previous aggregative estimates have been biased towards findings of stronger Goodwin cycle effects.

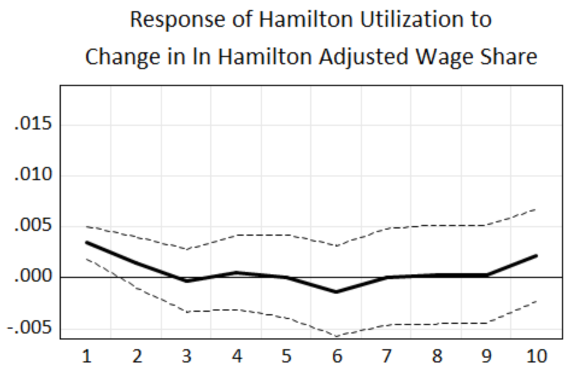
4.4 Cyclically Adjusted Wage Share Estimates

In order to further explore the ways in which the cyclical effects of demand on productivity affect estimates of the relationship between aggregate demand and the functional distribution of income, another set of specifications separates the cyclical variation in labor productivity from the wage share. VARs are estimated with three variables: a measure of demand, the cyclically adjusted wage share, and the cyclical component of labor productivity. Because they include both the cyclical component of productivity and the adjusted wage share from which this cyclical variation has been removed, these estimates include all of the information from the wage share. However, because these two variables are included separately, more specific ordering restrictions can be used, and more precise estimates can be obtained.

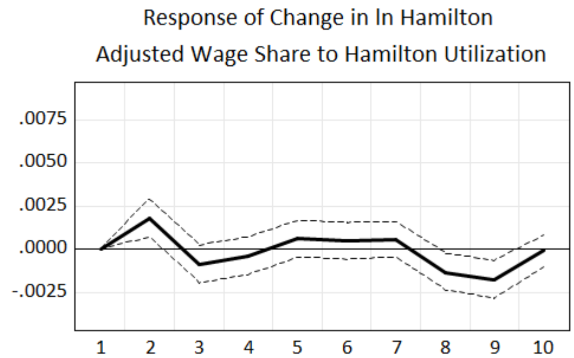
Figure 9 shows the results for the specification including the Hamilton adjusted wage share, the Hamilton utilization rate, and the Hamilton cyclical component of productivity (in that order). The results now show significant wage-led demand effects, even when maintaining the ordering restriction that the adjusted wage share is only impacted by demand with a lag. However, these effects are fairly small and significant for only one period.[44] The effects of demand on the adjusted wage share are mixed.[45] Significant profit-squeeze effects

[44] The results imply that a one standard deviation shock to Δ *ln Hamilton adjusted wage share* (an increase of 1.06 percentage points in the growth rate of the adjusted wage share) leads to a cumulative increase over ten periods of 0.0067 in the Hamilton utilization rate (about 16% of a standard deviation).

[45] It is possible that separating the cyclical component of productivity from the rest of the wage share could lead to underestimates of profit-squeeze effects. One potential channel for a profit squeeze is a reduction in worker effort during booms, when job loss is less costly and less likely to occur. Such a reduction in effort would lead to lower productivity and profitability. In this model, such effects would largely be captured by the cyclical component of productivity, rather than the adjusted wage share. However, given the initial



(a)



(b)

Sample period: 1952 Q2 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: Δ ln Hamilton adjusted wage share, Hamilton utilization, Hamilton cyclical component of productivity
Complete results shown in Figure A.20 in the Appendix

Figure 9: Selected IRFs for the Hamilton Adjusted Wage Share Model

are found in the second period, but significant wage-squeeze effects are found in periods 8 and 9.[46] The complete IRFs, shown in Figure A.20 of the Appendix, illustrate procyclical movements of the cyclical component of productivity. A positive shock to utilization leads to an increase in the cyclical component of productivity that is significant for three periods. These effects become negative and significant in periods 8 and 9.

These results are sensitive to variable ordering. However, there is little theoretical justification for any other possible ordering. The argument for allowing contemporaneous effects of demand on the wage share is no longer applicable when the cyclical variation in productivity has been separated from the wage share measure, and Lavoie's (2017) argument suggests that demand should precede the cyclical component of productivity in the ordering.

positive response of the cyclical component of productivity to a positive demand shock, it does not appear that there are any large negative effects of booms on productivity through effort.

[46]The accumulated response shows positive and significant in periods 2 and 7 with no other significant effects.

Using the HP adjusted wage share, the HP utilization rate, and the HP cyclical component of productivity (in that order), estimates are similarly indicative of wage-led demand effects,[47] but no significant effects of demand on the adjusted wage share are found. These estimates similarly reflect a response of the cyclical component of productivity to a utilization shock that is initially positive and significant but becomes negative and significant. Results for this specification can be found in Figure A.21 of the Appendix. Unreported results show that similar effects are found using any of the other three measures of demand and a combination of the adjusted wage share and cyclical component of productivity constructed using either the Hamilton method or the HP filter.[48]

These findings provide further evidence that the Goodwin cycle effects found by previous aggregative studies (or at least those using similar data and techniques) reflect a misinterpretation of cyclical variation in labor productivity, rather than a true underlying relationship between demand and distribution. Evidence of this cycle of profit-led demand and profit-squeeze effects is not found when the cyclical effects of demand on productivity are accounted for. Instead, demand appears to be wage-led and the effects of demand on distribution are found to be mixed or insignificant. Therefore, the results of this disaggregated analysis suggest that the relationship between these variables would be better characterized

[47] These effects are significant for the first six quarters, and they are larger than those found when using the measures constructed with the Hamilton method. A one standard deviation shock to Δ *ln HP adjusted wage share* (an increase of 0.81 percentage points in the growth rate of the adjusted wage share) leads to a cumulative increase over ten periods of 0.0134 in the *ln HP utilization* (about 66% of a standard deviation).

[48] When using the Hamilton method, wage-led demand effects are found for all three measures of demand, but these effects are only significant when using the growth rate of GDP. No significant effects of demand on the adjusted wage share are found using the CBO output gap or the Fed utilization rate. However, when using the GDP growth rate results are similar to those found for the Hamilton utilization rate, indicating significant positive effects in the second period and significant negative effects in the ninth period. When using the HP adjusted wage share and the HP cyclical component of productivity instead, no significant effects of demand on the adjusted wage share are found using any of the three measures of demand. However, significant wage-led demand effects are found for the CBO output gap (although this result is sensitive to differencing *ln CBO output gap*) and the growth rate of GDP. The effect of the adjusted wage share on the Fed utilization rate is found to be positive but insignificant. Positive and significant effects of demand on the cyclical component of productivity are found using any measure of demand and either cyclically adjusted wage share. These effects are followed by negative and significant lagged effects in all cases except models using the growth rate of GDP (or when using Δ *ln CBO output gap* instead of *ln CBO output gap*).

by wage-led demand and cyclical effects of demand on productivity, rather than a Goodwin cycle pattern.

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 procyclically with utilization. A prevalent view among practitioners of the aggregative approach has been that findings of wage-led demand in structural studies are the direct result of a failure of these studies to account for the effects of demand on the wage share. The findings of this study suggest that this conclusion should be revisited.

Like most previous aggregative estimates, the baseline model 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, do not properly account for cyclical productivity effects. Because labor productivity is a component of the wage share and is likely to vary procyclically over the course of the business cycle (Lavoie, 2017), the effect of demand on productivity needs to be considered when exploring the relationship between the wage share and aggregate demand. The results of specifications that adjust for these cyclical productivity effects suggest that these observed Goodwin cycle effects are likely spurious. Using models in which the two main components of the wage share—the real wage rate and labor productivity—are separated, profit-led demand and profit-squeeze effects are found to be strongest when using orderings restrictions that treat all contemporaneous correlation between productivity and demand as an effect of productivity on demand. When demand is instead allowed to have a contemporaneous effect on productivity, as would be appropriate if productivity varies cyclically, these effects are substantially weaker. Furthermore, when using specifications that separate the cyclical component of productivity from the wage share to allow for more precise ordering restrictions, the Goodwin cycle pattern is no longer found. Such specifications produce estimates of wage-led demand and estimated effects of demand on distribution that are either insignificant or mixed—featuring some profit-squeeze and some wage-squeeze effects. These results are found using either the preferred Hamilton technique or the HP filtering technique conventionally used in the literature. These findings are also generally robust to various measures of demand, although significance varies in some cases.

These findings suggest that existing evidence of Goodwin cycle effects is the result of biased estimates. Indeed, the appearance of profit-led demand seems to be a misinterpretation of procyclical variation in labor productivity, and evidence of profit-squeeze effects is weaker when productivity effects are accounted for. As a result, it is time to rethink the popular Goodwin cycle story of the relationship between demand and distribution over the course of the business cycle. Rather than profit-led demand and profit-squeeze effects, we should characterize this relationship as a combination of wage-led demand and procyclical productivity effects.

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A Appendix

Table A.1: 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	Reject 10%	Reject 5%	Reject 5%	Difference
Δ 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
Δ 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 to reject	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
Δ ln real wage rate	1947 Q2-2016 Q4	N	Reject 10%	Reject 1%	Reject 1%	Difference
Δ Δ ln real wage rate	1947 Q3-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
ln productivity	1947 Q1-2016 Q4	Y	Fail	Fail	Reject 1%	Difference
Δ ln productivity	1947 Q2-2016 Q4	N	Reject 1%	Reject 1%	Reject 5%	Stationary

Continued on next page

Table A.1 – continued from previous page

Variables	Sample	Trend	ADF	PP	KPSS	Result
ln HP adjusted wage share	1947 Q1-2016 Q4	Y	Fail	Reject 10%	Reject 5%	Difference
Δ ln HP adjusted wage share	1947 Q2-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
ln Hamilton adjusted wage share	1949 Q4-2016 Q4	Y	Fail	Fail	Reject 10%	Difference
Δ ln Hamilton adjusted wage share	1950 Q1-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
HP cyclical component of productivity	1947 Q1-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
Hamilton cyclical component of productivity	1949 Q4-2016 Q4	N	Reject 5%	Reject 1%	Fail	Stationary

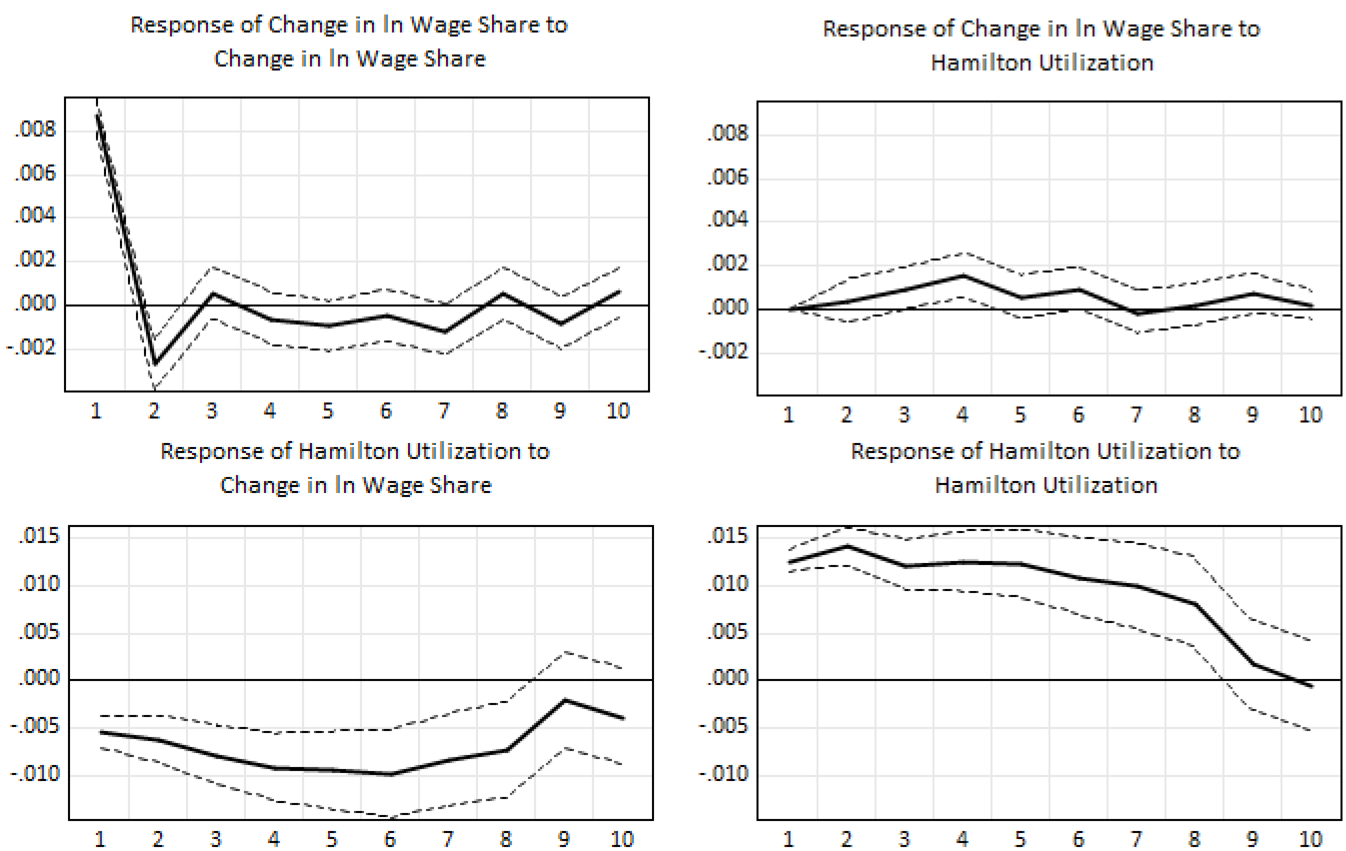
Null hypotheses: ADF Test – Unit Root, PP Test – Unit Root, KPSS Test – Stationarity

Table A.2: Variable Definitions and Data Sources

Variable	Definition	Units	Source
Wage share	Wage share index for the business sector	Index, 2009 = 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†
Real GDP	Real gross domestic product, seasonally adjusted	Billions of chained 2009 dollars	BEA†
Business sector output	Business sector current dollar output index	Index, 2009 = 100	BLS
CBO potential output	Real potential gross domestic product	Billions of chained 2009 dollars	CBO†
CBO output gap	100 * Real GDP / CBO potential output	Percentage*100	Author's calculations
Nominal GDP	Nominal gross domestic product	Billions of dollars	BEA†
Labor productivity	Business sector labor productivity index, output per hour	Index, 2009 = 100	BLS
Real hourly wage rate	Ratio of labor compensation to hours worked for the business sector, adjusted for inflation using the Consumer Price Index.	Index, 2009 = 100	BLS

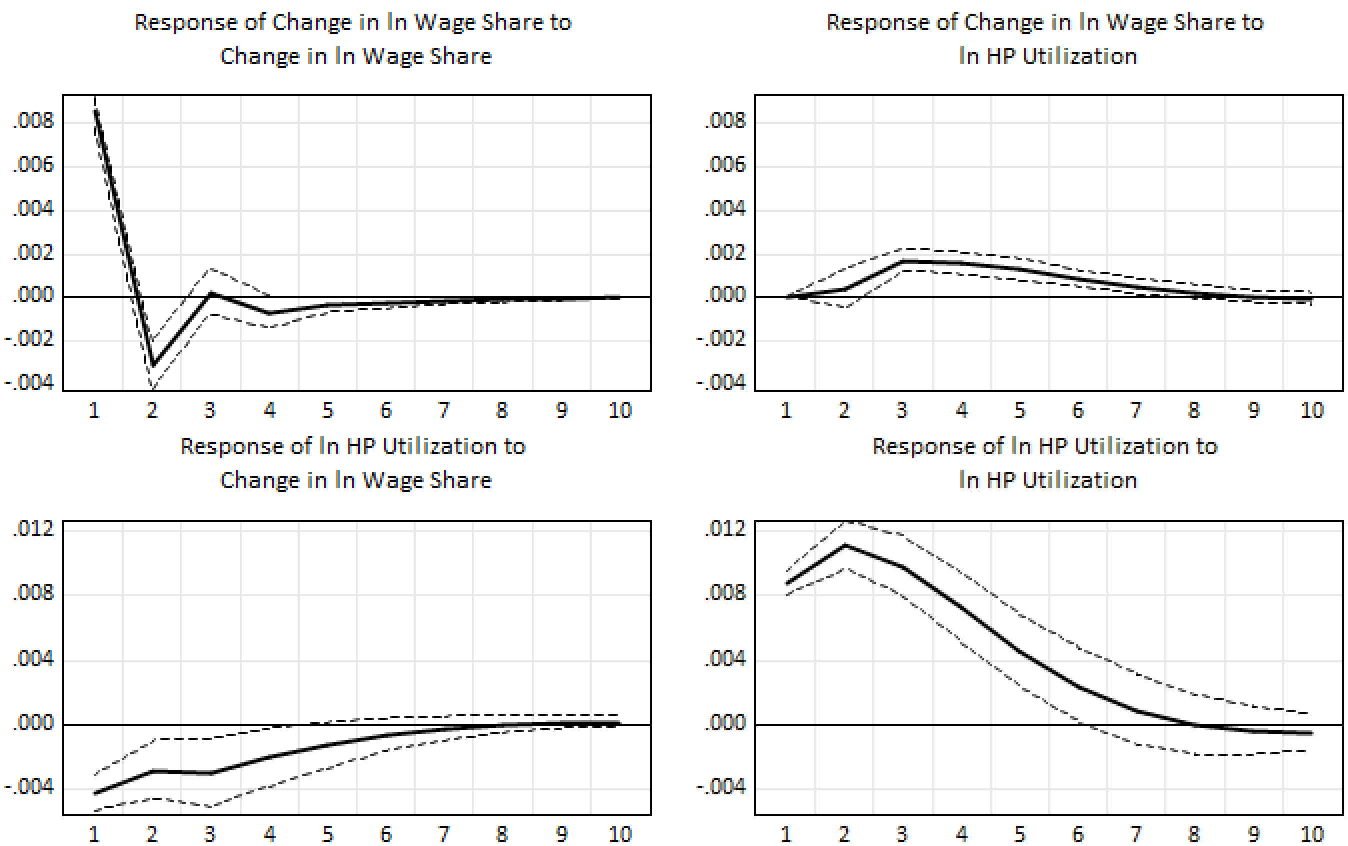
† indicates series downloaded from the Federal Reserve Bank of St. Louis FRED Database

Details regarding construction of the Hamilton utilization rate, HP and Hamilton adjusted wage shares, and HP and Hamilton cyclical components of productivity are discussed in Section 3.2.



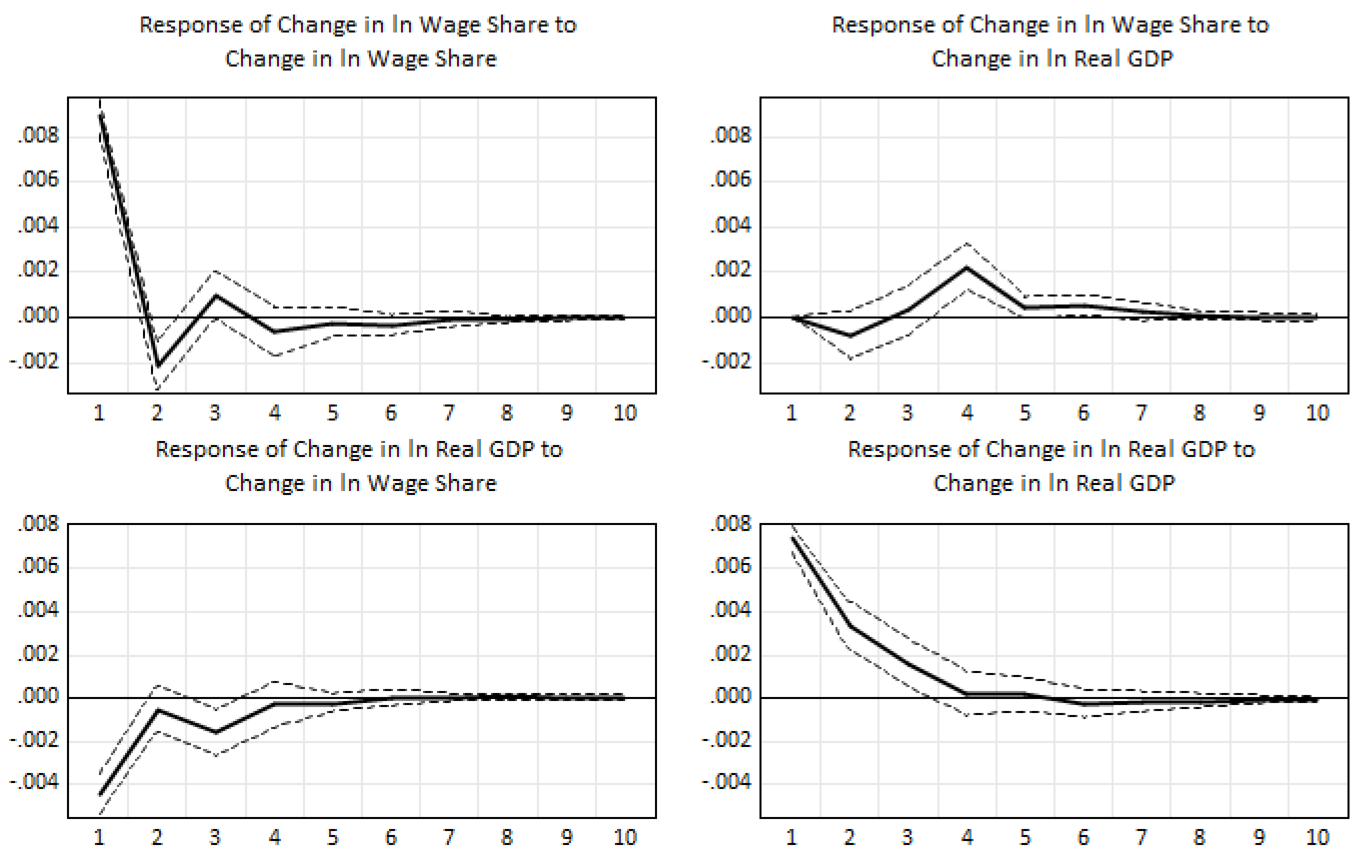
Sample period: 1952 Q1 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: Δ ln wage share, Hamilton utilization

Figure A.1: Complete IRFs for Baseline Model with Hamilton Utilization Rate



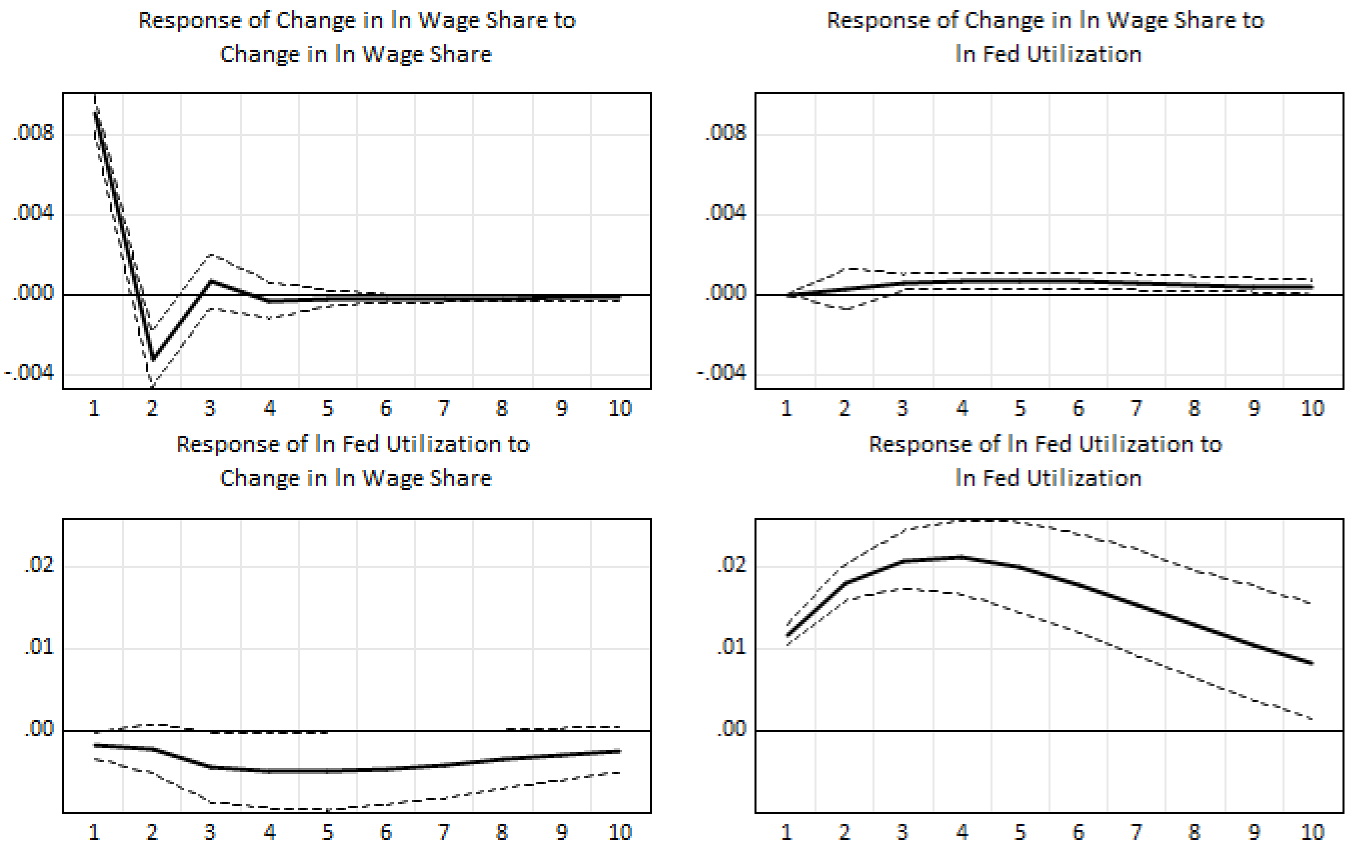
Sample period: 1947 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln HP utilization

Figure A.2: Complete IRFs for the Baseline Model with HP Utilization Rate



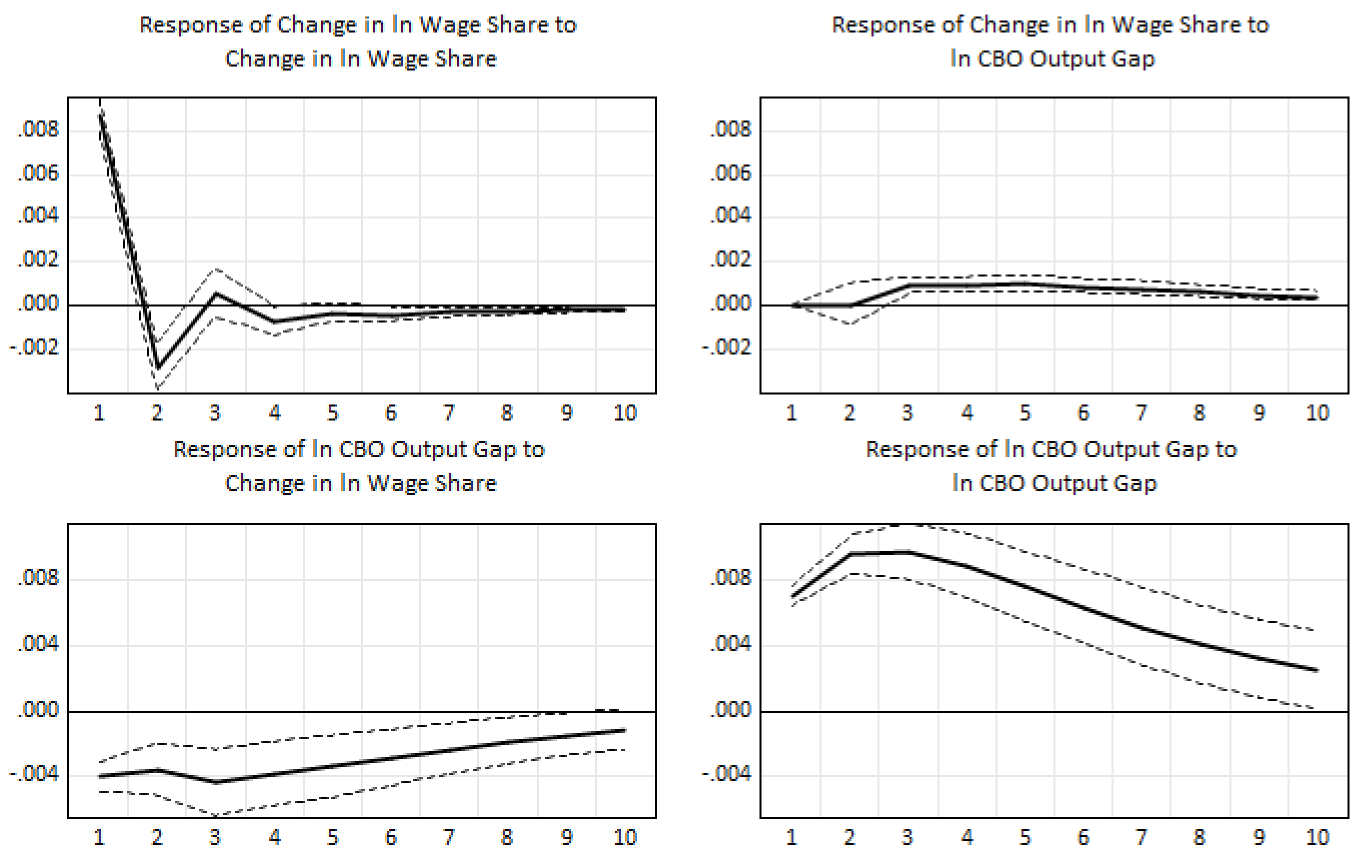
Sample period: 1948 Q1 - 2016 Q4
Model specification: 3 lags and constant term
Variable ordering: Δ ln wage share, Δ ln real GDP

Figure A.3: Complete IRFs for Baseline Model with Real GDP



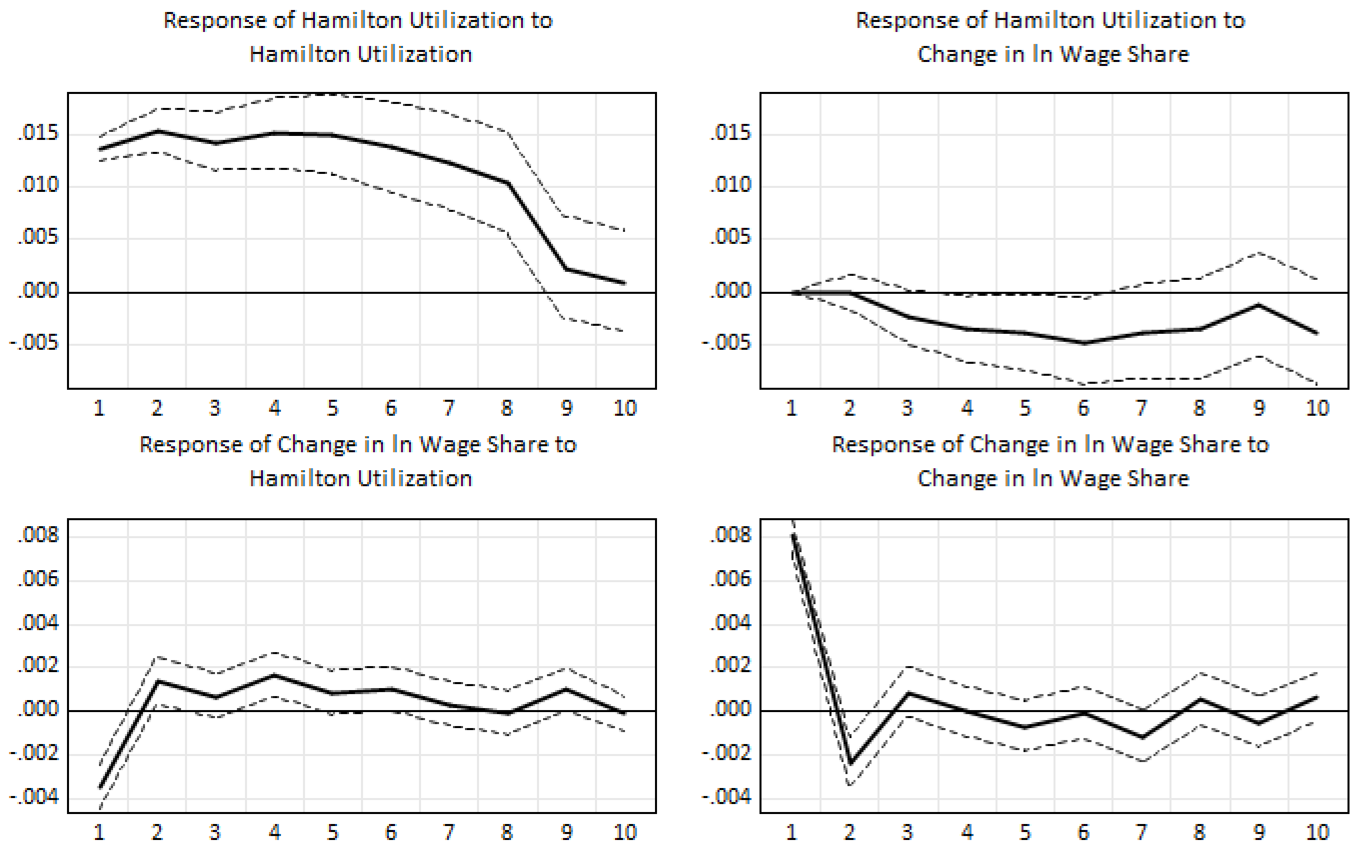
Sample period: 1967 Q3 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln Fed utilization

Figure A.4: Complete IRFs for Baseline Model with Federal Reserve Utilization Rate



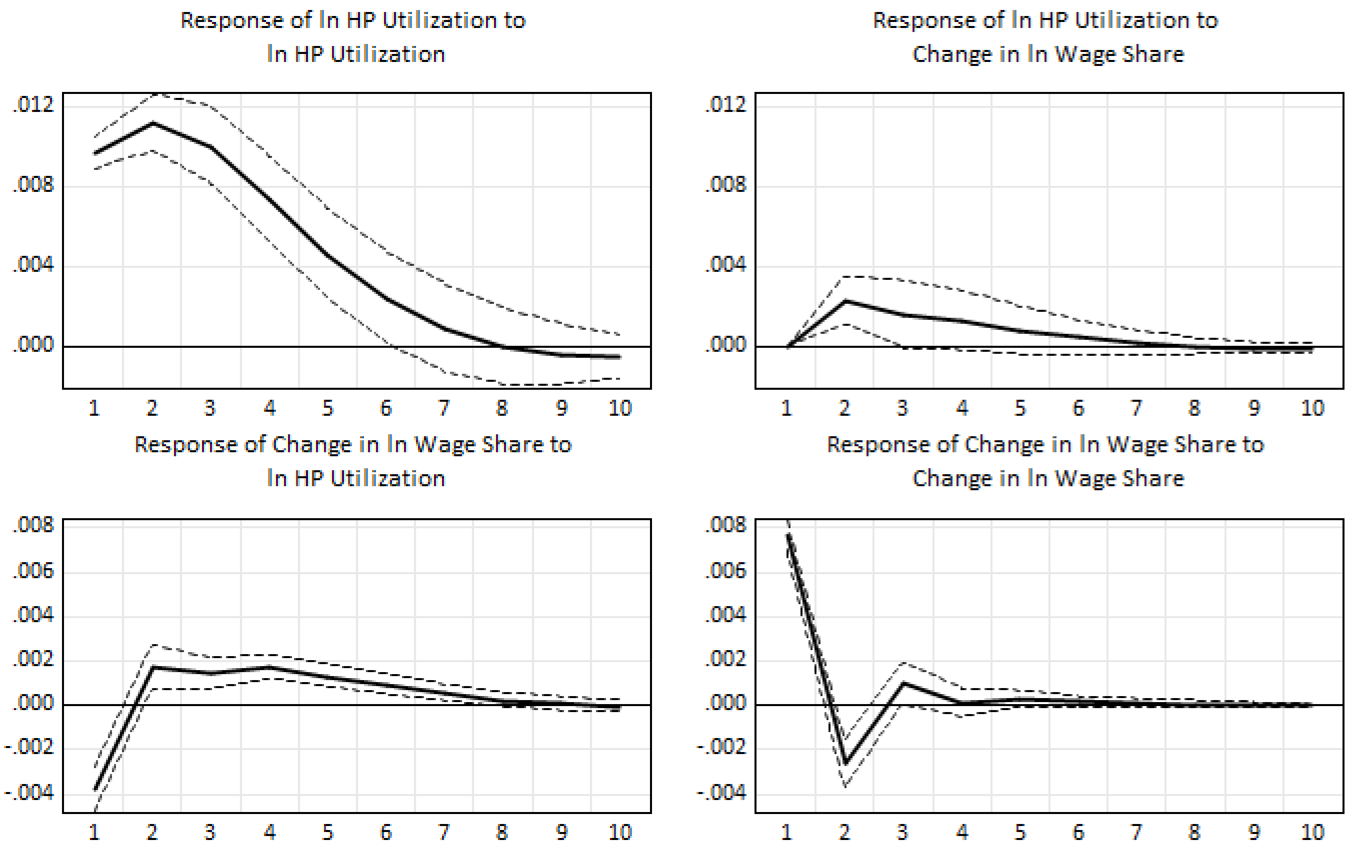
Sample period: 1949 Q3 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln CBO output gap

Figure A.5: Complete IRFs for Baseline Model with CBO Output Gap



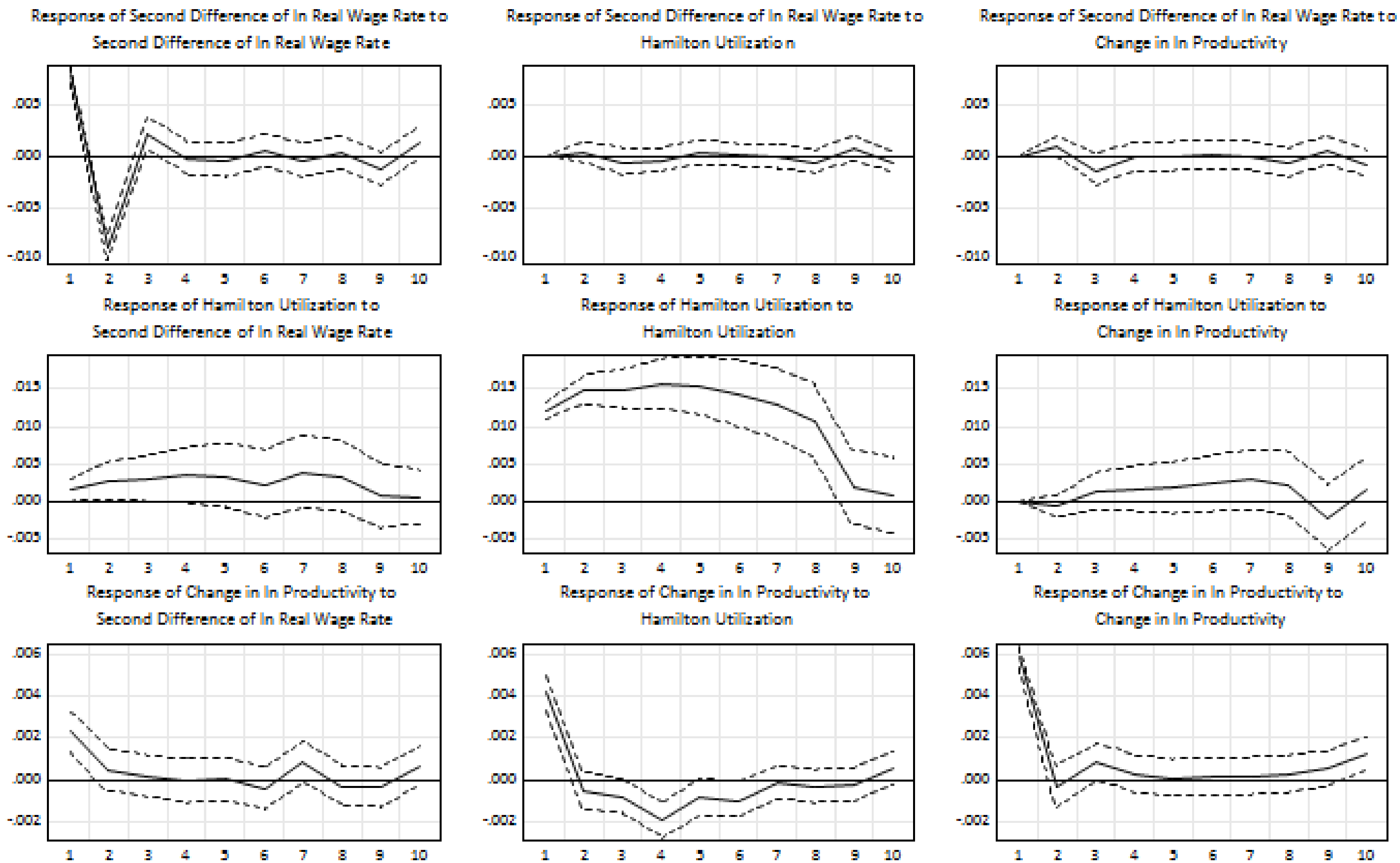
Sample period: 1952 Q1 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: Hamilton utilization, Δ ln wage share

Figure A.6: Complete IRFs for Reverse Ordering Model with Hamilton Utilization



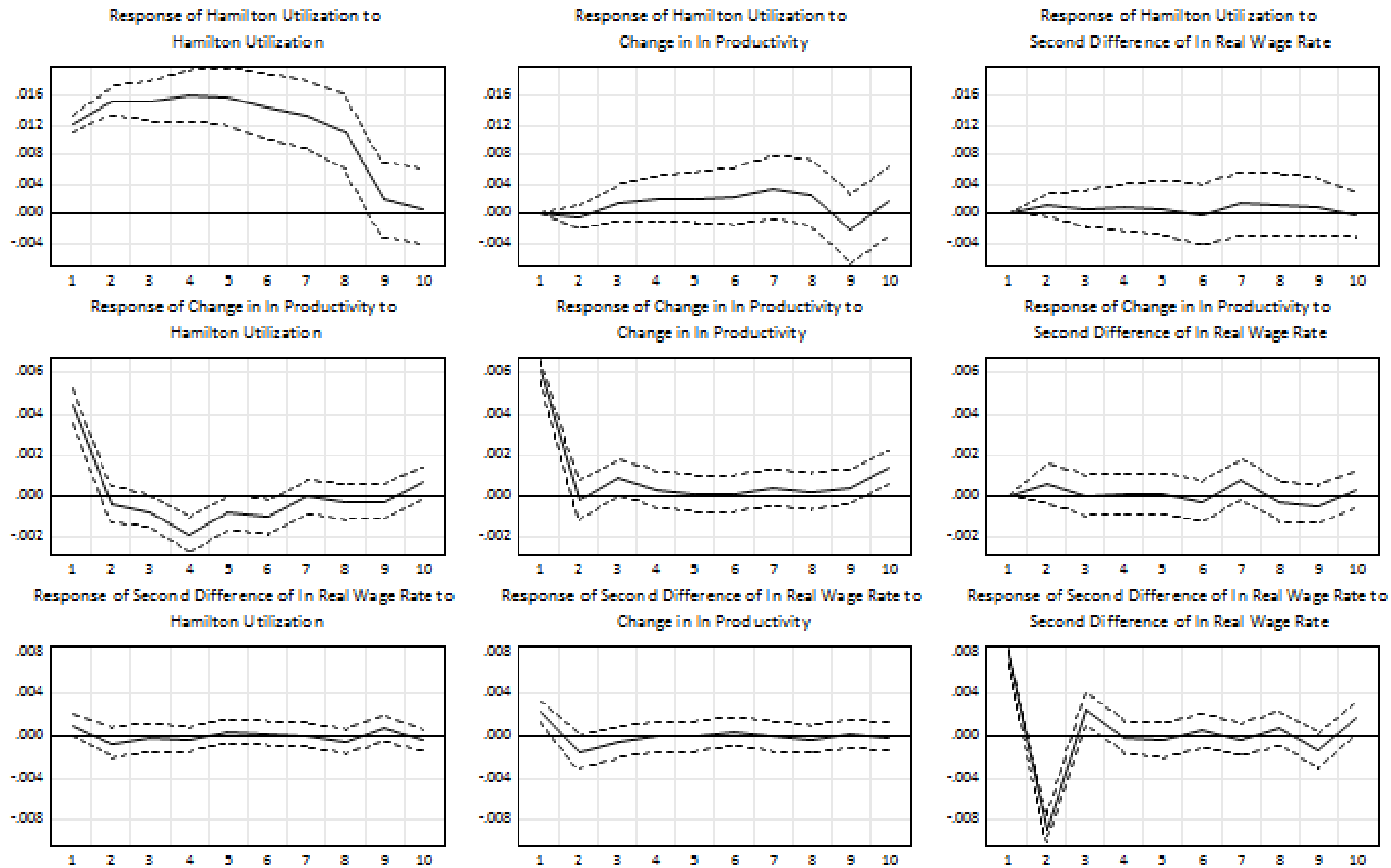
Sample period: 1947 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: ln HP utilization, Δ ln wage share

Figure A.7: Complete IRFs for Reverse Ordering Model with HP Utilization



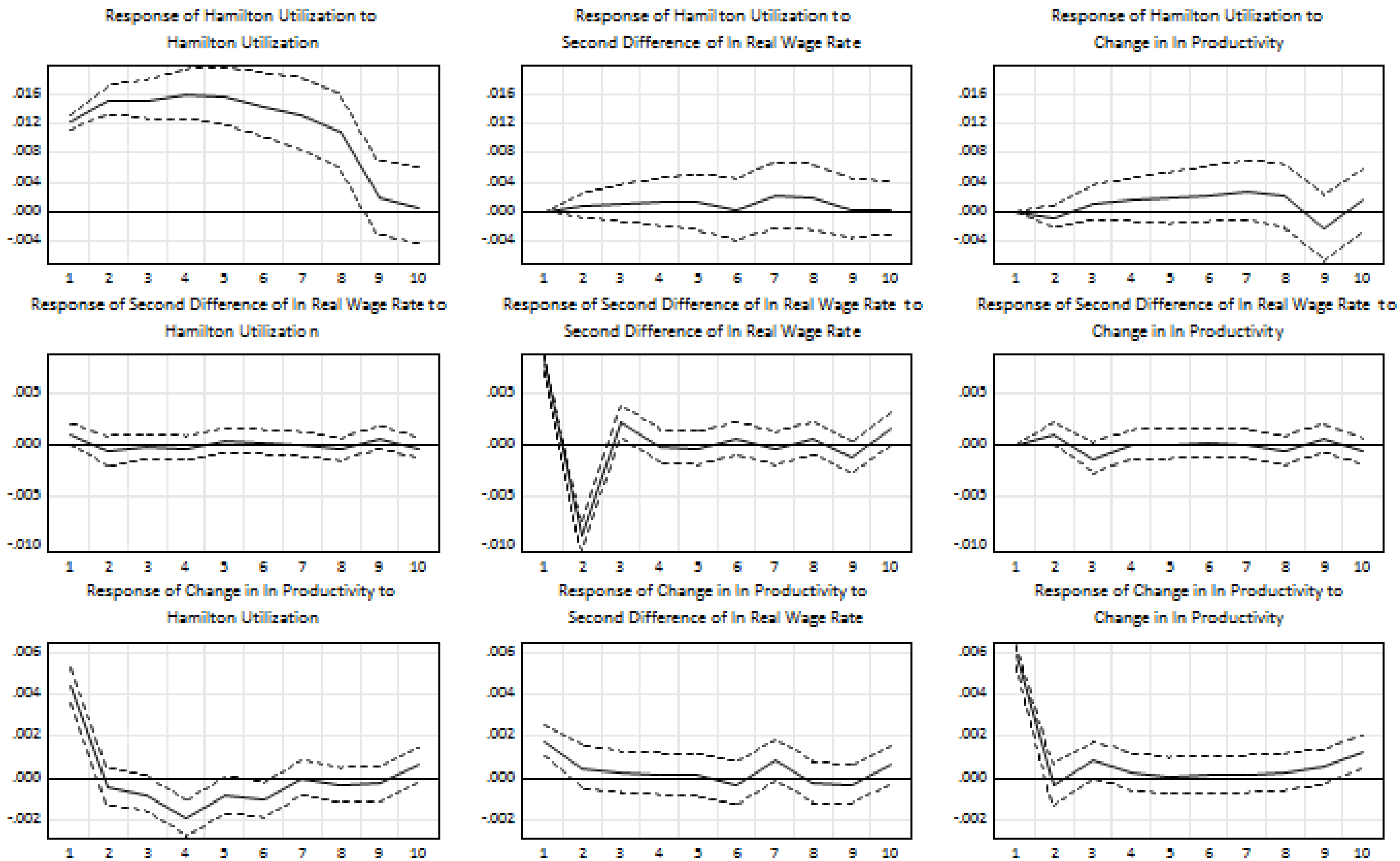
Sample period: 1952 Q1 - 2016 Q4; Model specification: 9 lags and constant term
Variable ordering: Δ Δ real wage rate, Hamilton utilization, Δ ln productivity

Figure A.8: Complete IRFs for Order 1 with Hamilton Utilization



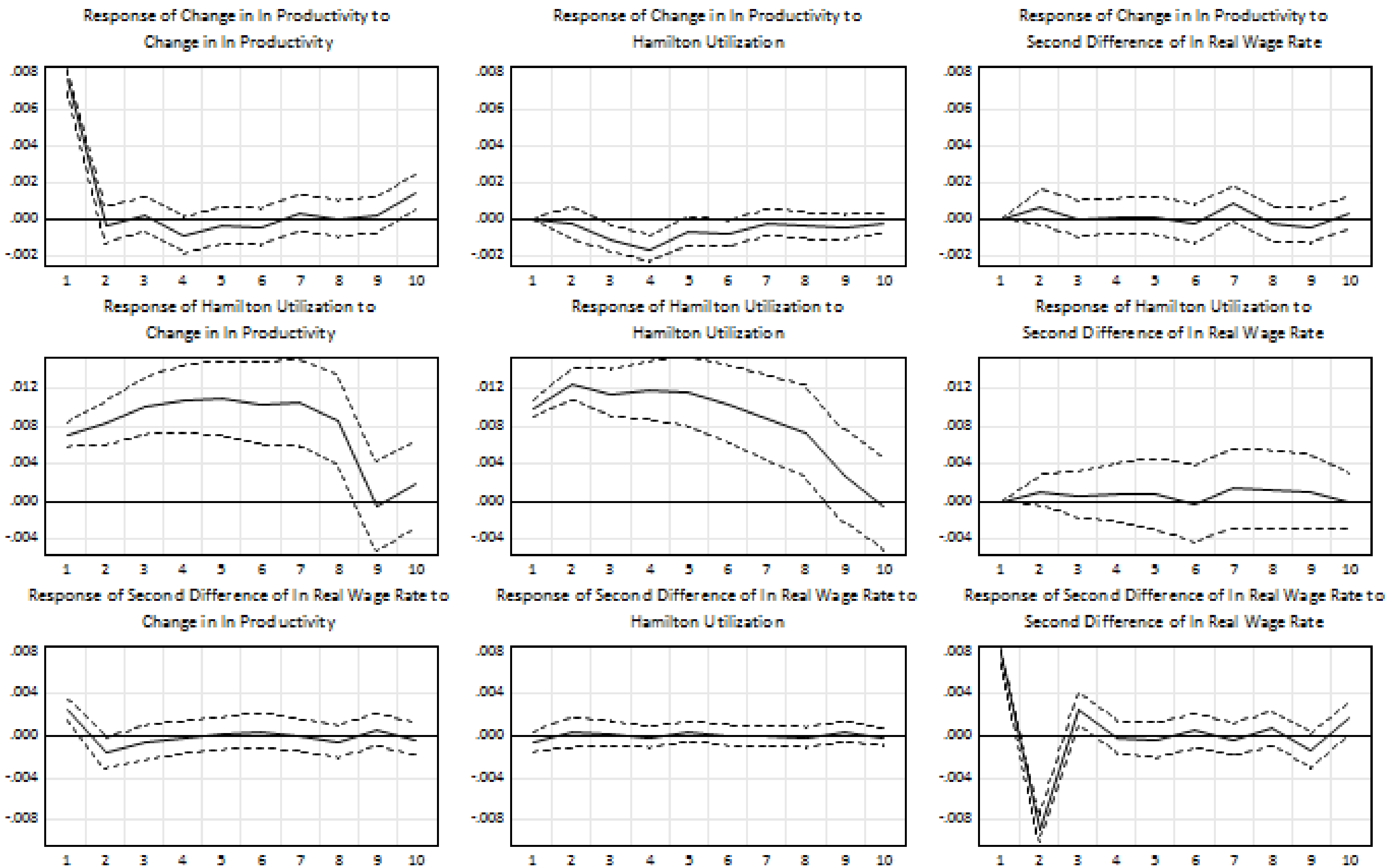
Sample period: 1952 Q1 - 2016 Q4; Model specification: 9 lags and constant term
Variable ordering: Hamilton utilization, Δ ln productivity, Δ Δ real wage rate

Figure A.9: Complete IRFs for Order 2 with Hamilton Utilization



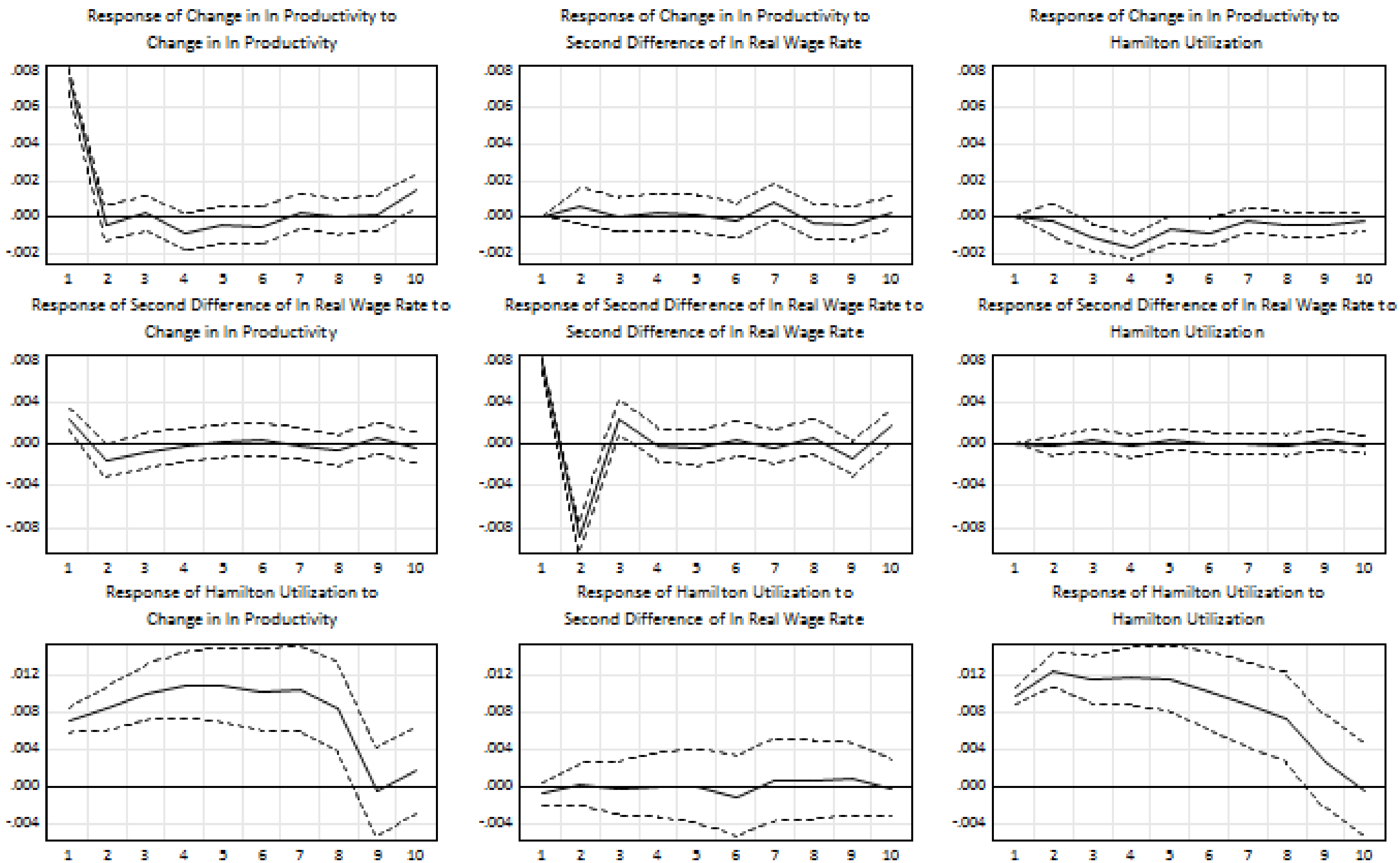
Sample period: 1952 Q1 - 2016 Q4; Model specification: 9 lags and constant term
Variable ordering: Hamilton utilization, $\Delta\ \Delta$ real wage rate, Δ ln productivity

Figure A.10: Complete IRFs for Order 3 with Hamilton Utilization



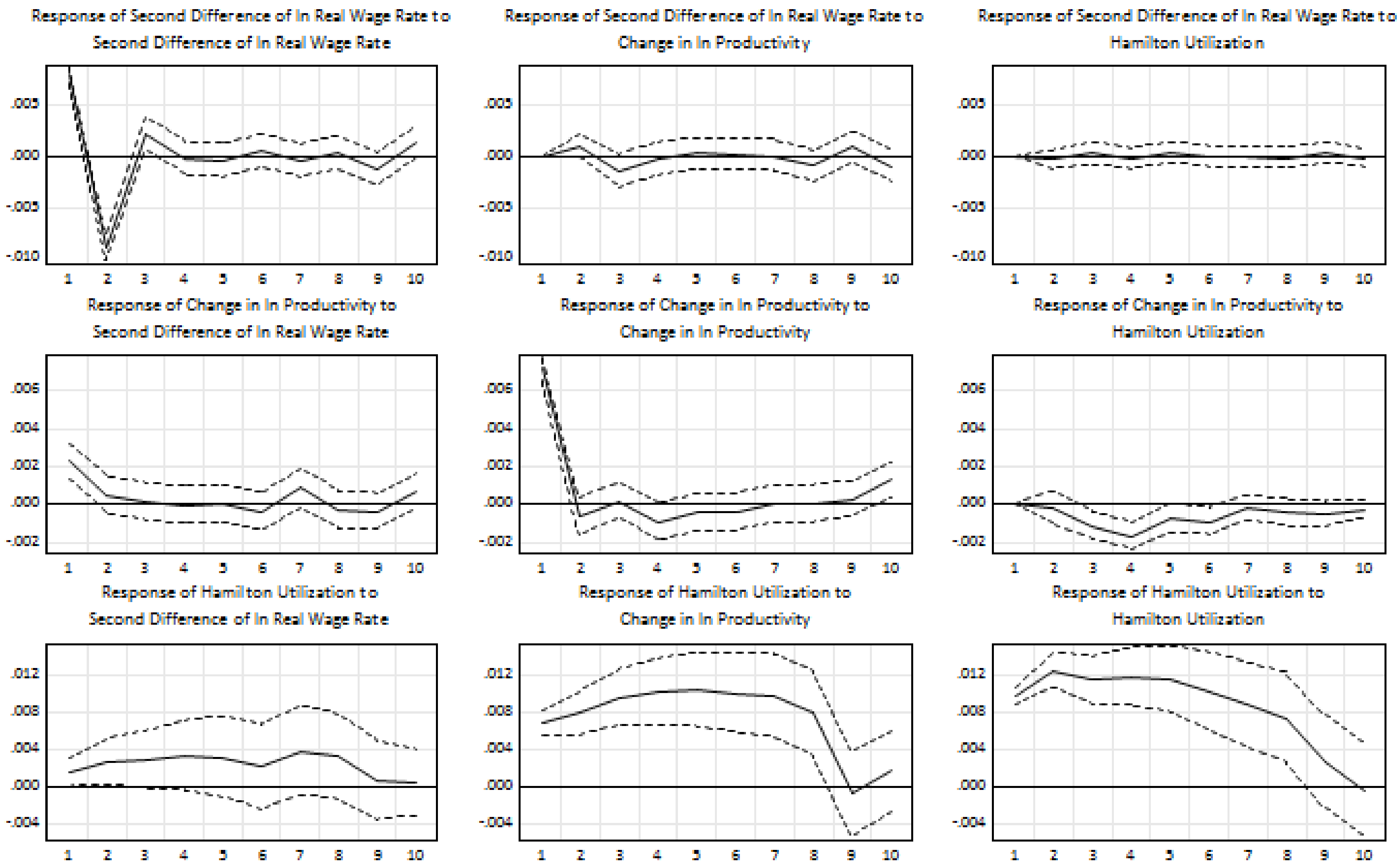
Sample period: 1952 Q1 - 2016 Q4; Model specification: 9 lags and constant term
Variable ordering: Δ ln productivity, Hamilton utilization, Δ Δ real wage rate

Figure A.11: Complete IRFs for Order 4 with Hamilton Utilization



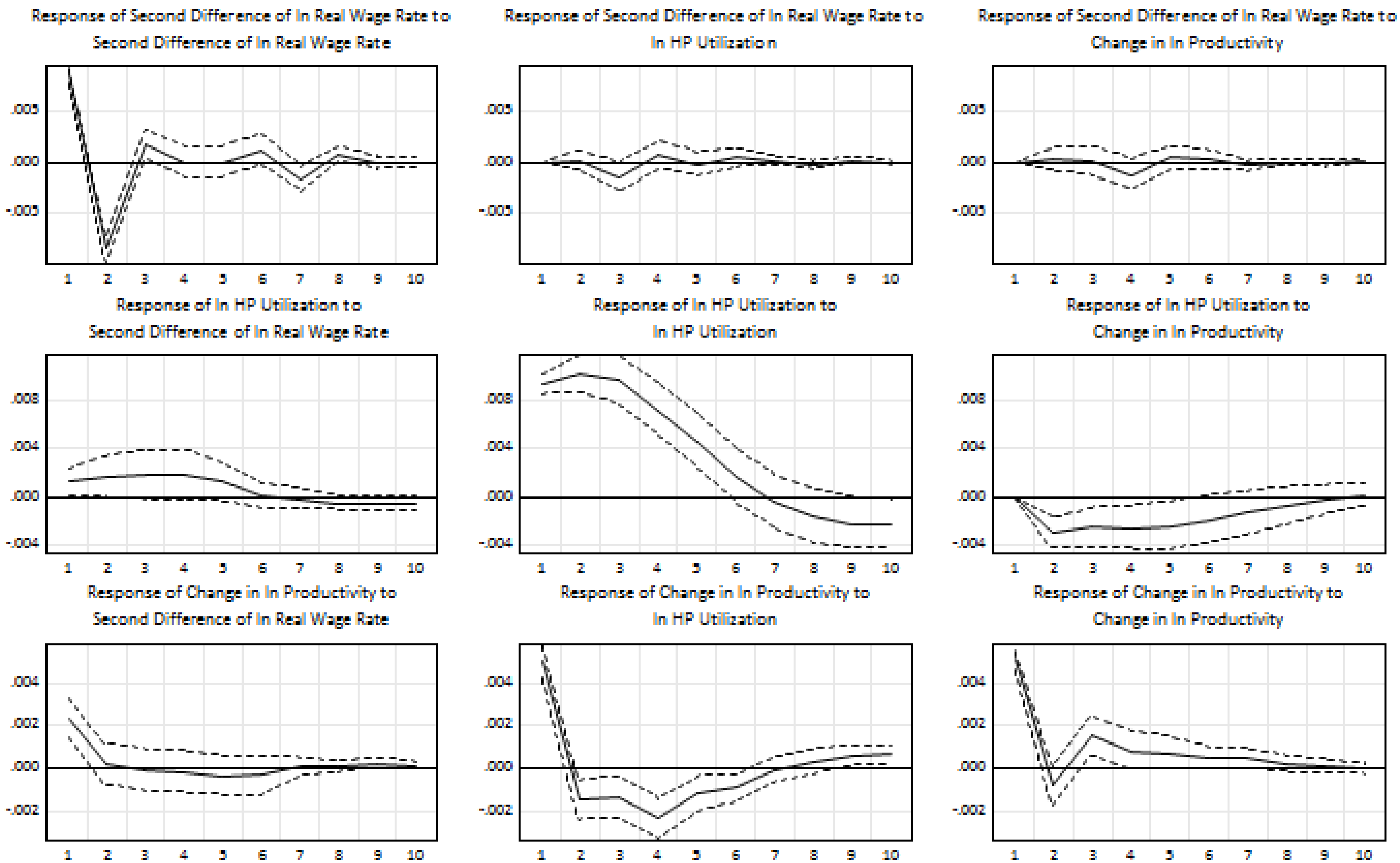
Sample period: 1952 Q1 - 2016 Q4; Model specification: 9 lags and constant term
Variable ordering: Δ ln productivity, Δ Δ real wage rate, Hamilton utilization

Figure A.12: Complete IRFs for Order 5 with Hamilton Utilization



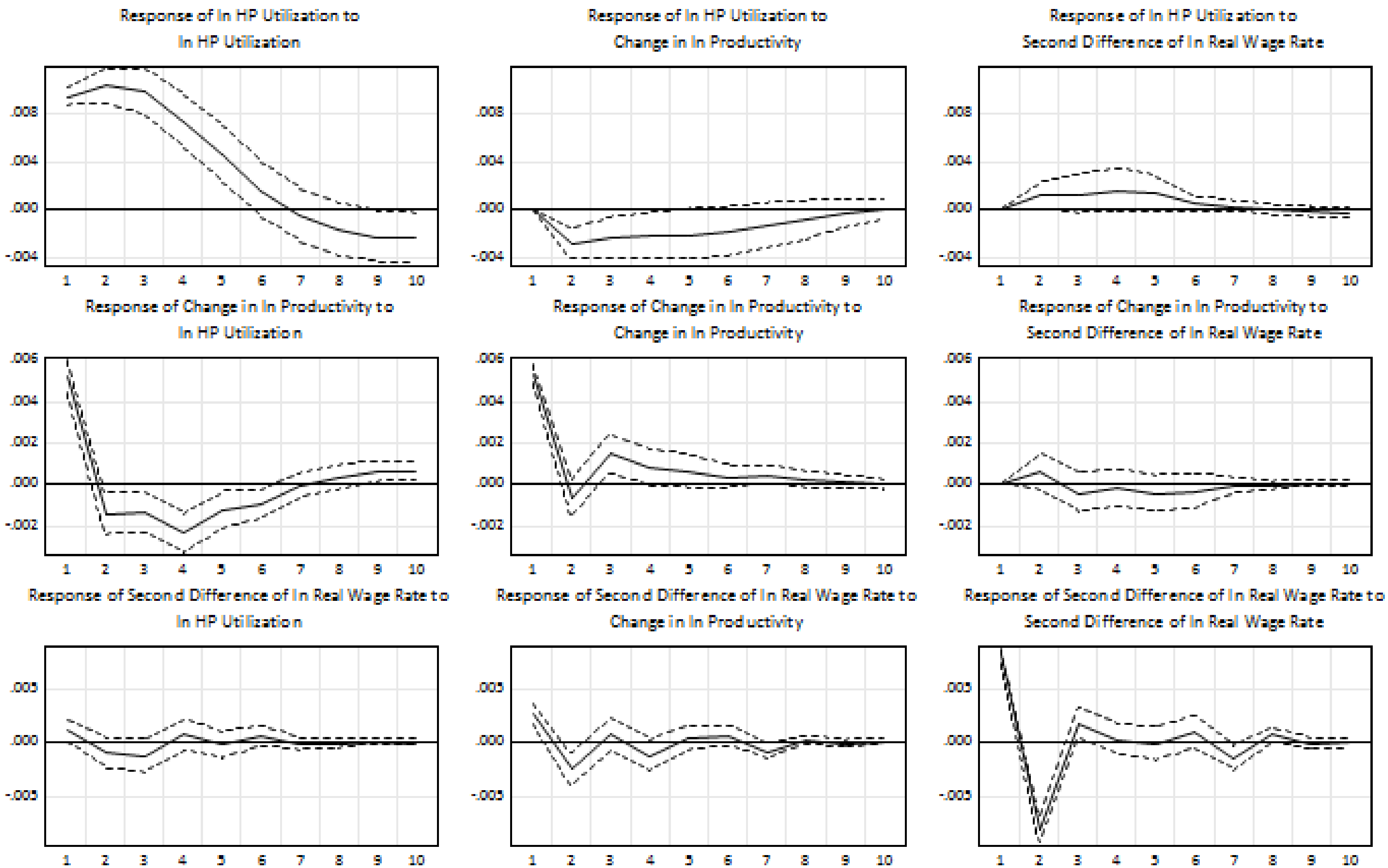
Sample period: 1952 Q1 - 2016 Q4; Model specification: 9 lags and constant term
Variable ordering: Δ Δ real wage rate, Δ ln productivity, Hamilton utilization

Figure A.13: Complete IRFs for Order 6 with Hamilton Utilization



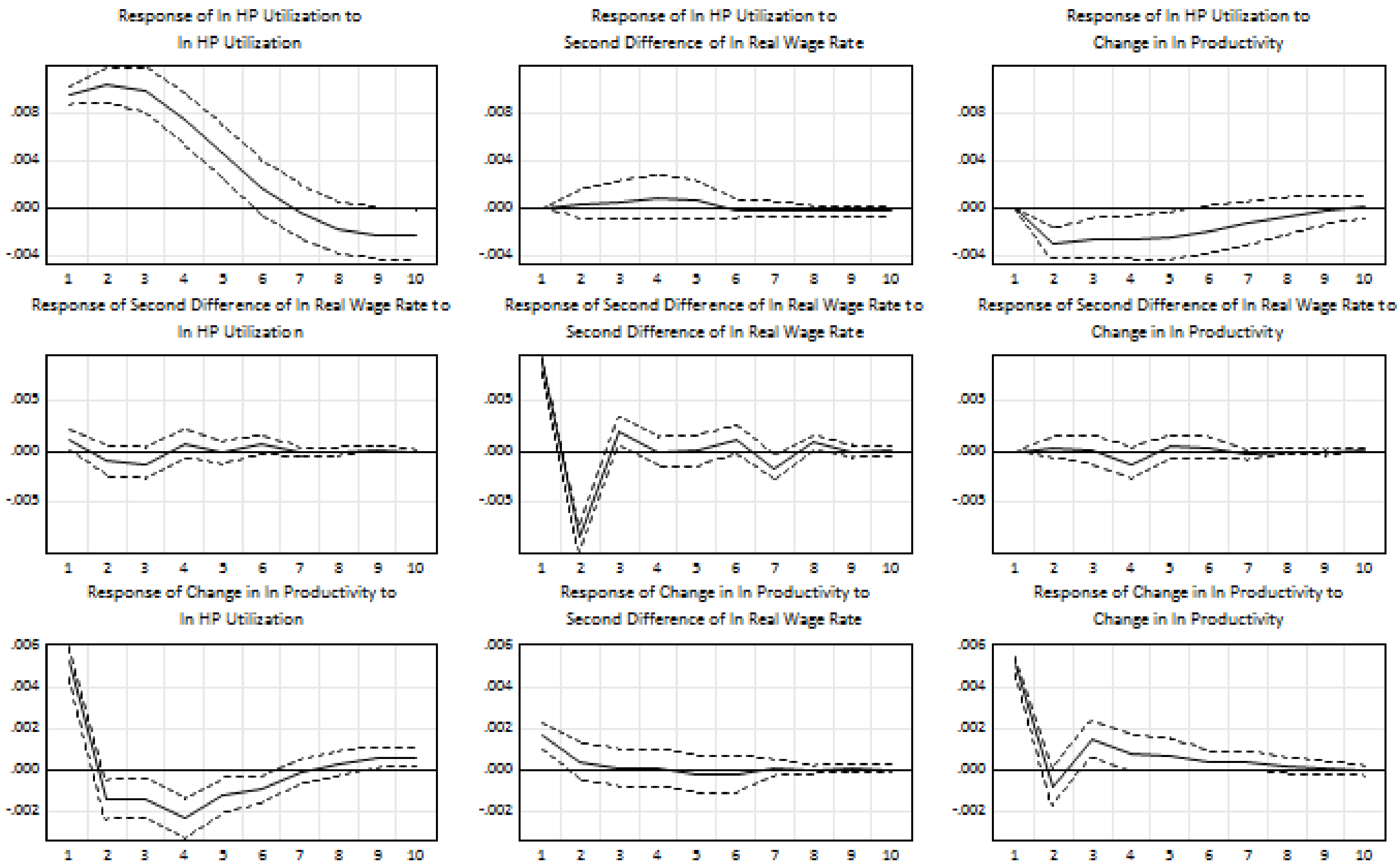
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term
Variable ordering: Δ Δ real wage rate, ln HP utilization, Δ ln productivity

Figure A.14: Complete IRFs for Order 1 with HP Utilization



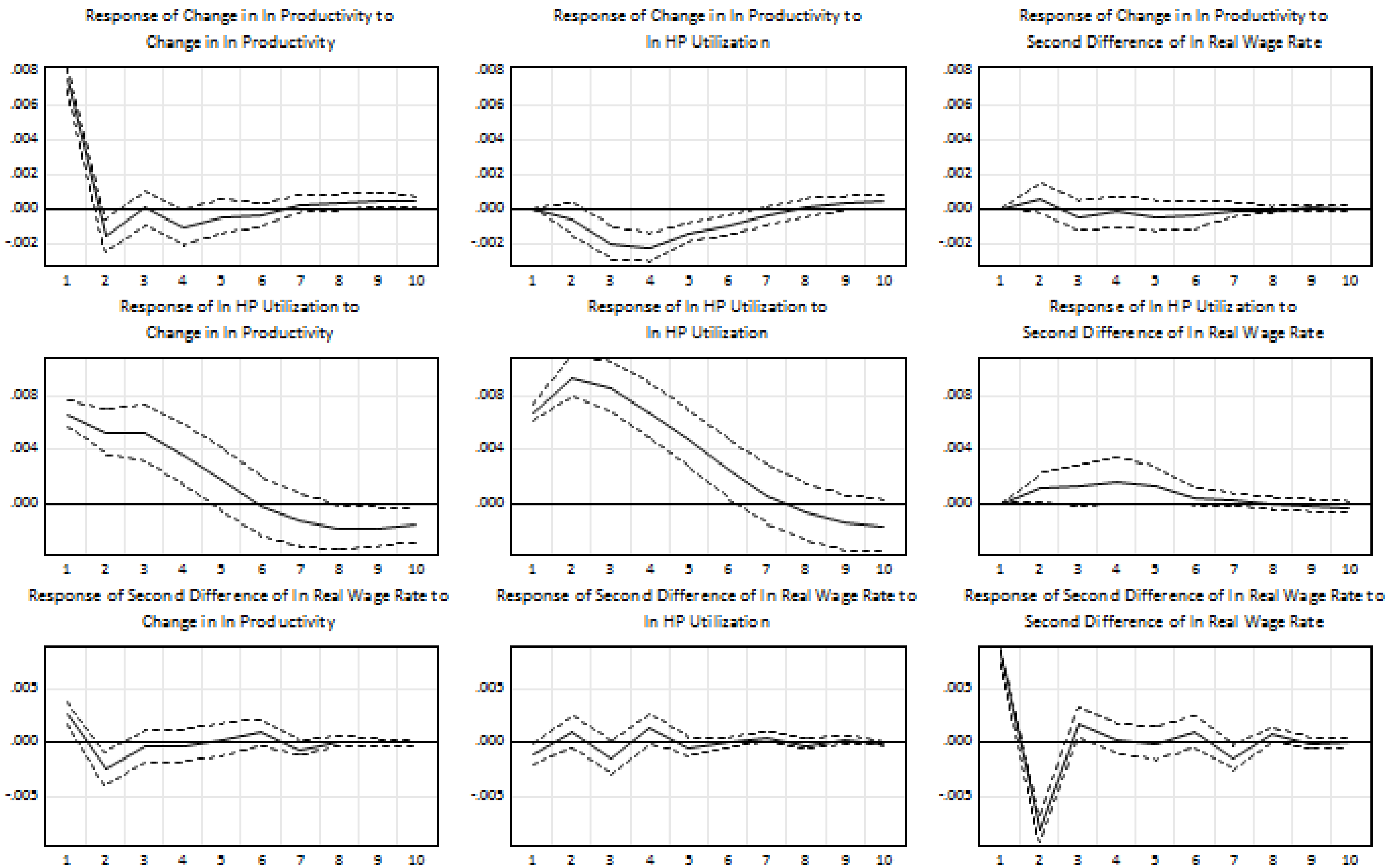
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term
Variable ordering: ln HP utilization, Δ ln productivity, Δ Δ real wage rate

Figure A.15: Complete IRFs for Order 2 with HP Utilization



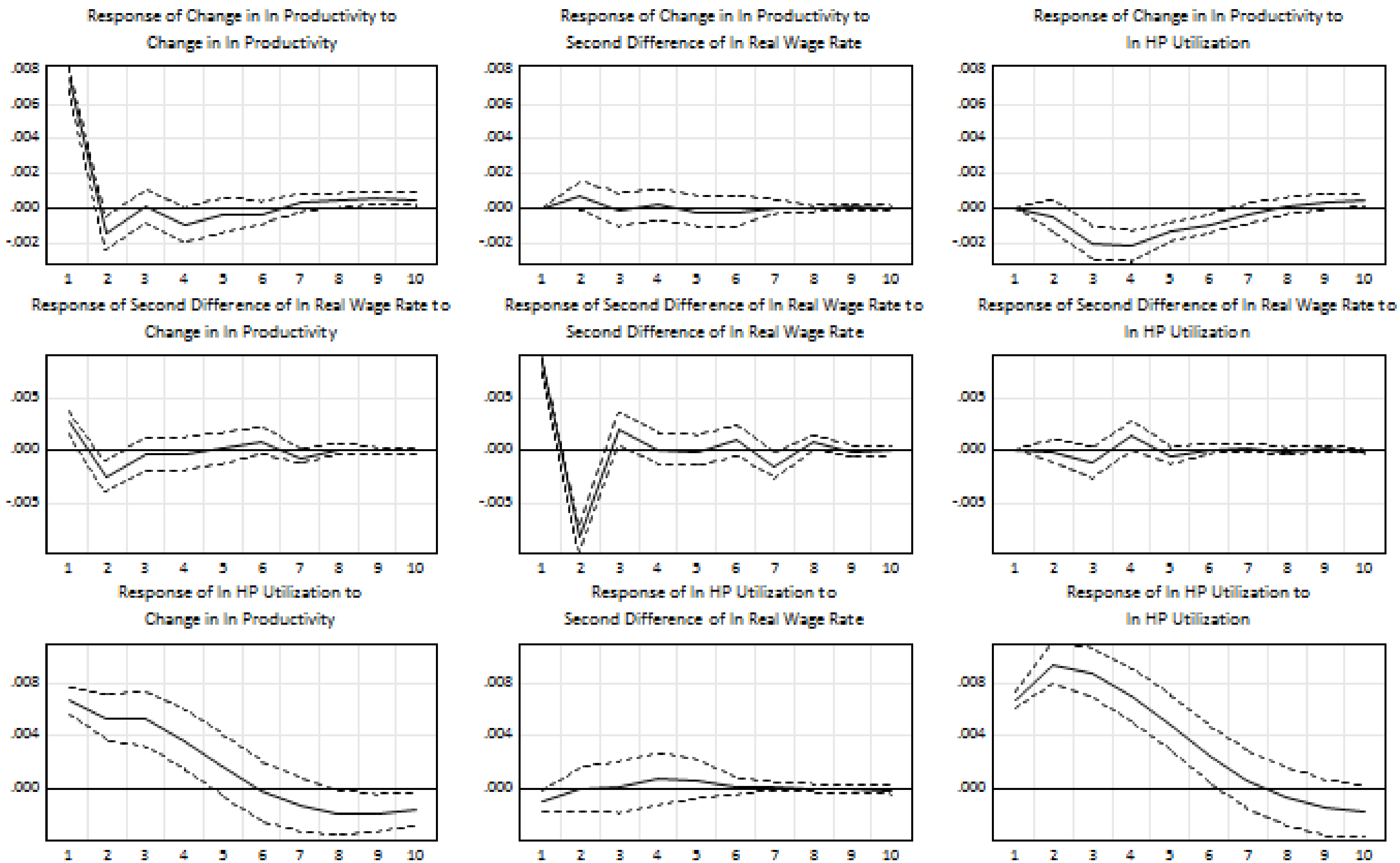
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term
Variable ordering: ln HP utilization, Δ Δ real wage rate, Δ ln productivity

Figure A.16: Complete IRFs for Order 3 with HP Utilization



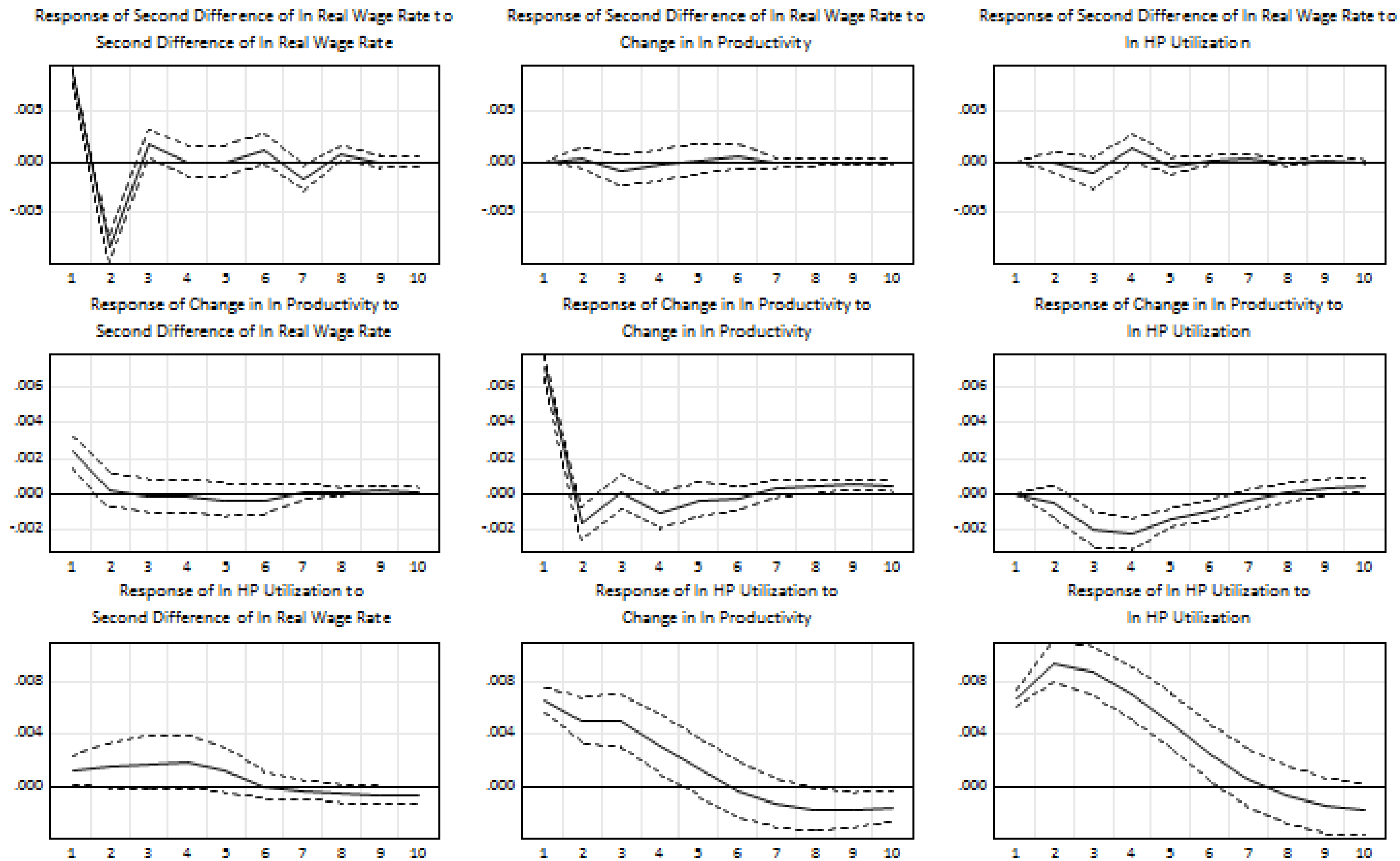
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term
Variable ordering: Δ ln productivity, ln HP utilization, Δ Δ real wage rate

Figure A.17: Complete IRFs for Order 4 with HP Utilization



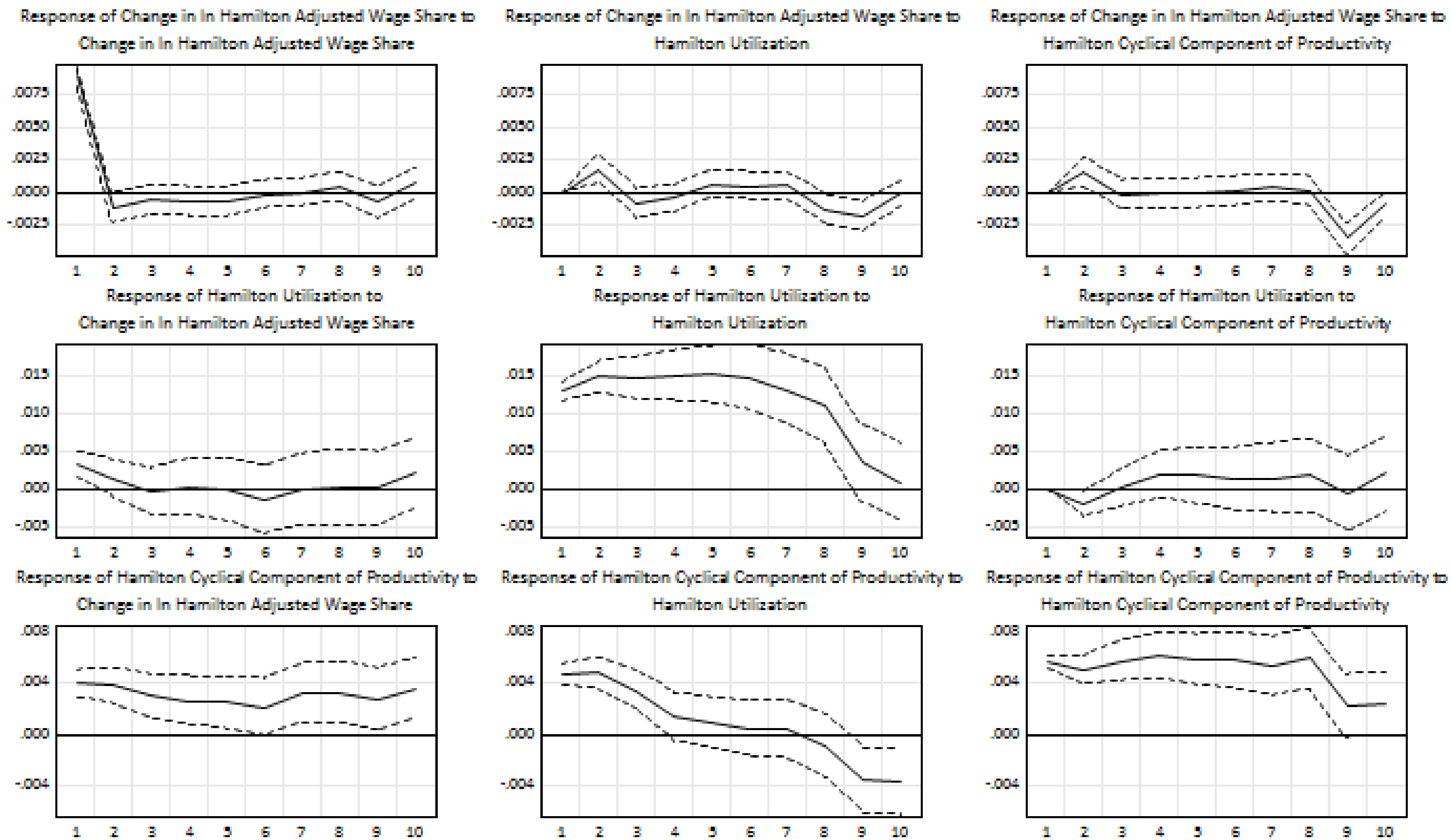
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term
Variable ordering: Δ ln productivity, Δ Δ real wage rate, ln HP utilization

Figure A.18: Complete IRFs for Order 5 with HP Utilization



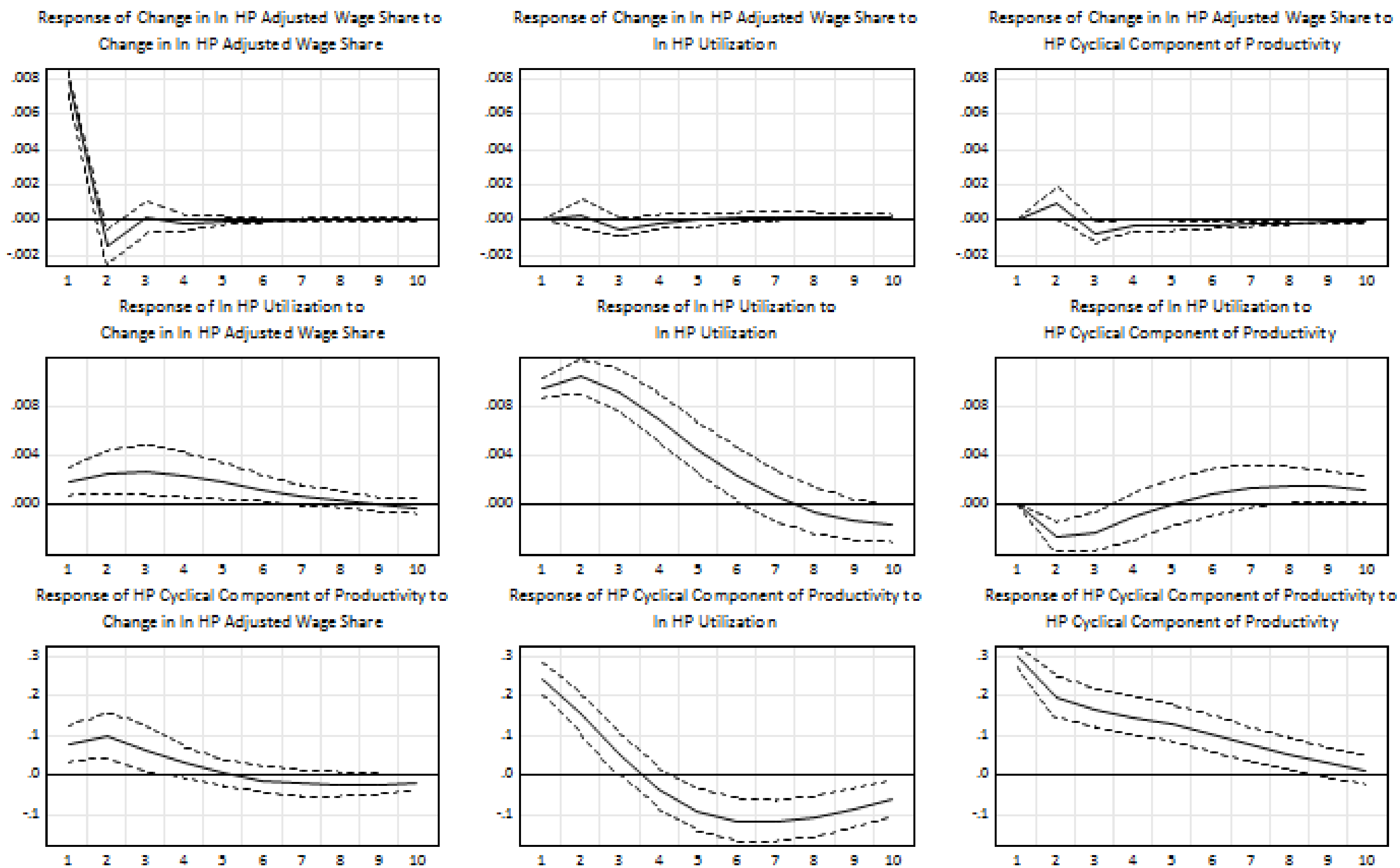
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term
Variable ordering: Δ Δ real wage rate, Δ ln productivity, ln HP utilization

Figure A.19: Complete IRFs for Order 6 with HP Utilization



Sample period: 1952 Q2 - 2016 Q4; Model specification: 9 lags and constant term
Variable ordering: Δ ln Hamilton adjusted wage share, Hamilton utilization, Hamilton cyclical component of productivity

Figure A.20: Complete IRFs for the Hamilton Adjusted Wage Share Model



Sample period: 1947 Q4 - 2016 Q4; Model specification: 2 lags and constant term
Variable ordering: Δ ln HP adjusted wage share, ln HP utilization, HP cyclical component of productivity

Figure A.21: Complete IRFs for the HP Adjusted Wage Share Model