THREE ESSAYS ON THE EMPIRICAL ESTIMATION OF
WAGE-LED AND PROFIT-LED DEMAND REGIMES

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ABSTRACT

This dissertation explores three questions related to empirical estimation of the relationship between aggregate demand and the functional distribution of income—i.e. the share of income going to labor (the wage share) vs. the share going to capital (the profit share). Previous studies exploring this relationship tend to find different results depending on the methodological approach that they follow. Aggregative studies, which estimate a bi-directional system of the wage share and demand, tend to find evidence of profit-led demand and a profit squeeze. Structural studies, which separately estimate the effects of the wage share on the components of aggregate demand while treating distribution as exogenous, more often find that demand is wage-led. Chapter 1 tests whether aggregative estimates are biased if they omit key variables or fail to account for the cyclical effects of demand on productivity—one of the two main components of the wage share. It finds no evidence of omitted variable bias. However, when the cyclical effects of demand on productivity are accounted for, the short-run relationship between the wage share and demand is found to be characterized by wage-led demand and cyclical productivity effects, rather than profit-led demand and a profit squeeze. Chapter 2 tests whether structural studies are biased if they do not account for endogenous effects of demand on the wage share or the systemic relationships between the different components of aggregate demand. Overall, no evidence of such bias is found. In fact, estimates of

systems with endogenous distribution for the two models for which valid instruments could be found indicate that demand is wage-led. Furthermore, the results indicate that demand becomes more wage-led when the models are estimated in this way. Chapter 3 set out to test whether the effects of the wage share on demand differ in the short and long run. However, its findings suggest that the wage share is not a strong predictor of long-run output growth. It argues that more attention should be paid to the main components of the wage share—labor productivity and the real wage—which appear to be stronger determinants of growth.

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CHAPTER 1

THE EFFECTS OF LABOR PRODUCTIVITY IN AGGREGATIVE ESTIMATES OF THE U.S. DEMAND-DISTRIBUTION RELATIONSHIP

1.1 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., 2011), which estimate the relationship between the wage share and the capacity utilization rate, tend to find uniformly profit-led results.

[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.

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). Stockhammer (2017b) 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.

Proponents of the aggregative approach argue that the wage-led findings of structural studies are driven by improperly treating the wage share as exogenous. However, aggregative studies might be biased by other types of misspecification. 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. Another potential source of misspecification is omitted variable bias, which could occur because aggregative studies often do not include any control variables—only lags of the two endogenous variables (Blecker, 2016). Stockhammer (2017b) argues that failure to control for financial variables may bias the results of aggregative studies. Finally, measurement error could also introduce bias. More specifically, the use of a Hodrick and Prescott (HP)

(1997) filter to calculate the utilization rate measure in some aggregative studies may bias the results (Blecker, 2016; Barrales and von Arnim, 2017).

Although the literature has theorized that these potential sources of misspecification may bias existing aggregative estimates, these hypotheses have not yet been empirically tested. This chapter calculates several aggregative estimates of the bi-directional relationship between demand and the functional distribution of income in the U.S. to test whether models following the approach typically used in the aggregative literature suffer from omitted variable bias or measurement error, and whether a failure to account for the cyclical variation of productivity biases the results.

The results strongly suggest that evidence of Goodwin cycle effects is the result of failure to control for cyclical variations in productivity. Although Goodwin cycle effects are found using several different measures of demand and no evidence of omitted variable bias is found, it appears that the appearance of Goodwin cycles actually stems from a misinterpretation of the cyclical effects of demand on labor productivity. When these productivity effects are accounted for—either by using filters to remove the cyclical variation from the productivity component of the wage share or by using identifying restrictions that allow demand to have a contemporaneous effect on productivity—demand is found to be wage-led. These results suggest that estimates of Goodwin cycle effects are actually capturing a positive effect of demand on productivity, rather than a negative effect of the wage share on demand. 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.

This chapter contributes to the literature by testing for various sources of bias in aggregative estimates. 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 removed. It is also the first study to use Hamilton (2017) filter to examine the relationship between the wage share and capacity utilization.

It should be noted that all of the results in this chapter 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 chapter proceeds as follows. Section 1.2 presents the general theoretical foundations and provides a brief overview of the literature. Section 1.3 discusses the empirical strategy, while Section 1.4 discusses the results. Section 1.5 provides some concluding thoughts.

1.2 Theoretical Framework and Literature Review

1.2.1 Theoretical Framework

A sizable literature exists on the empirical relationship between demand and the function distribution of income.[2] 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;

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

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.[3]

$$Y = AD = C + I + G + NX \tag{1.1}$$

Equation (1.1) simply 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:

$$C = C(Y, \psi, Z_c) \tag{1.2}$$

$$I = I(Y, \psi, Z_I) \tag{1.3}$$

$$NX = NX(Y, P, Z_X, Z_M); P = P(\psi, Z_P) \tag{1.4}$$

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:

[3] 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).

$$Y = AD = C(Y, \psi, Z_C) + I(Y, \psi, Z_I) + G + NX(Y, P, Z_X, Z_M) \tag{1.5}$$

The following assumptions are commonly made regarding the signs of the partial derivatives of the components of aggregate demand: $C_Y > 0$, $C_\psi > 0$, $I_Y > 0$, $I_\psi < 0$,[4] $NX_Y < 0$, $P_\psi > 0$, $NX_P < 0$. 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.

$$\frac{\partial Y}{\partial \psi} = \frac{\partial AD/\partial \psi}{1 - \partial AD/\partial Y} \tag{1.6}$$

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 (1.7) to be satisfied:

$$\frac{\partial AD}{\partial Y} = \frac{\partial AD}{\partial C} + \frac{\partial AD}{\partial I} + \frac{\partial AD}{\partial NX} < 1 \tag{1.7}$$

Therefore, in a stable system, the denominator of equation (1.6) 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 (2017b) note that studies following this approach usually find evidence that $\partial AD/\partial \psi > 0$, i.e., demand is

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[4] This assumption is debatable, as Chapter 2 finds evidence of a positive sign for this partial derivative.

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:

$$Y = Y(\psi, Z_C, Z_I, Z_X, Z_M, Z_P) \tag{1.8}$$

Aggregative models typically combine this with an equation for the wage share, like equation (1.9) to make distribution endogenous.

$$\psi = \psi(Y, Z_\psi) \tag{1.9}$$

Those following the aggregative approach typically try to estimate difference equation versions of equations (1.10) and (1.11) 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.

$$\dot{u} = f(u, \psi) \tag{1.10}$$

$$\dot{\psi} = g(\psi, u) \tag{1.11}$$

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 growth 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).[5] 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 (1.10) and (1.11) 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 1.1, 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 chapter will estimate the slopes of these nullclines.

1.2.2 Literature Review

Barbosa-Filho and Taylor (2006) estimated a difference equation version of the system in equations (1.10) and (1.11) for the U.S. from 1948-2002 using a reduced form VAR with two lags.[6] They found evidence of a Goodwin cycle, i.e. profit-led demand

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

[6]The model that they estimate is not a standard VAR, because they estimate the equations for the utilization rate and the wage share separately, using data in levels for one and data in log levels for the other.

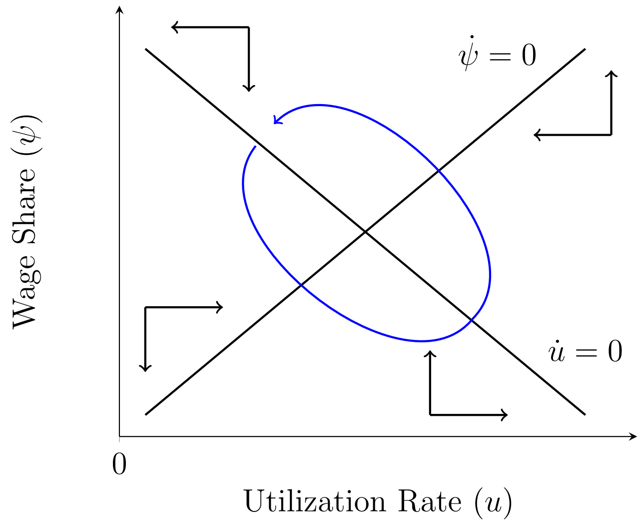

Figure 1.1: System with Profit-led Demand and Profit-squeeze Effects
Adapted from Barbosa-Filho and Taylor (2006)

and a profit squeeze.[7] 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.[8] Other aggregative studies have found evidence of similar dynamics using different techniques or country samples. Kiefer and Rada (2015) 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

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

[8] 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.

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. Complicating matters, Nikiforos and Foley (2012) find evidence that the distributive schedules 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 early aggregative study conducted by Stockhammer and Onaran (2004) is an outlier. They estimated structural VARs including the the profit share, the utilization rate (measured as the ratio of the output gap to potential output), the growth of labor productivity, unemployment, and capital accumulation for the U.S., the U.K., and France using semiannual data from the late 1960s or early 1970s to 1997, finding wage-squeeze effects and no significant effect of distribution on demand. As they do not report the results of a model including only the profit share and utilization, it is not known whether the differences between their findings and those of other aggregative studies stem from the inclusion of additional variables.[9]

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

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[9]Controlling for productivity may eliminate some of the bias caused by the cyclical effects of demand on productivity. However, it is likely not the best way to account for cyclical productivity effects because labor productivity shocks will appear twice in the model, affecting both the productivity series itself and the profit share. Their results are consistent with the view that demand has a positive effect on productivity, as they find a positive and statistically significant effect of demand on productivity in all three countries. In the cases of the U.S. and the U.K., these effects are eventually followed by negative lagged effects, which are significant for the U.K., but not the U.S.

be explained by differing objects of analysis, and must be the results of methodological differences.

It is possible that misspecification of aggregative models contributes to these differences. The literature has identified several issues that may bias the results of previous aggregative models. One major issue is that aggregative models often do not include any control variables, other than lags of the two endogenous variables. As the structural approach involves separately estimating the wage share's effect on the individual components of aggregate demand (generally excluding government expenditures), researchers following this approach typically include control variables that may affect a particular component of demand in the individual estimation equation for that component. On the other hand, many studies following the aggregative approach do not include any control variables at all (see e.g. Barbosa-Filho and Taylor, 2006; Carvalho and Rezai, 2016; Barrales and von Arnim, 2017). Blecker (2016) suggests that omitted variable bias is likely in such models.

In addition to including capital accumulation, unemployment, and productivity growth in their model, Stockhammer and Onaran (2004) test the sensitivity of their results to controlling for the real interest rate, inflation, and the change in inflation. They find that adding these variables has little effect on the results. Another aggregative study, conducted by Fernandez (2005), did find profit-led demand in the U.S. even though it incorporated some control variables, including measures of international labor cost competitiveness and government spending. However, unlike other studies that have found a significant profit-squeeze effect, Fernandez (2005) found that the profit share was not affected by utilization, but was significantly related to international labor cost competitiveness.

Although Fernandez (2005) and Stockhammer and Onaran (2004) included some control variables, there are still several potential sources of omitted variable bias that have not been tested. For example, Stockhammer (2017a) suggests that aggregative studies may be biased because they do not include any financial variables, such wealth and debt, which have been shown to have a large impact on demand (Stockhammer and Wildauer, 2016). This is a notable omission because Stockhammer and Michell (2016) argue that observed Goodwin cycle effects, could result from the interaction of financial fragility and demand, and therefore do not necessarily provide evidence of profit-led demand. This suggests the possibility that existing aggregative estimates of the relationship between the wage share and aggregate demand may be biased because they do not account for the significant amount of consumption and housing investment that is financed by wealth or debt. For example, in the case of the United States, the profit-led relationship observed in aggregative studies could be the result of the downward trend in the wage share coinciding with sharp increases in debt and asset values prior to the financial crisis of 2008.

Furthermore, as Lavoie (2014, 323-5) argues, the presence of overhead or managerial labor can also cause labor productivity to vary procyclically with the utilization rate.[10] Because the wage share is equal to the hourly wage divided by labor productivity, as shown in equation (1.12),[11] 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.[12]

[10]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).

[11]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.

[12]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

$$\psi = \frac{worker\ compensation}{output} = \frac{worker\ compensation/hours}{output/hours} \\ = \frac{real\ hourly\ wage\ rate}{labor\ productivity} \tag{1.12}$$

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:

> ...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, no studies following the aggregative approach have yet controlled for the role of cyclical variation in labor productivity in estimating the relationship between the utilization rate and the wage share.

The presence of managerial labor also complicates the interpretation of the wage share. The wage share vs. profit share distinction does not cleanly divide up the income going to workers and capitalists, as theoretical models generally assume, because wage earners are a heterogeneous group, including those ranging from production workers, who earn little to no capital income, to executives, whose incomes include both profits from capital ownership and large salaries, which are included in the measurement of total wages. Palley (2017) argues that an increase in the wages paid to workers (as opposed to a general increase in the wage share) always increases demand, and illustrates this with a theoretical model. This suggests that it may also be important to consider how wages are distributed among workers.

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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).

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 (2017, abstract) offers this explanation for why this technique should never be used:

> ... (1) HP introduces spurious dynamic relations that have no basis in the underlying data-generating process. (2) Filtered values at the end of the sample are very different from those in the middle, and are also characterized by spurious dynamics. (3) 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.

The utilization rate may not be a sensible way to measure demand, even if potential output were not calculated using a 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.[13] These variables

[13] 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.

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 its 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.

It is possible that problems stemming from the measurement of demand as the utilization rate may explain some of the differences between the results of aggregative and structural studies. Indeed, the two approaches tend to use different measures of demand. Many aggregative studies measure demand using the utilization rate or the output gap, while structural studies typically use a measure of real output, such as real GDP. The former are more likely to be biased, given the problems with estimating potential output. As Stockhammer (2017b) notes, this could contribute to the general differences in the results of these studies.

1.3 Empirical Strategy

1.3.1 Methodology

To test whether aggregative models are sensitive to the addition of control variables, the use of alternative variable measurements, or the treatment of productivity effects, this chapter first estimates a baseline model, including only the wage share and utilization rate, and then compares the results to several alternative specifications that include control variables or a different measure of one of the key variables. The 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:

$$\boldsymbol{y_t} = \boldsymbol{\mu} + \sum_{j=1}^{L} \boldsymbol{F_j} \boldsymbol{y_{t-j}} + \boldsymbol{e_t} \tag{1.13}$$

where t is the time period, $\boldsymbol{y_t}$ is a vector of dependent variables, and $\boldsymbol{F_j}$ is the coefficient matrices to be estimated, $\boldsymbol{\mu}$ is the constant, $\boldsymbol{e_t}$ is the error term, $j = 1, \ldots, L$ 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 chapter will not conduct such a variable decomposition, it will simply use the log transformation.[14] Another important difference from the Barbosa-Filho and Taylor (2006) model is that they include an exogenous trend. No trend is included in the baseline model because neither the log utilization rate nor the first difference of the log wage share exhibits a trend.

Following this estimation, modified versions of the model are estimated and compared to the results of the baseline model. Some specifications include control variables

[14] All other variables, with the exception of the interest rate, are logged as well.

in the data matrix, $\boldsymbol{y_t}$, in addition to the wage share and utilization rate. Some specifications will control for wealth, household debt, and corporate debt to test Stockhammer's (2017b) hypothesis that the exclusion of such financial variables could lead to omitted variable bias. Other important macroeconomic variables, including the interest rate, the exchange rate, and government spending are also included as control variables in another specification. The exchange rate should capture the international labor competitiveness effects that Fernandez (2005) found to be important, whereas government spending and the interest rate are included to proxy for the effects of fiscal and monetary policy. The six control variables are not included together in a single specification, but instead separated into two groups, in order to prevent the number of parameters from growing too large. All of the control variables, with the exception of the interest rate, are log transformed. 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:[15]

$$\boldsymbol{y_t} = [\Delta\ ln\ wage\ share_t, ln\ utilization_t] \tag{1.14}$$

This ordering imposes the restriction that the log utilization rate does not affect 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.[16] In fact, if the wage share is countercyclical due to the procyclicality of labor productivity, as shown 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 used later 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 measure of the wage

[15]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 most specifications (excluding those with control variables, for which many possible orderings are possible), GIRFs would not provide any additional information, as they simply combine IRFs from estimates with different orderings. For this reason, GIRFs are not used.

[16]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.

share from which the cyclical variation in the labor productivity component has been removed.

1.3.2 Data

All models are estimated using quarterly U.S. data. The baseline model is estimated using a sample period of 1947-2016, while some other specifications have shorter samples due to data constraints. Following Barbosa-Filho and Taylor (2006) and Carvalho and Rezai (2016), the baseline utilization rate is measured as the ratio of output to potential output, where the potential output series is constructed by taking the trend component of output obtained by applying an HP filter to the output series.[17] The output series is the BLS index of real business sector output. The resulting series, and all other series measured as percentages, are multiplied by 100 to give them the same scale as the wage share measure, described below. A graph of the HP utilization rate—i.e. the baseline measure of utilization—can be seen in Figure 1.2.

Due to some of the documented issues with the HP filter, this measure of the utilization rate could be biased. Therefore, three alternative measures of the utilization rate are used to test for sensitivity to this measurement choice. The first uses an alternative filtering technique, as proposed by Hamilton (2017), to construct a utilization rate from the business sector output index. Hamilton 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 (1.15), while the predicted values from this regression represent the trend component

[17]The standard value of the smoothing parameter for quarterly data, 1,600, is used for filtering.

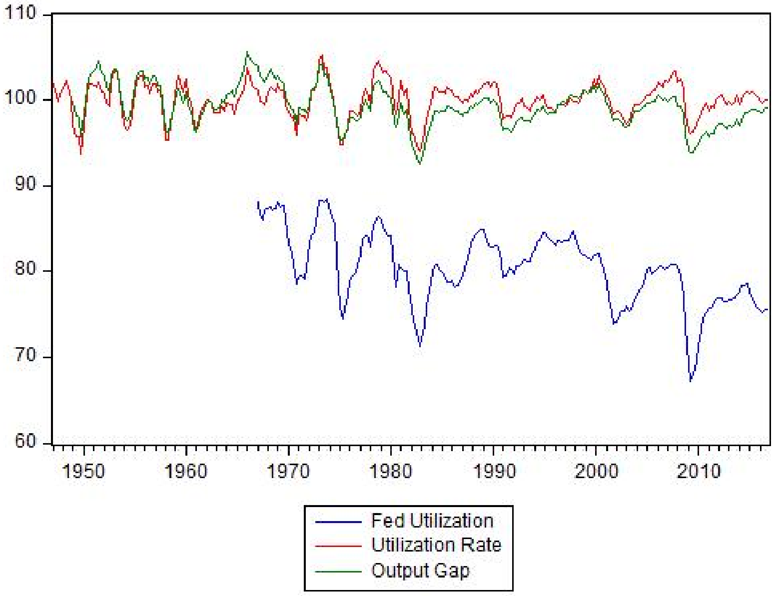

Figure 1.2: Three Utilization Measures for the U.S., 1947-2016

Sources: Refer to Table A.2 in Appendix A

$$ln\ output_t = \alpha + \sum_{i=8}^{11} \boldsymbol{\beta_i}\ ln\ output_{t-i} + \epsilon_t \tag{1.15}$$

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.[18] 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.

[18]This is what Hamilton (2017) recommends for analysis of business cycle effects.

A graph of the Hamilton utilization rate, along with the natural log of the output series and its Hamilton-filtered trend, is shown in Figure 1.3. As the graph shows, the estimated potential output series tends to vary cyclically, lagging behind the cyclical changes in output. This is a desirable feature of a potential output series, based on Cerra 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 stayed flat. 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. However, it is still useful as a point of comparison.

The other two measures of utilization are not constructed with filters. Both of these measures—the Federal Reserve's capacity utilization index and the output gap—were previously used by Barrales and von Arnim (2017).[19] Both of these measures are calculated as ratios of output to a measure of potential output, or capacity. However, in contrast to the baseline measure, which estimates potential output as the filtered trend in the aggregated output series, the Fed index estimates capacity based upon plant-level survey data, whereas the output gap measure utilizes the U.S. Congressional Budget

[19]Barrales and von Arnim (2017) also use a third measure to proxy for the utilization rate—the income-capital ratio. This chapter 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.

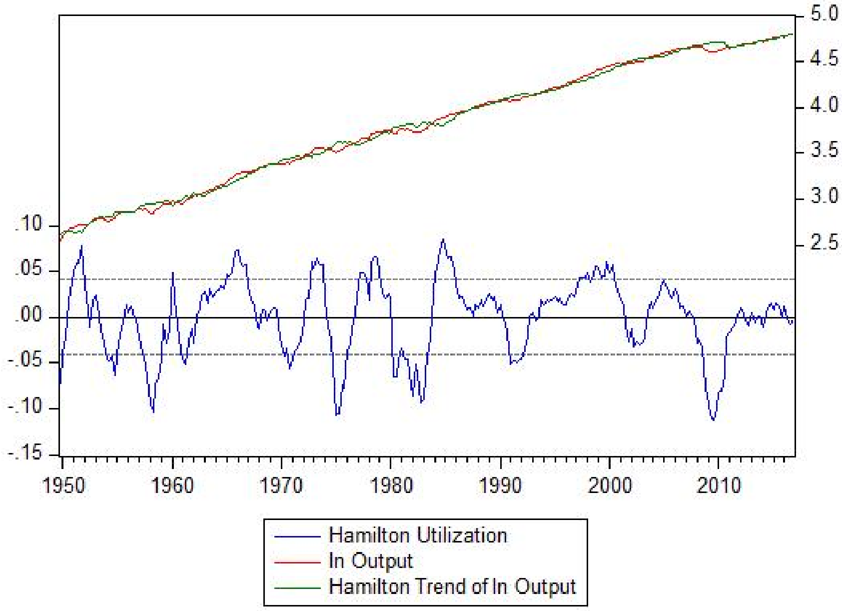

Figure 1.3: Business Sector Output and Its Hamilton-filtered Components, 1947-2016

Office's (CBO) estimate of potential output (Barrales and von Arnim, 2017). The latter is constructed by dividing the Bureau of Economic Analysis' (BEA) real GDP series by the CBO potential output series, which is estimated within a growth accounting framework.[20] These two series are compared to the HP filtered-utilization rate in Figure 1.2.

Although these measures of utilization do not rely on filtering techniques for their construction, they are 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. For these reason, the growth rate of real GDP is used as a measure of demand to test for sensitivity to using a measure of demand that is not based on this conception of the business cycle. This measure also has the added benefit of greater similarity to the measurement of demand in structural studies.

[20]See Barrales and von Arnim (2017) for a more detailed comparison of these measures with the HP filter utilization rate.

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.[21] 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 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 (1.16).

$$\begin{aligned}\psi &= \frac{100 * nominal\ hourly\ compensation/CPI}{100 * nominal\ output\ per\ hour/output\ deflator} \\ &= \frac{real\ hourly\ wage\ rate}{labor\ productivity} * \frac{CPI}{output\ deflator}\end{aligned} \tag{1.16}$$

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

[21]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).

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 filter.[22] The adjusted wage shares are calculated using equation (1.17). For the HP adjusted wage share, ln trend productivity is calculated by taking the natural log of the HP trend component of the labor productivity series.[23] For the Hamilton adjusted wage share, ln trend productivity is found by taking the predicted values from OLS estimates of equation (1.18).[24]

$$\mathit{ln\ adjusted\ wage\ share}_t = \mathit{ln\ real\ wage\ rate}_t - \mathit{ln\ trend\ productivity}_t \tag{1.17}$$

$$\mathit{ln\ productivity}_t = \alpha + \sum_{i=8}^{11} \boldsymbol{\beta_i}\ \mathit{ln\ productivity}_{t-i} + \epsilon_t \tag{1.18}$$

A separate measure of the wage share removes the compensation of managers and executives. Because the business sector wage share index contains the compensation of highly paid managers and executives (Bureau of Labor Statistics, 2017), one alternative measure of the wage share includes only the wages of production and nonsupervisory workers in order to account for the issue raised by Palley (2017). This measure is calculated

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

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

[24]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.

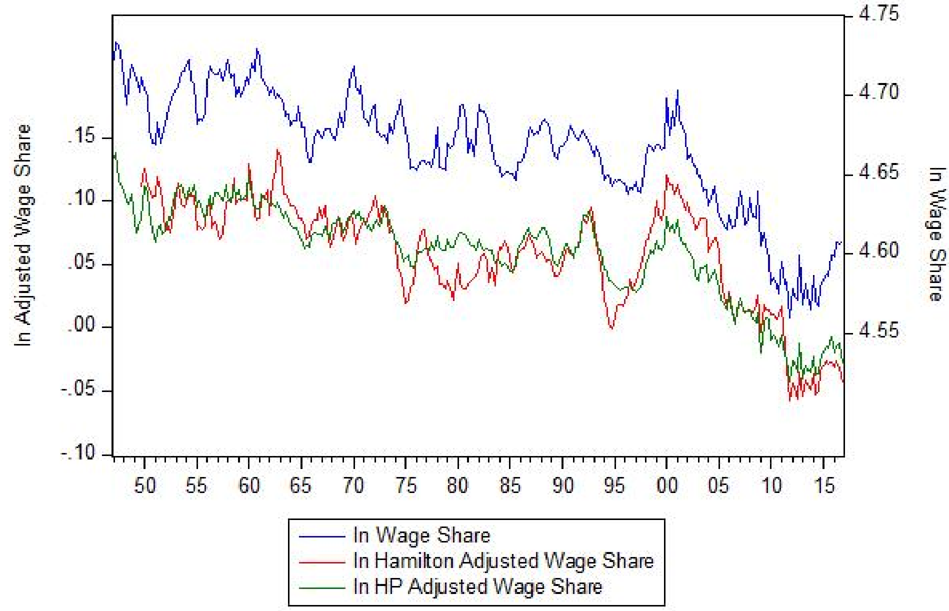

Figure 1.4: Comparison of Wage Share and Adjusted Wage Shares, 1947-2016

Sources: Refer to Table A.2 in Appendix A

by dividing the BLS index of aggregate weekly payrolls of production and nonsupervisory workers in the total private sector by the BLS index of business sector output.[25] It should be noted that this measure is not directly comparable to the baseline wage share measure because the baseline measure is calculated as total compensation divided by output, while the production worker wage share is calculated as aggregate weekly payrolls divided by output. This is an important difference, as the production worker wage share does not include bonus pay or benefits (Bureau of Labor Statistics, 2016). A graph of the production worker wage share is shown in Figure A.1 in Appendix A. Notably, this series shows a much steeper decline than the wage share series for all workers. Some of the difference

[25]The total private sector is used because there is no available measure of wages for production and nonsupervisory workers for the business sector. However, it is thought that the wages for production and nonsupervisory workers in the total private sector are a reasonably good proxy for those in the business sector.

in the trends of the two series can likely be explained by the exclusion of benefits in the production worker wage share series.

In addition to testing whether the results are sensitive to alternative measures of the endogenous variables, this chapter tests whether the results change when controlling for other factors. Several control variables are tested, including the real long-term interest rate, the real effective exchange rate, measures of corporate and household debt, and wealth. These variables were selected for inclusion because they were found to be significant in the structural model of Stockhammer and Wildauer (2016). However, different data sources were used when they were thought to be more accurate. Stockhammer and Wildauer (2016) acknowledge that their choice of variables and data sources was driven in part by a lack of sufficient data for many of the countries in their panel, particularly in the case of wealth. However, this chapter does not share these same constraints, as it focuses only on the United States, which has ample data available. The real long-term interest rate is calculated by subtracting a measure of inflation expectations from the Federal Reserve's 10-year treasury constant maturity rate. Here inflation expectations are measured as average inflation over the past ten years, where inflation is measured as the percentage change in the BLS' CPI series.[26] The real effective exchange rate is the real broad-based U.S. dollar index from the Federal Reserve. Corporate and household debt are measured as total liabilities for corporate businesses and for households and nonprofit

[26] A measure of the real long-term interest rate is preferable to a shorter interest rate, because it is expected that long term interest rates are those that are most important for investment decisions, which impact demand. The interest rate on 10 year treasuries is believed to be a strong proxy for the long-term interest rates that firms must pay. However, converting this to a real measure requires a measure of long-term inflation expectations. Treasury Inflation-Protected Securities (TIPS) provide a market-based measure of inflation expectations on 10 year treasuries, but data on this series are only available beginning in 2003. The Federal Reserve Bank of Cleveland uses a model to estimate the real interest rate on 10 year treasuries, but data for this series is not available before 1982. A proxy for inflation expectations can be used to provide coverage for a larger sample period. Average inflation over the past ten years is a reasonable proxy for inflation expectations if firms have adaptive expectations. This series is highly correlated with both the market-based TIPS measure and the Federal Reserve Bank of Cleveland's model-based estimates. The correlation coefficients are 0.901 and 0.815, respectively.

organizations, respectively, while wealth is measured as total assets for households and nonprofit organizations. These three financial series are obtained from the Federal Reserve and transformed into shares of GDP. In addition to these variables, the BEA measure of real gross government consumption and investment expenditures is included to control for the effects of fiscal policy. Variable measurement and data sources are summarized in Table A.2 in Appendix A.

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% level.[27] Using this decision rule, only 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.[28] Selected unit root test results

[27]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).

[28]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 have a qualitative difference on the results.

are shown in Table A.1 of Appendix A. Models were estimated using the log levels of stationary variables and the log difference of variables with unit roots.[29]

1.4 Econometric Results

1.4.1 Baseline Model

The baseline model is estimated for the sample of 1947 Q2 to 2016 Q4 and includes a constant term and two lags. This model uses the variable ordering shown in equation (1.13), in which the log-differenced wage share is placed before the log of the HP utilization rate. Selected impulse response functions for this specification are shown in Figure 1.5. These represent responses to a one standard deviation shock, along with confidence bands of $\pm$ two standard errors that correspond roughly to a 5% significance level.

The response of utilization to a wage share shock, shown in panel (a) Figure 1.5, is significantly negative in the first four periods and diminishes towards zero 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 quarters 3-6, 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 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 *ln HP utilization* (roughly 69% of a standard deviation). Similarly, a one standard deviation shock to *ln HP utilization* (an increase of 0.0202) leads to an increase of 0.0066 in Δ *ln wage share* (approximately 69% of a standard deviation).[30] Unreported results

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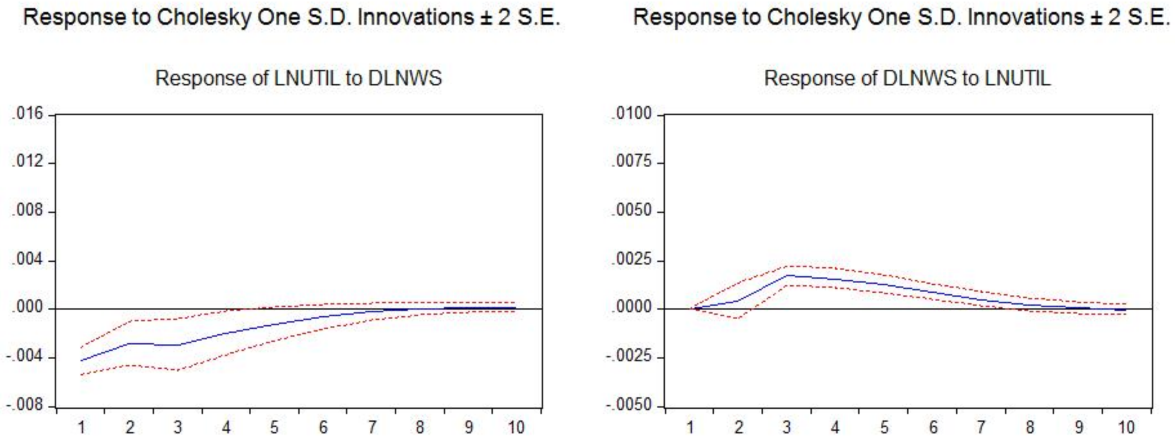
[29]Note that no models were estimated as vector error correction (VEC) models because there was no evidence of cointegration between the wage share and the only nonstationary measure of demand—real GDP.

[30]These descriptions are based on the cumulative effects over ten periods.



(a) Response of ln HP utilization to a positive shock in Δ ln wage share

(b) Response of Δ ln wage share to a positive shock in ln HP utilization

Sample period: 1947 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln HP utilization
Complete results shown in Figure A.2 of Appendix A

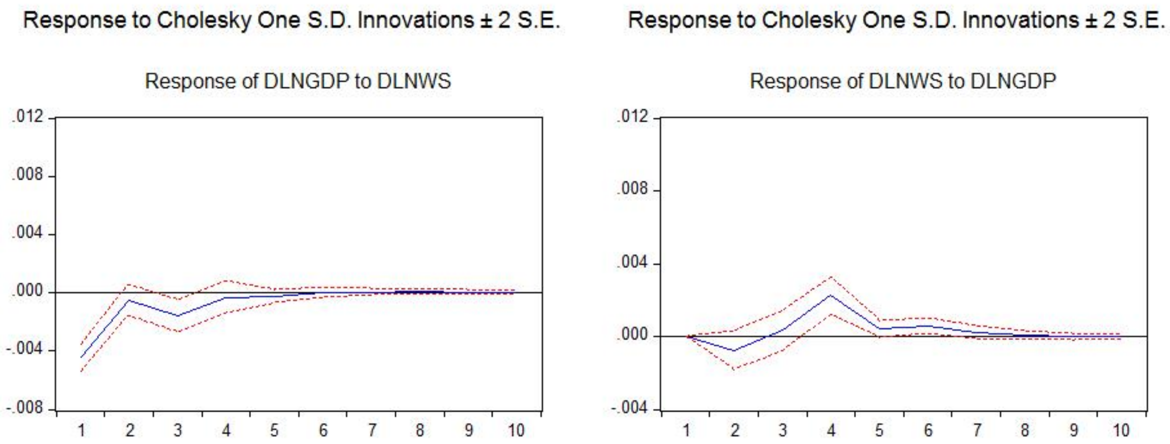
Figure 1.5: Selected IRFs for the Baseline Model

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.[31]

1.4.2 Alternative Variable Measurements

Whereas aggregative studies measure demand as the utilization rate, defined as the ratio of output to potential output, structural studies typically measure demand using the level, or growth rate, of output. However, it does not appear that the choice of measurement contributes to the general differences in the results, as the qualitative results of the baseline model are robust to the use of measures of demand that are closer

[31]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, neither change has a substantial effect on the results, as the profit-led demand and profit-squeeze distribution are still present in both of these specifications. Other unreported results show that the findings are similarly robust to using the data series without log transforming them, and to including an exogenous trend.



(a) Response of Δ ln real GDP to a positive shock in Δ ln wage share

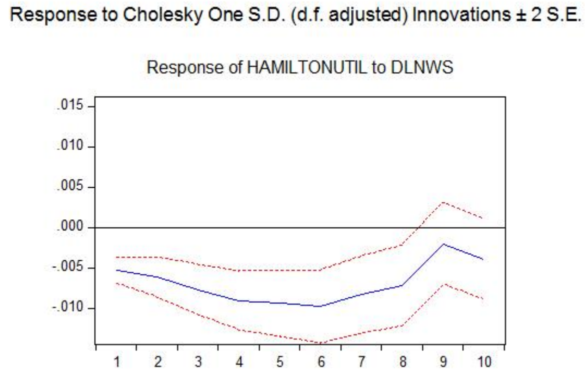
(b) Response of Δ ln wage share to a positive shock in Δ ln real GDP

Sample period: 1948 Q1 - 2016 Q4
Model specification: 3 lags and constant term
Variable ordering: Δ ln wage share, Δ ln real GDP
Complete results shown in Figure A.3 of Appendix A

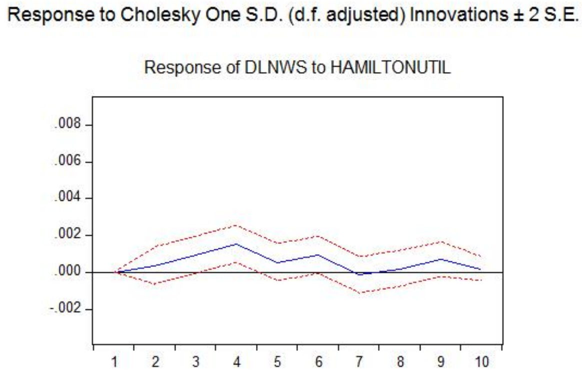
Figure 1.6: Selected IRFs for the Real GDP Model

to those used by structural studies. Figure 1.6 shows the key results of a model using the log difference of real GDP in place of the utilization rate.

As with the baseline model, the IRFs indicate profit-led demand and profit-squeeze effects. While the direction and magnitudes of these effects are similar whether demand is measured with the HP utilization rate or growth rate of real GDP, the effects are less persistent and significant for fewer quarters in the latter case. Unreported results show that using the growth rate of the BLS business sector output index in place of the growth rate of real GDP leads to IRFs that are nearly identical to those in Figure 1.6. Because the profit-led demand and profit-squeeze effects are found both in the baseline model and in models using measures of demand that are closer to those used in structural studies, it does not appear that the general differences in the results of aggregative and structural models can be explained by their differences in the measurement of demand.



(a) Response of Hamilton utilization to a positive shock in Δ ln wage share



(b) Response of Δ ln wage share to a positive shock in Hamilton utilization

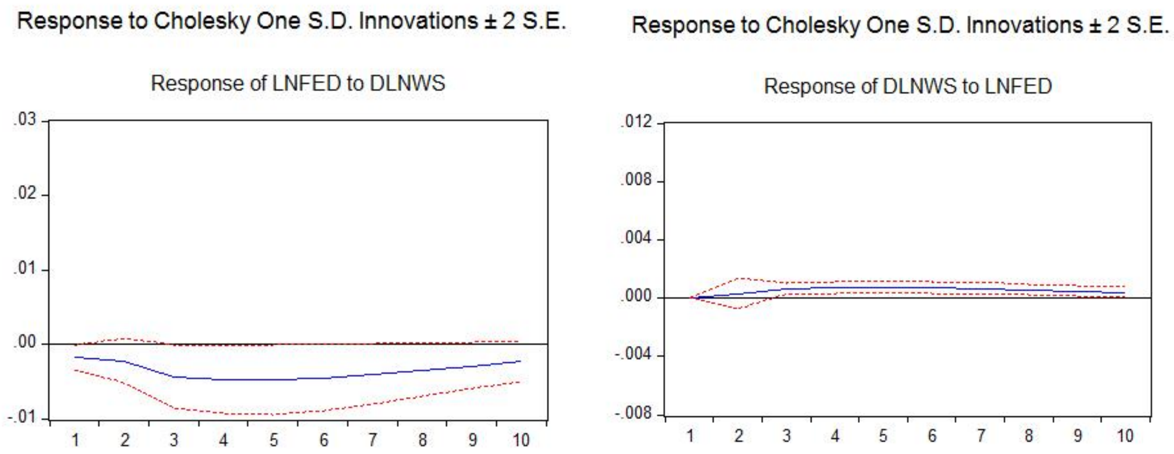
Sample period: 1952 Q1 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: Δ ln wage share, Hamilton utilization
Complete results shown in Figure A.4 of Appendix A

Figure 1.7: Selected IRFs for the Hamilton Utilization Rate Model

These Goodwin cycle effects are also found when using the utilization rate constructed with the Hamilton filter. The IRFs for this model are shown in Figure 1.7. The profit squeeze effects are similar to those found when using the HP utilization rate, while the profit-led demand effects are actually found to be larger and more persistent. The increased persistence of the profit-led demand effects 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.[32]

Significant profit-led demand and profit-squeeze effects are also found in models that use the other two measures of the utilization rate—either the output gap or Federal Reserve utilization rate. However, in both of these cases the magnitude of the profit-

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



(a) Response of ln Fed utilization to a positive shock in Δ ln wage share

(b) Response of Δ ln wage share to a positive shock in ln Fed utilization

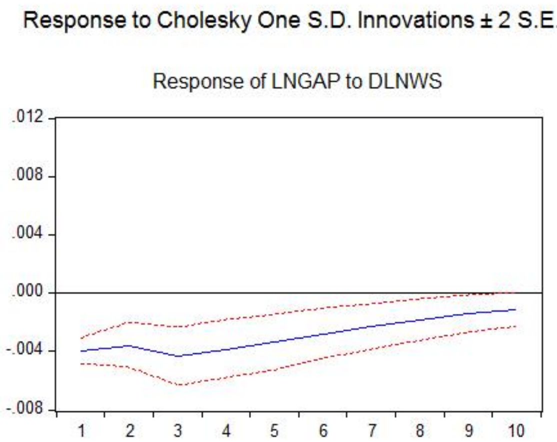
Sample period: 1967 Q3 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln Fed utilization
Complete results shown in Figure A.5 of Appendix A

Figure 1.8: Selected IRFs for the Federal Reserve Utilization Rate Model

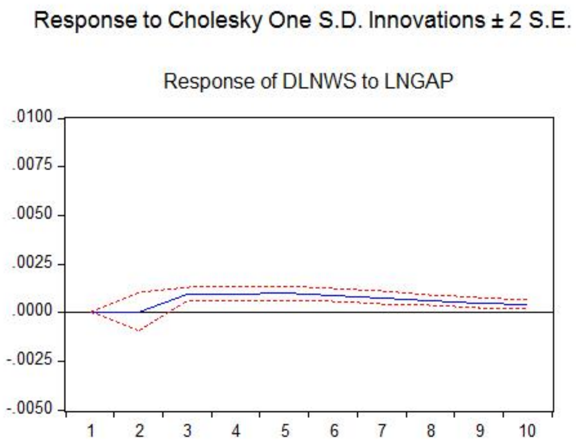
squeeze effect is smaller than in the HP and Hamilton utilization rate models, although it remains statistically significant at the 5% level. The magnitude of the profit-led demand effects is generally similar in both of these specifications and the baseline model, although the initial effects are weaker in the model using the Federal Reserve utilization rate.[33] 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 output gap than in the baseline model. Selected IRFs for these two models are shown in Figures 1.8 and 1.9.

Taken as a whole, these results suggest that the baseline model is qualitatively robust to the use of alternative measures of demand because all of these specifications

[33] Although the sample period for this specification is shorter than the sample for the baseline model due to limited data on the Federal Reserve utilization series, the differences in results cannot simply be attributed to differences in sample periods. Unreported results show that the results of the baseline model change little when using a sample of 1967 Q3 - 2016 Q4.



(a) Response of ln output gap to a positive shock in Δ ln wage share



(b) Response of Δ ln wage share to a positive shock in ln output gap

Sample period: 1949 Q3 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln output gap
Complete results shown in Figure A.6 of Appendix A

Figure 1.9: Selected IRFs for the Output Gap Model

found evidence of significant profit-led demand and profit-squeeze effects. However, the strongest evidence of these effects is found when using a utilization rate constructed with a filter. When using non-filtered measures of the utilization rate, the observed profit-squeeze effects are weaker and the profit-led demand effects are less persistent in the model using the growth rate of real GDP. This suggests that using a measure of utilization constructed with the use of a HP filter may slightly bias the results towards findings of stronger Goodwin Cycle effects.[34]

Furthermore, the results of the baseline model are robust to using an alternative measure of the wage share that excludes the wages of supervisory workers. In fact, the

[34]Although HP utilization rate yields the stronger estimates of profit-led demand and profit-squeeze effects than most other measures of demand, this measure will still be used for later specifications in order to test the robustness of these results. The robustness of the results with this measure are of particular importance, given its previous use in the literature (see Barbosa-Filho and Taylor, 2006; Carvalho and Rezai, 2016).

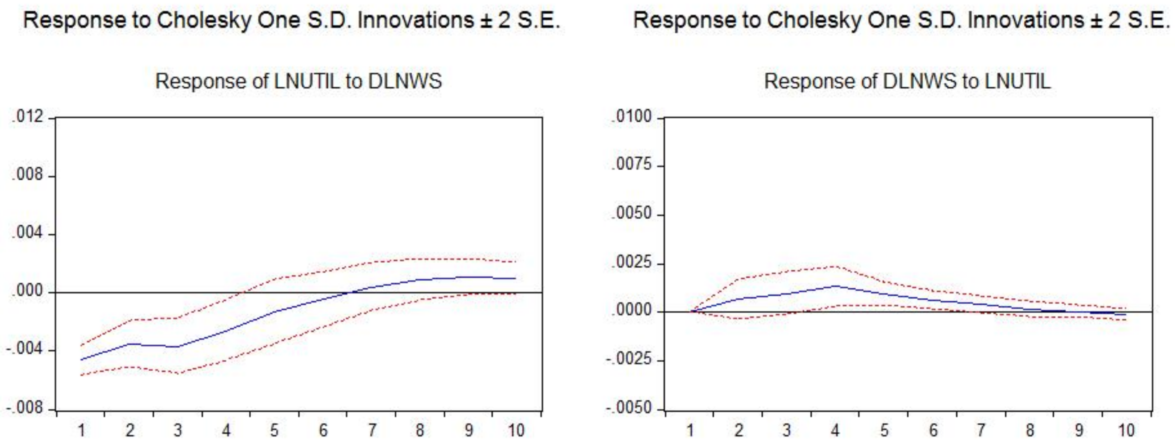
observed profit-led demand and profit-squeeze effects are actually slightly larger when using the production worker wage share in place of the overall wage share measure that includes wages for all workers. This is a surprising result, because it was expected that the presence of managerial wages might bias estimates towards finding more profit-led demand. It is unclear what is driving the slightly larger magnitudes of Goodwin cycle effects in this model.[35] The results for this model are shown in Figure A.7 of Appendix A. Results for specifications including the cyclically adjusted wage shares are discussed in Section 1.4.5.

1.4.3 Financial Control Variables

Figure 1.10 shows selected results for a model controlling for household debt, corporate debt, and wealth (all expressed as shares of GDP). Although Stockhammer (2017b) suggests that excluding financial variables from the model is likely to lead to omitted variable bias, these IRFs are very similar to those of the baseline model. Therefore, these results do not support Stockhammer's hypothesis. However, it should be noted that these are likely short-run estimates, and it is possible that these financial variables have more of an impact in the longer run. The results showing the relationship between utilization and the wage share are robust to a number of different variable orderings changing the order of the control variables relative to the wage share and utilization. They are also robust to measuring household debt, corporate debt, and wealth in their real dollar values, rather than as shares of GDP.[36]

[35]The differences in results do not appear to be driven by differences in the sample period. Although the sample period for the specification using the production worker wage share is shorter due to data limitations, unreported results show that the results of the baseline model change little when using the sample period of 1964 Q4 - 2016 Q4, as in the production worker wage share model. It is possible that other differences between this measure and the baseline wage share measure are contributing to these results. In addition to the presence of managerial wages, the two measures differ in their measurement of labor compensation and in their sectoral definition.

[36]The effects of the control variables on utilization and the wage share are sensitive to variable ordering. However, there are some findings that are common to most orderings. In most specifications, both corporate and household debt have either a positive effect or no significant effect on the wage



(a) Response of ln HP utilization to a positive shock in Δ ln wage share

(b) Response of Δ ln wage share to a positive shock in ln HP utilization

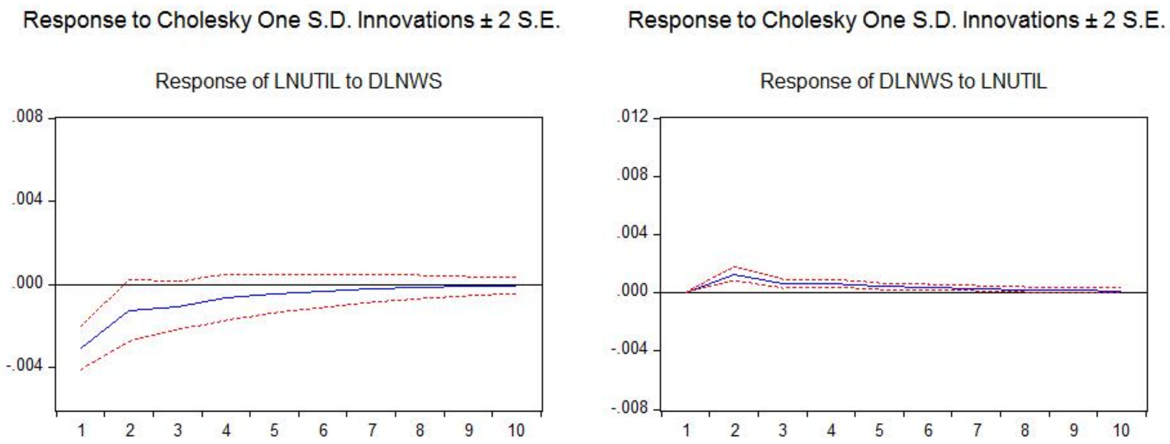
Sample period: 1953 Q2 - 2016 Q4
Model specification: 4 lags and constant term
Variable ordering: Δ ln corporate debt, Δ ln wage share, Δ ln wealth, Δ ln household debt, ln HP utilization
Complete results shown in Figure A.8 in Appendix A

Figure 1.10: Selected IRFs for Financial Control Variable Model

1.4.4 Macro Policy Control Variables

The next specification uses three important macroeconomic variables in place of the financial control variables—the interest rate, the exchange rate, and government spending/GDP. The key IRFs are shown in Figure 1.11. As with the financial control variables, the addition of these control variables does not change the interpretation of the effect on

share. Estimates generally indicate that wealth has a positive effect on the wage share, and an initial negative effect, followed by a positive lagged effect, on utilization. Corporate debt is generally found to have a positive effect on utilization, or at least an initial positive effect followed by negative lagged effects. Conversely, household debt generally has either a negative effect, or an initial negative effect followed by a lagged positive effect, on utilization. The effects of corporate debt on the utilization rate make intuitive sense, as firms may take on debt to pay for investment spending. However, the effects of wealth and household debt on utilization are surprising. If wealth and debt are drivers of consumer demand, as Stockhammer and Wildauer (2016) suggest, then it would be expected that an increase in these variables would have a positive effect on demand–at least in the short run. The complete IRFs for one specification are shown in Figure A.8 in Appendix A. Results for specifications with other variable orderings are available from the author upon request.



(a) Response of ln HP utilization to a positive shock in Δ ln wage share

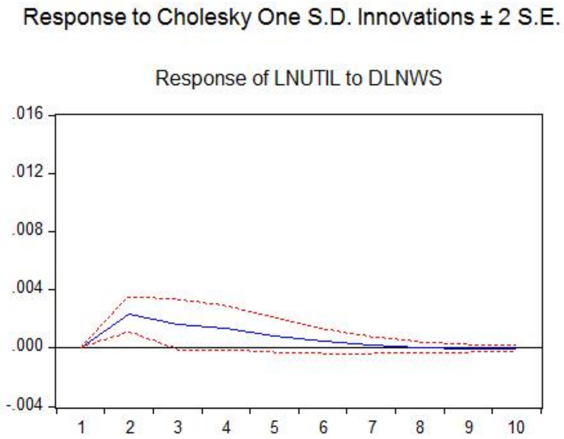
(b) Response of Δ ln wage share to a positive shock in ln HP utilization

Sample period: 1973 Q3 - 2016 Q4
Model specification: 1 lag and constant term
Variable ordering: Δ ln government spending, Δ interest, Δ ln exchange, Δ ln wage share, ln HP utilization
Complete results shown in Figure A.9 in Appendix A

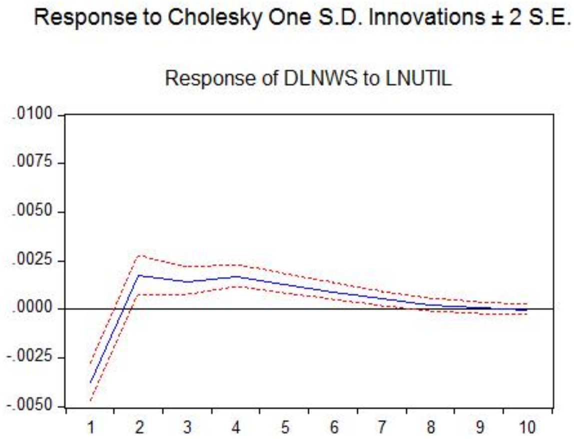
Figure 1.11: Selected IRFs for Macro Policy Control Variable Model

the estimated relationship between the wage share and utilization, although the profit-led demand effects become insignificant after one quarter. These results are also robust to changing the order of the control variables relative to the wage share and utilization.[37]

[37]The full set of results for this model are shown in Figure A.9 in Appendix A. The effects of all three macro policy variables on the wage share are small and insignificant. This is generally robust to alternative orderings of these variables relative to the wage share, although in some specifications the response of the wage share to a change in one of these variables is very small but statistically significant. The exchange rate is found to have a negative effect on the utilization rate. This result is expected, as a higher value of the dollar should decrease net exports and therefore demand. This result is similar to the previous finding by Fernandez (2005) that international labor competitiveness has a significant effect on the utilization rate. However, the estimated effects of the interest rate and government spending on utilization are both anomalous. Government spending is found to have a negative effect on demand, and the interest rate is found to have a positive effect on demand. The effects of these three variables on utilization are generally robust to different orderings of these variables in relation to the utilization rate, although some effects become insignificant in some specifications.



(a) Response of ln HP utilization to a positive shock in Δ ln wage share



(b) Response of Δ ln wage share to a positive shock in ln HP utilization

Sample period: 1947 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: ln HP utilization, Δ ln wage share
Complete results shown in Figure A.10 in Appendix A

Figure 1.12: Selected IRFs for Model with Reverse Ordering

1.4.5 Productivity Effects

Ordering Restrictions and Wage Share Decomposition Estimates

All of 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 12 shows how the results change when the ordering is reversed, as in equation (1.19), and it is instead assumed that the wage share does not have a contemporaneous effect on the utilization rate.

$$\boldsymbol{y_t} = [ln\ utilization_t, \Delta\ ln\ wage\ share_t] \tag{1.19}$$

The results are drastically different when changing the ordering restrictions. The response of utilization to a wage share shock, shown in panel (a), is now positive, indicating that demand is wage-led rather than profit-led. However, the magnitude is smaller than the estimated profit-led effects in the baseline model, and the positive effect is only significant for one quarter. The response of the wage share to a utilization shock, shown in the bottom-left corner, is initially negative before becoming positive after 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.[38] This initial negative effect of the utilization rate shock on the wage share could be explained by positive effects of utilization on productivity.

Although the ordering assumptions used in the baseline model, and shown in equation (1.14), are more consistent with the existing empirical literature than the reverse ordering, shown in equation (1.19), 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

[38]Qualitatively similar results are found in most specifications in which the utilization rate comes before the wage share in the variable ordering. Although the magnitudes vary across specifications and some alternative specifications show lagged profit-led effects that are small and insignificant following the initial estimate of significant wage-led demand, these findings are generally robust to a number of changes, including taking the first difference of the utilization rate, not taking the first difference of the wage share, including an exogenous trend, controlling for the set of financial variables or the set of macro policy variables, and using various alternative variable measures. The biggest exception is the specification using the Hamilton utilization rate, with the optimal lag length of 9. This specification shows no initial effect of the wage share on demand, but a significant lagged profit-led demand effect. 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. Another 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.

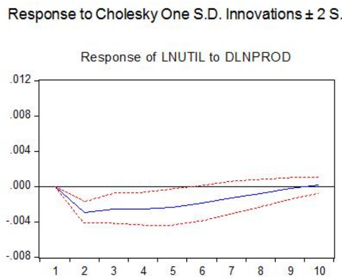
Table 1.1: Possible Orderings in Wage Share Decomposition Model

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

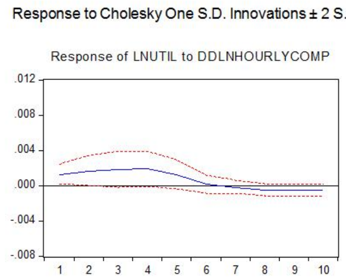
in the wage share that are driven by those very changes in the utilization rate (through its effects on labor productivity).

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 1.1. Four of these orderings align with different ordering of the two variable model, because the restrictions related to the utilization rate are the same for both mian components of the wage share. However, the other two orderings present new cases, because the two main components of the wage share have different orderings relative to the utilization rate.

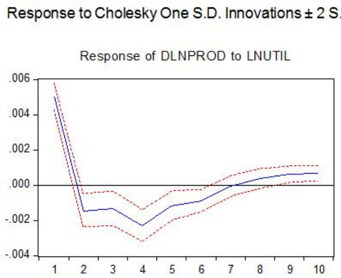
The results of these models suggest that differences in the results of the baseline model and the model using the reverse variable ordering can largely be explained by their differing assumptions regarding the relationship between the utilization rate and labor productivity. In Orders 1-3, the utilization rate has a contemporaneous effect on labor productivity, but productivity has only a lagged effect on utilization. The results for the specification using Order 1, in which the utilization rate has a contemporaneous effect on labor productivity but not real hourly compensation, are shown in Figure 13. The results for Orders 2 and 3, which feature the same ordering as the model shown in Figure 12, but with the wage share broken into its two main components, can be found in Figures A.11



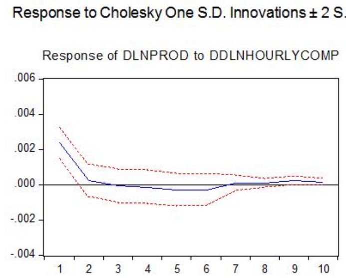
(a) Response of ln HP utilization to a positive shock in Δ ln productivity



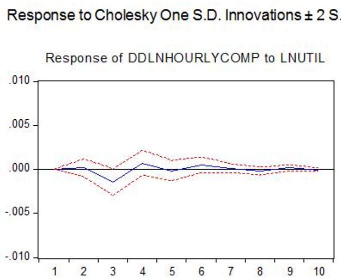
(b) Response of ln HP utilization to a positive shock in Δ Δ ln real hourly wage rate



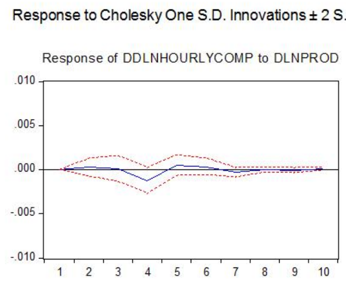
(c) Response of Δ ln productivity to a positive shock in ln HP utilization



(d) Response of Δ ln productivity to a positive shock in Δ Δ ln real hourly wage rate



(e) Response of Δ Δ ln real hourly wage rate to a positive shock in ln HP utilization



(f) Response of Δ Δ ln real hourly wage rate to a positive shock in Δ ln productivity

Sample period: 1948 Q3 - 2016 Q4
Model specification: 4 lags and constant term
Variable ordering: Δ Δ real hourly wage rate, ln HP utilization, Δ ln productivity
Complete results shown in Figure A.11 in Appendix A

Figure 1.13: Selected IRFs for Model Using Order 1

and A.12 in Appendix A. In all three of these specifications, an increase in real hourly compensation is found to have a positive effect on utilization,[39] and productivity is found to have a negative effect on utilization.[40] Thus, an increase in the wage share caused either by an increase in real hourly compensation or a decrease in labor productivity would have a positive effect on the utilization rate. Therefore, the results of these specifications are indicative of wage-led demand and supportive of Lavoie's (2017) view. In all three of these specifications, the contemporaneous effects of a positive utilization shock on productivity are positive and significant, suggesting that productivity is procyclical, as Lavoie (2017) suggests. The lagged effects of a utilization shock on productivity then turn negative and significant for the next few quarters before becoming positive again. However, these lagged effects are smaller than the positive contemporaneous effects. The response of real hourly compensation to a utilization shock in these three specifications depends on the exact ordering. In Orders 2 and 3 the contemporaneous response of the real wage rate to a positive utilization rate is small, but positive and significant, while the contemporaneous response in Order 1 and the lagged responses in all three specifications are insignificant.

The results are drastically different when reversing the ordering assumptions relating labor productivity and the utilization rate. Orders 4-6 impose the restriction that the utilization rate has no contemporaneous effect on labor productivity, but labor productivity can have a contemporaneous effect on the utilization rate. The results for the specification using Order 4 are shown in Figure 14, while the results for Orders 5 and 6 are shown in Figures A.13 and A.14 in Appendix A. In these models, the response of uti-

[39]Note that the positive response of utilization to a positive real hourly compensation shock is insignificant at the 5% level in Order 3, but significant in Orders 1 and 2. The negative effect of productivity on utilization is statistically significant at the 5% level in all three of these cases.

[40]The finding that a productivity shock has a negative effect on utilization could also be explained by reduced input use and investment following an improvement in technology (Basu et al., 2004).

lization to a positive productivity shock is generally positive and significant,[41] while the effect of an increase in utilization on productivity is generally negative and significant.[42] The latter relationship could also reflect workers reducing their effort when the economy is booming and they have more bargaining power. 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. The response of utilization to a positive real wage rate shock is significantly positive in Orders 4 and 6, and significantly negative in Order 5.[43] However, the effects of productivity on utilization are much larger than the effects of the real wage rate on utilization in all three specifications. This suggests that the profit-led demand observed in the baseline model (and other specifications using the same ordering of the wage share and the utilization rate) are primarily driven by the positive effect of productivity on the utilization rate that are observed when imposing the restriction that utilization does not have a contemporaneous effect on the wage share (and therefore productivity).

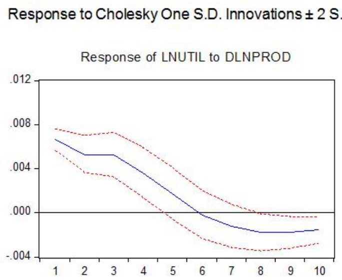
These results indicate that the model's findings are highly dependent upon its treatment of productivity effects.[44] When it is implicitly assumed that productivity drives utilization, the model is likely to yield estimates of profit-led demand. However, when the

[41]This finding is in line with the real business cycle theory view that improvements in productivity generate economic expansions.

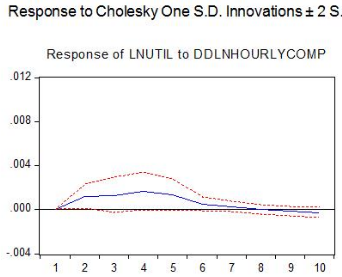
[42]Note that in these three specifications the response of productivity to a positive utilization shock is negative after a lag of 8-10 quarters, and the response of utilization to a positive productivity shock is positive after a lag of 9-10 quarters. While these effects are small, they are statistically significant at the 5% level.

[43]The response of the real wage rate to a utilization shock is small in Orders 4-6. However it is statistically significant at the 5% level in the case of Order 4.

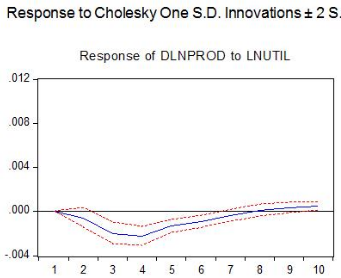
[44]This conclusion is not driven by the decision to use the second difference of the real hourly compensation series. Unreported results show that when using the first difference instead of the second, the only qualitative differences are found in the effect of a utilization shock on real hourly compensation and in the estimated relationship between productivity and real hourly compensation. All of the other results are robust to using the first difference of real hourly compensation.



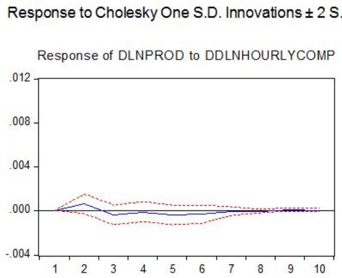
(a) Response of ln HP utilization to a positive shock in Δ ln productivity



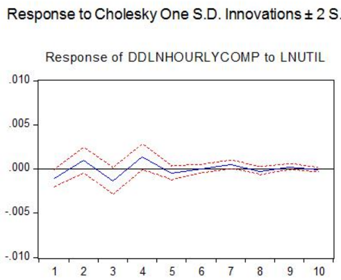
(b) Response of ln HP utilization to a positive shock in Δ Δ ln real hourly wage rate



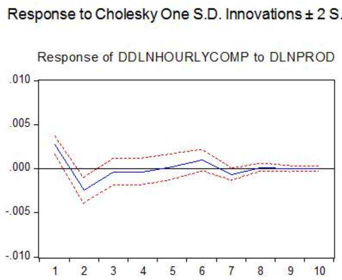
(c) Response of Δ ln productivity to a positive shock in ln HP utilization



(d) Response of Δ ln productivity to a positive shock in Δ Δ ln real hourly wage rate



(e) Response of Δ Δ ln real hourly wage rate to a positive shock in ln HP utilization



(f) Response of Δ Δ ln real hourly wage rate to a positive shock in Δ ln productivity

Sample period: 1948 Q3 - 2016 Q4
Model specification: 4 lags and constant term
Variable ordering: Δ ln productivity, ln HP utilization, Δ Δ real hourly wage rate
Complete results shown in Figure A.14 in Appendix A

Figure 1.14: Selected IRFs for Model Using Order 4

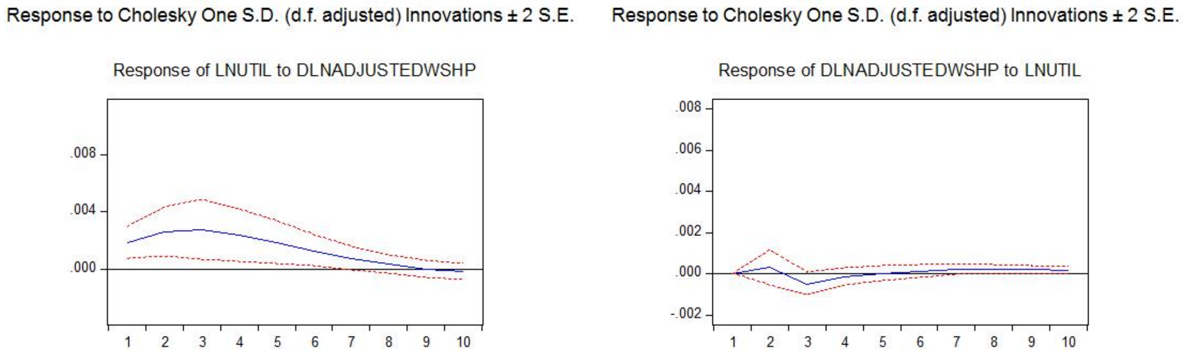
model accounts for the potential cyclicality of productivity and assumes that productivity has only a lagged effect on utilization, estimates suggest that demand is wage-led.

Unreported results for similar specifications that replace the HP utilization rate with the alternative measures of demand lead to the same conclusion.[45] Therefore, all specifications provide evidence that estimated profit-led demand effects will be larger if the contemporaneous correlation between productivity and demand—which likely reflects the positive effect of demand on productivity—are instead interpreted as effects of productivity on demand. If productivity is in fact positively affected by demand over the course of the business cycle, it is likely that some previous aggregative estimates have been biased towards profit-led estimates.

Cyclically Adjusted Wage Share Estimates

In order to further explore the ways in which the cyclical effects of demand on productivity affect estimates of wage-led and profit-led demand, 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 two main components of the wage share. However, because these two variables are included

[45]When using either the output gap or real GDP, demand is found to be affected positively by wages (although the significance of these effects varies depending on the exact ordering) and negatively by productivity—indicating wage-led demand—if demand is allowed to have a contemporaneous effect on productivity. When using orderings that do not allow demand to have a contemporaneous impact on productivity, specifications using either of these measures indicate that demand is likely to be more profit-led because productivity has a strong positive effect on demand. Productivity is found to have a positive effect on demand using any ordering in specifications where demand is measured with the Fed or Hamilton utilization rate. However, these effects are found to be larger and more significant when demand is allowed to have a contemporaneous effect on productivity.



(a) Response of ln HP utilization to a positive shock in Δ ln HP adjusted wage share

(b) Response of Δ ln HP adjusted wage share to a positive shock in ln HP utilization

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
Complete results shown in Figure A.17 in Appendix A

Figure 1.15: Selected IRFs for the HP Adjusted Wage Share Model

separately, more precise ordering restrictions can be used, and more specific estimates can be obtained.

Figure 1.15 shows the results for the specification including the HP adjusted wage share, the HP utilization rate, and the HP 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.[46] Furthermore, these effects are economically meaningful, as they imply that a

[46]Wage-led demand effects are found using this ordering and all other measures of demand. These effects are generally significant, except in the case of the Fed utilization rate. When using the Hamilton utilization rate, these effects are initially insignificant, but become significant with a lag. None of these estimates show a significant impact of demand on the adjusted wage share. It is likely that these estimates are sensitive to the choice of the filtering method. Previous attempts to construct a cyclically adjusted wage share using a band-pass filter to remove cycles in productivity at the business cycle periodicity of 8-32 quarters resulted in less dramatic changes. Using this measure of the adjusted wage share and HP utilization rate with the baseline variable ordering resulted in estimates with significant contemporaneous profit-led demand effects that were smaller than those in the baseline model, along with insignificant lagged wage-led demand effects. However, these estimates are not an exact comparison to those presented in this section because the model excluded the cyclical component of labor productivity.

one standard deviation shock to Δ *ln HP adjusted wage share* (a .81 percentage point increase in the growth rate of the adjusted wage share) leads to an increase of 0.0134 in *ln HP utilization* (about 66% of a standard deviation).[47] Little effect of demand on the HP adjusted wage share is found.

The sign of the effects of the HP adjusted wage share on the utilization rate is robust to ordering, although the significance of this estimate is not.[48] When this ordering restriction is reversed, but both variables are allowed to have a contemporaneous effect on the cyclical component of productivity, insignificant wage-led demand effects are found.[49] The results for this specification are shown in Figure A.18 of Appendix A. Using this ordering, a significant profit-squeeze effect is found. However, the specification using the initial ordering of this three variable model is preferred, as the theoretical justification for allowing contemporaneous effects of demand on the wage share is no longer applicable when the cyclical variation on productivity is separated from the wage share measure.

Similar results are found when using the Hamilton adjusted wage share and the Hamilton cyclical component of productivity. Selected IRFs for the specification including the Hamilton adjusted wage share, the Hamilton utilization rate, and the Hamilton cyclical component of productivity (in that order) are shown in Figure 1.16. The results show a significant and persistent wage-led demand effect,[50] along with a significant lagged

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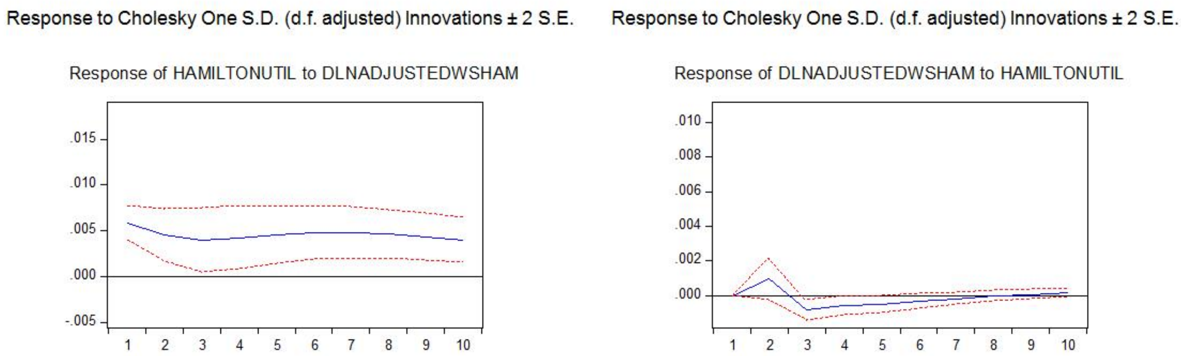
[47]This description is based on the cumulative effect over ten periods.

[48]These wage-led estimates are robust to other orderings as well, although significance varies. When the cyclical component of productivity comes first in the ordering, demand is found to be insignificantly wage-led, regardless of the order of the other two variables. Insignificant wage-led demand effects are also found using the ordering in which utilization is first and the adjusted wage share is last. When the adjusted wage share is first and utilization last, significant wage-led demand effects are found.

[49]When using this ordering and other measures of demand, wage-led demand effects are found in all specifications, but are only significant in the case of the Hamilton utilization rate, and only with a lag.

[50]This result is sensitive to alternate orderings. Among the other possible orderings, significant wage-led demand effects are found only in the case where the adjusted wage share comes first and the utilization rate comes last. In the ordering where utilization comes first and the adjusted wage share last, demand is insignificantly wage-led, with effects close to zero. In orderings where the cyclical component of



(a) Response of Hamilton utilization to a positive shock in Δ ln Hamilton adjusted wage share

(b) Response of Δ ln Hamilton adjusted wage share to a positive shock in Hamilton utilization

Sample period: 1950 Q3 - 2016 Q4
Model specification: 2 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.19 in Appendix A

Figure 1.16: Selected IRFs for the Hamilton Adjusted Wage Share Model

wage squeeze. When reversing the ordering of the Hamilton adjusted wage share and the Hamilton utilization rate, significant wage-led demand effects are found, but only with a lag. Using this ordering, there is an initial profit-squeeze effect that is statistically significant, followed by significant wage squeeze effects that are smaller in magnitude. However, the initial ordering is preferred for the reason discussed above. The results for this specification are shown in Figure A.20 of Appendix A.

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productivity comes first, the effect of the adjusted wage share on utilization is negative, but insignificant and close to 0. The findings are also robust to the measurement of demand. No significant effects of the adjusted wage share on demand are found when using alternate measures of demand with the Hamilton adjusted wage share and cyclical component of productivity. Using the ordering in which the adjusted wage share comes first and utilization second, specifications for all other measures show insignificant wage-led demand. Specifications with the reverse ordering (and the cyclical component of productivity remaining last) show small and insignificant profit-led demand, followed by lagged wage-led demand effects that are similarly small and insignificant for all measures—except in the case of the Fed utilization rate, where these lagged wage-led demand effects are not found.

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. No evidence of this cycle of profit-led demand and profit-squeeze effects is found once the cyclical effects of demand on productivity are accounted for. Instead, the results of this disaggregated analysis suggest that the relationship these variables is characterized by wage-led demand and cyclical effects of demand on productivity.

1.5 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. These results are generally robust to the exclusion of supervisory labor income from the wage share and the use of alternative measures of demand—although the strongest evidence of these effects is found using utilization rates constructed with filters. Other measures of demand yield estimates with weaker profit-squeeze effects or less persistent profit-led demand. The results are also robust to controlling for sets of financial and macro policy variables.

However, the results of other specifications suggest that these observed Goodwin cycle effects may be spurious. 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. When these productivity effects are accounted for, demand is found to be wage-led. In models where the two main components of the wage share—the real wage rate and labor productivity—are separated, demand is found to be profit-led only in cases where demand is assumed to have only a lagged effect on productivity and all contemporaneous correlation between productivity and demand is viewed as an effect of productivity—and therefore the wage share—on demand. When demand is allowed to have a contemporaneous effect on productivity, as would be appropriate if productivity varies cyclically, demand is found to be wage-led. Furthermore, models in which the cyclical component of productivity is separated from the wage share similarly indicate wage-led demand effects. Although significance varies in some cases, these effects are robust to alternate measurements of demand and all orderings in which demand has a contemporaneous effect on the cyclical component of productivity.

The finding that the relationships of the individual components of the wage share with utilization play an important role in determining whether demand is wage-led or profit-led suggest that more attention should be paid to these relationships. Chapter 3 explores the effects of the real wage rate and labor productivity on output in more detail using a panel of 11 OECD countries.

These findings suggest that existing evidence of profit-led demand—or at least the evidence found using data and techniques similar to those used in this chapter—is the result of biased estimates. Indeed, the appearance of profit-led demand appears to be a misinterpretation of procyclical variation in labor productivity. 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.

CHAPTER 2

A SYSTEMS APPROACH TO ESTIMATING STRUCTURAL MODELS OF THE U.S. DEMAND-DISTRIBUTION RELATIONSHIP

2.1 Introduction

There is significant debate among economists regarding the nature of the relationship between aggregate demand and the functional distribution of income. Despite a considerable amount of empirical research, the literature remains divided on the subject. Whereas some studies find evidence of wage-led demand (e.g. Stockhammer and Wildauer, 2016; Stockhammer et al., 2018; Onaran and Galanis, 2012; Onaran et al., 2011; Onaran and Obst, 2016), others find a cyclical relationship comprised of profit-led demand and profit-squeeze effects (e.g. Barbosa-Filho and Taylor, 2006; Carvalho and Rezai, 2016; Kiefer and Rada, 2015).

Blecker (2016) notes that the results of previous empirical studies tend to depend upon the econometric methodology used in estimates. Those who follow the aggregative approach of estimating the bi-directional relationship between demand and the wage share as a system generally find evidence of profit-led demand and a profit squeeze.[1] On the other hand, those who follow the structural approach of separately estimating the effects of the wage share on each component of aggregate demand, treating the wage share as exogenous, usually find evidence of wage-led demand. Although Blecker (2016) suggests that the two types of studies may be capturing effects at different time horizons,[2] most of the debate has focused on whether the methodologies employed by one approach or the other may lead to biased results.

Although there are potential problems with previous aggregative studies, as discussed in Chapter 1, proponents of the aggregative approach argue that the general differences in the results of aggregative and structural studies are attributable to misspecification of structural models. One potential source of misspecification in previous structural models is their treatment of the wage share as exogenous. Barrales and von

[1]The results of Chapter 1 suggest that these findings may be a misinterpretation of the procyclical effects of demand on labor productivity.

[2]This hypothesis is tested in Chapter 3.

Arnim (2017) find evidence of bi-directional Granger causality between demand and the wage share. Therefore, they suggest that ignoring the effects of demand on the wage share is likely to produce biased estimates and argue that most evidence of wage-led demand is driven by this improper specification. Similarly, Kiefer and Rada (2015) argue that studies in which the wage share is assumed to be exogenous are not comparable to those in which both demand and distribution are simultaneously determined, and that it is misleading to interpret structural estimates as an aggregate demand equation.[3] Improperly treating other endogenous variables, such as GDP, as exogenous could also lead to specification errors.

Previous structural estimates could also be biased because they fail to account for the dynamic interactions between the components of aggregate demand. Blecker (2016) argues that these studies may not properly capture these interactions between variables, such as accelerator and multiplier effects, because they use an estimation method wherein separate equations are estimated for each component of aggregate demand, instead of as a system. This approach to estimating these models is known as a "single equation" or "separate equation" approach. Furthermore, separate estimation of each equation ignores the possibility that there may be common shocks to each equation. Due to these shortcomings, even proponents of the structural approach (see Onaran and Galanis, 2012) concede that overlooking the systemic dimension of their models could lead to biased results.

Although proponents of the aggregative approach argue that findings of wage-led demand in structural studies are driven by these specification problems, to the author's knowledge this supposition has never been tested. This chapter contributes to the literature by testing the extent to which structural models are biased by failing to account for

[3]They argue that the results of structural studies should instead "be interpreted as the joint outcomes of the random shocks to distribution and utilisation that have been typical and the inherent dynamic behaviour of these variables . . ." (Kiefer and Rada, 2015, p. 1337).

the systemic relationship between variables. To do this, it compares the estimates for a series of structural models found using the traditional method of estimating each equation separately to those found by estimating the same models as systems, using the Generalized Method of Moments (GMM). This chapter estimates two models based on previous studies—Onaran and Galanis (2012) and Stockhammer and Wildauer (2016)—and a synthetic model that combines elements of previous models with some new features. These models are estimated for the U.S. economy, which is a prime candidate for this exercise given the availability of sufficient data on a number of economic variables. Long data series are needed to generate enough observations to estimate these complex systems with a large number of parameters. As many previous studies have estimated models of the U.S. economy, the choice of the U.S. as the country of analysis also allows for comparisons with the previous literature.

This chapter finds no evidence that separate estimation of the aggregate demand equations or treatment of the wage share as exogenous makes systems that are truly profit-led appear wage-led. In fact, systems estimates of all three model are indicative of wage-led demand, although the GMM estimates for one of the three models are not valid, as valid instruments could not be found. Furthermore, the two models for which valid instruments could be found produce estimates that are more wage-led when they are estimated as systems. Therefore, no evidence is found suggesting that the finding of wage-led demand in most previous studies is driven by biased estimates. The evidence actually suggests that any bias caused by use of the single equation approach leads to underestimates of the magnitude of wage-led demand effects.

In addition to testing the extent to which estimates based on the structural approach are biased, this study makes several other contributions to the literature. It further expands upon previous structural models by disaggregating total investment into nonresidential and residential investment, although it fails to find the expected negative effects of the wage share on nonresidential investment. Although Stockhammer et al. (2018) differentiate between corporate and total investment, to the author's knowledge no study has yet examined the effect of the functional distribution of income on residential and nonresidential investment. It is also the first study to model a wage share equation as part of a structural model, although other studies (e.g. Stockhammer, 2017a) have examined the determinants of the wage share previously. Furthermore, this study develops a framework for modeling the relationship between demand and distribution that is more in line with theoretical models (e.g. Blecker, 1989). Following this approach, both the wage share and demand are ultimately determined by unit labor costs. The wage share and net exports are direct functions of unit labor costs, while unit labor costs influence consumption and investment indirectly through the wage share.

The rest of this chapter proceeds as follows. Section 2.2 discusses the relevant literature. Section 2.3 describes the empirical strategy employed in this chapter. Section 2.4 discusses the results, and Section 2.5 provides some concluding remarks.

2.2 Literature Review

Many studies have been conducted following the structural approach. Although they often examine different countries and include different variables in addition to the wage share (or profit share) and aggregate demand, these studies generally make use of the same basic methodology. This methodology involves separately estimating individual components of aggregate demand to determine how each is affected by distribution. The distributional effects on each component are then added up to determine the total effect of a change in the functional distribution of income on aggregate demand. In practice, most studies treat government spending as exogenous and focus on the effects of the functional distribution of income on private aggregate demand (i.e. the sum of consumption, investment, and net exports). Some studies further limit the focus of their analysis to private, domestic aggregate demand by excluding exports and imports (see e.g. Stockhammer and

Stehrer, 2011; Stockhammer et al., 2018), whereas Naastepad and Storm (2006) estimate an export equation, but not an import equation.

In many structural studies (see e.g. Naastepad and Storm, 2006; Hein and Vogel, 2008; Stockhammer et al., 2009, 2011; Onaran and Galanis, 2012; Onaran and Obst, 2016), the effect of the functional distribution of income on consumption is found by first regressing consumption (C) on wages (W) and profits (R) to estimate the marginal propensities to consume (MPCs) out of wages and out of profits, c_W and c_R, respectively.[4] These MPCs are then used calculate the marginal effect (at the sample mean) of a change in the profit share on the ratio of consumption as a share of GDP (Y). Following the description presented by Onaran and Galanis (2012), these marginal effects are found using the formula in equation (2.1) and the sample mean values of C/R and C/W.

$$\frac{\partial(C/Y)}{\partial(1-\psi)} = c_R\frac{C}{R} - c_W\frac{C}{W} \tag{2.1}$$

Note that ψ represents the wage share, and therefore $1-\psi$ is the profit share, which is equivalent to R/Y. Therefore, the marginal effect of a 1 percentage point increase in the wage share on C/Y would be the negative of the value found by equation (2.1). Following this methodology, researchers consistently find that the MPC out of wages is greater than the MPC out of profits, and that therefore an increase in the profit share (or a decrease in the wage share) has a negative effect on C/Y (Naastepad and Storm, 2006; Hein and Vogel, 2008; Stockhammer et al., 2009, 2011; Onaran and Galanis, 2012; Onaran and Obst, 2016).

[4] In practice, most researchers first transform variables (for this equation and for others) with the natural logarithm because some of the data series used exhibit exponential trends. Many also estimate models in first differences to eliminate unit roots, or estimate Error Correction Models (ECM) if there is evidence of cointegration. In some cases, lagged wages and profits are also added to this regression (see e.g. Stockhammer et al., 2009; Onaran and Galanis, 2012), and some studies include a lagged dependent variable (e.g. Stockhammer et al., 2009; Onaran and Galanis, 2012; Onaran and Obst, 2016).

Some other studies (see Stockhammer and Stehrer, 2011; Stockhammer and Wildauer, 2016; Stockhammer et al., 2018) take a more direct approach to estimating the marginal effect of the wage share on consumption by including the wage share in the consumption equation, instead of wages and profits. These studies generally come to the same conclusion—that an increase in the wage share (or decrease in the profit share) increases consumption. There are a few exceptions to this, as Stockhammer and Stehrer (2011), who estimate effects for 12 OECD countries at different lag lengths, and Stockhammer et al. (2018), who use historical data to estimate their model for four different countries, occasionally find evidence of statistically significant negative effects of the wage share on consumption. Onaran et al. (2011) similarly include the profit share directly in their consumption equation, and take the additional step of disaggregating it into rentier and non-rentier profit shares. They find that increases in either the rentier or non-rentier profit share have a negative effect on C/Y.

The effect of distribution on investment I is generally found by regressing investment (or the ratio of investment to GDP, I/Y) on the profit share (or wage share), along with other variables such as a long-term interest rate, and GDP (to account for accelerator effects) (see e.g. Hein and Vogel, 2008; Naastepad and Storm, 2006; Onaran and Galanis, 2012; Stockhammer and Wildauer, 2016; Stockhammer and Stehrer, 2011; Stockhammer et al., 2018; Onaran and Obst, 2016). [5] The marginal effect of an increase in the profit share on I/Y at the sample mean of I/R is then found using equation (2.2), where i_π is the profit share coefficient from the investment equation (Onaran and Galanis, 2012).

$$\frac{\partial(I/Y)}{\partial(1-\psi)} = i_\pi \frac{I}{R} \tag{2.2}$$

[5] Stockhammer et al. (2009) and Stockhammer and Stehrer (2011) take a slightly different approach, by using total profits in place of the profit share.

There is more variation in the estimated effects of the functional distribution of income on investment than on consumption. Some studies do find consistent evidence that the profit share has a positive effect on investment. For example, Naastepad and Storm (2006) find that the lagged profit share has a positive and significant effect on the ratio of investment to aggregate demand in all of the countries that they examine. Onaran and Galanis (2012) and Onaran and Obst (2016) also find that the profit share generally leads to increased investment, as any negative effects that they find are statistically insignificant. However, it should be noted that in the latter case, effects are insignificant in nearly half of the 15 countries of analysis. Other studies find more mixed results. For example, Hein and Vogel (2008) find that the profit share has a positive effect on investment in some countries, and a negative effect in others. Similarly, Stockhammer and Stehrer (2011) find statistically insignificant effects for the majority of their specifications testing different lag lengths for each country. Among their statistically significant results, they found a roughly equal number of positive and negative coefficients on the wage share in their investment equations. Stockhammer and Wildauer (2016) estimate their model for a panel of OECD countries, finding that the wage share has a positive contemporaneous effect and a negative lagged effect on investment, with the sign of the total effect depending on the exact estimation method. Stockhammer et al. (2009) and Stockhammer et al. (2011) take a slight different approach by including total profits in the investment equation, rather than the profit share. The results are similarly mixed, as the former finds a positive effect of profits on investment, and the latter a negative effect.

The variation in findings and number of insignificant estimated effects could indicate that distribution does not have a strong effect on investment. Stockhammer and Stehrer (2011) suggest that one explanation for the limited evidence of distributional effects on investment in their study is that investment is primarily driven by expected demand. Furthermore, profits may only be short-run determinant of investment, with long-run changes driven by accelerator effects, and to a lesser extent changes in the user cost of capital. Blecker (2017) summarizes this argument. Another possible explanation for the weak estimated effects of the profit share on investment is that the functional distribution of income has different effects on different components of investment. Stockhammer et al. (2018) find a positive effect of the wage share on total investment, but a negative effect on corporate investment. They argue that the estimated effect on total investment is likely driven by the positive effect of a higher wage share on residential investment. It is also possible that inconsistency of the estimated effects of distribution on investment is attributable to differing effects of changes in the rentier and non-rentier profit shares. Onaran et al. (2011) find that an increase in the rentier profit share decreases investment, while an increase in the non-rentier profit share increases investment.

There are similar differences in the estimated effects of the interest rate in these investment functions. Stockhammer and Wildauer (2016) find the expected result of a negative and significant coefficient on the interest rate in the investment equation of their panel study, but others, such as Stockhammer et al. (2009), Onaran and Galanis (2012), and Hein and Vogel (2008), find no significant effects. Stockhammer et al. (2011) find a significant negative effect when looking at their entire sample, but not for the subsample of 1987-2005. Onaran and Obst (2016) and Obst et al. (2017) find significant negative effects in some countries, but not others, and even one significant positive effect in the latter study. Stockhammer et al. (2018) find negative effects of the interest rate on investment in most specifications, but positive effects in some others. Onaran et al. (2011) exclude the interest rate from their model because they found similar positive effects when it was included. However, most studies do consistently find the expected accelerator effects—i.e. significant positive effects of GDP (or another measure of demand) on investment.

Most studies follow a stepwise process to estimate the effects of the wage share on exports and imports (e.g. Stockhammer et al., 2009, 2011; Onaran et al., 2011; Onaran and Galanis, 2012; Obst et al., 2017; Onaran and Obst, 2016). As described by Onaran and Galanis (2012), this process involves first regressing the domestic price level (P) and the export price level (P_x) on nominal unit labor costs (ULC) and import prices (P_m), and then regressing exports (X) on the exchange rate, the ratio of (P_x/P_m), and foreign income ($Y*$), and imports (M) on the nominal exchange rate, the ratio of (P/M_m), and Y. Noting that the wage share is equivalent to real unit labor costs ($RULC$)[6] and that ULC are the product of $RULC$ and (P), the marginal effects of a change in the wage share on X/Y and M/Y are found using equations (2.3) and (2.4), respectively, where e_{XP_x} is the estimated effect of P_x on X, e_{MP} is the estimated effect of P on M, e_{P_xULC} and e_{PULC} are the estimated effects of ULC on P_x and P, e_{PULC} is the estimated effect of ULC on P, and the sample mean values of X/Y, M/Y, and $RULC$ are used.

$$\frac{\partial(X/Y)}{\partial\psi} = e_{XP_x}\ e_{P_xULC}\ \frac{1}{1-e_{PULC}}\ \frac{X/Y}{RULC} \tag{2.3}$$

$$\frac{\partial(M/Y)}{\partial\psi} = e_{MP}\ e_{PULC}\ \frac{1}{1-e_{PULC}}\ \frac{M/Y}{RULC} \tag{2.4}$$

Note that although these studies model nominal unit labor costs as a function of the functional distribution of income, theory suggests that causality may flow in the other direction, with unit labor costs determining the wage and profit shares. For example, Blecker (1989) models the price level as a function of nominal unit labor costs and firms' markup rate, and the profit share as the ratio of average revenue (or the difference between

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[6]Note that if the wage share is measured as the ratio of labor compensation to GDP at factor costs, as in Onaran and Galanis (2012), Obst et al. (2017), and Onaran and Obst (2016), as opposed to the ratio of labor compensation to GDP, then the real unit labor costs are equivalent to the wage share times the ratio of GDP at factor costs to GDP.

the price level and unit labor costs) to the price level. A simplification of this model appears is shown in equations (2.5) – (2.10).[7]

$$y = \frac{Y^{Net}}{L} \tag{2.5}$$

Labor productivity (y) is defined as the ratio of net output (or national income) (Y^{Net}) to the amount of employed labor (L). Y^{Net} can then be thought of as the product of the utilization rate (u), the capital-capacity ratio—or the income-capital ratio at potential output—and the capital stock, (K).

$$Y^{Net} = uvK \tag{2.6}$$

The wage share is the ratio of nominal labor compensation—i.e. the product of the nominal wage rate (W^n) and the quantity of labor—to nominal output (PY). It can also be viewed as the ratio of nominal labor compensation to nominal labor productivity.

$$\psi = \frac{W^n L}{PY^{Net}} = \frac{W^n}{Py} \tag{2.7}$$

Prices are assumed to be the result of a markup over costs. Therefore the price level (P) is the product of the markup factor (τ), which is assumed to be greater than one, and unit labor costs (W^n/y).

$$P = \tau \frac{W^n}{y} = \tau ULC \tag{2.8}$$

In this open economy framework, markups depend on the competitiveness of domestic goods relative to foreign goods. As Blecker (1989) explains, domestic firms are

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[7]The discussion of this model follows Blecker (1989) closely. However, the notation of some variables is changed for consistency with the rest of the chapter, and the government sector is eliminated for simplicity.

able to increase their markups when domestic goods are more competitive. However, if domestic goods become less competitive, firms must cut their markups in order to prevent the loss of their market share. The model assumes a constant elasticity of the markup with respect to relative import prices ($\theta > 0$).

The markup is then modeled as a function of a target markup ($\bar{\tau}$) and the relative import price ($eP*/P$), where e is the nominal exchange rate (measured in domestic currency per unit of foreign exchange) and $P*$ is the foreign price level.

$$\tau = \bar{\tau}(eP*/P)^{\theta} \tag{2.9}$$

If the markup varies with the competitiveness of domestic goods in this manner, the wage share becomes a function of unit labor costs, as in equation (2.10).

$$\psi = (\frac{ULC}{eP*})^{\theta/(1+\theta)}\bar{\tau}^{-1/(1+\theta)} \tag{2.10}$$

This framework is more conceptually appealing, because the functional distribution of income is not a targeted variable, but rather the byproduct of firms' pricing decisions and the unit labor costs determined by labor bargaining and market forces. However, to the author's knowledge this approach to modeling the relationship between unit labor costs and the wage share has not previously been implemented in a structural study.[8]

Following the stepwise approach outlined in equations (2.3) and (2.4), studies generally find that the profit share has a positive effect on X/Y, a negative effect on M/Y, and therefore a positive effect on the ratio of net exports to GDP, NX/Y. Stockhammer et al. (2009), Onaran et al. (2011), and Stockhammer et al. (2011) find this result in their respective studies of the Euro area, the U.S., and Germany. Onaran and Galanis (2012),

[8]Fernandez (2005), estimating an aggregative model, used $ULC/eP*$ as a variable in a regression for the profit share, but he did not include a measure of the markup.

Onaran and Obst (2016), and Obst et al. (2017) find this general pattern for all of the countries that they examine, although in some cases the effects are insignificant.

Some earlier studies follow a slightly different approach to estimating net export effects. Hein and Vogel (2008) estimate NX/Y as a direct function of the profit share, GDP, and foreign income, finding that the profit share has positive contemporaneous effects on NX/Y, but negative lagged effects, leading to insignificant total effects in most cases, excepting the small, open economies of Austria and the Netherlands. Stockhammer et al. (2009) report the results of similar specifications for the Euro area, finding that real unit labor costs have a negative effect of NX/Y that are significant in two of their three specifications. Stockhammer and Wildauer (2016) estimate separate equations for exports and imports, but include the wage share directly in both equations. They find a negative effect of the wage share on exports, which is statistically significant in one of the two specifications that they report, and small and insignificant positive effects of the wage share on imports. Naastepad and Storm (2006) estimated only an export equation, finding that real unit labor costs have a negative effect on export growth in all countries except the U.S., where positive, but insignificant, effects were found.

The marginal effects of changes in the profit share (or wage share) on each component can then be added to determine the net effect on private aggregate demand. The results of studies following this methodology are often indicative of wage-led demand—i.e. an increase in the wage share (or decrease in the profit share) increases demand—especially for larger, advanced economies. Stockhammer and Wildauer (2016) find that their panel of 18 OECD countries is wage led on average, Onaran and Obst (2016) find that the EU15 as a whole is wage led, and Stockhammer et al. (2009) find that the Euro area as a whole is wage led. Onaran et al. (2011) find small wage-led demand effects in the U.S.[9] Stock-

[9]They also conclude that redistribution of income from wage earners to rentiers is more contractionary than an increase in the total profit share, while the largest contractionary effects come from redistribution from non-rentier profits to rentiers.

hammer et al. (2011) determine that Germany is wage led, but becoming less wage led with increasing globalization. Hein and Vogel (2008) find evidence of wage-led demand in larger economies, and profit-led demand only in the smaller, more open economies of Austria and the Netherlands. Similarly, Onaran and Obst (2016) and Onaran and Obst (2016) find that the vast majority of the EU15 countries are wage-led (11/15 and 14/15, respectively), with the cases of profit-led demand coming only in small, open economies—Austria, Belgium, Denmark, and Ireland. Onaran and Galanis (2012) find mixed results for a wider sample of countries, with a roughly equal number of wage-led and profit-led countries, with demand found to be wage-led in most developed countries and profit-led in most developing countries, with some exceptions in each group. Naastepad and Storm (2006) find that demand is wage led in 6 of the 8 countries that they examine, the exceptions being the U.S. and Japan. Stockhammer and Stehrer (2011) and Stockhammer et al. (2018) find evidence that private, domestic demand (i.e. consumption plus investment) is wage-led in the majority of the countries that they look at, with the few exceptions resulting from the theoretically implausible finding of a negative effect of the wage share on consumption.[10] Some studies also examine the cross-country effects of declining wage shares by estimating the effects of a simultaneous decline in the wage share in all countries in the sample on each individual country. Onaran and Obst (2016), Obst et al. (2017), and Onaran and Galanis (2012) find that some profit-led economies contract when their wage share decreases along with the wage shares of their trading partners.

Structural studies that examine the U.S. generally find that the U.S. economy is wage led. As explained above, Onaran et al. (2011), who focus on the U.S., find that the U.S. economy is moderately wage led. Onaran and Galanis (2012) find that demand in the U.S. is wage led because the negative effects of a higher profit share on consumption

[10]France is the lone exception in Stockhammer et al. (2018), while estimates of profit-led domestic demand in Stockhammer and Stehrer (2011) are generally sensitive to lag length, except in the case of the U.K.

outweigh the positive effects on net exports. They also find a positive, but insignificant effect of the profit share on investment. Hein and Vogel (2008) also find wage-led demand effects for the U.S. that are primarily driven by effects on consumption. They find negative effects of the profit share on investment, but these effects are insignificant. In the case of net exports, they find that positive contemporaneous effects of the profit share are canceled out by negative lagged effects. Stockhammer et al. (2018) find positive effects of the wage share on both consumption and total investment, although they find a negative effect of the wage share on corporate investment using long-term historical data. Stockhammer and Stehrer (2011) find differing effects of the wage share on consumption and investment depending on the lag length, but most estimated effects for the U.S. are insignificant. The one significant estimate that they obtain is a positive effect of the wage share on investment in a model with 8 quarterly lags. Naastepad and Storm (2006) is an exception to the general finding of wage-led demand effects in the U.S. They find that the U.S. is profit led, as the negative effects of real wage growth on investment outweigh the positive effects on consumption, while the effects on export growth are positive but insignificant.

Some studies expand on this basic framework to include more variables. Onaran et al. (2011) add housing and financial wealth to their consumption function, finding that both have a positive effect on consumption. Stockhammer et al. (2018) also examine the role of wealth, finding that it has a positive effect on consumption (with size and significance varying across countries), and a mixed effect on investment, as the estimated effect of an increase in wealth on investment is positive in some countries and negative in others. Stockhammer and Wildauer (2016) also include two measures of asset prices in their model—property prices and stock prices—to proxy for wealth. They also include personal inequality, corporate debt, and household debt. They find mixed effects of stock prices and personal inequality on both consumption and investment, with insignificant estimates in most specifications. However, they do find that property prices have a positive effect on both consumption and investment and household debt has a positive effect on consumption, while both household and corporate debt reduce investment. Obst et al. (2017) add the government sector to the model—including taxes, transfers, government spending, and government debt—in order to assess the impact of fiscal policies. They find that redistribution of income towards wages has a larger positive impact on demand when combined with more progressive taxation and increased public spending, and that the combination of these policies also leads to a more balanced budget.

The structural approach to estimating the relationship between aggregate demand and the functional distribution of income that these studies use has a number of advantages, including ease of interpretation and the ability to identify the effects of distribution on each component of aggregate demand (Blecker, 2017; Onaran and Galanis, 2012; Onaran and Obst, 2016; Stockhammer, 2017b). In comparison to techniques used by practitioners of the aggregative approach, such as vector autoregressions, they also allow for more flexibility, the inclusion of more variables, and more precise specifications, e.g. variables can be allowed to affect one component of aggregate demand but not another and different distributional variables can be included in each equation (Onaran and Obst, 2016).

However, the methodology used by previous structural studies also has some significant downsides. The primary criticism of previous structural studies is that their treatment of the wage share as an exogenous variable could lead to biased results. This assumption of exogeneity is likely not accurate, as Stockhammer and Stehrer (2011) find that causality flows from both consumption and investment to the wage share in Granger causality tests, and Barrales and von Arnim (2017) show that both demand and the wage share Granger cause one another. Barrales and von Arnim (2017) and Kiefer and Rada (2015) argue that structural models are improperly specified for this reason, and hence their results are unlikely to be valid. A number of structural studies acknowledge the potential bias caused by endogeneity (as well as ignoring the systemic aspect of the model), although they continue to think that the benefits of the approach outweigh the problems (Onaran and Galanis, 2012; Onaran and Obst, 2016; Obst et al., 2017). Similar problems could also arise from treating other variables as exogenous. For example, GDP is often included in equations for individual components of aggregate demand. Although GDP will likely impact consumption and imports, due to demand effects, and investment through accelerator effects, changes in these components of aggregate demand also affect GDP, by definition. Failing to account for this aspect of the relationship could therefore also introduce bias.

Some studies have tried to eliminate potential endogeneity bias by excluding the contemporaneous effects of the wage share on demand, and including only lagged variables, which are predetermined (Stockhammer and Stehrer, 2011; Naastepad and Storm, 2006; Onaran et al., 2011).[11] However, while this resolves the endogeneity problem, it adds another source of potential misspecification by ignoring potential contemporaneous effects of the wage share on demand. Stockhammer and Stehrer (2011) argue that the bias caused by ignoring contemporaneous effects is likely to be limited by their use of quarterly data, as their model only assumes that distribution affects demand with a one quarter lag. Excluding contemporaneous effects may also cause other econometric problems, as Stockhammer et al. (2018) find evidence of autocorrelation in specifications with no contemporaneous effects, but no evidence of autocorrelation when they are included.[12]

[11] Naastepad and Storm (2006) only exclude contemporaneous effects in their investment equation, while including them in their consumption and export equations.

[12] Different studies use different lag structures, even beyond their treatment of contemporaneous effects. E.g. Onaran et al. (2011) use a distributed lag model to determine the number of lags for each variables, beginning with 8 quarterly lags for each variable and dropping insignificant variables until only significant variables remain. Stockhammer and Stehrer (2011) test lag length sensitivity by using 2, 4, 6, and 8 quarterly lags for each variable. The former uses a different number of lags for each variable and allows for lagged dependent variables, while the latter does not include lagged dependent variables and uses an equal number of lags for all independent variables in an equation. Stockhammer et al. (2011) generally do not include any lagged variables, but occasionally use different lag structures when they expect that it will improve their results. Hein and Vogel (2008) include lagged variables only to correct

Another problem with this empirical approach, as previously implemented, is that it does not account for the systemic aspects of the structural models. For example, by estimating each equation separately, previous studies implementing this approach have not accounted for potential correlation among the errors of each equation. It is also likely that this estimation technique of separately estimating each equation will not properly capture the dynamic interactions between variables. Blecker (2016, p. 379) explains how the separate estimation of each equation could lead to bias in this way:

> . . . if a rise in profitability stimulates investment and this in turn boosts consumption via the multiplier, this will be captured by an aggregative model as a positive effect of profits on demand, whereas in separate estimates of consumption and investment functions the effect on consumption would be picked up by the total income variable rather than the distributional variable. Similarly, if a rise in the wage share boosts consumer demand and this in turn stimulates investment via the accelerator effect, this would be incorporated in an aggregative model but might not be reflected in separate estimates of an investment function (in which the impact would be picked up by the utilization or accelerator term, not by the distributional variable).

Some studies (such as Onaran et al., 2011; Onaran and Obst, 2016) partially address this by calculating the indirect effects of a change in distribution through the multiplier, following the estimation of each equation separately.

To the author's knowledge, no structural study has yet attempted to overcome endogeneity problem and the potential bias caused by overlooking the systemic dimension of the model by estimating a system of equations in which the functional distribution of income and the components of private aggregate demand are simultaneously determined. Some studies (e.g. Onaran and Galanis, 2012; Stockhammer and Stehrer, 2011; Onaran and Obst, 2016) note that distribution could be endogenized using an instrumental variables approach, but cite econometric challenges, such as the difficulty of finding good

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for autocorrelation. Naastepad and Storm (2006) include no lagged variables, except those that are used to replace contemporaneous independent variables in their investment equation to avoid endogeneity. Onaran and Galanis (2012), Obst et al. (2017), and Onaran and Obst (2016) begin with one lag of both dependent and independent variables and drop those that are insignificant, except in cases where keeping insignificant variables prevents autocorrelation.

instruments and the need for long data series, as reasons for not pursuing it. This study follows such an approach, using the Generalized Method of Moments (GMM) to estimate systems of equations in which both the wage share and the components of private aggregate demand are endogenously determined. The systems are estimated for the U.S., for which data availability allows for sufficiently long data series to estimate systems with large numbers of parameters and the ability to find instruments for wage share. The U.S. has also been one of the countries most frequently analyzed in structural studies. Therefore, the choice of the U.S. economy as the country of analysis allows for ample comparisons with the previous literature.

2.3 Empirical Strategy

2.3.1 Econometric Approach

In order to test the extent to which treating the wage share as exogenous and ignoring the systemic dimension of the model biases structural estimates, this chapter compares the results of models estimated using the same data and the same sets of equations, but two different estimation strategies. The equations are first estimated separately using Ordinary Least Squares (OLS), as is traditional in the literature surveyed above, and then as a system using GMM. Using GMM, the components of private aggregate demand, the price variables, and the wage share are all simultaneously determined.

To ensure that the findings are not sensitive to the specification of the equations themselves, this exercise will be performed for three alternative models using annual U.S. data from 1963-2014. The first is based on the model used by Onaran and Galanis (2012) for the United States. This model is used because it is representative of most structural models,[13] its equations will provide a sufficient number of instruments for the GMM estimation, and it provides a set of estimates for the U.S. that can be used for

[13]The model that they use is very similar to those used in many other studies (e.g. Stockhammer et al., 2009, 2011; Onaran and Obst, 2016; Obst et al., 2017).

comparison. The model based on Onaran and Galanis (2012) (henceforth the OG model) consists of equations (2.11) through (2.16), where i is the real long-term interest rate, Ig is government investment, and E is the nominal exchange rate.[14]

$$\Delta\ ln\ C = F^{C}(\ \Delta\ ln\ R,\ \Delta\ ln\ W) \tag{2.11}$$

$$\Delta\ ln\ I = F^{I}(\ \Delta\ ln\ \psi,\ \Delta\ ln\ Y,\ i,\ \Delta\ ln\ Ig) \tag{2.12}$$

$$\Delta\ ln\ P = F^{P}(\ \Delta\ ln\ ULC,\ \Delta\ ln\ P_m) \tag{2.13}$$

$$\Delta\ ln\ P_x = F^{P_x}(\ \Delta\ ln\ ULC,\ \Delta\ ln\ P_m) \tag{2.14}$$

$$\Delta\ ln\ X = F^{X}(\ \Delta\ ln\ P_x/P_m,\ \Delta\ ln\ Y*,\ \Delta\ ln\ E) \tag{2.15}$$

$$\Delta\ ln\ M = F^{M}(\Delta\ ln\ P/P_m,\ \Delta\ ln\ Y,\ \Delta\ ln\ E) \tag{2.16}$$

Each equation is estimated using an autoregressive distributed lag (ARDL) model to determine the appropriate lag length for each variable. Using this method, all possible combinations of lag lengths (ranging from 0 to 4 lags for each variable) are evaluated, and the model with the best fit is selected. The Schwarz criterion is used to evaluate model fit, because it imposes a higher penalty for each additional parameter than other information criteria, and therefore results in a model with fewer parameters. This is desirable, as the sample size is limited and the system will be inestimable by GMM if the number of parameters is too large. Each equation includes a lagged dependent variable (with the optimal lag length), a constant, and an error term. As in Onaran and Galanis (2012) and many other studies in the literature, variables are transformed into natural logarithms because many of the data series exhibit exponential trends. The only exception is the real interest rate, which is left as a percentage, as is common practice in the literature.

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[14]Note that F^j denotes an implicit function for variable j.

As in Chapter 1, three unit root tests are performed to determine whether to difference each series—the Augmented Dickey Fuller (ADF) test with lag length determined by MAIC (Ng and Perron (2001)), the Phillips-Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The first difference of a series is taken unless at least two of the following conditions is met: 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% level. Following this decision rule, all variables except the real interest rate are differenced because they are found to have unit roots. The unit root tests are then performed on the differenced series to ensure stationarity. Only ΔP is found to be non-stationary. For this reason, the sensitivity of the results to using the first or second difference of P is tested.[15] The results of the unit root tests are shown in Table B.1 of Appendix B.

It should be noted that this model is not an exact replication of the model used in Onaran and Galanis (2012), because there are data and methodological differences between this study and theirs. The two studies make use of different data sources and sample periods. There are also some measurement differences. For example, they use the profit share, rather than the wage share, in their investment equation. Furthermore, lag length differs across the two models. They include a maximum of one lag for each variable, because they begin with one lag of each variable and drop those that are insignificant, whereas this study uses an ARDL model to determine lag length and allows up to 4 lags for each variable. They also add autoregressive terms to some equations, and use error correction models (ECMs) for equations (2.14) and (2.16). Autoregressive terms are not used in for estimates in this chapter because allowing for longer lag lengths should eliminate autocorrelation, and ECMs are not used because incorporating them in the system GMM estimates is not feasible. However, ECM results for equation (2.14)—which

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[15] The second difference of this variable is found to be stationary.

is the only equation where evidence of cointegration is found—are reported as a sensitivity test.

The second model is based on the specification in Stockhammer and Wildauer (2016) (henceforth the SW model). This model is used because it includes a number of control variables for each component of private aggregate demand that can be used as instruments in GMM estimation. This model also provides an interesting counterpoint to the OG model in that it takes a more direct approach to estimating the effect of the wage share on each component. While the OG model indirectly estimates the effect of the wage share on consumption, exports, and imports, the SW model includes the wage share directly in each of these equations. The SW model is shown in equations (2.17) – (2.20), where HD and CD denote household and corporate debt, respectively, while HA, Q, and HP represent household assets (or wealth), personal inequality, and home prices, respectively. Note that exports are included in the import equation to account for the import of intermediate goods.

$$\Delta\ ln\ C = F^{C}(\ \Delta\ ln\ Y,\ \Delta\ ln\ \psi,\ \Delta\ ln\ HD,\ \Delta\ ln\ HA,\ \Delta\ ln\ Q) \tag{2.17}$$

$$\Delta\ ln\ I = F^{I}(\ \Delta\ ln\ Y,\ \Delta\ ln\ \psi,\ i,\ \Delta\ ln\ HD,\ \Delta\ ln\ CD,\ \Delta\ ln\ HA,\ \Delta\ ln\ Q) \tag{2.18}$$

$$\Delta\ ln\ X = F^{X}(\ \Delta\ ln\ Y*,\ \Delta\ ln\ \psi,\ \Delta\ ln\ E,\ \Delta\ ln\ HP) \tag{2.19}$$

$$\Delta\ ln\ M = F^{M}(\ \Delta\ ln\ Y,\ \Delta\ ln\ \psi,\ \Delta\ ln\ E,\ \Delta \ln\ X, \Delta\ ln\ HP) \tag{2.20}$$

As with the OG model, each equation includes a lagged dependent variable (with the optimal lag length), a constant, and an error term, and the lag length for each variable is selected using an ARDL model and the Schwarz Criterion. All variables are found to integrated of order one, with the exception of the real interest rate, which is stationary. There is no evidence that any of these equations is cointegrated.

Like the OG model, the SW model estimated in this chapter is not an exact replication of the original study. One important difference between these estimates and those of by Stockhammer and Wildauer (2016) is that they estimate their model for a panel of countries, while this chapter only uses U.S. data. Another important difference is that they use housing prices and stock prices to proxy for wealth due to limitations on the availability of wealth data for some countries. As this chapter does not have the same constraints, it measures wealth more directly using household assets. This chapter also uses a different measure of personal inequality—the income share of the top 5%—rather than the Gini index and top 1% income share. The Gini index is not used because a sufficiently long data series is not available,[16] while the top 5% share is used in place of the top 1% share because Cynamon and Fazzari (2016) find that increases in the top 5% share led to increases in debt-financed consumption prior to the Great Recession and decreased consumption during the Great Recession, while Stockhammer and Wildauer (2016) find no significant effect of the top 1% share on consumption. Furthermore, they model real imports and exports as a function of the property price index, which is intended to capture asset price inflation. This chapter uses a home price index, rather than a broader property price index, to maintain consistency with the measure of housing prices that is initially used in the residential investment equation (discussed below). Finally, while Stockhammer and Wildauer (2016) include only lagged effects of the wage share in their export equation, this chapter includes contemporaneous effects of the wage share in all equations.[17]

As Onaran and Galanis (2012) and Stockhammer and Wildauer (2016) treat the wage share as exogenous, they do not have equations for the wage share. However, such an equation is necessary in order to endogenize the wage share in the system estimates. One

[16]The Gini series created by the U.S. Census Bureau does not begin until 1967.

[17]It is not known why Stockhammer and Wildauer (2016) omit the contemporaneous effects from this equation.

key variable to include in this equation is Y, as distribution is expected to change with demand. For example, the profit squeeze effect found in many aggregative studies, and discussed in more detail in Chapter 1, predicts that the wage share will rise with demand. Such effects could be explained by decreased bargaining power of workers when the labor market is slack. It is also important to include a number of control variables in this equation, as valid instruments for the wage share are needed for the GMM estimation. The wage share equation that will be used for the OG and SW models is not strongly motivated by theory, and is not intended to provide a thorough analysis of the determinants of the wage share. Instead, it includes variables previously found to affect the wage share in an admittedly ad hoc attempt to find valid instruments.[18]

Although no previous structural study has included a wage share equation, research on the determinants of the wage share can provide some guidance on what variables to include. Stockhammer (2017a) finds that proxies for factors such as financialization, globalization, and the decline of the welfare state have contributed to falling wage shares in a panel study of OECD economies. Therefore, variables capturing these trends are strong candidates for inclusion in the wage share equation. The size of the financial sector (F) is used to capture financialization, globalization is measured using foreign trade (FT) (or the ratio of global trade to global GDP, excluding U.S. trade and U.S. GDP to avoid endogeneity).[19] Union density (UD) is used to capture labor bargaining power, which may also serve as a proxy for the friendliness of the policy environment towards labor. Although Stockhammer (2017a) does not find strong effects of technological change on the wage share, a capital intensity (K) variable is included in the model to test whether it affects the wage share. The real exchange rate (RE) is also included because theory (see

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[18] A more theoretically grounded wage share equation will be introduced later for the synthetic model.

[19] As the U.S. is a large economy, it is possible that some effects of changes in the U.S. economy on global trade may remain even after U.S. trade is excluded.

e.g. Blecker, 1989) suggests international trade competitiveness plays an important role in determining the wage share, and Fernandez (2005) finds that trade competitiveness is the main determinant of the profit share. Another variable that may affect firms' profitability, and therefore the wage share, is the market power of firms. The average markup (MU) is included to capture these effects. Finally, an index of business confidence (BC) is included to account for firms' expectations. It is thought that this variable will affect the wage share because firms' demand for labor, and their decisions regarding labor compensation, are likely to depend on their expectations.[20]

While all of these variables are initially included, F, UD, RE, and MU are eventually dropped because they are found to be insignificant when the other variables are included in the model. BC is significant when these four other variables are included in the model, but becomes insignificant when they are all excluded. However, it is left in the model because it is borderline significant, with a p-value of 0.106, and it can provide an additional instrument for the GMM estimation. The resulting wage share equation is shown in equation (2.21).[21]

$$\Delta \; ln \; \psi = F^{\psi}(\; \Delta \; ln \; Y, \; \Delta \; ln \; FT, \; \Delta \; ln \; K, \; \Delta \; ln \; BC) \tag{2.21}$$

The final model is a synthetic model, featuring some elements of the OG and SW models, as well as some innovations. Although the OG and SW models are representative of much of the structural literature, they have some shortcomings. First, by estimating investment effects in an equation for aggregate investment, they may be missing differing

[20]This variable is correlated with the growth rate of GDP, as the two series have a correlation coefficient of 0.76. However, business confidence is included in addition to the growth rate of GDP, because it is expected to provide additional information about the wage share that is valuable.

[21]Note that all series included in this equation are differenced because they are found to be integrated of order one. There is no evidence of cointegration in this equation. This equation also includes a lagged dependent variable (with the optimal lag length), a constant, and an error term.

effects of the wage share on residential and nonresidential investment. Furthermore, their export and import equations are not consistent with theoretical models of the relationship between unit labor costs in an open economy, as seen, e.g., in Blecker (1989). The SW model ignores the role of unit labor costs in determining exports and imports, and instead estimate these equations as functions of the wage share. While the OG model treats exports and imports as functions of unit labor costs, it assumes that unit labor costs are a function of the wage share, when theory suggests that causality should flow in the opposite direction.[22] The synthetic model addresses these concerns.

The consumption equation, shown in equation (2.22), combines some elements of both models.[23] The approach of estimating the MPCs out of wages and profits is preferred over including the wage share directly in the consumption equation, along with GDP, because it is thought to be more precise. This equation also controls for household debt, because some significant effects of household debt on consumption are found in the SW model (although the long-run elasticity is found to be insignificant).

$$\Delta\ ln\ C = F^C(\ \Delta\ ln\ W,\ \Delta\ ln\ R,\ \Delta\ ln\ HD) \tag{2.22}$$

As discussed in Section 2.2, structural studies do not consistently find strong effects of the wage share on investment. It is possible that this is due to competing effects of the wage share on residential and nonresidential investment. Because the use of an aggregate investment function may be concealing competing effects of the wage share on different components of investment, separate equations are estimated for residential and nonresi-

[22]It should be noted that Granger causality tests do not confirm the expected theoretical relationship. The results of these tests suggest that $\Delta lnwageshare$ Granger causes $\Delta lnULC$, but $\Delta lnULC$ does not Granger cause $\Delta lnwageshare$. This could be due to the fact that the ULC series is constructed from the wage share series. Despite this result, the model that is more in line with theory is preferred.

[23]As in the OG and SW models, all equations include a lagged dependent variable (with the optimal lag length), as well as a constant and an error term.

dential investment. These effects are particularly important to consider, because Fiebiger (2018) argues that household investment can be an important driver of demand over the course of the business cycle.[24] Although Stockhammer et al. (2018) find negative effects of the wage share on corporate investment and positive effects on total investment, to the author's knowledge no study has yet estimated the effects of the wage share on residential investment. This study further builds upon the work of Stockhammer et al. (2018) by incorporating fixed residential and nonresidential investment into a full structural model with open economy effects, and by testing how the results are influenced by treating the wage share as endogenous. Nonresidential investment (NI) is modeled as a function of the wage share and the variables from the OG and SW equations that are likely to influence firms' investment decisions, namely i, ψ, Ig, CD. Y is included to account for accelerator effects, and BC is added as an additional variable to capture Keynesian animal spirits effects. The resulting nonresidential investment equation is shown in equation (2.23).

$$\Delta\ ln\ NI = F^{NI}(\Delta\ ln\ Y,\ \Delta\ ln\ \psi,\ i,\ \Delta\ ln\ CD,\ \Delta\ ln\ IG,\ ln\ BC) \tag{2.23}$$

Because structural models do not typically focus on residential investment (RI), the residential investment equation is based on the model of residential investment developed by Arestis and González-Martínez (2014). They model real residential investment as a function of housing prices (HP), interest rates, disposable income, the unemployment rate, and the volume of banking credit ($VBCC$). Y is used in place of disposable income to retain consistency with the other equations, and the unemployment rate is excluded

[24]It should be noted that residential and household investment are not exactly equivalent. As Fiebiger (2018) explains, household investment includes both residential investment by households and nonresidential investment by nonprofit institutions that serve households. However the disaggregation of investment into its residential and nonresidential components should still capture some of the effects of household investment.

because the growth rates of Y and the unemployment rate are highly correlated.[25] The other variables are included in the model, although the real long-term interest rate is used instead of the mortgage rate that they use in their model due to lack of a sufficiently long data series for the mortgage rate. Along with these variables two variables from the SW investment equation, HD and HA, are added, along with consumer confidence (CC) and ψ. Equation (2.24) contains the residential investment equation.

$$\begin{aligned} \Delta\ ln\ RI = F^{RI}(&\Delta\ ln\ Y,\ \Delta\ ln\ \psi,\ i,\ \Delta\ ln\ HD,\ \Delta\ ln\ HA, \Delta\ ln\ VBC, \\ &\Delta\ ln\ HP,\ \Delta\ ln\ CC) \end{aligned} \tag{2.24}$$

This model takes a different approach to estimating export and import effects than both the OG and SW models. While estimating exports and imports as indirect functions of ULC tends to yield stronger results than including the wage share directly in the trade equations—as discussed in Section 2.2 and affirmed in this chapter's estimates of the OG and SW models—this approach has its own downsides. First, it requires the estimation of four equations to determine the effects of unit labor costs on exports and imports. This leads to a system of equations with a large number of equations that is difficult to estimate as a system when additional variables are added to other equations (e.g. the residential and nonresidential investment equations). Furthermore, this approach to ultimately estimating the effect of the wage share on exports and imports rests on the theoretically unsatisfying assumption that unit labor costs are determined by the wage share. As discussed earlier, the theoretical model of Blecker (1989), suggests that the wage share, or real unit labor costs, should instead be considered to result from nominal unit labor costs and the price level, which is itself determined in large part by unit labor costs. For these reasons, the wage share is modeled as a function of ULC, P_m, and MU—the main determinants of the wage share in the Blecker (1989) model—as shown in equation

[25] The correlation coefficient for these two variables over the sample period is -0.812.

(2.25).

$$\Delta\ ln\ \psi = F^{\psi}(\ \Delta\ ln\ MU,\ \Delta\ ln\ ULC,\ \Delta\ ln\ P_m) \tag{2.25}$$

Unit labor costs are then modeled as a function as a function of Y, in order to endogenize unit labor costs. K, FT, F, RE, UD and BC are initially included in this equation to provide instruments for ULC, with these variables affecting the wage share indirectly through unit labor costs. However, F, UD, and BC are found to be insignificant and are therefore dropped, resulting in equation (2.26).

$$\Delta\ ln\ ULC = F^{ULC}(\ \Delta\ ln\ GDP,\ \Delta\ ln\ K, \Delta\ ln\ RE, \Delta\ FT) \tag{2.26}$$

Following this approach, private aggregate demand is ultimately affected by nominal unit labor costs, rather than the wage share. Exports and imports are directly affected by ULC, as in equations (2.27) and (2.28),[26] while consumption and investment are indirectly affected by ULC, through its effect on the wage share. Both equations are also functions of demand—either foreign or domestic GDP—and import prices.

$$\Delta\ ln\ X = F^{X}(\Delta\ ln\ Y*,\ \Delta\ ln\ RE,\ \Delta\ ln\ ULC,\ \Delta \ln\ P_m) \tag{2.27}$$

$$\Delta\ ln\ M = F^{M}(\ \Delta\ ln\ Y,\ \Delta\ ln\ RE,\ \Delta\ ln\ ULC,\ \Delta \ln\ P_m) \tag{2.28}$$

This approach to modeling the wage share is thought to be superior to the method of estimating all components of private aggregate demand as functions of the wage share. However, this method is not implemented for the OG and SW models, because such an approach would not be consistent with the rest of those models. The SW model does not include unit labor costs at all, so separately estimating equations for the wage share and

[26]Note that import prices are included in the export equation to reflect the importance of the relative difference between export and import prices for determining exports, as in the OG model. Export prices are excluded because they are endogenously affected by unit labor costs.

unit labor costs would provide little value. While the OG model does include unit labor costs, estimating the wage share as a function of unit labor costs would not be consistent with the assumptions used in calculating the marginal effects, which assume that unit labor costs are a function of the wage share.

As with the OG and SW models, each equation includes a constant and an error term, and lag length for each variable is determined by the ARDL model. All variables, with the exception of the real interest rate and business confidence, are first differenced because they are found to be integrated of order one. There is no evidence that any of the equations are cointegrated.[27]

These three models are first estimated equation-by-equation, using OLS and treating the wage share as exogenous. The estimated effect of a redistribution of income is then found by adding the marginal effects, following the methods of Onaran and Galanis (2012) and Stockhammer and Wildauer (2016). These results are then compared to the net effects found by estimating identical systems of equations, using the same variables with the lag lengths for each found using the ARDL model, using systems GMM. Using GMM, the parameters are estimated using moment conditions like those in equation (2.29), where t indexes time, $\boldsymbol{z_t}$ denotes the set of all exogenous variables in the model, ϵ_{tj} is the error term for equation j, y_{tj} is the dependent variable for equation j, and $\boldsymbol{x'_{tj}}$ is the set of independent variables for equation j, and (see Greene, 2011).

$$E[\boldsymbol{z_t}\ \epsilon_{tj}] = E[\boldsymbol{z_t}(y_{tj} - \boldsymbol{x'_{tj}\beta_j})] = 0 \tag{2.29}$$

In other words, the exogenous variables are assumed to be uncorrelated with the error term in each equation. All of the variables excluding the components of private aggregate

[27]Imports are found to be cointegrated with ULC, but not the other variables in the equation. Similarly, ULC are found to be cointegrated with Y, and there is mixed evidence of cointegration between ULC and RE. However, ULC is not cointegrated with K or FT.

demand, Y, ψ, W, R, ULC, P, P_x, P/P_m, and P_x/P_m are assumed to be exogenous. Any lags of the endogenous variables that are included in the model are also assumed to be exogenous.

Following the systems GMM approach, all of the equations are simultaneously determined and the exogenous variables are used as instruments for the endogenous variables to estimate the model. The same set of instruments, including all of the exogenous variables and the constant, is used for each equation in the system. The systems are initially estimated using only variables that are included in the model as instruments. This estimation method is identical to the three-stage least squares estimator, except for that fact that some of the variables that do not appear as dependent variables in any equation are treated as endogenous and therefore not used as instruments. However, using this approach the overidentifying restrictions for each of the three models are found to be invalid, based on Hansen's J-statistic. Therefore, additional lags of the variables included in the model are added as instruments.[28] The estimates found using the original instrument set—i.e. only the variables in the model—are presented for comparison, but due to the lack of valid instruments their results should not be trusted.

[28]Different instrument lists are used for each of the three models. The OG model is estimated using 4 lags of all of the endogenous variables—i.e. all of the dependent variables, wages, profits, GDP, unit labor costs, and the two price ratios—as instruments, and no additional lags of the exogenous variables. The instrument list for the SW model includes 3 lags of all of the variables in included in the model, except the log difference of the home price index, only two lags of which are included because this series does not have an observation for 1963 and including a third lag in the instrument list would result in having fewer observations than parameters. The synthetic model includes at least 2 lags of all the variables in the model, with 4 lags of the wage share and 3 lags of wages. Although all of these variables were specified as instruments, Stata dropped some variables from the instrument lists in estimates of the OG model (both for estimates with no additional instruments, and those with additional instruments) and the SW model. The approach to determining the instruments for each model is admittedly ad hoc, as different instrument sets were tested in an effort to find instruments for which Hansen's J-statistic failed to reject the null hypothesis of valid instruments. The estimates themselves were not considered in choosing the instrument sets, only the validity of the instruments. Even when adding these additional instruments for the SW model, the Hansen J-statistic rejects the null hypothesis of valid overidentifying restrictions at the 10% level. However, data constraints prevented the use of additional lags as instruments, so these estimates were used because they provided the strongest possible instruments, given the available data.

The GMM estimates are calculated using a two-step approach in Stata, in which parameter estimates are found using an initial weighting matrix, which is updated based on these parameter estimates. The updated weighting matrix is then used to obtain the final parameter estimates. The initial weighting matrix assumes that the moment equations are independent and identically distributed, while the updated weighting matrix assumes that the errors are homoskedastic, conditional on the instruments, but does not assume that the equations are independent (StataCorp, 2017).

The Breusch-Pagan-Godfrey test is used to test for heteroskedasticity,[29] while the Breusch-Godfrey Lagrange multiplier test is used to test for serial correlation up to 2 lags. Both tests are conducted based on the OLS estimates. Except where noted, the tests fail to reject the null hypotheses of homoskedasticity and no serial correlation up to 2 lags.

2.3.2 Data

All of these models are estimated using annual U.S. data from 1963-2014.[30] Data on GDP, consumption, investment, exports, and imports all come from the BEA national income accounts, and all are measured in chained 2009 dollars. Residential and nonresidential investment are based on the BEA's measures of total private, fixed residential and nonresidential investment and are converted to real values with corresponding price indexes. Real government investment is calculated by deflating the BEA's nominal government investment series with the price deflator for government investment. The domestic price level, export prices, and import prices are measured using the BEA's implicit price deflators for GDP, exports of goods and services, and imports of goods and services, respectively. The P/P_m and P_x/P_m price ratios are then calculated by dividing the GDP

[29]For some equations, there is an insufficient number of observations to use the White heteroskedasticity test. The Breusch-Pagan-Godfrey test is therefore used for all equations for the purpose of consistency.

[30]Note that some unreported estimates include one fewer observation, as the home price series is only available from 1964-2014 when it is first differenced.

deflator and the export price deflator by the import price deflator. W is measured as total compensation paid to employees, including wages and salaries and supplements to wages and salaries. R is measured as the gross operating surplus, constructed as the sum of net operating surplus and private consumption of fixed capital. Nominal series for both W and R come from the BEA's NIPA accounts and are converted to real series with the GDP deflator. The wage share is constructed by taking the ratio of the nominal labor compensation series to the BEA's nominal GDP series and rescaling it by multiplying by 100.[31] Nominal unit labor costs are calculated as the product of the wage share and the domestic price level.

Nominal series on household debt, corporate debt, and wealth come from the Federal Reserve and are converted to percentages of GDP by dividing by nominal GDP. The top 5% income share is measured as the share of pre-tax income earned by 95th-100th percentiles from the World Inequality Database. Real and nominal exchange rate series come from the Darvas (2012) database. These measures are preferred over the Federal Reserve's trade weighted U.S. dollar indexes, which are more commonly used, because the Fed series begin in 1973 and using them would substantially reduce the sample size. While the Federal Reserve series would be preferable if the sample sizes were equal, the Fed series is highly correlated with the Darvas (2012) series. For the period 1973-2014, the two nominal exchange rate series have a correlation coefficient of 0.991, while the two real exchange rate series have a correlation coefficient of 0.932.[32]

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[31] Note that the sum of W and R is equal to gross domestic income, which is equivalent to GDP in theory, but not in practice. Therefore, measuring the wage share in this way results in an implicit profit share that is equal to the sum of R and the statistical discrepancy—or the measured difference between gross domestic income and GDP—divided by GDP.

[32] Both real exchange rate series are based on consumer price indexes. However, there are some differences in the methodologies used to construct the two pairs of exchange rate series. The trade weights used for the Fed indexes vary every year, while those used by Darvas (2012) do not vary. The Fed indexes are based on exchange rates with 26 currencies, while the Darvas (2012) series are based on trade among 67 countries (including the U.S.). For more details, refer to Loretan (2005) and Darvas (2012).

The real long-term interest rate is measured as the difference between the Federal Reserve's 10-year treasury constant maturity rate and inflation expectations, which are measured as average inflation over the previous 10 years.[33] OECD GDP, excluding the U.S., is used as a proxy for foreign income. This variable is calculated by subtracting the OECD's measure of U.S. GDP from its measure of OECD GDP, both of which are measured in 2010 U.S. dollars. Foreign trade openness is calculated using World Bank data, and is measured as the ratio of world trade excluding U.S. trade to world GDP excluding U.S. GDP. U.S. trade is excluded to avoid endogeneity. Real home prices are measured by deflating the Bank for International Settlements' index of prices for new one family houses by the GDP deflator. The volume of banking credit is measured by deflating the Federal Reserve's series on bank credit at all commercial banks by the GDP deflator. The consumer confidence series comes from the OECD's composite indicator of consumer confidence in the U.S., which is normalized so that the long-term average is equal to 100. Business confidence is measured using the same indicator for manufacturing businesses.

The union density measure is calculated as the ratio of the OECD's data on U.S. union members and employees.[34] To proxy for financialization, a measure of the size of the financial sector is used. This is constructed by dividing the BEA's measure of income for the finance, insurance, and real estate sectors by nominal GDP.[35] The average

[33] See Chapter 1 for more details. This measure is used in the total investment, residential investment, and nonresidential investment equations. While Freddie Mac's 30-year fixed mortgage average rate, is a theoretically preferable interest rate for the residential investment equation, this series does not begin until 1971. The correlation coefficient for this mortgage rate and the long-term interest rate between 1971 and 2014 is .770.

[34] The union membership data comes from two separate data sets, one of which is based on administrative data and the other of which is a survey-based measure. The former series has data for 1960-1980, while the latter has data for 1973-2016. For years in which the two series overlap, the average of the two series is used. There is a missing observation in 1982, which is imputed as the average of the 1981 and 1983 values.

[35] Data for this measure comes from NIPA tables 6.1B, 6.1C, and 6.1D, and the exact definition of the sector varies across these datasets. Overlapping observations are identical for tables 6.1B and 6.1C,

markup is used to proxy for the average market power of firms. This data comes from the series created by De Loecker and Eeckhout (2017), in which firm-level data is used to calculate markups for each firm, and the average markup is weighted by firm market share.[36] Capital intensity, or the capital-labor ratio, is measured by dividing an estimate of the capital stock at constant prices, constructed by Feenstra et al. (2015), by the BLS measure of the civilian labor force. Data sources and variable definitions are summarized in Table B.2 of Appendix B.

2.4 Econometric Results

2.4.1 The Onaran and Galanis Model

The results for the consumption equation in the OG model are shown in Table 2.1. Both short-run and long-run elasticities (denoted LR) are reported.[37] The ARDL model suggests including one lag of the dependent variable, and no lags of the independent variables. The results are consistent with previous findings, as the MPC out of wages is found to be higher than the MPC out of profits. The coefficients differ little across the two sets of estimates. The short-run wage share coefficient is found to be 0.526 in both the OLS and GMM estimates,[38] while the coefficient on profits is 0.181 in the

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but not for tables 6.1C and 6.1D. The values from table 6.1C are used for years of overlap between tables 6.1C and 6.1D.

[36]The data series is available on one of the authors' website: https://sites.google.com/site/deloeckerjan/data-and-code.

[37]The long-run elasticity of the dependent variable with respect to each independent variable is calculated as the sum of the contemporaneous coefficient and any lagged coefficients (if applicable) on the independent variable divided by 1 minus the sum of the coefficients on lags of the dependent variable. The significance level for each long-run coefficient is based on Wald tests of the hypothesis that the long-run coefficient is equal to 0. Significance levels for the OLS estimates are based on an F-test, while those for the GMM estimates are based on a Chi-squared test. Standard errors are not reported for the long-run coefficients estimated using GMM, because they are not available in the output of Wald tests conducted in Stata.

[38]In this case, and throughout the remainder of the chapter, "GMM estimates" refers to the estimates found using additional instruments. Although those found using only the variables in the model as instruments are reported for reference, they are not thought to be valid and are therefore not discussed.

former and 0.161 in the latter. Onaran and Galanis (2012) found very similar coefficients on contemporaneous wages and profits for the U.S., at 0.536 and 0.181, respectively. However, they also included lagged wages and profits, finding negative effects of both, which were statistically significant in the case of profits.[39]

The finding that the MPC out of wages is higher than the MPC out of profits suggests that an increase in the wage share would lead to an increase in consumption. This result is robust to estimating the equation as part of a system in which wages and profits are assumed to be endogenous, with the coefficients on these variables estimated using an instrumental variables approach. In fact, the MPC differential between wages and profits is actually found to be slightly larger when using this approach than when estimating the consumption equation on its own. The marginal effect of an increase in the wage share on C/Y is calculated using equation (2.30) and the sample mean values of C/W and C/R.[40]

$$\frac{\partial(C/Y)}{\partial\psi} = c_W\frac{C}{W} - c_R\frac{C}{R} \tag{2.30}$$

Following this methodology, the estimated marginal effect of a 1 percentage point increase in the wage share on C/Y is 0.259 when using the single equation OLS approach, and 0.305 when using the systems GMM approach. Both are lower than the 0.426 found by Onaran and Galanis (2012).

The results for the OG investment equation are shown in Table 2.2. The ARDL model suggests one lagged dependent variable, four lags of GDP, and no lags of the other independent variables. The wage share is found to have a positive effect on investment using both estimation strategies. Although Onaran and Galanis (2012) find the oppo-

[39]The two models have different lag lengths because they use different approaches to choosing the number of lags. Whereas Onaran and Galanis (2012) begin with one lag of each variable, this chapter uses the optimal lag length in an ARDL framework.

[40]Note that c_W and c_R are the long-run coefficients on wages and profits, respectively. The sample means are summarized in Table B.3 of Appendix B. All marginal effects are calculated using elasticities rounded to the nearest thousandth.

Table 2.1: OG Model Consumption Equation

Dependent Variable: $\Delta\ ln\ Consumption_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	0.012***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)
$\Delta\ ln\ Consumption_{t-1}$	-0.019	-0.030	0.019
	(0.098)	(0.099)	(0.092)
$\Delta\ ln\ Wages_t$	0.526***	0.589***	0.526***
	(0.087)	(0.096)	(0.083)
LR $Wages$	0.517***	0.572***	0.536***
	(0.062)		
$\Delta\ ln\ Profits_t$	0.181***	0.152***	0.161***
	(0.047)	(0.050)	(0.043)
LR $Profits$	0.178***	0.148***	0.165***
	(0.054)		
R^2	0.772		
Adjusted R^2	0.757		
Schwarz Criterion	-6.368		
Hansen J-statistic		172.447*	318.725
N	51	48	48
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

site effect in their estimates for the U.S., their result is insignificant, and the estimated effects of the functional distribution of income on investment are inconsistent across the structural literature, as described in Section 2.2. Stockhammer et al. (2018) argue that positive effects of the wage share on investment could reflect increased residential investment when the wage share is higher. Although both the short-run and long-run wage share coefficients are insignificant in the OLS estimates of the investment equation, they become larger and significant at the 5% level when estimating the model as a system using GMM.

Table 2.2: OG Model Investment Equation

Dependent Variable: $\Delta\ ln\ Investment_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	-0.017	-0.001	-0.015
	(0.014)	(0.013)	(0.011)
$\Delta\ ln\ Investment_{t-1}$	-0.220	-0.118	-0.117
	(0.138)	(0.101)	(0.100)
$\Delta\ ln\ Wages\ Share_t$	0.695	2.085***	0.994**
	(0.530)	(0.618)	(0.415)
LR $Wage\ Share$	0.570	1.866***	0.890**
	(0.437)		
$\Delta\ ln\ GDP_t$	4.051***	4.153***	4.179***
	(0.223)	(0.191)	(0.183)
$\Delta\ ln\ GDP_{t-1}$	0.298	-0.515	-0.297
	(0.631)	(0.487)	(0.471)
$\Delta\ ln\ GDP_{t-2}$	-1.081***	-1.023***	-0.956***
	(0.229)	(0.171)	(0.167)
$\Delta\ ln\ GDP_{t-3}$	-0.360	-0.396*	-0.337*
	(0.276)	(0.205)	(0.198)
$\Delta\ ln\ GDP_{t-4}$	-0.879***	-0.817***	-0.744***
	(0.230)	(0.172)	(0.165)
LR GDP	1.665***	1.254***	1.652***
	(0.445)		
$Interest\ Rate_t$	0.005	0.005*	0.005*
	(0.004)	(0.003)	(0.003)
LR $Interest\ Rate$	0.004	0.004*	0.004*
	(0.003)		
$Government\ Investment_t$	-0.437***	-0.353***	-0.365***
	(0.113)	(0.085)	(0.083)
LR $Government\ Investment$	-0.359***	-0.316***	-0.327***
	(0.087)		
R^2	0.927		
Adjusted R^2	0.909		
Schwarz Criterion	-3.795		
Hansen J-statistic		172.447*	318.725
N	48	48	48
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

Table 2.3: OG Model Domestic Price Equation

Dependent Variable: Δ *ln Domestic Price*$_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	0.003**	0.003**	0.003**
	(0.002)	(0.001)	(0.001)
Δ *ln Domestic Price*$_{t-1}$	0.603***	0.487***	0.514***
	(0.081)	(0.065)	(0.064)
Δ *ln ULC*$_t$	0.230***	0.385***	0.353***
	(0.063)	(0.058)	(0.054)
LR *ULC*	0.579***	0.751***	0.727***
	(0.111)		
Δ *ln Import Prices*$_t$	0.067***	0.044***	0.046***
	(0.014)	(0.012)	(0.012)
Δ *ln Import Prices*$_{t-1}$	0.046***	0.042***	0.044***
	(0.014)	(0.011)	(0.011)
Δ *ln Import Prices*$_{t-2}$	-0.037**	-0.030***	-0.034***
	(0.016)	(0.011)	(0.012)
LR *Import Prices*	0.189***	0.108***	0.116***
	(0.050)		
R^2	0.954		
Adjusted R^2	0.948		
Schwarz Criterion	-7.424		
Hansen J-statistic		172.447*	318.725
N	50	48	48
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

The marginal effect of a 1 percentage point increase in the wage share on I/Y is calculated using equation (2.31), where i_ψ is the wage share coefficient in the investment equation and the sample mean of I/W is used.

$$\frac{\partial(I/Y)}{\partial(\psi)} = i_\psi \frac{I}{W} \tag{2.31}$$

The estimated marginal effect using the single equation approach is 0.154, while it is 0.241 using the systems approach.

Table 2.4: OG Model Export Price Equation

Dependent Variable: Δ *ln Export Prices$_t$*

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	0.004	0.003	0.003
	(0.004)	(0.004)	(0.004)
Δ $ln\ Export\ Prices_{t-1}$	0.184***	0.173***	0.163***
	(0.059)	(0.056)	(0.055)
Δ $ln\ ULC_t$	0.044	0.056	0.074
	(0.121)	(0.122)	(0.117)
LR ULC	0.054	0.067	0.088
	(0.146)		
Δ $ln\ Import\ Prices_t$	0.502***	0.508***	0.508***
	(0.035)	(0.034)	(0.034)
LR $Import\ Prices$	0.615***	0.614***	0.606***
	(0.058)		
R^2	0.909		
Adjusted R^2	0.903		
Schwarz Criterion	-5.543		
Hansen J-statistic		172.447*	318.725
N	51	48	48
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

Both sets of estimates provide evidence of strong accelerator effects[41] and crowding out—as the coefficient on government investment is negative and significant. Both estimates also indicate the theoretically unexpected result of a positive effect of interest rates on investment. However, this result is statistically insignificant in the OLS estimates and only weakly significant in the GMM estimates. As discussed in Section 2.2, many studies fail to find negative effects of interest rates on investment.

The results for the domestic price and export price equations are shown in Tables 2.3 and 2.4. Both import prices and nominal unit labor costs are found to have a positive effect on both price levels in both the single equation and systems estimates. However,

[41]The long-run coefficients on GDP in the single equation and systems estimates are 1.665 and 1.652, respectively.

the coefficient on unit labor costs in the export price equation is insignificant in both sets of results. The estimated effects of unit labor costs in both equations are similar to those found by Onaran and Galanis (2012) for the U.S., as they obtain an estimated coefficient of 0.211 in the domestic price equation and a coefficient of 0.049 in the export price equation, the former of which is significant at the 5% level and the latter of which is significant only at the 10% level.[42] These values align closely with the corresponding short-run coefficients of 0.230 and 0.044 found using the single equation approach, although the estimated effects of unit labor costs on both price levels is larger when using the systems method.[43]

It should be noted that the export price equation is likely misspecified. The Breusch-Pagan-Godfrey test suggests the presence of heteroskedasticity. The use of Newey-West heteroskedasticity and autocorrelation consistent standard errors does not change the significance of any of the variables in OLS estimates, other than the constant. The system cannot be estimated with a heteroskedasticity and autocorrelation consistent weighting matrix because attempts to estimate this model with such an estimator result in failure to converge to an optimal weighting matrix. Furthermore, Johansen cointegration tests suggest that export prices, unit labor costs, and import prices are cointegrated. When estimating a cointegrating regression for this equation using fully modified least squares, unit labor costs become significant. However, incorporating a cointegrating regression into the estimation of the system is not feasible. Therefore, the equation is estimated in

[42]It should be noted that both of their equations include only lagged unit labor costs, while this model includes only contemporaneous unit labor costs.

[43]Unit root tests suggest that the first difference of the logged domestic price level series contains a unit root. As a sensitivity test, the second difference of this series is used in its place. In OLS estimates of this specification, the short-run coefficients on import prices are jointly insignificant, and the coefficient on unit labor costs is close to zero, with a p-value above 0.99. When the second differences of both unit labor costs and the domestic price level are used, the coefficient on unit labor costs in OLS estimates has the expected sign, but it remains insignificant with a p-value near 0.12. In this specification, import prices remain jointly insignificant. For these reasons, the specification with the first difference of the domestic price level is preferred.

log differences in the system, like the other equations. The results for the cointegrating regression are shown in Table B.4 of Appendix B.

The export and import results are shown in Tables 2.5 and 2.6. In both cases the price ratios, P_x/P_m and P/P_m, have statistically significant effects and the expected signs—negative for the former and positive for the latter. Combined with the positive effects of unit labor costs on both domestic and export prices, these results suggest that higher unit labor costs reduce net exports. In both cases, the demand variables—i.e. foreign income for exports and U.S. GDP for imports—have the expected positive signs and have statistically significant effects. The nominal exchange rate has the expected sign in the export equation—with a stronger dollar reducing exports.[44] Unexpectedly, the elasticity of imports with respect to the exchange rate is found to be negative, but the effects are small—with long-run elasticities of -0.052 for the OLS estimates and -0.045 for the GMM estimates. This anomaly will be eliminated in the synthetic model, where the import equation is better specified (see below).

The marginal effects of a 1 percentage point increase in the wage share on X/Y and M/Y are calculated using equations (2.32) and (2.33), as in Onaran and Galanis (2012). Note that the wage share is equivalent to real unit labor costs, and is divided by 100 in both equations because the wage share series ranges from 0 to 100 and is therefore not on the same scale as X/Y and M/Y.[45] Here the estimated long-run coefficients on the P_x/P_m and P/P_m are used as the values of e_{XP_x} and e_{MP}, respectively.

$$\frac{\partial(X/Y)}{\partial\psi} = e_{XP_x}\, e_{P_xULC}\, \frac{1}{1-e_{PULC}}\, \frac{X/Y}{\psi/100} \tag{2.32}$$

[44]The long-run elasticity of exports with respect to the exchange rate is -0.322 in the OLS estimates and -0.244 in the GMM estimates.

[45]Note that Onaran and Galanis (2012) use wage share and real unit labor cost series that range from 0 to 1.

Table 2.5: OG Model Export Equation

Dependent Variable: $\Delta\ ln\ Exports_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	0.014	0.016*	0.015
	(0.010)	(0.009)	(0.009)
$\Delta\ ln\ Exports_{t-1}$	0.476***	0.374***	0.381***
	(0.114)	(0.100)	(0.101)
$\Delta\ ln\ X/M\ Price\ Ratio_t$	-0.476***	-0.446***	-0.438***
	(0.141)	(0.133)	(0.127)
LR $X/M\ Price\ Ratio$	-0.908***	-0.712***	-0.708***
	(0.306)		
$\Delta\ ln\ Foreign\ Income_t$	2.439***	2.337***	2.417***
	(0.306)	(0.287)	(0.287)
$\Delta\ ln\ Foreign\ Income_{t-1}$	-1.824***	-1.597***	-1.649***
	(0.371)	(0.343)	(0.345)
LR $Foreign\ Income$	1.174**	1.181***	1.240***
	(0.519)		
$\Delta\ ln\ Nominal\ Exchange\ Rate_t$	-0.169**	-0.156**	-0.151**
	(0.082)	(0.074)	(0.073)
LR $Nominal\ Exchange\ Rate$	-0.322*	-0.250**	-0.244*
	(0.172)		
R^2	0.707		
Adjusted R^2	0.675		
Schwarz Criterion	-3.847		
Hansen J-statistic		172.447*	318.725
N	51	48	48
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

$$\frac{\partial(M/Y)}{\partial\psi} = e_{MP}\ e_{PULC}\ \frac{1}{1 - e_{PULC}}\ \frac{M/Y}{\psi/100} \tag{2.33}$$

Using these formulas, the single equation estimates yield marginal effects of -0.015 on exports and 0.080 on imports. Taking the difference of these two effects, the marginal effect of a 1 percentage point increase in the wage share on NX/Y is -0.095. Using systems GMM the marginal effect on exports is -0.030, and the effect on imports is 0.132, leading

Table 2.6: OG Model Import Equation

Dependent Variable: Δ $ln\ Imports_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	-0.009	-0.011*	-0.012*
	(0.007)	(0.007)	(0.007)
Δ $ln\ Imports_{t-1}$	-0.052	-0.060	-0.057
	(0.066)	(0.059)	(0.059)
Δ $ln\ P/M\ Price\ Ratio_t$	-0.065	-0.060	-0.059
	(0.073)	(0.065)	(0.064)
Δ $ln\ P/M\ Price\ Ratio_{t-1}$	0.435***	0.389***	0.375***
	(0.077)	(0.069)	(0.068)
LR $P/M\ Price\ Ratio$	0.352***	0.310***	0.299***
	(0.096)		
Δ $ln\ GDP_t$	2.448***	2.549***	2.559***
	(0.216)	(0.217)	(0.202)
LR GDP	2.327***	2.404***	2.421***
	(0.224)		
Δ $ln\ Nominal\ Exchange\ Rate_t$	0.180*	0.169**	0.166**
	(0.090)	(0.080)	(0.079)
Δ $ln\ Nominal\ Exchange\ Rate_{t-1}$	-0.176	-0.163*	-0.161*
	(0.108)	(0.095)	(0.094)
Δ $ln\ Nominal\ Exchange\ Rate_{t-2}$	0.183*	0.178**	0.175*
	(0.103)	(0.091)	(0.090)
Δ $ln\ Exchange\ Rate_{t-3}$	-0.242***	-0.230***	-0.227***
	(0.086)	(0.076)	(0.075)
LR $Nominal\ Exchange\ Rate$	-0.052	-0.043	-0.045
	(0.101)		
R^2	0.883		
Adjusted R^2	0.859		
Schwarz Criterion	-4.018		
Hansen J-statistic		172.447*	318.725
N	49	48	48
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

to a marginal effect on NX/Y of -0.162. These results suggest that increases in the wage share reduce net exports by raising the price of domestic goods relative to foreign goods. Both estimates are larger than those in Onaran and Galanis (2012), where the marginal effect of an increase in the profit share on NX/Y is found to be 0.037 (suggesting that the wage share would have a marginal effect of -0.037).

The marginal effect of a 1 percentage point increase in the wage share on private aggregate demand is found by adding the marginal effects on consumption, investment, and net exports.[46] These marginal effects are summarized in Table 2.7. Using the single equation approach, the total effect of an increase in the wage share is 0.318—suggesting that private aggregate demand is wage led. This estimate is similar to the one obtained by Onaran and Galanis (2012) for the U.S. They estimate a marginal effect of an increase in the profit share on private excess demand of -0.388, suggesting that an increase in the wage share would lead to an increase of 0.388.[47] The estimated marginal effect obtained using systems GMM is very close to this estimate, at 0.384. Both the positive effects of an increased wage share on consumption and investment and the negative effects on net exports are larger in magnitude when using the systems approach rather than the single equation approach. However, the total effect based on the systems estimates is more wage led than the total effect using the single equation approach. This suggests that while the shortcomings of the structural approach may bias the results, in the context of this model, the bias makes the estimates less wage led—not more so, as critics of the structural approach have suggested.

[46]The marginal effects on each component of private excess demand are rounded to the nearest thousandth before they are summed.

[47]Note that they treat the insignificant effects of the profit share on investment as zero, while this sum includes insignificant effects. Insignificant effects can be treated as zero when using the single equation approach, because the estimates for one equation do not affect the estimates for the other equations. However, this is not true for the estimates obtained using systems GMM. It would be inaccurate to treat insignificant effects as zero in this context, because the other estimated marginal effects would change if insignificant marginal effects were actually zero (e.g. if the insignificant variables were removed from the model). For this reason, insignificant effects are included for the GMM estimates. They are also included in the OLS estimates to maintain comparability. If insignificant effects were treated as zero, the marginal effects on I/Y for the OLS estimates would disappear, as would the marginal effects on X/Y for both sets of estimates (because the effect of ULC on export prices is insignificant). This would result in net effects of 0.179 for the OLS estimates and 0.414 for the GMM estimates.

Table 2.7: OG Model: Marginal Effects of a 1 Percentage Point Increase in the Wage Share

	OLS	**Systems GMM**
C/Y	0.259	0.305
I/Y	0.154	0.241
NX/Y	-0.095	-0.162
Private Excess Demand/Y	0.318	0.384

Both the OG and SW systems are completed by the same wage share equation. GDP is added to this equation to make the wage share endogenous, and control variables are included to provide instruments for the wage share in the GMM estimation process. Global trade, capital intensity, business confidence, the size of the financial sector, union density, the real exchange rate, and the average markup are initially included as control variables. However, the latter four are dropped because they are found to be insignificant when the former three variables are included in the model.[48] Although business confidence is insignificant, it is borderline significant, with a p-value of 0.1056, so it is left in the model to provide an additional instrument for the wage share.

Table 2.8 shows the estimates for this equation that result from estimation of the OG system using GMM and the separate estimation of the equation using OLS. In all both estimates, GDP is found to have a positive effect on the wage share, with long-run elasticities of 0.363 for the single equation estimates, 0.384 for the estimates from the OG system. These results suggest that the wage share increases with demand, or in other words that there is a profit squeeze. In both sets of estimates, foreign trade is found to have a positive contemporaneous effect on the wage share that is followed by a negative

[48]OLS estimates of the model including all of these variables are shown in Table B.5 of Appendix B. Because the inclusion of this many variables results in a model with implausible lag lengths for many variables, a maximum lag length of 2 is used. The least significant variable is dropped until only significant variables—or nearly significant variables in the case of business confidence—remain. Long-run coefficients are not reported for this specification because the decision to include or exclude variables was based on the significance of short-run coefficients.

Table 2.8: Wage Share Equation

Dependent Variable: $\Delta\ ln\ Wage\ Share_t$

Variable	**OLS**	**OG GMM**	**OG GMM**
Constant	1.210	1.040*	0.962
	(0.736)	(0.632)	(0.619)
$\Delta\ ln\ Wage\ Share_{t-1}$	0.152	0.215***	0.221**
	(0.110)	(0.084)	(0.089)
$\Delta\ ln\ GDP_t$	-0.033	0.026	0.000
	(0.088)	(0.080)	(0.074)
$\Delta\ ln\ GDP_t t-1$	0.341***	0.268***	0.299***
	(0.061)	(0.051)	(0.052)
LR GDP	0.363***	0.374***	0.384***
	(0.121)		
$\Delta\ ln\ Foreign\ Trade_t$	0.035	0.044**	0.043**
	(0.024)	(0.019)	(0.020)
$\Delta\ ln\ Foreign\ Trade_{t-1}$	-0.067**	-0.056***	-0.063***
	(0.028)	(0.022)	(0.023)
LR $Foreign\ Trade$	-0.038	-0.015	-0.025
	(0.044)		
$\Delta\ ln\ Capital\ Intensity_t$	-0.455**	-0.259	-0.345*
	(0.189)	(0.194)	(0.207)
$\Delta\ ln\ Capital\ Intensity_{t-1}$	0.428**	0.210	0.243
	(0.180)	(0.170)	(0.183)
LR $Capital\ Intensity$	-0.031	-0.062	-0.132
	(0.204)		
$ln\ Business\ Confidence_t$	-0.265	-0.228*	-0.211
	(0.160)	(0.138)	(0.135)
LR $Business\ Confidence$	-0.312	-0.290	-0.270
	(0.190)		
R^2	0.561		
Adjusted R^2	0.478		
Schwarz Criterion	-6.438		
Hansen J-statistic		172.447*	318.725
N	51	48	48
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

lagged effect. The reverse is found for capital intensity. The total effect of both variables on the wage share is negative. Long run elasticities of -0.038 and -0.025 are found for foreign trade while using OLS and GMM, respectively, and respective elasticities of -0.031 and -0.132 are found for capital intensity. These results indicate that globalization and higher capital intensity lead to a lower wage share, as expected. Business confidence has an unexpected sign in both sets of estimates, with the results suggesting that the wage share decreases when firms have greater levels of confidence. However, these effects are insignificant in both sets of estimates.

2.4.2 The Stockhammer and Wildauer Model

The results for the GMM estimates of the SW model should be interpreted with some caution, because the instruments may not be valid. Even after adding more lags of the variables in the model as instruments, the null hypothesis of valid overidentifying restrictions is rejected at the 10% level. The results are presented for comparison with the OLS estimates, but they should be taken with considerable caution.

The results for the consumption equation are shown in Table 2.9. The ARDL model suggests one lag of the dependent variable, one lag of GDP and household debt, and no lags of the other independent variables. In both sets of results, GDP and household debt are found to have positive effects on consumption, with respective long-run coefficients of 0.644 and 0.066 using the single equation approach, and 0.583 and 0.069 using the systems approach. Wealth and the top 5% are found to be insignificant in both sets of estimates.

The wage share coefficients are positive, as expected, and significant in both sets of estimates. The long-run wage share elasticities of consumption for the U.S. of 0.353 (for the OLS estimates) and 0.334 (for the GMM estimates) are both larger than the elasticities that Stockhammer and Wildauer (2016) find in most specifications of their panel model, which are generally near 0.14.[49]

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[49]Of course, the results are not comparable because their results are for the average country in their panel, rather than for the U.S.

Table 2.9: SW Model Consumption Equation

Dependent Variable: Δ *ln Consumption*$_t$

Variable	**OLS**	**Systems GMM**	**System GMM**
Constant	0.011***	0.011***	0.011***
	(0.003)	(0.003)	(0.002)
Δ $ln\ Consumption_{t-1}$	0.146	0.153	0.238
	(0.183)	(0.161)	(0.148)
Δ $ln\ GDP_t$	0.840***	0.846***	0.768***
	(0.082)	(0.086)	(0.072)
Δ $ln\ GDP_{t-1}$	-0.290**	-0.306**	-0.324***
	(0.137)	(0.134)	(0.115)
LR GDP	0.644***	0.637***	0.583***
	(0.099)		
Δ $ln\ Wage\ Share_t$	0.302**	0.283	0.254**
	(0.137)	(0.204)	(0.124)
LR $Wage\ Share$	0.353**	0.334	0.334*
	(0.172)		
Δ $ln\ Household\ Debt_t$	0.140**	0.146***	0.130***
	(0.058)	(0.056)	(0.050)
Δ $ln\ Household\ Debt_{t-1}$	-0.083*	-0.085**	-0.077**
	(0.047)	(0.041)	(0.039)
LR $Household\ Debt$	0.066	0.072	0.069
	(0.054)		
Δ $ln\ Wealth_t$	0.025	0.023	0.027
	(0.031)	(0.028)	(0.027)
LR $Wealth$	0.030	0.027	0.036
	(0.039)		
Δ $ln\ Top\ 5\%\ Share_t$	-0.034	-0.026	0.004
	(0.054)	(0.051)	(0.048)
LR $Top\ 5\%\ Share$	-0.039	-0.030	0.005
	(0.061)		
R^2	0.862		
Adjusted R^2	0.835		
Schwarz Criterion	-6.482		
Hansen J-statistic		107.403**	226.756*
N	51	49	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

Table 2.10 shows the results for the investment equation. For this model, the optimal specification includes two lags of the dependent variable and GDP, and no lags of the other independent variables. As in the OG model, the results for the SW investment equation indicate strong accelerator effects, with long-run elasticities on GDP equal to 1.693 in the OLS estimates and 1.657 in the GMM estimates. The interest rate coefficient in both equations is positive, but insignificant in the OLS estimates and only weakly significant in the GMM estimates, as was the case with the OG model. The top 5% share is insignificant, but household debt, corporate debt, and wealth are all found to have significant effects on investment. The debt variables have negative elasticities, while wealth has a positive elasticity. The latter finding differs from the negative effects of private wealth on investment found by Stockhammer et al. (2018). The wage share elasticities are positive in both specifications, although both are insignificant.

The export and import estimates are shown in Tables 2.11 and 2.12. In both equations the exchange rate has the expected signs, with a stronger dollar decreasing exports and increasing imports. However the exchange rate coefficient in the import equation is insignificant in both sets of estimates. As expected, the income elasticities in both equations are positive. The long-run foreign income elasticity in the export equation is equal to 2.2438 in the OLS estimates and 2.095 in the GMM estimates, while the respective GDP elasticities for imports are 2.373 and 2.701. The sign of the elasticity of imports with respect to exports is negative, and therefore the opposite of the expected effects. Exports are included in this equation to control for the import of intermediate goods, but the long-run elasticities of -0.265 (for the OLS estimates) and -0.280 (for the GMM estimates) suggest that higher imports lead to lower exports. It is possible that these coefficients are capturing the effects of omitted variables, such as import prices—which would have a positive relationship with exports and a negative relationship with imports.

Table 2.10: SW Model Investment Equation Part 1

Dependent Variable: $\Delta\ ln\ Investment_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	-0.009	-0.003	-0.010
	(0.013)	(0.012)	(0.010)
$\Delta\ ln\ Investment_{t-1}$	0.006	0.150*	0.156**
	(0.111)	(0.077)	(0.072)
$\Delta\ ln\ Investment_{t-2}$	0.304***	0.243***	0.227***
	(0.105)	(0.067)	(0.065)
$\Delta\ ln\ GDP_t$	3.762***	3.772***	3.879***
	(0.260)	(0.237)	(0.209)
$\Delta\ ln\ GDP_{t-1}$	-0.358	-1.203**	-1.135***
	(0.621)	(0.511)	(0.417)
$\Delta\ ln\ GDP_{t-2}$	-2.235***	-1.819***	-1.720***
	(0.508)	(0.338)	(0.322)
LR GDP	1.693***	1.235*	1.657***
	(0.612)		
$\Delta\ ln\ Wage\ Share_t$	0.167	0.820	0.379
	(0.501)	(0.696)	(0.424)
LR $Wage\ Share$	0.242	1.350	0.613
	(0.734)		
$Interest\ Rate_t$	0.003	0.003	0.004*
	(0.003)	(0.002)	(0.002)
LR $Interest\ Rate$	0.004	0.006	0.006
	(0.005)		
$\Delta\ ln\ Household\ Debt_t$	-0.520***	-0.366***	-0.375***
	(0.163)	(0.132)	(0.116)
LR $Household\ Debt$	-0.753***	-0.602***	-0.608***
	(0.260)		
$\Delta\ ln\ Corporate\ Debt_t$	-0.316***	-0.212***	-0.210***
	(0.075)	(0.051)	(0.049)
LR $Corporate\ Debt$	-0.458***	-0.349***	-0.340***
	(0.139)		
$\Delta\ ln\ Wealth_t$	0.720***	0.437***	0.430***
	(0.191)	(0.136)	(0.131)
LR $Wealth$	1.043***	0.719***	0.697***
	(0.326)		

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Variable	**OLS**	**Systems GMM**	**Systems GMM**
Δ *ln Top* 5% *Share*$_t$	0.085	0.120	0.075
	(0.194)	(0.147)	(0.138)
LR *Top* 5% *Share*	0.123	0.198	0.122
	(0.278)		
R^2	0.933		
Adjusted R^2	0. 913		
Schwarz Criterion	-3.761		
Hansen J-statistic		107.403**	226.756*
N	50	49	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

The wage share elasticities for the imports have the expected positive signs. However, they are small due to negative lagged effects that nearly offset the positive contemporaneous effects. Both long-run elasticities are close to 0, with values of 0.062 using the single equation approach, and 0.079 using the systems approach. Stockhammer and Wildauer (2016) also find that the effect of the wage share on imports is close to 0 when estimating this model for a panel of OECD countries. The elasticities of exports with respect to the wage share are much larger by comparison, with values of -3.876 for the OLS estimates and -2.524 for the GMM estimates. Both have the expected negative sign.

Following Stockhammer and Wildauer (2016), the elasticities are converted to marginal effects and added to obtain the marginal effect of an increase in the wage share on private excess demand, normalized by GDP, using equation (2.34):

$$\frac{\partial(Y^{PED})}{\partial\psi}\frac{1}{Y} = c_\psi \frac{C/Y}{\psi/100} + i_\psi \frac{I/Y}{\psi/100} + x_\psi \frac{X/Y}{\psi/100} - M_\psi \frac{M/Y}{\psi/100} \tag{2.34}$$

Table 2.11: SW Model Export Equation

Dependent Variable: $\Delta\ ln\ Exports_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	0.005	0.010	0.008
	(0.013)	(0.013)	(0.011)
$\Delta\ ln\ Exports_{t-1}$	0.449***	0.452***	0.457***
	(0.121)	(0.104)	(0.104)
$\Delta\ ln\ Foreign\ Income_t$	2.581***	2.625***	2.672***
	(0.369)	(0.332)	(0.320)
$\Delta\ ln\ Foreign\ Income_{t-1}$	-1.347***	-1.524***	-1.535***
	(0.445)	(0.397)	(0.383)
LR $Foreign\ Income$	2.238***	2.010***	2.095***
	(0.747)		
$\Delta\ ln\ Wage\ Share_t$	-0.045	0.427	0.329
	(0.534)	(0.662)	(0.467)
$\Delta\ ln\ Wage\ Share_{t-1}$	-0.344	-0.189	-0.180
	(0.483)	(0.422)	(0.416)
$\Delta\ ln\ Wage\ Share_{t-2}$	-0.518	-0.556	-0.522
	(0.446)	(0.380)	(0.379)
$\Delta\ ln\ Wage\ Share_{t-3}$	-1.230**	-1.020**	-0.996**
	(0.470)	(0.414)	(0.401)
LR $Wage\ Share$	-3.876**	-2.439	-2.524
	(1.916)		
$\Delta\ ln\ Nominal\ Exchange\ Rate_t$	-0.271***	-0.283***	-0.269***
	(0.082)	(0.071)	(0.070)
LR $Nominal\ Exchange\ Rate$	-0.491***	-0.517***	-0.495***
	(0.177)		
$\Delta\ ln\ Home\ Prices_t$	-0.209	-0.197	-0.195
	(0.176)	(0.154)	(0.151)
LR $Home\ Prices$	-0.379	-0.360	-0.359
	(0.321)		
R^2	0.712		
Adjusted R^2	0.646		
Schwarz Criterion	-3.520		
Hansen J-statistic		107.403**	226.756*
N	49	49	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

Table 2.12: SW Model Import Equation

Dependent Variable: $\Delta\ ln\ Imports_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	0.000	-0.004	-0.004
	(0.011)	(0.009)	(0.008)
$\Delta\ ln\ Imports_{t-1}$	0.013	-0.029	-0.014
	(0.088)	(0.081)	(0.070)
$\Delta\ ln\ GDP_t$	2.343***	2.766***	2.740***
	(0.302)	(0.349)	(0.269)
LR GDP	2.373***	2.688***	2.701***
	(0.298)		
$\Delta\ ln\ Wage\ Share_t$	1.021*	1.074*	1.054**
	(0.512)	(0.601)	(0.421)
$\Delta\ ln\ Wage\ Share_{t-1}$	-0.959**	-0.995***	-0.975***
	(0.446)	(0.328)	(0.321)
LR $Wage\ Share$	0.062	0.077	0.079
	(0.658)		
$\Delta\ ln\ Nominal\ Exchange\ Rate_t$	0.108	0.103	0.096
	(0.093)	(0.074)	(0.064)
LR $Nominal\ Exchange\ Rate$	0.110	0.100	0.095
	(0.095)		
$\Delta\ ln\ Exports_t$	0.097	0.073	0.069
	(0.121)	(0.124)	(0.088)
$\Delta\ ln\ Exports_{t-1}$	-0.359***	-0.341***	-0.353***
	(0.105)	(0.085)	(0.074)
LR $Exports$	-0.265*	-0.261***	-0.280***
	(0.134)		
$\Delta\ ln\ Home\ Prices_t$	-0.159	-0.470***	-0.458***
	(0.181)	(0.141)	(0.132)
LR $Home\ Prices$	-0.161	-0.457***	-0.451***
	(0.186)		
R^2	0.817		
Adjusted R^2	0.782		
Schwarz Criterion	-3.624		
Hansen J-statistic		107.403**	226.756*
N	51	49	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

Table 2.13: SW Model: Marginal Effects of a 1 Percentage Point Increase in the Wage Share

	OLS	**Systems GMM***
C/Y	0.406	0.384
I/Y	0.065	0.165
X/Y	-0.506	-0.330
M/Y	0.010	0.013
Private Excess Demand/Y	-0.045	0.206

*These results are based on invalid instruments.

where Y^{PED} denotes private excess demand and c_ψ, i_ψ, x_ψ, and m_ψ represent the estimated long-run elasticities of consumption, investment, exports, and imports with respect to the wage share. The sample mean values of C/Y, I/Y, X/Y, and M/Y, are used, and the sample mean of the wage share is again divided by 100 to get it on the same scale as the ratios of the components of private aggregate demand to GDP. The results are shown in Table 2.13.

The OLS estimates find a negative marginal effect of an increase in the wage share on private excess demand, indicating profit-led demand. This finding is primarily driven by the large negative effects of a higher wage share on exports. In the GMM estimates, demand is found to be wage-led, as in both sets of estimates for the OG model.[50] The positive consumption effects and negative export effects are found to be smaller when the model is estimated as a system, while the investment and import effects become larger. The finding that estimates of the SW model become more wage-led when estimating it as a system should be viewed with great caution, given the questions about the validity of the instruments. However, it is nevertheless noteworthy that no evidence of the bias towards more wage-led findings in the single equation approach is found.

[50]Treating insignificant effects as zero would eliminate the effects on investment and imports for both sets of estimates, and those on exports for the GMM estimates. This would result in net effects of -0.100 for the OLS estimates and 0.384 for the GMM estimates.

Table 2.14: Wage Share Equation

Dependent Variable: $\Delta\ ln\ Wage\ Share_t$

Variable	**OLS**	**SW GMM**	**SW GMM**
Constant	1.210	1.574**	1.289*
	(0.736)	(0.739)	(0.683)
$\Delta\ ln\ Wage\ Share_{t-1}$	0.152	0.175*	0.163
	(0.110)	(0.101)	(0.102)
$\Delta\ ln\ GDP_t$	-0.033	0.009	-0.039
	(0.088)	(0.095)	(0.081)
$\Delta\ ln\ GDP_t t-1$	0.341***	0.350***	0.356***
	(0.061)	(0.057)	(0.056)
LR GDP	0.363***	0.436***	0.379***
	(0.121)		
$\Delta\ ln\ Foreign\ Trade_t$	0.035	0.049**	0.044**
	(0.024)	(0.022)	(0.022)
$\Delta\ ln\ Foreign\ Trade_{t-1}$	-0.067**	-0.076***	-0.077***
	(0.028)	(0.025)	(0.025)
LR $Foreign\ Trade$	-0.038	-0.033	-0.039
	(0.044)		
$\Delta\ ln\ Capital\ Intensity_t$	-0.455**	-0.526**	-0.516**
	(0.189)	(0.228)	(0.233)
$\Delta\ ln\ Capital\ Intensity_{t-1}$	0.428**	0.324*	0.384**
	(0.180)	(0.161)	(0.175)
LR $Capital\ Intensity$	-0.031	-0.246	-0.157
	(0.204)		
$ln\ Business\ Confidence_t$	-0.265	-0.344**	-0.282*
	(0.160)	(0.161)	(0.149)
LR $Business\ Confidence$	-0.312	-0.417**	-0.337*
	(0.190)		
R^2	0.561		
Adjusted R^2	0.478		
Schwarz Criterion	-6.438		
Hansen J-statistic		107.403**	226.756*
N	51	49	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

The GMM estimates of the wage share equation in the SW system are shown in Table 2.14, along with the OLS estimates for comparison. As in the OLS estimates and the GMM estimates of the OG system, a positive effect of GDP on the wage share is found. The elasticity of 0.379 is similar to those found for the other two sets of estimates. Similar effects are also found for foreign trade and capital intensity, with long run elasticities of -0.039 and -0.157, respectively. Unlike in the other two sets of estimates, where the effects of business confidence on the wage share are found to be negative but insignificant, the negative effects of business confidence on the wage share are found to be weakly significant in the GMM estimates of the SW system. It is possible that this negative sign is driven by correlation between profits and business confidence. While business confidence should increase labor demand, benefiting workers, the positive relationship between business confidence and profits may outweigh these effects. However, the evidence for negative effects is weak. It is important to remember that these results may not be valid, as valid instruments could not be found for the GMM estimates. To improve on the OG and SW models, a new model is estimated combining elements of both models, as well new features. The results for this model are discussed in Section 2.4.3.

2.4.3 Synthetic Model

The synthetic model uses a different approach for modeling the wage share equation. Following the theoretical model of Blecker (1989), the wage share is estimated as a function of unit labor costs, import prices, and the average markup—which is used a proxy for the target markup. The ARDL model suggests including one lag of the dependent variable and ULC, and two lags of P_m. This equation, along with the ULC, RI, and M equations in this model, are estimated with no constant. The constant term, which captures effects of a time trend in specifications in log differences, is dropped from these equations to reduce the number of parameters in order to make the system estimable. Unreported estimates show that the OLS results for these equations are not qualitatively different when the constant term is removed.[51] The results for the wage share equation are shown in Table 2.15.[52]

All variables are found to be significant with the expected signs in both specifications. The elasticity of the wage share with respect to the average markup is negative in both sets of estimates, suggesting that increased market concentration gives firms more bargaining power and leads to lower labor costs. The long-run elasticities with respect to import prices are negative, with values of -0.160 for the OLS estimates and -0.151 for the GMM estimates. The elasticities with respect to ULC are positive, at 0.197 (for the OLS estimates) and 0.194 (for the GMM estimates). This indicates that the wage share rises as nominal unit labor costs rise, as expected.

The marginal effects of a 1 percentage point increase in unit labor costs on the wage share are calculated using equation (2.35), where ψ_{ULC} represents the long-run elasticity of the wage share with respect to ULC, the sample mean of ULC/ψ (which is equivalent to the domestic P level) is used, and the resulting product is divided by 100 to get a value on the same scale as the other marginal effects.[53]

$$\frac{\partial \psi}{\partial ULC} = \psi_{ULC} \frac{ULC}{\psi} \frac{1}{100} \tag{2.35}$$

This formula yields marginal effects of 0.323 (for the OLS estimates) and 0.318 (for the GMM estimates).

[51]Note that the system results cannot be tested for sensitivity to the inclusion of these constant terms, because the model including them results in a greater number of parameters than observations. The constant term is left in the other equations because it is either statistically significant or close to significant in the OLS estimates. Constant terms with p-values below 0.2 were left in the model.

[52]Note that additional observations are added to the beginning of the sample for variables that are lagged in the synthetic model. This is done to maximize the sample size and therefore the number of parameters that can be estimated in the system.

[53]This is necessary because the domestic price level is an index with 2009=100.

Table 2.15: Synthetic Model Wage Share Equation

Dependent Variable: $\Delta\ ln\ Wage\ Share_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
$\Delta\ ln\ Wage\ Share_{t-1}$	0.504***	0.461***	0.518***
	(0.092)	(0.086)	(0.082)
$\Delta\ ln\ ULC_t$	0.732***	0.649***	0.711***
	(0.060)	(0.063)	(0.055)
$\Delta\ ln\ ULC_{t-1}$	-0.634***	-0.557***	-0.617***
	(0.066)	(0.066)	(0.059)
LR *ULC*	0.197***	0.171***	0.194***
	(0.055)		
$\Delta\ ln\ Import\ Prices_t$	-0.075***	-0.059***	-0.066***
	(0.013)	(0.013)	(0.012)
$\Delta\ ln\ Import\ Prices_{t-1}$	-0.042***	-0.047***	-0.044***
	(0.012)	(0.011)	(0.011)
$\Delta\ ln\ Import\ Prices_{t-2}$	0.037***	0.032***	0.037***
	(0.014)	(0.012)	(0.012)
LR *Import Prices*	-0.160***	-0.138***	-0.151***
	(0.038)		
$\Delta\ ln\ Markup_t$	-0.139***	-0.152***	-0.135***
	(0.038)	(0.034)	(0.034)
LR *Markup*	-0.280***	-0.282***	-0.280***
	(0.071)		
R^2	0.829		
Adjusted R^2	0.807		
Schwarz Criterion	-7.564		
Hansen J-statistic		176.676***	316.207
N	52	52	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

As the synthetic model illustrates the relationship between demand and unit labor costs, unit labor costs—rather than the wage share—are modeled as a function of GDP. The wage share is therefore affected by demand indirectly, through unit labor costs. Similarly, unit labor cost is modeled as a function of the other control variables used in the previous wage share equation, excluding the average markup which is included in the wage share equation because it affects the wage share directly in the Blecker (1989) model.[54] These control variables are included in the ULC equation to provide instruments for its estimation using GMM. Capital intensity, foreign trade, and the real exchange rate are included in the model because they are found to be significant. The size of the financial sector, union density, and business confidence are dropped because they are found to be insignificant.[55] The estimates of the resulting model are shown in Table 2.16.

All of the variables in this equation are found to be significant in both sets of estimates. Large effects of GDP on ULC are found, with long-run elasticities of 1.867 (for the OLS estimates) and 2.007 (for the GMM estimates).[56] In each case there is a negative contemporaneous effect with a larger lagged positive effect, resulting in these positive long-run elasticities. As expected, both capital intensity and the real exchange rate are found to have negative effects on unit labor costs. It is surprising that foreign trade is found to have a positive and significant effect on ULC, as globalization is expected to decrease wages due to greater competition from foreign workers. However, this could reflect the rising skill content of work in advanced countries, like the U.S., that results from specialization and trade, and the need to compensate labor for that skill.

The consumption equation is based on the one used in the OG model, with wages and profits included separately instead of the wage share and GDP. However, household debt is included because some significant effects of household debt on consumption were found in the SW model (even though the long-run effects were insignificant). The resulting estimates are shown in Table 2.17. As in the SW model, household debt is found to have

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[54]Note that if these variables are included directly in the wage share equation, along with unit labor costs and import prices, many of the variables become insignificant, including GDP.

[55]The results for the OLS estimates of the model including all of these variables is shown in Table B.6 of Appendix B. For these estimates, a maximum lag length of 2 was used, because including this many variables in the model led to implausible lag lengths for most variables. None of the insignificant variables was found to be significant even when the other insignificant variables were excluded. Long-run coefficients are not reported for this specification because the decision to include or exclude variables was based on the significance of the short-run coefficients.

[56]The negative contemporaneous effect of GDP on unit labor costs could reflect a positive effect of demand on productivity, as Chapters 1 and 3 discuss.

Table 2.16: Synthetic Model Unit Labor Costs Equation

Dependent Variable: $\Delta\ ln\ ULC_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
$\Delta\ ln\ ULC_{t-1}$	0.802***	0.801***	0.806***
	(0.040)	(0.038)	(0.039)
$\Delta\ ln\ GDP_t$	-0.139**	-0.092	-0.117*
	(0.069)	(0.066)	(0.064)
$\Delta\ ln\ GDP_{t-1}$	0.508***	0.475***	0.506***
	(0.065)	(0.060)	(0.062)
LR GDP	1.867***	1.928***	2.007***
	(0.462)		
$\Delta\ ln\ Capital\ Intensity_t$	-0.520***	-0.524***	-0.562***
	(0.162)	(0.145)	(0.168)
LR $Capital\ Intensity$	-2.630**	-2.639***	-2.896**
	(1.027)		
$\Delta\ ln\ Real\ Exchange\ Rate_t$	-0.079**	-0.072***	-0.074***
	(0.030)	(0.027)	(0.027)
LR $Real\ Exchange\ Rate$	-0.400**	-0.361**	-0.382**
	(0.184)		
$\Delta\ ln\ Foreign\ Trade_t$	0.161***	0.152***	0.158***
	(0.029)	(0.026)	(0.027)
LR $Foreign\ Trade$	0.813***	0.767***	0.815***
	(0.227)		
R^2	0.871		
Adjusted R^2	0.857		
Schwarz Criterion	-6.217		
Hansen J-statistic		176.676***	316.207
N	52	52	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

a positive effect on consumption. In this case, both the short-run and long-run elasticities are found to be significant. The estimated MPCs for wages and profits are both positive, with a higher estimated MPC out of wages than profits, indicating that a higher wage share leads to higher consumption. As with the OG model, the estimated MPC out of wages is larger and the MPC out of profits smaller in the GMM estimates than in the OLS estimates. The marginal effects of a 1 percentage point increase in ULC on C/Y

Table 2.17: Synthetic Model Consumption Equation

Dependent Variable: $\Delta\ ln\ Consumption_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	0.013***	0.014***	0.015***
	(0.003)	(0.003)	(0.002)
$\Delta\ ln\ Consumption_{t-1}$	-0.148	-0.223**	-0.233**
	(0.107)	(0.110)	(0.096)
$\Delta\ ln\ Wages_t$	0.589***	0.663***	0.652***
	(0.086)	(0.098)	(0.078)
LR $Wages$	0.513***	0.542***	0.528***
	(0.052)		
$\Delta\ ln\ Profits_t$	0.162***	0.152***	0.128***
	(0.045)	(0.049)	(0.040)
LR $Profits$	0.141***	0.125***	0.104***
	(0.045)		
$\Delta\ ln\ Household\ Debt_t$	0.111**	0.098**	0.106***
	(0.047)	(0.043)	(0.040)
LR $Household\ Debt$	0.096**	0.080**	0.086***
	(0.037)		
R^2	0.797		
Adjusted R^2	0.780		
Schwarz Criterion	-6.429		
Hansen J-statistic		176.676***	316.207
N	52	52	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

are calculated using equation (2.36).

$$\frac{\partial(C/Y)}{\partial ULC} = c_W \frac{C}{W} - c_R \frac{C}{R} \tag{2.36}$$

The marginal effects of a 1 percentage point increase in the wage share on C/Y are calculated using equation (2.30). The estimated marginal effects for the OLS estimates are equal to 0.324, while the value for the GMM estimates is 0.411. Both values are larger than their counterparts in the OG model, while the marginal effects are larger in the OLS

Table 2.18: Synthetic Model Nonresidential Investment Equation

Dependent Variable: $\Delta\ ln\ Nonresidential\ Investment_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	-6.910***	-4.701**	-4.931**
	(2.564)	(2.343)	(2.148)
$\Delta\ ln\ Nonresidential\ Investment_{t-1}$	0.493***	0.492***	0.490***
	(0.101)	(0.086)	(0.080)
$\Delta\ ln\ GDP_t$	2.727***	2.815***	2.587***
	(0.287)	(0.293)	(0.236)
$\Delta\ ln\ GDP_{t-1}$	-1.546***	-1.551***	-1.552***
	(0.386)	(0.366)	(0.331)
$\Delta\ ln\ GDP_{t-2}$	-0.990***	-1.020***	-1.045***
	(0.180)	(0.156)	(0.150)
LR GDP	0.377	0.479	-0.019
	(0.746)		
$\Delta\ ln\ Wage\ Share_t$	1.134***	1.416***	1.626***
	(0.407)	(0.507)	(0.359)
LR $Wage\ Share$	2.235**	2.785**	3.190***
	(0.931)		
$ln\ Business\ Confidence_t$	-0.921*	-1.146**	-0.892**
	(0.524)	(0.497)	(0.418)
$ln\ Business\ Confidence_{t-1}$	2.426***	2.170***	1.967***
	(0.407)	(0.450)	(0.426)
LR $Business\ Confidence$	2.964**	2.015*	2.110**
	(1.302)		
R^2	0.867		
Adjusted R^2	0.846		
Schwarz Criterion	-4.241		
Hansen J-statistic		176.676***	316.207
N	52	52	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

estimates of the SW model, but smaller in the GMM estimates (which were based on invalid instruments).

The nonresidential investment equation is originally estimated as a function of GDP, the wage share, business confidence, corporate debt, government investment, and the real interest rate. However, corporate debt and government investment do not yield significant coefficients, and the short-run lagged and contemporaneous effects of the interest rate are found to be jointly insignificant in the OLS estimates. Therefore, these variables are dropped. The resulting estimates for nonresidential investment are shown in Table 2.18.

Business confidence is found to have a positive effect on nonresidential investment, with elasticities of 2.964 (for the OLS estimates) and 2.110 (for the GMM estimates). The elasticities of nonresidential investment with respect to GDP have the expected positive sign in the OLS estimates, but are small relative to the estimated accelerator effects for the OG and SW models. Furthermore, an implausible negative sign is found on contemporaneous business confidence in the GMM estimates, but the long-run elasticity is still positive. The elasticity for the OLS estimates is 0.377, while the corresponding value for the GMM estimates is -0.019. It is possible that some of the accelerator effects are being picked up by business confidence, which is correlated with $\Delta\ ln\ GDP$,[57] or the wage share, which is also found to have large positive effect on nonresidential investment, even though a negative sign is expected. There are several possible explanations for this anomalous sign. It is possible that this sign reflects increased investment in labor saving technology when firms face higher labor costs.[58] However, it could also stem from misspecification of the nonresidential investment function or measurement error (as the more relevant measure of distribution may be a wage share for the business or nonfinancial corporate sector). It is also possible that the estimates are picking up reverse causality, as the instruments may not properly account for endogeneity even though they appear to be valid.

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[57]Unreported estimates show larger accelerator effects in OLS estimates of the same equation excluding business confidence

[58]Therefore, it's possible that the estimates are picking up some supply-side effects, in addition to demand-side effects.

Table 2.19: Synthetic Model Residential Investment Equation

Dependent Variable: Δ *ln $Residential\ Investment_t$*

Variable	**OLS**	**Systems GMM**	**Systems GMM**
$\Delta\ ln\ Residential\ Investment_{t-1}$	0.326***	0.351***	0.400***
	(0.083)	(0.074)	(0.069)
$\Delta\ ln\ GDP_t$	4.720***	4.555***	4.480***
	(0.489)	(0.509)	(0.424)
$\Delta\ ln\ GDP_{t-1}$	-4.162***	-3.981***	-3.900***
	(0.545)	(0.560)	(0.468)
LR GDP	0.829*	0.884**	0.966**
	(0.440)		
$\Delta\ ln\ Wage\ Share_t$	0.629	0.734	-0.005
	(1.000)	(1.235)	(0.882)
$\Delta\ ln\ Wage\ Share_{t-1}$	2.255**	2.309***	2.615***
	(0.871)	(0.776)	(0.739)
LR $Wage\ Share$	4.281**	4.691**	4.349**
	(1.986)		
$\Delta\ ln\ Household\ Debt_t$	2.130***	1.762***	1.478***
	(0.405)	(0.375)	(0.345)
$\Delta\ ln\ Household\ Debt_{t-1}$	-1.325***	-0.949**	-0.730**
	(0.433)	(0.388)	(0.369)
$\Delta\ ln\ Household\ Debt_{t-2}$	-0.860**	-0.921***	-0.946***
	(0.388)	(0.340)	(0.327)
LR $Household\ Debt$	-0.082	-0.166	-0.328
	(0.570)		
R^2	0.814		
Adjusted R^2	0.785		
Schwarz Criterion	-2.385		
Hansen J-statistic		176.676***	316.207
N	52	52	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

As with the other equations residential investment equation is initially estimated using an ARDL model with a maximum of four lags of the dependent and independent variables. When including GDP and the wage share in the equation along with all of the control variables—home prices, the real interest rate, the volume of credit, wealth, consumer confidence, and household debt—the ARDL model yields implausible recommended lag lengths (e.g. 4 lags of the dependent variable, and interest rates from four years ago affecting investment today) and a high number of parameters (37) that would make the overall system inestimable given the data availability. For this reason, the maximum number of lags for the independent variables is reduced to 2. After making this adjustment, wealth and consumer confidence are dropped because they are found to be insignificant. Credit was excluded from the model because it had a theoretically implausible sign—suggesting that residential investment decreases as more credit is available. Finally, the real interest rate and home prices are dropped because the short-run contemporaneous and lagged elasticities of each were found to be jointly insignificant. Although GDP and household debt were also found to be jointly insignificant, they were retained in the model because the results for these variables are of interest. The resulting estimates are shown in Table 2.19.[59]

Household debt is found to have a negative effect on residential investment, with elasticities of -0.082 (for the OLS estimates) and -0.328 (for the GMM estimates). As expected, these effects start out positive, but become negative over time. The elasticities of residential investment with respect to GDP are larger than those for nonresidential investment, and both have the expected signs, with elasticities of 0.829 (for OLS) and 0.966 (for GMM). As expected, the wage share is found to have a positive effect on residential investment in both the OLS and GMM estimates, with respective elasticities of 4.281 and 4.349.

The marginal effects of a 1 percentage point increase in the wage share on nonresidential and residential investment are calculated using equations (2.37) and (2.38), where

[59]Note that the ARDL model suggests the same specification for a model including these variables when the maximum lag length for independent variables is raised back to 4.

ni_ψ and ri_ψ represent the elasticities of nonresidential and residential investment with respect to the wage share, and the sample means of NI/W and RI/W are used.

$$\frac{\partial(NI/Y)}{\partial(\psi)} = ni_\psi \frac{NI}{W} \tag{2.37}$$

$$\frac{\partial(RI/Y)}{\partial(\psi)} = ri_\psi \frac{RI}{W} \tag{2.38}$$

Using the OLS estimates, a 1 percentage point increase in the wage share is found to have a marginal effects of 0.438 on NI/Y and 0.407 on RI/Y, while the GMM estimates finds corresponding marginal effects of 0.625 and 0.414. It does not appear that the positive effects of the wage share on I/Y in the OG and SW models can be explained by positive effects on residential investment outweighing negative effects on nonresidential investment, as the disaggregated model finds positive effects of the wage share on both components of investment.

Exports are estimated as a function of unit labor costs, foreign income, the real exchange rate, and import prices. Although the ARDL model suggests including one lag of import prices and no lags of unit labor costs, when estimated using OLS this specification produces short-run coefficients for import prices that are jointly insignificant and a coefficient for unit labor costs that is positive and close to 0—with a p-value greater than 0.9. More reasonable estimates for unit labor costs are found when the ARDL model is forced to include a lag of unit labor costs. Even though this specification has a slightly worse model fit, it is preferred because it is thought to more accurately capture the effects of unit labor costs on exports. The results for this model are shown in Table 2.20.

Foreign income is found to have the expected positive effect, with elasticities of 0.977 and 1.530 for the OLS and GMM estimates, respectively. The real exchange rate and import prices have the expected signs, although the effects of import prices are

Table 2.20: Synthetic Model Export Equation

Dependent Variable: Δ *ln Exports*$_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Constant	0.019*	0.017*	0.017*
	(0.010)	(0.009)	(0.009)
Δ *ln Exports*$_{t-1}$	0.461***	0.372***	0.383***
	(0.111)	(0.094)	(0.093)
Δ *ln Foreign Income*$_t$	2.123***	1.972***	2.094***
	(0.315)	(0.283)	(0.280)
Δ *ln Foreign Income*$_{t-1}$	-1.597***	-1.383***	-1.150***
	(0.357)	(0.309)	(0.321)
LR *Foreign Income*	0.977*	0.937**	1.530***
	(0.535)		
Δ *ln ULC*$_t$	0.229	0.743*	0.120
	(0.393)	(0.402)	(0.364)
Δ *ln ULC*$_{t-1}$	-0.495*	-0.781***	-0.490*
	(0.292)	(0.284)	(0.254)
LR *ULC*	-0.495	-0.060	-0.599
	(0.491)		
Δ *ln Real Exchange Rate*$_t$	-0.329***	-0.356***	-0.316***
	(0.118)	(0.107)	(0.103)
LR *Real Exchange Rate*	-0.611**	-0.568***	-0.512***
	(0.261)		
Δ *ln Import Prices*$_t$	0.143	0.049	0.109
	(0.099)	(0.092)	(0.086)
LR *Import Prices*	0.266	0.077	0.177
	(0.184)		
R^2	0.743		
Adjusted R^2	0.702		
Schwarz Criterion	-3.848		
Hansen J-statistic		176.676***	316.207
N	52	52	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

insignificant. As expected, the elasticities of exports with respect to unit labor costs are found to be negative, at -0.495 for the OLS estimates and -0.599 for the GMM estimates. However, the long-run coefficients are insignificant in both sets of estimates.

Table 2.21: Synthetic Model Import Equation

Dependent Variable: Δ ln $Imports_t$

Variable	**OLS**	**Systems GMM**	**Systems GMM**
Δ ln $Imports_{t-1}$	-0.201***	-0.204***	-0.211***
	(0.072)	(0.069)	(0.057)
Δ ln GDP_t	2.305***	2.360***	2.649***
	(0.185)	(0.178)	(0.161)
LR GDP	1.920***	1.960***	2.187***
	(0.152)		
Δ ln ULC_t	0.937**	0.870**	0.772**
	(0.405)	(0.439)	(0.314)
Δ ln ULC_{t-1}	-0.523	-0.541*	-0.679***
	(0.320)	(0.324)	(0.245)
LR ULC	0.345*	0.273	0.077
	(0.199)		
Δ ln $Import\ Prices_t$	-0.022	-0.000	0.013
	(0.105)	(0.103)	(0.078)
Δ ln $Import\ Prices_{t-1}$	-0.388***	-0.365***	-0.299***
	(0.084)	(0.076)	(0.063)
LR $Import\ Prices$	-0.342***	-0.303***	-0.236***
	(0.097)		
Δ ln $Real\ Exchange\ Rate_t$	0.213*	0.226**	0.253***
	(0.118)	(0.108)	(0.087)
LR $Real\ Exchange\ Rate$	0.178*	0.188**	0.209***
	(0.099)		
R^2	0.827		
Adjusted R^2	0.804		
Schwarz Criterion	-3.856		
Hansen J-statistic		176.676***	316.207
N	52	52	49
Additional Instruments		No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

For the import equation, the ARDL model selects one lag of the dependent variable, import prices, and unit labor costs, and no lags for the other independent variables.[60]

[60]The Breusch-Godfrey test suggests the presence of serial correlation in this equation. If a second lag of the dependent variable is added, the test fails to reject the null hypothesis of no serial correlation up to 2 lags. Adding this additional lagged dependent variable does not qualitatively change the results of the OLS estimates. The addition of this variable increases the number of parameters, and as a result

The results for this equation are shown in Table 2.21. GDP, import prices, and the real exchange rate all have the expected signs, with positive elasticities for GDP and the real exchange rates and a negative elasticity for import prices. The positive and significant sign on the real exchange rate elasticity reverses the anomalous negative sign on the exchange rate coefficient found in the OG model estimates. The elasticities of imports with respect to ULC also have the expected signs, with values of 0.345 for the OLS specification and 0.077 for the GMM estimates. However, the long-run elasticity is small and insignificant in the GMM estimates, and only weakly significant in the OLS estimates.

The marginal effects of a 1 percentage point increase in ULC on X/Y and M/Y are found using equations (2.39) and (2.40), where x_{ULC} and m_{ULC} are the elasticities of exports and imports with respect to unit labor costs. These formulas are based on those used to calculate the marginal effects of the wage share on exports and imports in Stockhammer and Wildauer (2016). The sample means of X/Y and M/Y are used, and ULC are rescaled by dividing by 10,000 because they are calculated as the product of a series that ranges from 0 to 100 (the wage share) and an index with a base value of 100 (the domestic price level).

$$\frac{\partial(X/Y)}{\partial(ULC)} = x_{ULC}\frac{X/Y}{ULC/10,000} \tag{2.39}$$

$$\frac{\partial(M/Y)}{\partial(ULC)} = m_{ULC}\frac{M/Y}{ULC/10,000} \tag{2.40}$$

Based on these calculations, the OLS estimates yields an export elasticity of -0.107 and an import elasticity of 0.095. In the GMM estimates, the estimated export elasticity is

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the system cannot be estimated using GMM with the same set of instruments without the addition of further data. Using two lags of all variables in the system, and one additional lag of the wage share, GMM estimates including an additional lag of imports in the import equation find similar marginal effects of an increase in unit labor costs on net exports— -0.112 as opposed to -0.150. However, the Hansen overidentification test rejects the null hypothesis of valid overidentifying restrictions at the 10% level. For this reason the model with only one lag of imports is preferred.

Table 2.22: Synthetic Model: Marginal Effects of a 1 Percentage Point Increase in the Unit Labor Costs

	OLS	**Systems GMM**
ψ	0.323	0.318
C/Y	0.105	0.131
NI/Y	0.141	0.199
RI/Y	0.131	0.132
X/Y	-0.107	-0.129
M/Y	0.095	0.021
Private Excess Demand/Y	0.175	0.312

-0.129, while the import elasticity is 0.021. These result in marginal effects of ULC on NX/Y of -0.202 for OLS and -0.150 for GMM.

The marginal effects of a 1 percentage point increase in ULC on private excess demand are calculated using equation (2.41). Marginal effects are calculated for an increase in ULC rather than the wage share because the wage share is modeled as a function of ULC. Therefore, changes in consumption, nonresidential investment, and residential investment are indirect functions of ULC.

$$\frac{\partial(Y^{PED})}{\partial(ULC)}\frac{1}{Y} = (\frac{\partial C/Y}{\partial\psi} + \frac{\partial NI/Y}{\partial\psi} + \frac{\partial RI/Y}{\partial\psi})\frac{\partial\psi}{\partial ULC} + \frac{\partial NX/Y}{\partial ULC} \tag{2.41}$$

The first term is the sum of the marginal effects of the wage share on C/Y, NI/Y, and RI/Y, calculated using equations (2.36) – (2.38). This sum is multiplied by the marginal effect of ULC on the wage share—found in equation (2.35)—to obtain the marginal effects of ULC on C/Y, NI/Y, and RI/Y. These are added to the marginal effects of ULC on NX/Y, which is calculated as the difference between equations (2.39) and (2.40), to arrive at marginal effect of ULC on total excess demand. These marginal effects are summarized in Table 2.22.

These calculations yield marginal effects of 0.175 for the OLS estimates and 0.312 in the GMM estimates.[61] Both estimates suggest that demand is wage-led. As with the other two models, demand is found to be more wage-led when using the system estimation method than when using the single equation approach. These results therefore suggest that any bias caused by use of the single equation approach may lead to underestimates of wage-led demand effects, rather than overestimates, as critics of this approach have argued. One interpretation of this finding is that the dynamic interactions between the components of private aggregate demand—including multiplier and accelerator effects—lead, on net, to stronger wage-led demand effects. Therefore, the single equation approach may underestimate the degree of wage-led demand by not fully capturing these dynamic interactions.

2.5 Concluding Remarks

This chapter introduces a new method for estimating structural models of demand and distribution. While previous structural studies have drawn criticism for failing to account for simultaneity bias and the systemic dimension of the models, these issues can ameliorated by estimating structural models as a system of simultaneous equations in which the wage share and the components of private aggregate demand are all endogenously determined. This chapter estimates three sets of structural models as a system, using GMM, and compares the results to those found estimating the models in the traditional manner, with separate OLS estimates for each equation. Two of the estimated models are based on the previous studies of Onaran and Galanis (2012) and Stockhammer and Wildauer (2016). The third combines elements of previous studies with some new features, including disaggregation of investment into nonresidential and residential

[61] The effects of unit labor costs on exports were insignificant in both sets of estimates, while the effects on imports were insignificant in the GMM estimates. Treating these effects as zero would yield net effects of 0.282 for the OLS estimates and 0.462 for the GMM estimates.

investment, and modeling the wage share as a function of unit labor costs, as is suggested by theory.

Although critics of the structural approach argue that its typical finding of wage-led, rather than profit-led, demand is driven by bias stemming from its failure to address the endogeneity of the wage share or the systemic dimension of the model, no evidence is found to support this hypothesis. In no case is demand found to be wage-led in single equation estimates and profit-led in systems estimates. In fact, for two models the systems estimates show stronger wage-led demand effects than the single equation estimates. For the third model, the GMM estimates are not valid because valid instruments could not be found. This suggests that any specification error caused by use of the single equation approach biases results towards findings of less wage-led demand—not more, as critics of this approach have suggested. Therefore, it does not appear that differences in the findings of structural and aggregative models can be explained by the shortcomings of previous structural models that have been suggested by the literature, at least in the case of the U.S.

In all three models, as in previous research, the wage share is found to have a positive effect on consumption and a negative effect on net exports. Surprisingly, all three models indicate a positive effect of the wage share on investment. This result remains even when the models are estimated as systems. Furthermore, when investment is disaggregated in the synthetic model, the wage share is found to have a positive effect on both residential and nonresidential investment. The positive effect of the wage share on nonresidential investment could reflect greater investment in labor saving technology when the cost of labor is higher. However, it is also possible that the investment equation is misspecified. The relationship between income distribution and investment remains an important area of future research, as structural estimates are often in disagreement with theoretical predictions, as is the case in this chapter. Further exploration of the systemic dimensions of structural models remains a potentially fruitful area of research as well, as different types of distributional shocks (e.g. shocks to ULC vs. shocks to the average markup) could have different effects.

CHAPTER 3

THE EFFECTS OF WAGES, PRODUCTIVITY, AND DISTRIBUTION IN THE SHORT AND LONG RUN

3.1 Introduction

This chapter examines the relationship between output and the functional distribution of income and the short and longer run. Although many empirical studies have examined this relationship, there is no consensus in the literature because these studies often find conflicting results. As Blecker (2016) points out, the results tend to follow a pattern, with the findings depending on the methodological approach that is employed. Those who follow the aggregative approach of jointly estimating a pair of equations for the wage share and a single measure of demand tend to find cyclical effects wherein an increase in the wage share decreases demand, and increases in demand lead to increases in the wage share (see e.g. Barbosa-Filho and Taylor, 2006; Kiefer and Rada, 2015; Carvalho and Rezai, 2016; Barrales and von Arnim, 2017). On the other hand, those following the structural approach of separately estimating the effects of the wage share on each component of aggregate demand generally find demand is wage-led—or increases with the wage share—in most countries[1] and assume no effects of demand on distribution (e.g. Stockhammer et al., 2009; Stockhammer and Wildauer, 2016; Onaran and Galanis, 2012; Onaran and Obst, 2016).

It is possible that these differing results could be capturing results at different time horizons. Blecker (2016) argues that demand may be more profit-led in the short-run and more wage-led in the longer term, with aggregative studies typically capturing the former and structural studies capturing the latter. His argument that demand is more wage-led in the longer term is based on the idea that the positive effects of a higher wage share on consumption are likely to materialize more slowly than the likely negative effects of higher labor costs on investment and net exports, while these negative effects may be more short lived. He argues, based on accelerator models of investment, that although

[1]Countries for which evidence of profit-led demand is found in these studies generally have small, open economies.

profitability may affect the timing of investment over the course of the business cycle, its long-run level is primarily determined by output growth. Furthermore, while countries can temporarily increase net exports by decreasing wages relative to productivity, these benefits may eventually be offset by currency appreciation, technology transfers, or policy changes in other countries designed to eliminate this competitive advantage. On the other hand, he argues that the wage share is likely to have a larger effect on consumption in the long run because consumers reliant on labor income may borrow to temporarily offset reductions in wages, but cannot do so indefinitely.

According to Blecker (2016), the technical choices made by practitioners of the aggregative approaches make them more likely to capture short-run, cyclical effects, while the methodological choices made by those following the structural approach likely lead them to capture longer-term effects. For example, aggregative studies often measure demand with a utilization rate that is constructed by dividing output by its Hodrick and Prescott (HP) (1997) filtered trend. This technique forces the mean of utilization to equal zero and eliminates long-term variation in demand. On the other hand, he argues that structural studies may fail to capture some of the short-run effects of the wage share on investment by using potentially misspecified investment equations and failing to account for accelerator effects.

The first aim of this chapter is to test whether the observed relationship between the wage share and demand is more wage-led in the longer run. This hypothesis is tested by using a panel vector autoregression (PVAR) to estimate the relationship between the wage share and demand for a panel of 11 OECD countries at different data frequencies. The model is first estimated with quarterly data, and then the results are compared to those found using data averaged at lower frequencies, including annual over three- and five-year periods. The use of panel data is necessary to provide a sufficient sample size for estimation at the five-year frequency. Furthermore, in recent years panel studies have become more common in the literature examining this relationship (see e.g. Stockhammer and Wildauer, 2016; Kiefer and Rada, 2015). The initial results indicate that demand becomes less profit-led over time. Furthermore, although a few significant effects are found at the quarterly and annual frequencies, no significant effects of the wage share on output are found at higher frequencies.

Although these results provide some support for Blecker's (2016) hypothesis, he does not consider the potential role of cyclical variation in labor productivity in influencing short-run aggregative estimates. Lavoie (2017) argues that estimates of the short-run cyclical relationship between the wage share and demand using high frequency data are likely to be biased towards profit-led estimates if they do not account for the procyclical effects of demand on labor productivity.[2] The results of Chapter 1 support this hypothesis. Therefore, it is possible that the relationship between the wage share—i.e. the ratio of the real wage rate to labor productivity—and demand does not differ substantially in the short and longer run, but estimates obtained using lower and higher frequency data differ due to greater levels of bias in the latter. This could explain some of the differences in the results of aggregative and structural studies, as many of the former use quarterly data, while many structural studies use annual data.

Furthermore, the finding in Chapter 1 that the relationships between the main components of the wage share—the real wage rate and labor productivity—and the utilization rate play a big role in determining whether estimates are wage-led or profit-led suggests that these components should be considered more fully. Any changes in the relationship between the wage share and output at different time horizons are likely driven by differing relationships between the wage share's main components and output. The relationship between the wage share and demand is further complicated by the fact that the two main

[2]See Chapter 1 for further discussion of this issue.

components of the wage share may affect one another, as noted by Lavoie (2017) and Storm and Naastepad (2017).

Because it is possible that the differences in these estimates reflect different levels of bias at low and higher frequencies, rather than a fundamental difference in the relationship at different time horizons. To test whether the differences in estimates at different frequencies are the result of different levels of bias caused by the cyclical effects of demand on labor productivity, the same exercise is conducted using an adjusted wage share measure, from which the cyclical variation in productivity has been removed using a Hamilton (2017) filter. In estimates using this cyclically adjusted wage share, no significant relationship with output is found. This suggests that profit-led demand effects found at higher frequencies are driven by a misinterpretation of procyclical variation in labor productivity. The lack of any significant effects at lower frequencies suggests that the wage share may not be a strong determinant of output.

Further analysis of the relationship between output and the components of the wage share is conducted to explore why no strong relationship between the wage share and output is found (after correcting for productivity effects). PVAR models are estimated at different frequencies to explore these relationships in the short- and longer-run. Quarterly estimates of this wage share decomposition model resemble those found in estimates of a similar model using U.S. data in Chapter 1. The results are suggestive of wage-led demand when the identifying restrictions allow demand to have a contemporaneous impact on productivity, but suggest profit-led demand when alternative restrictions are used. These findings suggest that the short-run relationship between the wage share and output is characterized by wage-led demand and procyclical productivity effects. However, results found using lower frequency data present a more complex relationship. They indicate that increases in either real wage growth or productivity growth lead to increased output growth, and that the growth of these components are positively related. This suggests that growth in labor productivity and the real wage rate, rather than the difference between them (i.e. the wage share) drives long-run output growth. This conclusion is supported by the results of forecast error variance decomposition, which show that labor productivity and the real wage rate explain a greater portion of the variation in output than the wage share does, especially at lower frequencies.

Based on these findings, it is argued that focusing on the relative shares of labor and capital income may not be the most useful way of looking at the effects of income distribution on macroeconomic outcomes, because growth in either component of the wage share can benefit the economy in the long run, regardless of the difference between them. As a result, the wage-led vs. profit-led demand debate may need to be reframed. Instead of viewing growth as wage-led or profit-led—where wages and profits refer to their shares of income—it may be better to think of growth as being driven by a combination of wage and productivity growth.

Although this chapter set out to explore the effects of the wage share on demand in the short- and longer-run, its primary contribution is its exploration of the relationships between output and the components of the wage share. Although Chapter 1 explored these relationships in the context of the short run, to the author's knowledge no study has yet examined them in the longer-run. Furthermore, it extends this analysis beyond the U.S. to a panel of 11 OECD countries. This chapter also contributes to the literature by applying a method of comparing short-run and long-run estimates that has not previously been used to study the relationship between demand and the functional distribution of income. To the author's knowledge, it is also the first study to estimate this relationship using a PVAR, although Stockhammer and Wildauer (2016) and Kiefer and Rada (2015) have previously used other panel estimation techniques to examine this relationship.

The rest of the chapter proceeds as follow. Section 3.2 summarizes the related literature. Section 3.3 provides an overview of the empirical strategy, while Section 3.4 discusses the results. Finally, Section 3.5 provides some concluding remarks.

3.2 Literature Review

Only a few previous empirical studies have directly examined how the relationship between demand and the functional distribution of income varies over different time horizons. Overall, the results are mixed but tend to support the view that demand is more wage-led in the long run. Barrales and von Arnim (2017) use wavelet decomposition to examine the relationship between the wage share and different measures of demand—the income-capital ratio, the output gap, and the employment rate—at different periodicities in the U.S. Over the business cycle frequency of 4-8 years, they consistently find evidence of Goodwin cycle effects,[3] wherein demand rises with the profit share, but the profit share decreases as demand rises—in other words there is profit-led demand and a profit squeeze.[4] They find similar effects over 8-16 year periods, but the results are more mixed at longer periodicities. Looking at 16-32 year periods, Goodwin cycle effects are found prior to 1980, but in later years this pattern breaks down, with demand moving either independently or in the same direction as the wage share—possibly indicating wage-led demand. For the longest periodicity of roughly 60 years, they find evidence of an aborted Goodwin cycle. Their results show profit-led demand and profit-squeeze effects from the late 1940s to the late 1990s, but a strong positive relationship between the wage share

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[3]The term "Goodwin cycle" here refers to neo-Goodwin cycles, such as those found by Barbosa-Filho and Taylor (2006). See Chapter 1 for further discussion of neo-Goodwin cycles.

[4]Stockhammer and Michell (2016) argues that counter-clockwise cycles of the wage share and output do not necessarily provide evidence of profit-led demand. They show that similar cycles can be generated through the relationship between demand and financial fragility, even in the absence of profit-led demand. Fiebiger (2018) argues that these observed cycles could be driven by cyclical changes in household investment and debt spending.

and demand after this time.[5] Therefore, while they find some evidence of profit-led demand (and corresponding profit squeeze effects) at every periodicity, these findings are much more consistent for business cycles than for longer-term periods. Furthermore, their long-run results are indicative of possible wage-led demand effects in later years.

Charpe et al. (2018) also use wavelet analysis in their study of the long-run relationship between the wage share and the growth rate of GDP per capita. Using over 100 years of historical data for the U.S., U.K., and France, they find evidence that strongly supports the hypothesis that demand is more wage-led in the long run. Using both relative phase analysis and regressions including control variables from the endogenous growth literature, they find that the wage share has a negative effect on growth in the short run, but a positive effect in the long run. Furthermore, they find larger correlations between the two variables at lower frequencies, suggesting that long-run analysis is more appropriate than analysis of business cycle effects. Araujo and Santos (2018) find similar results for the U.S. from 1967 to 2016, as the results of their wavelet analysis indicate profit-led demand in the short run and wage-led demand in the long-run.

Sánchez and Luna (2014) use a different method of examining short- and long-run relationships between the functional distribution of income and demand in Mexico. They use a vector autoregression (VAR) to identify short-run effects and a cointegration analysis to identify long-run effects, finding a positive relationship between the profit share and real GDP in the short run and a negative relationship in the long run. Their findings are therefore consistent with the results obtained by Charpe et al. (2018).

The results of spectral analysis conducted by Caldentey and Vernengo (2013) for 8 developed economies show that the dynamic correlations and coherency indicators be-

[5]Tavani et al. (2011) examine long-run cycles in the relationship between and a measure of demand—in this case the employment rate, using penalized spline estimation. They similarly find evidence of a long-run Goodwin cycles. Unlike in Barrales and von Arnim (2017), their estimated cycle is not aborted. However, this could be because their sample ends in 2004. The technical details of their estimation process are discussed in Tavani et al. (2010).

tween the real wage and real GDP are generally positive and stronger at lower frequencies than higher frequencies. This suggests that higher wages are associated with higher levels of output in the long run rather than in the short run. However, this does not necessarily provide insights into the the relationship between demand and the functional distribution of income, because they include only one component of the wage share and do not consider the relationship of output with productivity. Furthermore, their methodology does not provide any information about the direction of causality between wages and GDP (Blecker, 2016).

Halter et al. (2014) examine the relationship between the growth rate of GDP per capita and personal income inequality, measured by the Gini coefficient, for a panel of 106 countries from 1965-2005. They treat distribution as exogenous, estimating growth as a function of personal income inequality using the panel GMM estimator with data averaged over five-year periods. They find that increases in inequality initially increase growth in the next period, but lead to larger decreases in growth in the following period. Furthermore, when using data averaged over ten-year periods, they find a negative effect of inequality on growth. These findings therefore suggest that inequality has a positive short-run effect on growth, but a negative long-run effect.

Stockhammer and Wildauer (2016) and Kiefer and Rada (2015) used panel data to explore the relationship between demand and the functional distribution of income. Stockhammer and Wildauer (2016) estimate a structural model for a panel of 18 OECD countries using annual data from 1980-2013, finding that the average country is wage-led. However, they do not explore the differences across different time horizons. Kiefer and Rada (2015) estimate the relationship between the output gap and the wage share using quarterly panel data for 13 OECD countries. In their basic neo-Goodwin cycle model, they find evidence of profit-led demand and a profit squeeze. However, when they allow the long-run equilibrium to shift, they find long-term declines in both the wage share and demand. As Blecker (2016) notes, these findings could be viewed as consistent with long-run wage-led demand, but their model does not identify the direction of causality.

This chapter differs from previous studies in the approach it uses to estimate the relationship between demand and distribution. To the author's knowledge, this chapter is the first study to use a PVAR approach with impulse response function (IRF) analysis.[6] However, many aggregative studies employ similar methodologies for a single country, rather than using panel data (e.g. Barbosa-Filho and Taylor, 2006; Carvalho and Rezai, 2016; Silva de Jesus et al., 2018). This methodology is well suited to the type of analysis conducted in this chapter. Because data constraints prevent the estimation of models using data averaged over five-year periods for a single country, the use of panel data provides the necessary degrees of freedom for estimation of relationships at low frequencies. The PVAR model allows both demand and distribution to be endogenous, while the IRFs allow for clear interpretations of the response of one variable to a shock in the other, holding all else constant. Sánchez and Luna (2014) used a similar methodology—analyzing IRFs from a VAR model—but they focus on the developing economy of Mexico, and a different relationship may exist in developed economies, like the 11 OECD countries in the panel used for this chapter. This chapter also employs a different methodological approach to estimate short-run and longer-term relationship by estimating a PVAR with data averaged at different frequencies.

In addition to allowing an examination of longer-term relationships, the use of lower frequency data may also provide more valid estimates than high frequency data. Lavoie (2017) argues (and Chapter 1 shows) that estimates of the relationship between the utilization rate and the wage share using high frequency data will be biased towards findings of greater profit-led demand unless the cyclical effects of demand on labor productivity

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[6] Some of the specifications in Kiefer and Rada (2015) can be viewed as variations on a PVAR model, but they do not provide IRFs.

are taken into account.[7] Therefore, it is possible that differing estimates using low and high frequency data are capturing different levels of bias caused by this issue, rather than different effects at different time horizons. This chapter tests for this possibility by separately testing the differences between estimates at low and high frequencies using a measure of the wage share from which the cyclical variation in labor productivity has been removed.

Lavoie (2017) and Storm and Naastepad (2017) note an additional complication—that productivity may be endogenously affected by growth in real wages and output. Although they discuss this in the context of the effects of wage growth on employment, it also serves as an important reminder that the relationships between the components of the wage share and output, as well as with one another, should be considered when examining the longer-term relationship between the wage share and output. If the underlying components of the wage share affect both output growth and one another in the longer-run, then the estimated relationship between the wage share and output may not accurately capture the effects of changes in distribution on output.

For example, if increases in labor productivity lead to faster output growth and wage growth, then the wage share will change as long as the increases in productivity and wages are not exactly proportionate. Assuming that the resulting increase in wages is smaller than the increase in productivity, the wage share will fall. Empirical estimates of the relationship between the wage share and output would attribute the increase in output to the decrease in the wage share—i.e. the results would suggest profit-led demand. Following the same line of reasoning, demand would appear wage-led if increases in wage growth increase both productivity and output growth, and increase the wage share. While estimates would indicate an effect of the wage share on output, this relationship would be spurious. In other words, the growth rates of wages and productivity may be stronger

[7]See Chapter 1 for further discussion of this issue.

determinants of output growth than the difference between them—i.e. the growth rate of the wage share. This study explores this possibility by exploring the long-run relationships between real wages, labor productivity, and output.

3.3 Empirical Strategy

3.3.1 Econometric Approach

To explore these issues, a series of PVAR models are estimated using data at different time horizons.[8] The PVAR models are estimated using Blundell and Bond's (1998) panel systems GMM estimator, implemented using the R package developed by Sigmund and Ferstl (2017). This methodology estimates a PVAR of the form shown in equation (3.1), where $\boldsymbol{y}$ is a vector of stationary variables, $\boldsymbol{x}^{\perp}$ denotes the forward orthogonal transformation of vector $\boldsymbol{x}$, A is the coefficient matrix to be estimated, and $\boldsymbol{\epsilon}$ is the idiosyncratic error. $l = 1, ..., p$ indexes lags, $t = 1, ..., T$ indexes time, and $i = 1, ..., N$ indexes country.[9]

[8] PVAR models are estimated instead of panel vector error correction models (PVECMs) because evidence of cointegration is mixed and there are concerns that there would be insufficient data to estimate a PVECM model at the 5-year frequency. A PVECM model cannot be estimated using the output gap, because it is a stationary series, but the variables with unit roots could be cointegrated. However, panel cointegration tests, conducted in Eviews using quarterly data, are inconclusive. Three different panel cointegration tests are used: the Pedroni test (with individual intercepts and trends), the Kao test (with individual intercepts), and the Fisher-type combined Johansen test (assuming linear deterministic trends). The first two tests use the Modified Akaike Information Criterion to determine lag length, while the latter uses one lag. These tests are conducted on the following pairs of series: ln wage share and ln GDP, ln adjusted wage share and ln GDP, ln productivity and ln GDP, ln wages and ln GDP, and ln productivity and ln wages. The Kao and combined Johansen tests reject the null hypothesis of no cointegration for each pair. In most cases, the 11 test statistics computed for the Pedroni test give conflicting results. However, the majority of these test statistics fail to reject the null hypothesis of no cointegration for four of the five pairs of variables. For three of the five pairs (ln wage share and ln GDP, ln productivity and ln GDP, and ln productivity and ln wages) none of the Pedroni test statistics reject the null hypothesis at the 5% level. For the pair of ln wages and ln GDP, only 1 of the 11 Pedroni test statistics rejects the null hypothesis at the 5% level. The one exception is the pair ln adjusted wage share and ln GDP, for which 7 of the 11 test statistics reject the null hypothesis at the 5% level. Although some of these tests suggest that there may be cointegration, PVECM models are not estimated because there are concerns that there is insufficient data to estimate these models at the five-year frequency and identical models need to be estimated at each frequency for the purpose of comparison. The concern of insufficient data at the five-year frequency is based on the fact that data constraints prevent the estimation of combined Johansen tests using data at the five-year frequency.

[9] This equation is a modified version of equation (2) in Sigmund and Ferstl (2017).

$$\boldsymbol{y}_{i,t}^{\perp} = \sum_{l=1}^{p} \boldsymbol{A_l} \boldsymbol{y}_{i,t-l}^{\perp} + \boldsymbol{\epsilon}_{i,t} \tag{3.1}$$

Forward orthogonal transformation, as proposed by Arellano and Bover (1995), is used to eliminate unobserved individual effects.[10] This method is preferred over the first difference transformation, because the forward orthogonal transformation performs better in Monte Carlo simulations (Hayakawa, 2009).

In the context of a PVAR, the Blundell and Bond (1998) estimator makes use of the moment conditions shown in equations (3.2) and (3.3), where $\mathbb{T}$ denotes the set of observations for which the forward orthogonal transformation exists, $\mathbf{I}$ is an identify matrix, and μ_i represent individual country effects.[11]

$$E(\boldsymbol{\epsilon}_{i,t}^{\perp} \boldsymbol{y}_{i,j}^{T}) = 0, \quad j \in (1, ..., T-2),\ t \in \mathbb{T} \tag{3.2}$$

$$E((\boldsymbol{\epsilon}_{i,t} + (\mathbf{I} - \sum_{j=1}^{p} A_j)\mu_i)(\boldsymbol{y}_{i,t-1} - \boldsymbol{y}_{i,t-2})^T) = 0,\ t \in (3, 4, ..., T) \tag{3.3}$$

Equation (3.2) is based on the assumption that the level of $y_{i,t}$ is exogenous to the system of equations based on the forward orthogonal transformation. As Sigmund and Ferstl (2017) note, the condition in equation (3.3) will hold in the context of a stationary PVAR model because changes in the dependent variables will not be systematically related to the individual country effects.

In order to prevent the number of moment conditions from growing too large, the program developed by Sigmund and Ferstl (2017) uses a transformation matrix to collapse the instruments, and also allows users to specify a maximum number of lags to use as instruments. In order to ensure sufficient strength of the instruments, a maximum of

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[10] Sigmund and Ferstl (2017) implement the forward orthogonal transformation using the following equation: $y_{i,t+1}^{\perp} = c_{i,t}(y_{i,t} - 1/T_{i,t} \sum_{s>t} y_{i,s})$, where $c_{i,t} = \sqrt{T_{i,t}/(T_{i,t}+1)}$.

[11] These equations are taken from equations (3) and (17) of Sigmund and Ferstl (2017).

10 lags is imposed on the instruments and the Hansen overidentification test is used to test instrument validity.[12] The first lag is not used as an instrument because the current period observation of the first difference will be correlated with the first lag of the series in levels. As with the systems GMM estimates in Chapter 2, the system is estimated using a two-step procedure, in which the weighting matrix used in the second step is based on estimates from the first step.[13]

Lag length selection is based on the model selection criterion developed by Andrews and Lu (2001) for panel GMM estimation. The optimal lag length is chosen by selecting the model with the lowest value of the information criterion based on the Bayesian Information Criterion. This statistic is preferred over those based on the Akaike and Hannan-Quinn information criteria because Andrews and Lu (2001) find the former to be inconsistent, while the calculation of the latter depends on the user's parameter choice.

The estimated PVAR models include a measure of the wage share—or its two components—and a measure of demand. In order to test for sensitivity to variable measurement, two different measures of demand are used—the OECD output gap and the growth rate of real GDP. Because the cyclical variation in the labor productivity component of the wage share could bias the results, a measure of the wage share that is adjusted for this cyclical variation in productivity is used in addition to a basic wage share measure. The cyclically adjusted wage share is constructed by removing the cyclical component of labor productivity using the technique proposed by Hamilton (2017) to separate the cyclical component of time series data. Although the use of filtering techniques is not ideal, the author is not aware of any other method for isolating the cyclical component of a

[12]Individual results for the Hansen overidentification tests are not reported, because the test fails to reject the null hypothesis that the restrictions are valid in all specifications discussed in this chapter.

[13]Note that in cases where the algorithm constructed by Sigmund and Ferstl (2017) encounters a singular matrix it uses the general inverse in its place.

series. As discussed in Chapter 1, the Hamilton method is chosen because it is thought to be an improvement over other filtering techniques.[14]

Following this method, the trend of the natural log of labor productivity is found by taking the predicted values from the OLS estimation of equation (3.4):

$$\begin{aligned} ln\ real\ productivity_{i,t} &= \beta_0 + \beta_1\ ln\ productivity_{i,t-8} + \beta_2 ln\ productivity_{i,t-9} \\ &+\beta_3\ ln\ productivity_{i,t-10} + \beta_4\ ln\ productivity_{i,t-11} + \epsilon_{i,t} \end{aligned} \tag{3.4}$$

The natural log of the cyclically adjusted wage share is then found using equation (3.5):

$$ln\ adjusted\ wage\ share = ln\ wage\ share + ln\ productivity - ln\ trend\ productivity \tag{3.5}$$

This process removes the cyclical component of labor productivity—equal to the estimated $\hat{\epsilon_{i,t}}$ from equation (3.4)—from the wage share.

Note that $ln\ wage\ share + ln\ productivity = ln\ real\ wage\ per\ worker$ because the wage share is equal to the ratio of the real wages to output, or real wages per worker to output per worker.[15] Unlike in Chapter 1, where the cyclical component of productivity was included in the model to avoid excluding any information, this variable is excluded from the PVAR models because it is constructed as a stationary variable that cycles around a mean of 0. Therefore, it would provide little information when averaged at low frequencies.

In order to examine the longer-run relationships between the components of the wage share and output, three variable PVARs including labor productivity, real wages, and either real GDP or the output gap are estimated using data at different frequencies.

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[14]Hamilton (2017) argues that this method accomplishes the same goal as other filtering techniques like the Hodrick and Prescott (1997) filter—i.e. isolating the cyclical and trend components of a series, without many of the drawbacks like the generation of spurious relationships and the creation of filtered values that differ systematically in different portions of the sample.

[15]It is also equal to the ratio of real hourly wages to output per hour worked, but because the labor productivity series is measured as output per worker, the resulting real wage rate series is expressed per worker.

All variables are used in natural logarithm form except the output gap, which exhibits no trend and includes negative numbers. In order to ensure stationarity, panel unit root tests are conducted. Three panel unit root tests that allow for individual unit root processes are available in the Eviews software—the Im, Pesaran, and Shin (IPS), Fisher-type Augmented Dickey Fuller (ADF), and Phillips Perron (PP) tests. All three have the null hypothesis that the series under consideration has a unit root for all countries. The first difference of each series is taken unless two of the three tests reject the null hypothesis at the 5% significance level. By this criterion, only the output gap is found to be stationary. The wage share is found to be stationary if the tests do not include a trend, but all three tests fail to reject the null hypothesis of trend stationarity. Considering that the wage share series exhibits clear trends for some countries, and rejection of the null hypothesis does not imply that the series is stationary for every country, the series is differenced to ensure stationarity.[16] The cyclically adjusted wage share series, for which unit root test results are similarly inconclusive, is differenced for the same reason. Unit root test results are shown in Table C.1 of Appendix C.

Each model is first estimated using quarterly data. Then, to see how the results change at lower frequencies, the models are estimated using data averaged over one, three, and five-year periods. Each annual series is calculated as the average of the corresponding quarterly series. Three and five-year averages are then calculated as averages of the corresponding annual series.[17] Therefore, a lower frequency series of $ln\ x$ represents an

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[16]While the panel unit root tests for the ln wage share series are inconclusive, depending on the inclusion of a trend in the tests, unreported unit root tests conducted for single countries using quarterly data and all available observations suggest that the wage share is neither stationary nor trend stationary. Augmented Dickey Fuller and Phillips-Perron tests fail to reject the null hypothesis of a unit root at the 5% level for every country, whether a trend is included or not. Some tests for France, Japan, and Korea do reject the null hypothesis at the 10% level. Therefore, the evidence is highly suggestive of a unit root in the ln wage share series.

[17]Averages are only calculated for periods in which there is full coverage in the higher frequency series. For example, in five-year periods with only four years of data, the observation is dropped in the five-year average series.

average of quarterly $ln\ x$ series, rather than the natural log of the averaged series in levels. The same is true of series in growth rate—i.e. log differenced—form. This is done to ensure full comparability of the series across frequencies and to maximize the sample size.[18]

Following the estimation of each model, orthogonal impulse response functions based on Cholesky decomposition are used to examine the effects of a shock in one variable on another. This method is useful for identifying causal relationships, as it transforms the errors into independent structural shocks. However, the downside of this method is that the results depend on the ordering of the variables in $\mathbf{y}$. The orderings impose the restriction that variables do not have contemporaneous effects on those that come before them in the ordering, only lagged effects. This assumption is especially severe when using low frequency data, as it implies that it takes three or five years for some variables to impact others. While this is far from ideal, these assumptions are needed to identify causal effects.

For this reason, it is important to select an ordering that is theoretically plausible. The ordering in which the wage share comes before demand is preferred because it is more consistent with the previous literature and the underlying neo-Kaleckian theoretical model, which is outlined in Chapter 1. This ordering has been used by previous aggregative studies (e.g. Carvalho and Rezai, 2016), and the restrictions that it imposes, even at the lowest frequencies, are less severe than the assumption used by most structural studies and the theoretical model, that the wage share is not affected by demand. However, sensitivity to the ordering of the variables is tested.

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[18]It is not expected that the results would differ drastically if log transformations and differencing instead took place on lower frequency series. For example, the correlation coefficient between the annual average of the growth rate of real GDP and the growth rate of the annual average of the real GDP series is 0.892.

IRFs are reported along with confidence intervals. Bootstrapped confidence intervals are calculated using the algorithm created by Sigmund and Ferstl (2017). The procedure for calculating the confidence intervals involves cross-sectional resampling of the members of the panel with replacement. IRFs are then estimated for based on the resampled data. The confidence intervals reported in this chapter are based on 100 draws of the sample. Confidence intervals are not included for models including the output gap variable, because the scale of the confidence intervals makes the IRFS uninterpretable. The confidence intervals for specifications including the output gap grow exponentially around steps 9 and 10 of the IRFs. As the scale of the graphs adjusts to the size of the confidence intervals and the author is unable to adjust the axis scale, the IRFs become too small to interpret in graphs including the confidence intervals. However, the significance of these IRFs are discussed in the text.

3.3.2 Data

These models are estimated using balanced panel data for 11 OECD countries from 1979 Q1 - 2013 Q4. All data come from the OECD iLibrary. The panel dataset is based on the one used by Kiefer and Rada (2015), although this chapter uses a different econometric methodology to examine short- and long-run relationships. Following their empirical approach, the wage share is measured using an index of real unit labor costs, which is calculated as the ratio of the nominal unit labor cost index to the GDP deflator,[19] and the OECD's estimated output gap is used to measure demand. The output gap is measured as the ratio of the difference between output and potential output to potential output. Therefore, an increase in the output gap represents an expansion, while a decrease denotes a contraction. The OECD estimates of potential output are based on a Cobb-

[19]Because the GDP deflator indices for some countries have different base years, they are all rescaled so that 2010=1. As the nominal unit labor cost index has a base year of 2010, taking the ratio of these two series results in a wage share index where 2010=1.

Douglas production function with constant returns to scale (Organisation for Economic Co-operation and Development, 2018).

The output gap measure is used to provide some comparison to the study conducted by Kiefer and Rada (2015). This measure also has some desirable features. Unlike measures of the utilization rate constructed with filtering techniques (as discussed at length in Chapter 1), the OECD output gap estimates do allow for some long-term trends. However, this measure also has some flaws. Cerra and Saxena (2017) argue that the output gap is a conceptually flawed measure because changes in output can lead to permanent changes in ex-post estimates of potential output, and therefore demand shocks do not simply result in temporary deviations from potential output. Similarly, as Kiefer and Rada (2015) note, the OECD's estimates of potential output are often revised during periods of stagnation. Borio et al. (2013) show that real time estimates of the output gap based on data up to that time change dramatically ex-post when more data becomes available to construct the estimates. Furthermore, the output gap may not be a strong measure of longer-term output, because variations are likely to become smaller at low frequencies. Because of these shortcomings, the growth rate of real GDP—measured in 2010 U.S. dollars—is used as a measure of demand in other specifications in order to test for sensitivity to the use of the output gap measure.

Labor productivity is measured using an index with a base year of 2010. It is constructed as the ratio of real GDP to total employment.[20] The *ln real wage rate* series is constructed as the sum of *ln wage share* and *ln productivity*. As such, the real wage rate is measured as the real product wage,[21] and these two series comprise the entirety of

[20]Note that the real GDP series used to construct the productivity series is measured in each country's national currency, rather than U.S. dollars. However, as GDP is adjusted for inflation and productivity is measured using an index, the series remain comparable across countries.

[21]This wage rate series is equal to $nominal\ wage\ rate/GDP\ deflator$ or the product of $nominal\ wage\ rate/CPI$ and $CPI/GDP\ deflator$.

the wage share. A summary of the variable definitions and data sources is contained in Table C.2 of Appendix C.

Data for the wage share and the output gap is available for only 13 countries: Australia, Canada, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Sweden, the U.K, and the U.S. This is the same panel of countries that Kiefer and Rada (2015) use in specifications with an unbalanced panel. Ireland and Germany do not have data available before 1990 and 1991, respectively. They are dropped from the panel because these two countries would have only four observations at the 5-year frequency. Kiefer and Rada (2015) also drop these countries in specifications where they use a balanced panel. A larger balanced panel, including more countries and a longer sample period, could be used for specifications including real GDP instead of the output gap, but the same panel is used for all estimates to maintain consistency.

The panel is constructed with the goal of maximizing the sample size, while also ensuring comparability across estimates. The sample period of 1979 to 2013 is used for estimates across all frequencies, with the exception of the 3-year frequency, which begins a year earlier because it is not possible to divide a 35 year period into 3-year periods without basing some averages on an incomplete set of annual observations. The start date of the sample period is chosen to maximize the sample size while retaining a balanced panel. The start date that maximizes the number of observations is 1975 Q4. Because a sample beginning in 1976 would cover 38 years, it could include at most seven full 5-years periods. Therefore, a sample start date of 1979 Q1 is selected so that the most recent observations are included in the sample.

The panel ends in 2013 Q4 because the quarterly output gap series is only available through this time, because the OECD stopped calculating a quarterly output gap series beginning with Economic Outlook No. 91 (Organisation for Economic Co-operation and Development, 2018). Data for this series comes from the OECD's Economic Outlook No.

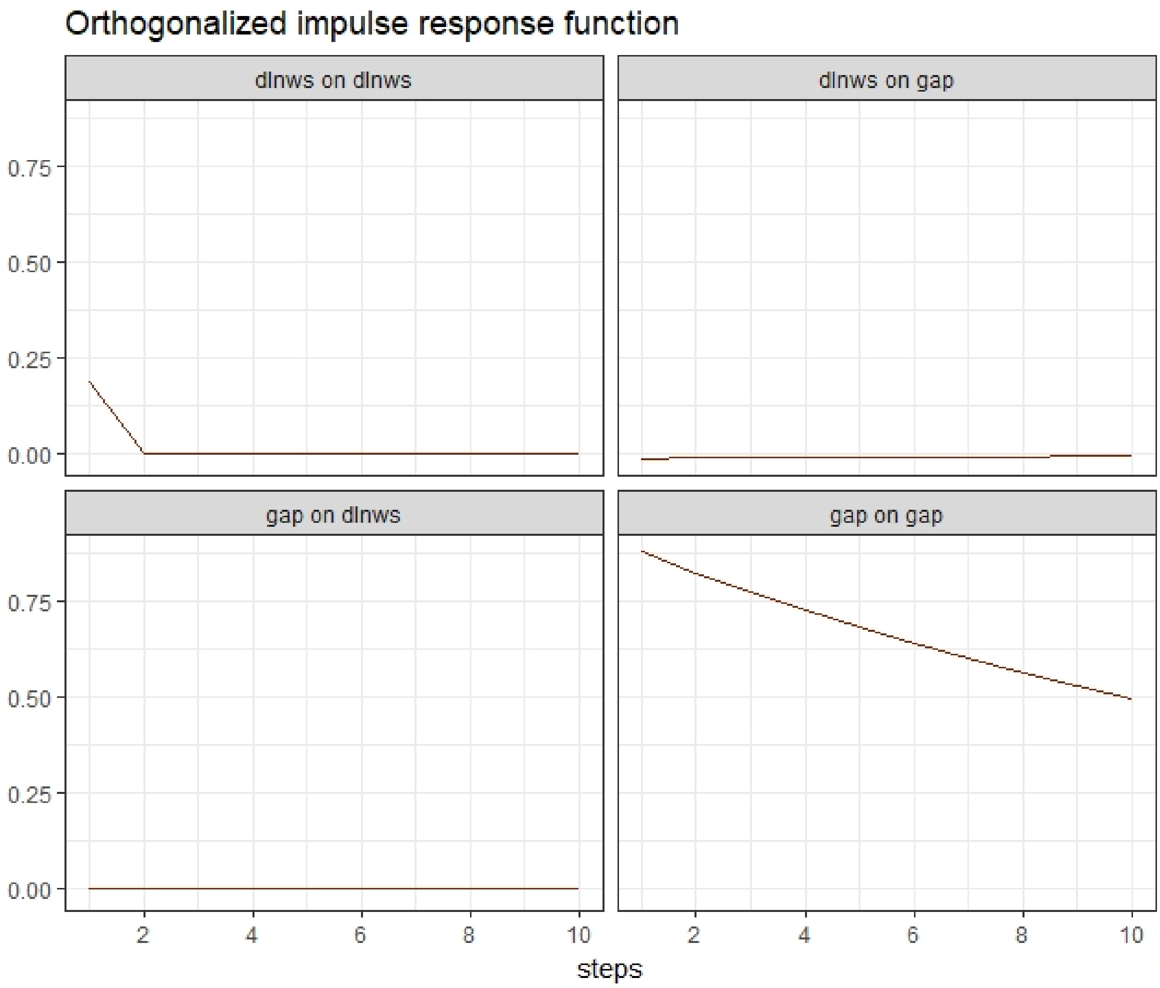
90, the last release of the Economic Outlook publication that included a quarterly output gap series. Data for the other series come from the most recent release of the Economic Outlook, at the time the data was extracted, No. 102. While this release of the Economic Outlook contains annual data on the output gap, this data was not used for estimates at the annual, 3-year, and 5-year frequencies in order to maintain comparability with the quarterly estimates. Because the Economic Outlook No. 90 was published in 2011, the observations for the output gap at the end of the sample are based on OECD forecasts. They are left in the sample in order to maximize the sample size.[22]

3.4 Econometric Results

3.4.1 Basic Wage Share Measure Models

The first specification tests the relationship between the growth rate of the wage share (i.e. Δ *ln wage share*) and the output gap, while imposing the ordering restriction that the output gap affects the wage share only after a one-period lag. The impulse response functions found by estimating this model with quarterly data are shown in Figure 3.1. The results show a very small profit-led demand effect, as the wage share has a small negative impact on the output gap. These profit-led demand effects are found to be significant at the 5% level only in the 2nd quarter (that is the quarter following the shock). No significant effects of the wage share on the output gap are found at the three higher frequencies. Although none of the effects are significant, the estimates do show that demand becomes more wage-led as the frequency lowers. Using the annual frequency, the initial effects are profit-led, but lagged effects are wage-led. Results for the lower frequencies indicate that the wage share has a positive effect on demand when

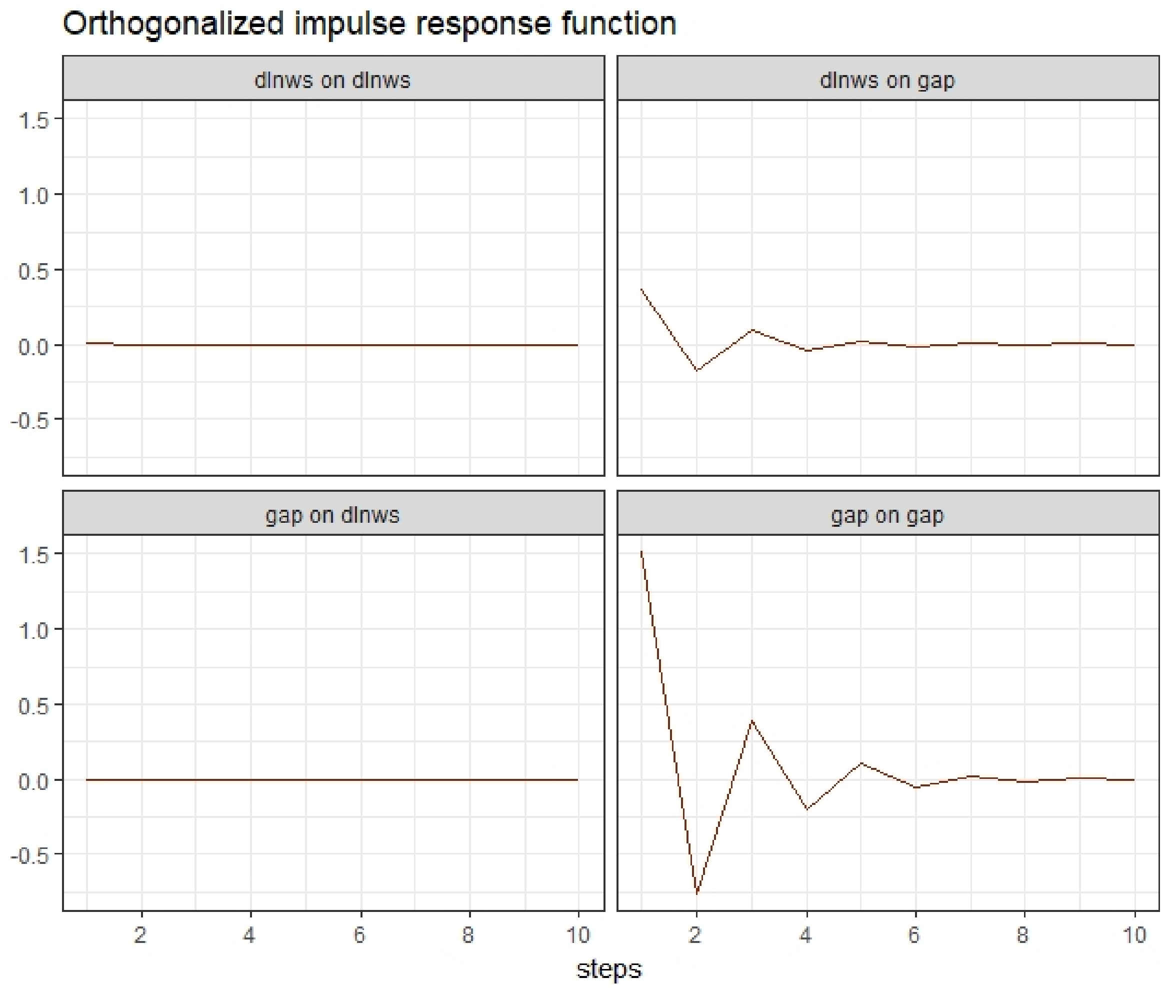
[22]The use of observations based on forecasts could be problematic, as they are likely not accurate. For the countries in the panel, the correlation between the annual average of the output gap observations from 2011-2013 and observations of the annual output gap series published in the Economic Outlook No. 102 (released in 2017) for the same years is only 0.285. Although these observations make up only a small portion of the sample, results for specifications using the output gap are tested for sensitivity to using the sample period of 1976-2010 (or 1975-2010 in the case of the three-year frequency).



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln wage share, output gap
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln wage share on Δ ln wage share, effect of Δ ln wage share on output gap, effect of output gap on Δ ln wage share, effect of output gap on output gap

Figure 3.1: Quarterly IRFs for the Wage Share - Output Gap Model

using data averaged over three or five-year periods. The IRFs for the five-year frequency are shown in Figure 3.2, while those for the annual and three-year frequencies are shown



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln wage share, output gap
Frequency: Five-year averages
Maximum number of instruments: 10
Clockwise: Effect of Δ ln wage share on Δ ln wage share, effect of Δ ln wage share on output gap, effect of output gap on Δ ln wage share, effect of output gap on output gap

Figure 3.2: Five-year IRFs for the Wage Share - Output Gap Model

in Figures C.1 and C.2 of Appendix C.[23] The estimated effects of the output gap on the

[23]The maximum number of instruments is reduced from 10 to 5 for the estimates using the three-year frequency because the results using up to 10 instruments show implausible results. In all four of the IRFs, effects oscillate between positive and negative, with the magnitude of the effects increasing over time. Similar results are found when increasing the number of lags from one to two. Because reasonable results are found when using a maximum of 5 instruments, and the Hansen overidentification

wage share are generally insignificant. The one exception is in the quarterly estimates, where significant wage-squeeze effects are found only in the 4th quarter.[24]

Unreported results indicate that these results are somewhat sensitive to the variable ordering. When using the reverse ordering that imposes the restriction that the wage share only affects the output gap with a one period lag, no clear pattern is found. Using the quarterly frequency, demand is found to be wage-led, with a magnitude similar to that for the profit-led demand effects found using this frequency and the original ordering. However, the confidence intervals suggest the presence of significant profit-led demand effects.[25] At lower frequencies, the effects of the wage share on demand are small and insignificant.[26] It is unsurprising that the estimated effects of the wage share on demand are weak when using this ordering, given that the strongest effects found when using the original ordering were the contemporaneous effects that are ruled out by assumption when the reverse ordering is used. No significant effects of the output gap on the wage share are found at any frequency.[27]

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test indicates that these instruments are valid, this specification is preferred. However, the results found using a maximum of 10 instruments are shown in Figure C.3 of Appendix C for reference. The results of an unreported specification using a maximum of 5 instruments for the model including these variables at the five year frequency show little difference from the results shown in Figure C.2.

[24]Unreported results show similar estimates when using an alternative sample of 1976-2010 (or 1975-2010 in the case of the three-year frequency) to remove observations of the output gap based on forecasts, although the IRFs differ somewhat. Using this sample period and quarterly data, small profit-led demand effects are found. As with the original sample period estimates, most effects are insignificant at the 5% level, but significant profit-led demand effects are found in the 2nd quarter and significant wage-squeeze effects are found in the 4th quarter. No significant relationship between the wage share and the output gap is found in either direction at any of the other frequencies at the 5% significance level. However, the estimates at lower frequencies are generally more wage-led than those at higher frequencies, as was the case in the estimates for the original sample period. These estimates used a maximum of 5 instruments at the annual and three-year frequencies.

[25]Hereafter, “significant effects” denotes the presence of a significant effect in at least one quarter. Using the reverse ordering and the alternative sample period, similar results are found at the quarterly frequency. Although the IRFs show evidence of wage-led demand, the confidence intervals suggest significant profit-led demand effects.

[26]A maximum of 5 instruments was used at the three-year frequency for these estimates.

[27]The findings of no significant effect of the output gap on the wage share at any frequency and no significant wage-led or profit-led demand effects at the annual, three-year, and five-year frequencies are

Because this ordering imposes the restriction that the wage share does not have a contemporaneous effect on demand, this set of identifying assumptions is not thought to be plausible at lower frequencies. Models in which effects of the wage share on demand are ruled out by assumption for up to three or five years are unlikely to provide any valuable insights into the long-run effects of the wage share on demand. For this reason, the initial ordering (in which the wage share has a contemporaneous effect on demand) is preferred. As discussed in Chapter 1, the main problem with the initial ordering is that it may lead to a misinterpretation of the cyclical effects of demand on labor productivity. That issue is addressed in the next section.

As with the output gap, the results for the model using the growth rate of real GDP show that the effects of distribution on demand become less profit-led as the frequency decreases, but most effects are insignificant. Significant profit-led demand effects at the 5% significance level are found only for the annual frequency. No significant effect of the GDP growth rate on the wage share are found at any frequency. IRFs for the quarterly and five-year frequencies are shown in Figures 3.3 – 3.4, respectively, while those for the annual and three-year frequencies are shown in Figures C.5 and C.6 of Appendix C. Figure 3.3 excludes the confidence intervals to make the magnitude more easily viewable, but IRFs with confidence intervals included are reported in Figure C.4.

As with the output gap model, these results are sensitive to the ordering of the variables in the PVAR. Unreported results show that no significant effects of the wage share on demand are found at any frequency when using the reverse ordering. However, significant wage squeeze effects are found to be significant at the 5% level in the annual and five-year frequencies. However, the results found using this reverse ordering should be viewed with skepticism for the reasons discussed above.

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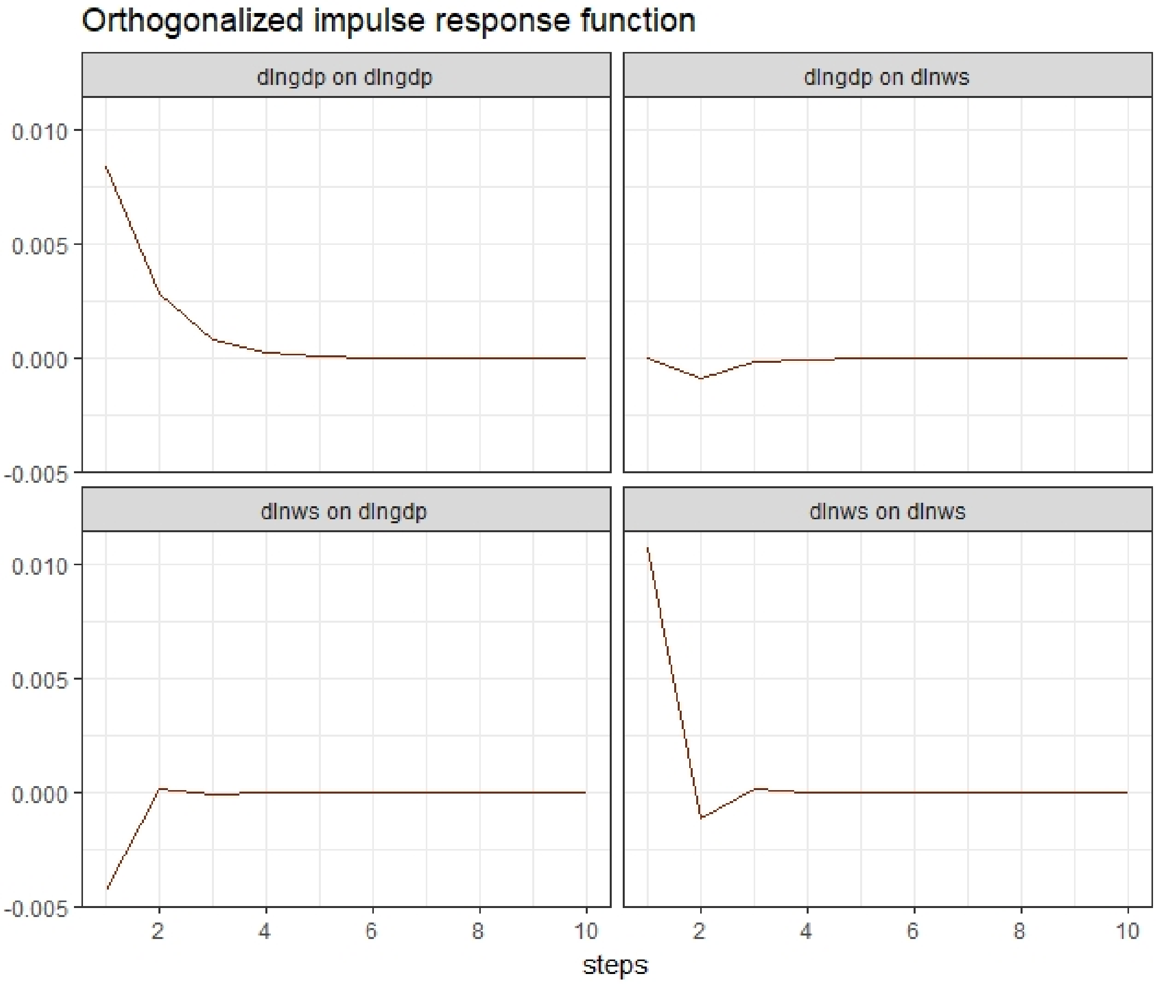
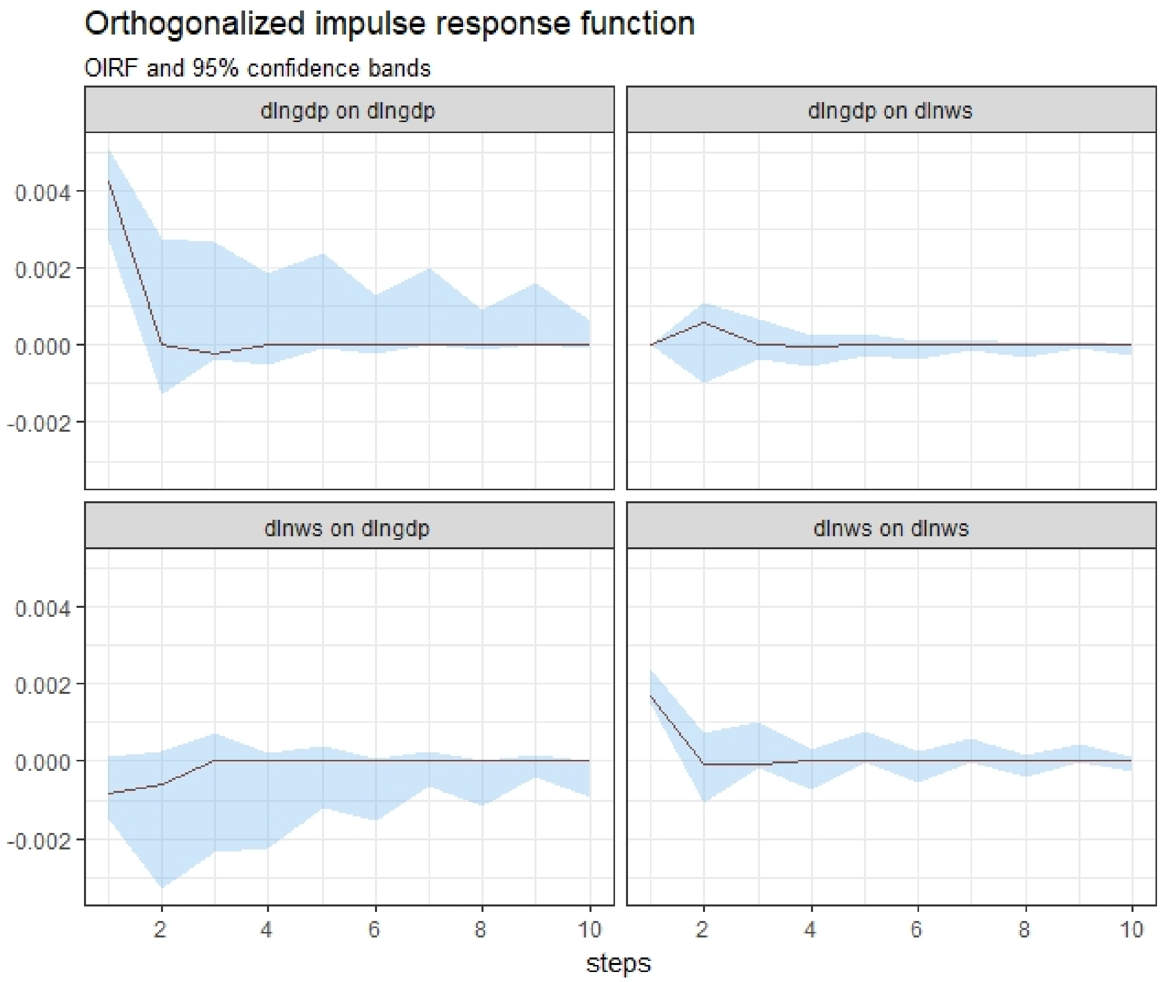
robust to the use of the alternative sample period (with a maximum of 5 instruments for the annual and three-year estimates).



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln wage share, Δ ln GDP
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln wage share, effect of Δ ln wage share on Δ ln GDP, effect of Δ ln wage share on Δ ln wage share

Figure 3.3: Quarterly IRFs for the Wage Share - Real GDP Growth Model

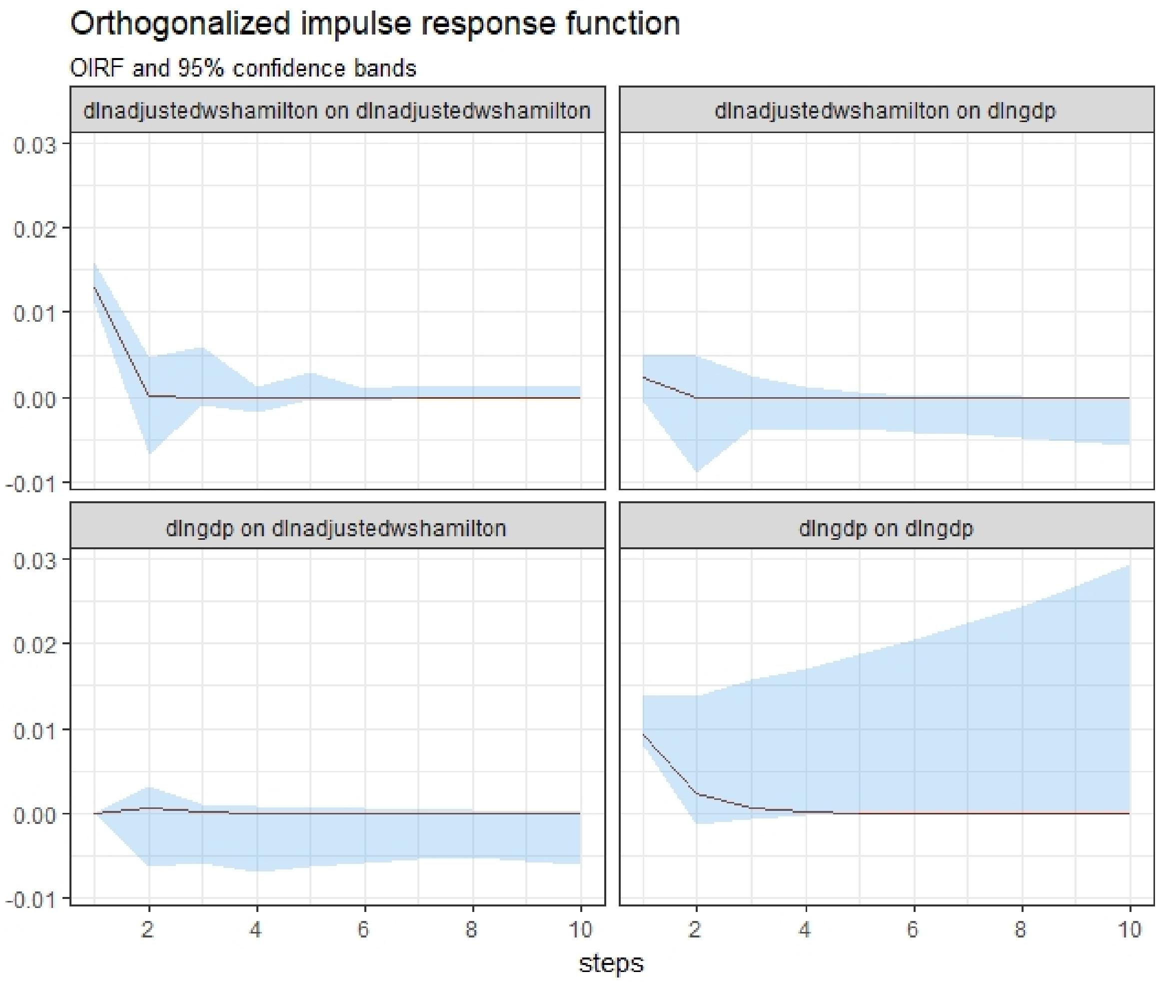
The results for the models including the basic wage share measure and either the output gap or the growth rate of GDP both show that demand becomes less profit-led at lower frequencies. Furthermore, significant effects of the wage share on demand are found only at higher frequencies—quarterly for the specification using the output gap and



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln wage share, Δ ln GDP
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln wage share, effect of Δ ln wage share on Δ ln GDP, effect of Δ ln wage share on Δ ln wage share

Figure 3.4: Five-year IRFs for the Wage Share - Real GDP Growth Model

annual for the specification using the GDP growth rate. This suggests that the profit-led demand effects captured by some aggregative models using high frequency data (e.g. Barbosa-Filho and Taylor, 2006; Carvalho and Rezai, 2016; Kiefer and Rada, 2015) are reflecting, at best, a very short-run relationship.

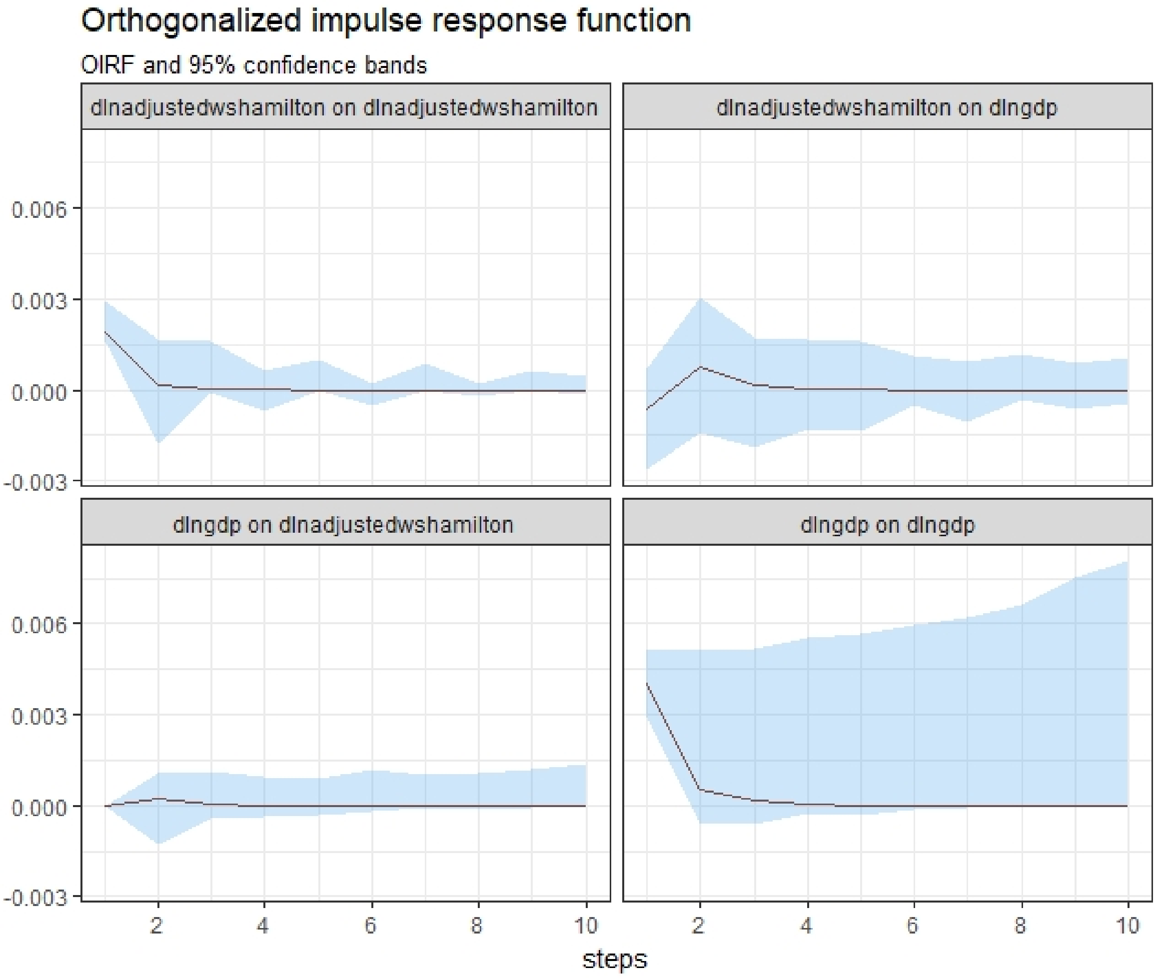


Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, Δ ln GDP
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on Δ ln GDP, effect of Δ ln GDP on Δ ln adjusted wage share, effect of Δ ln GDP on Δ ln GDP

Figure 3.5: Quarterly IRFs for Cyclically Adjusted Wage Share - Real GDP Growth Model

3.4.2 Cyclically Adjusted Wage Share Models

Although the initial results show that demand is less profit-led—or more wage-led—at lower frequencies, it is possible that these results are reflecting lower levels of



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, Δ ln GDP
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on Δ ln GDP, effect of Δ ln GDP on Δ ln adjusted wage share, effect of Δ ln GDP on Δ ln GDP

Figure 3.6: Five-year IRFs for Cyclically Adjusted Wage Share - Real GDP Growth Model

bias caused by cyclical variation in productivity in lower frequency data rather than true differences in the relationship at different time horizons. It is also possible that most of the estimated effects are insignificant because the procyclical variation in productivity is obscuring wage-led demand effects. To explore this issue, PVARs are estimated using a cyclically adjusted wage share along with either the output gap or the GDP growth rate.

The IRFs for the model including the growth rates of the cyclically adjusted wage share and real GDP, using the initial ordering, at the quarterly and five-year frequencies are shown in Figures 3.5 – 3.6. IRFs for the other two frequencies are shown in Figures C.7 and C.8 in Appendix C. No significant effects are found in either direction at the 5% level at any frequency. Although the results should be interpreted with caution due to the lack of significance, it is interesting to note that the estimates for this specification generally indicate that demand is wage-led. Therefore, these results provide some evidence to support the conclusion of Chapter 1 that estimates of profit-led demand found using high frequency data are based on a misinterpretation of procyclical variation in the labor productivity component of the wage share. When this variation in productivity is removed, the evidence of profit-led demand disappears, and the estimates suggest that demand is wage-led (albeit insignificantly), even in the short run.

In contrast to the results found using the unadjusted measure of the wage share, the IRFs for this model show that the wage-led demand findings become weaker at lower frequencies. Although all four frequencies show some evidence of wage-led demand, these effects become smaller as the frequency decreases. No significant wage-squeeze or profit-squeeze effects are found. Similarly, no significant effects are found in either direction when using the reverse ordering of these two variables. However, the first ordering is preferred, given that the main justification for allowing demand to affect the wage share contemporaneously is that it would capture cyclical productivity effects. Given that such effects are removed from the cyclically adjusted wage share, there is little motivation for using this reverse ordering.

Similar effects are found using the output gap in place of the growth rate of real GDP. No significant relationship between the wage share and the output gap is found in either direction at any of the four frequencies. Demand is found to be wage-led at the quarterly and annual frequencies,[28] but these effects disappear at the three and five-year frequencies, where some profit-led demand effects are found. However, none of these effects are statistically significant. Furthermore, no significant effect of the output gap on the wage share are found.[29] IRFs for these models are shown in Figures C.9 – C.12.

These results suggest that there is not a strong relationship between the wage share and output, as no significant effects between the cyclically adjusted wage share and output are found at any frequency. Although some significant profit-led demand effects are found using higher frequency data and an unadjusted wage share, these effects disappear when removing the cyclical variation in labor productivity. This suggests that the relationship between the wage share and output in found estimates using high frequency data is spurious, and that the two variables may not be strongly related once the cyclical effects of output on productivity are accounted for.

This view is supported by the results of the variance decomposition for the models using the basic wage share and the cyclically adjusted wage share.[30] In the real GDP model with the unadjusted wage share, the wage share explained roughly 20% of the variation in real GDP at the quarterly frequency, but only about 6% of the variation in real GDP at the five-year frequency. The cyclically adjusted wage share explains roughly 6% of the variation in real GDP at both the quarterly and five-year frequencies. This

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[28]Note that a maximum instrument number of 5 is imposed for these two estimates because implausible levels of variation in the IRFs were found when allowing up to 10 instruments. Results for the annual frequency should be viewed with some caution, because the Hansen J-statistic rejects the null hypothesis of valid overidentifying restrictions at the 5% level when using a maximum of 5 instruments. Results found using a maximum of 10 instruments are shown in Figures C.13 and C.14 of Appendix C.

[29]The results for the alternative sample period are similar in that the IRFs for these estimates show no significant relationship between the output gap and the cyclically adjusted wage share in either direction at any frequency, and the estimated wage-led demand effects are generally smaller at lower frequencies. A maximum of 5 instruments was used for these annual and three-year frequency estimates.

[30]The variance decomposition was found using the same model specifications used to obtain the IRFs for each model, and the ordering in which the wage share comes before demand.

suggests that much of the difference between the estimates for the quarterly and five-year frequencies can be explained by correlation between output and the cyclical component of productivity that gets averaged out at lower frequencies.[31]

3.4.3 Wage Share Decomposition Models

Most of the effects relating the wage share and output found in the previous sections are small and insignificant. To further investigate why this might be the case, PVARs including the growth rates of real GDP and the two components of the wage share—the real wage rate and labor productivity—are estimated at different frequencies.[32] The results for this model with two possible orderings at the quarterly frequency are shown in Figures 3.7 and 3.8. Order 1, shown in Figure 3.7, uses the ordering in which the real wage comes first and productivity comes last. Order 2, shown in Figure 3.8, uses the ordering in which the real wage comes first and the growth rate of GDP comes last. The quarterly IRFs for the other possible orderings are reported in Figures C.15 – C.18 of Appendix C.

Using quarterly data, the growth rate of the real wage is found to have a positive effect of the growth rate of real GDP in all specifications. These positive effects are statistically significant at the 5% level for all orderings in which wage growth comes first or second. The effect of productivity growth on real GDP growth depends on the ordering of the productivity and GDP growth rates. If output growth has a contemporaneous

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[31]The unadjusted wage share explains roughly 5% of the variation in the output gap at the 5-year frequency, and less than 0.1% at the quarterly frequency. The latter result is unsurprising given that the IRF for this frequency shows very little effect of the wage share on the output gap. The cyclically adjusted wage share explains about 4% of the variation in the output gap at the quarterly frequency, and about 2% at the five-year frequency. Using the alternative sample period, the unadjusted wage share explains less than 0.1% of the variation in the output gap at the quarterly frequency and about 17% at the five-year frequency, while the same measures for the cyclically adjusted wage share are roughly 4% and 1%, respectively.

[32]The GDP growth rate is emphasized over the output gap because of the shortcomings of the output gap measure discussed in Section 3.3.2.

effect on productivity, but productivity has only lagged effects on output growth, then output growth has a strong and significant positive effect on productivity growth, whereas productivity growth has only a weak (but statistically significant) effect on output growth. If the reverse ordering is imposed, and output growth is assumed to impact productivity growth only with a lag, then the positive effects of GDP growth on productivity growth are considerably smaller and insignificant, while productivity growth has a strong and significant positive effect on output growth.[33]

Therefore, these results follow a similar pattern to the one found for the wage share decomposition models estimated in Chapter 1 using quarterly U.S. data. When productivity is allowed to vary cyclically with demand, the results are suggestive of wage-led demand.[34] When the reverse ordering of productivity and the demand measure is used, the results are suggestive of profit-led demand, given the strong positive effect of productivity on demand (which will result in a negative effect of the wage share on demand). However, as Chapter 1 argued, orderings in which demand has a contemporaneous effect on productivity are likely more accurate. Therefore, the finding of profit-led demand likely represents a misinterpretation of the cyclical effects of demand on productivity.

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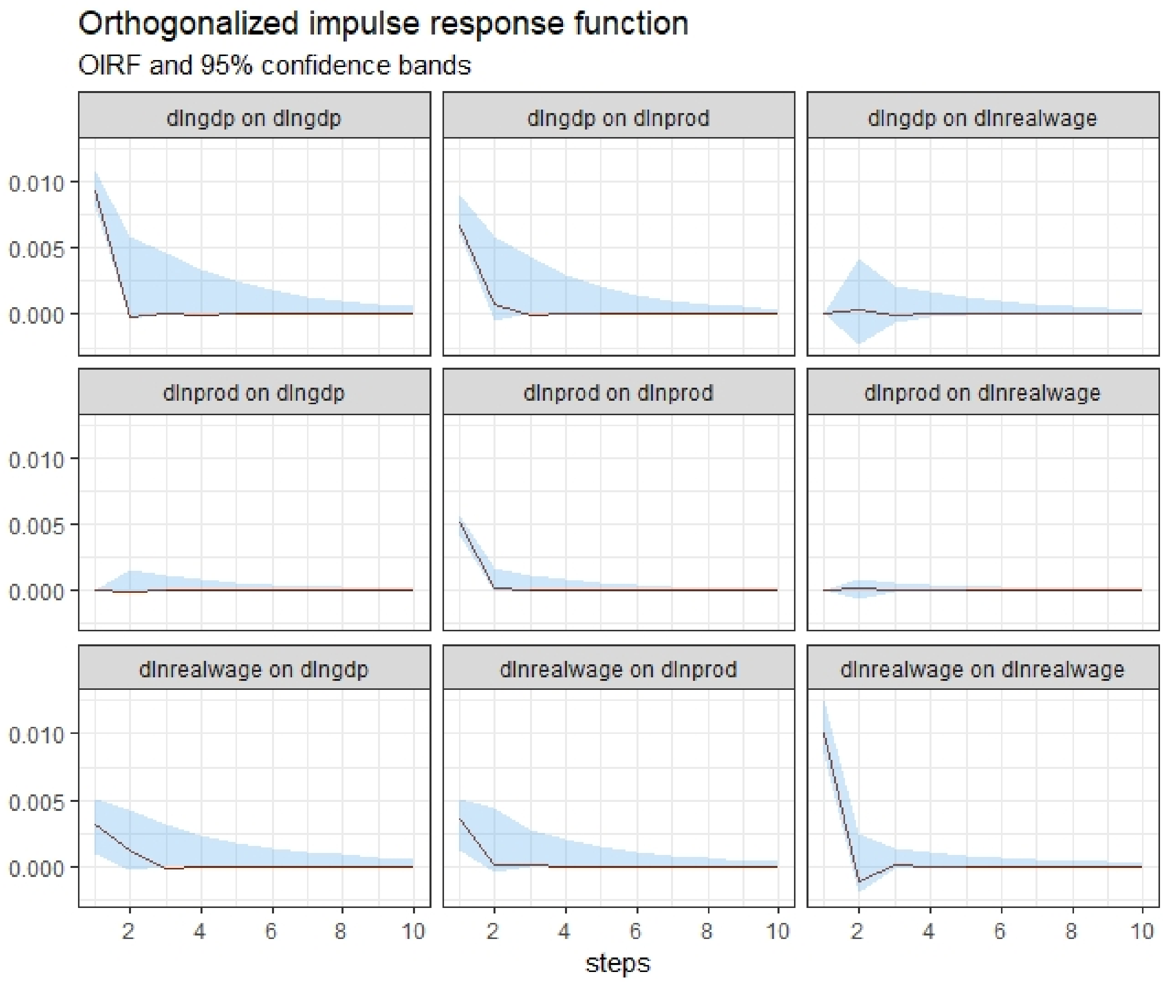
[33]Unreported results show that the effects of productivity growth on the output gap are positive for all orderings and significant for five of the six orderings. The exception is the ordering in which the output gap comes first and productivity growth comes second. No other relationships are found to be significant at the 5% level. As with the real GDP growth rate, the effects of productivity on the output gap are found to be larger when productivity comes before the output gap in the ordering. A different pattern is found when using the alternative sample period. In these estimates, productivity growth is found to have a negative effect on the output gap when the output gap precedes productivity growth in the variable ordering. These effects are statistically significant at the 5% level for two of these orderings, but not for the ordering in which the output gap comes first and productivity growth comes second. When reversing the order of productivity growth and the output gap, productivity growth is found to have a positive effect on the output gap. These effects are significant only for the ordering in which wage growth comes first and productivity growth comes second. No other significant relationships are found.

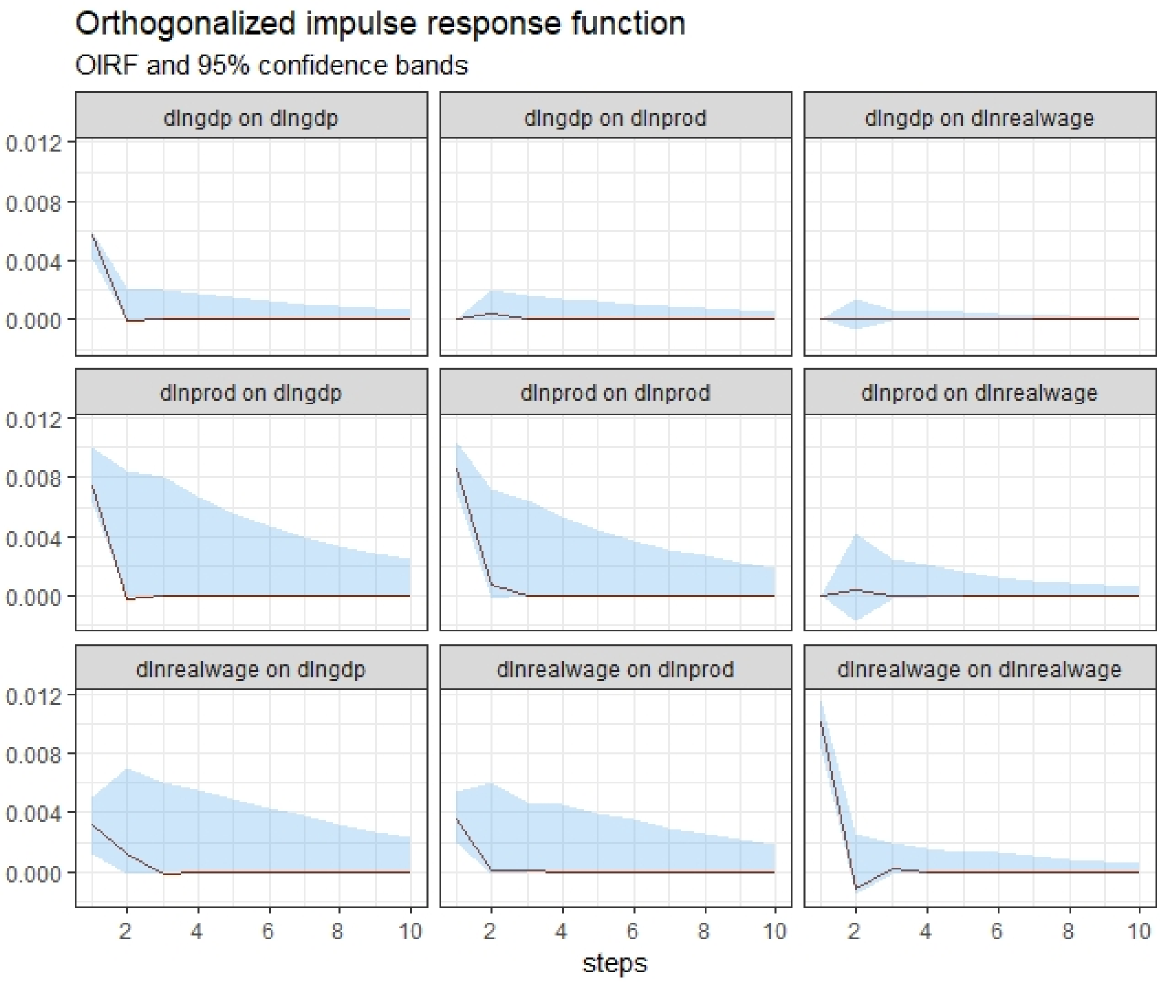
[34]In Chapter 1, the results for these orderings suggest wage-led demand because shocks to either of the main components of the wage share that will increase the wage share (i.e. a positive real wage shock or a negative productivity shock) will increase demand. This is the case for this chapter in Order 1 and 4. While Order 3 shows a slight positive effect of productivity on output, the complete IRFs are still suggestive of overall wage-led demand given the much larger positive effects of real wage growth on GDP growth.



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln real wage, Δ ln GDP, Δ ln productivity
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure 3.7: Quarterly IRFs for Wage Share Decomposition Model, Order 1

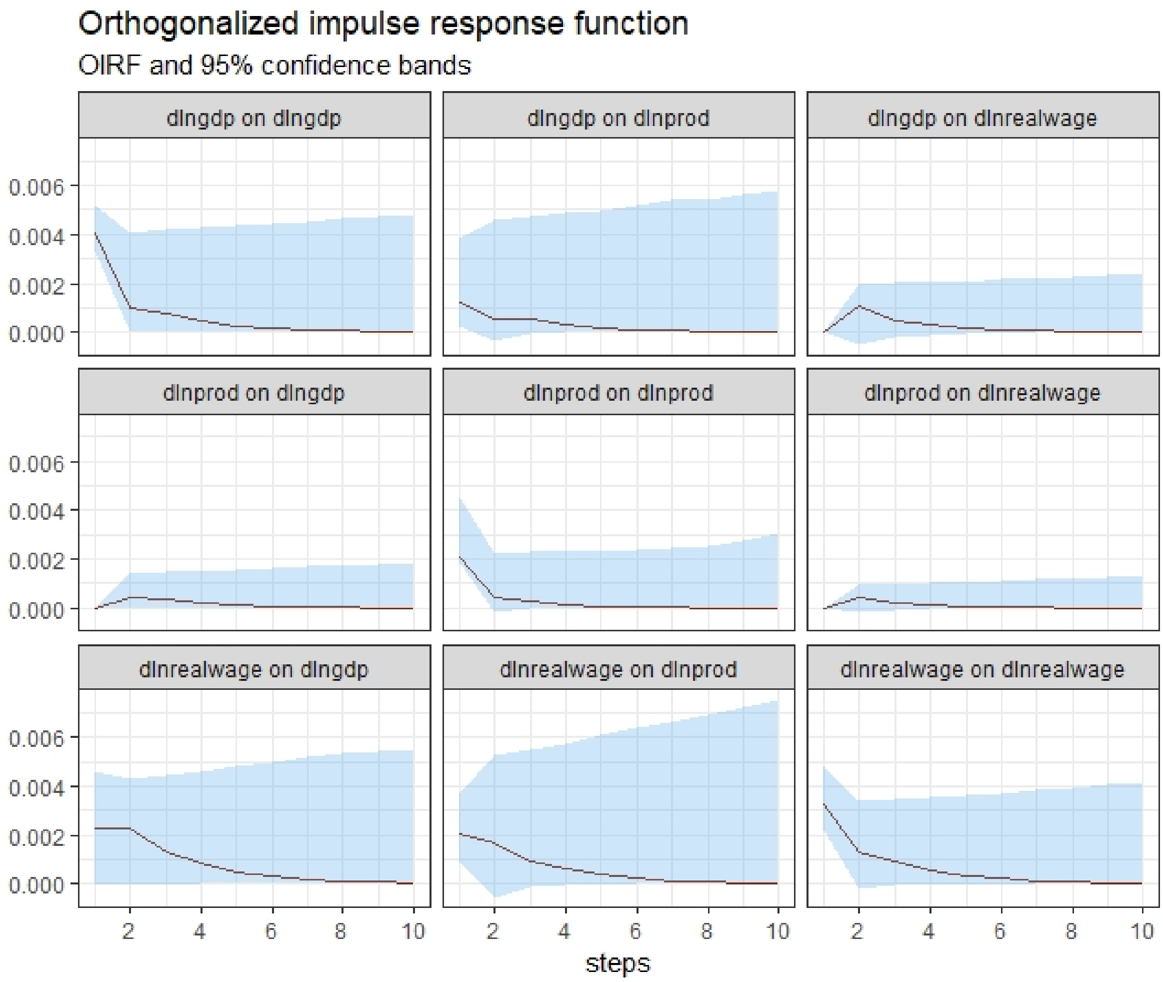
Assuming that the model allowing contemporaneous effects of output on productivity is more appropriate, the results of the wage share decomposition models estimated with the



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln real wage, Δ ln productivity, Δ ln GDP
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure 3.8: Quarterly IRFs for Wage Share Decomposition Model, Order 2

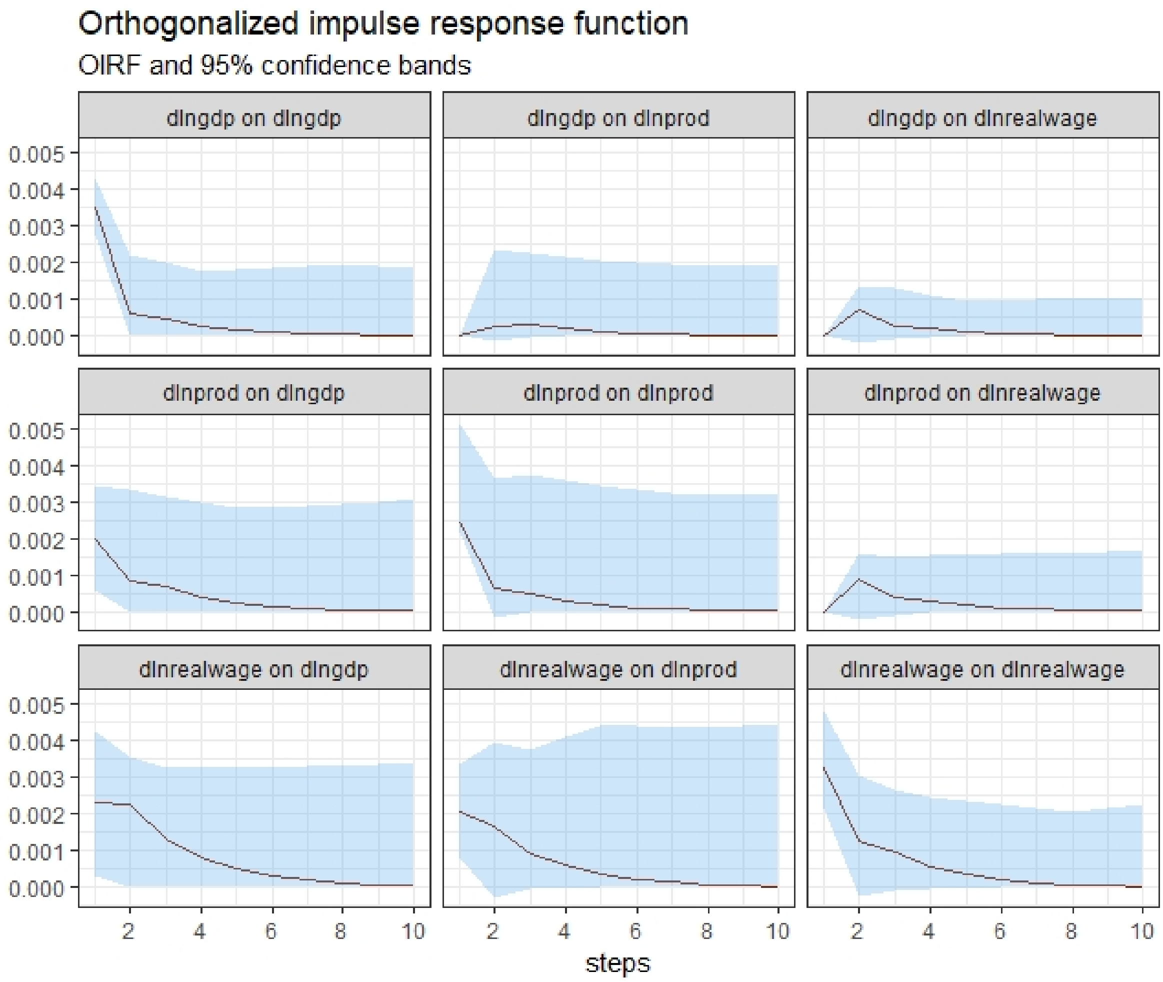
PVAR at the quarterly frequency suggest that the relationship between the wage share and demand is characterized by wage-led demand and cyclical productivity effects.



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln real wage, Δ ln GDP, Δ ln productivity
Frequency: Three-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure 3.9: Three-year IRFs for Wage Share Decomposition Model, Order 1

However, estimates of the wage share decomposition model at lower frequencies paint a different picture. The results for Orders 1 and 2 at the three-year frequency are



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln real wage, Δ ln productivity, Δ ln GDP
Frequency: Three-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure 3.10: Three-year IRFs for Wage Share Decomposition Model, Order 2

shown in Figures 3.9 and 3.10, while those for the five-year frequency are shown in Figures 3.11 and 3.12. The results for specifications using other orderings at these frequencies are shown in Figures C.25 – C.32 in Appendix C. The signs of the IRFs at these frequencies are generally robust to all possible orderings.[35] The relationships also have the same signs in the results found using the annual frequency, as reported in Figures C.19 – C.24 of Appendix C.[36]

The results show that both productivity and the real wage have positive effects on one another. For this reason, shocks to either of these components cannot be interpreted as shocks to the wage share.[37] However, these estimates can still provide some important insights. Although significance varies across estimates, all of the results suggest that increases in wage growth and productivity lead to increases in output, while an increase in either variable leads to an increase in the other.

Although the signs of these effects are robust to all variable orderings at either frequency, the significance varies depending on the ordering. At the three-year frequency the effect of productivity growth on GDP growth is significant at the 5% level in all orderings, but the effect of wage growth on GDP growth is significant for only four of the six possible orderings.[38] Productivity growth is found to have a significant effect on wage growth when it precedes wage growth in the variable ordering, but not when the ordering of these two variables is reversed. Similarly, the effect of wage growth on productivity growth is significant at the 5% level when wage growth comes before productivity growth in the variable ordering, but not in other cases. These effects are also economically meaningful.

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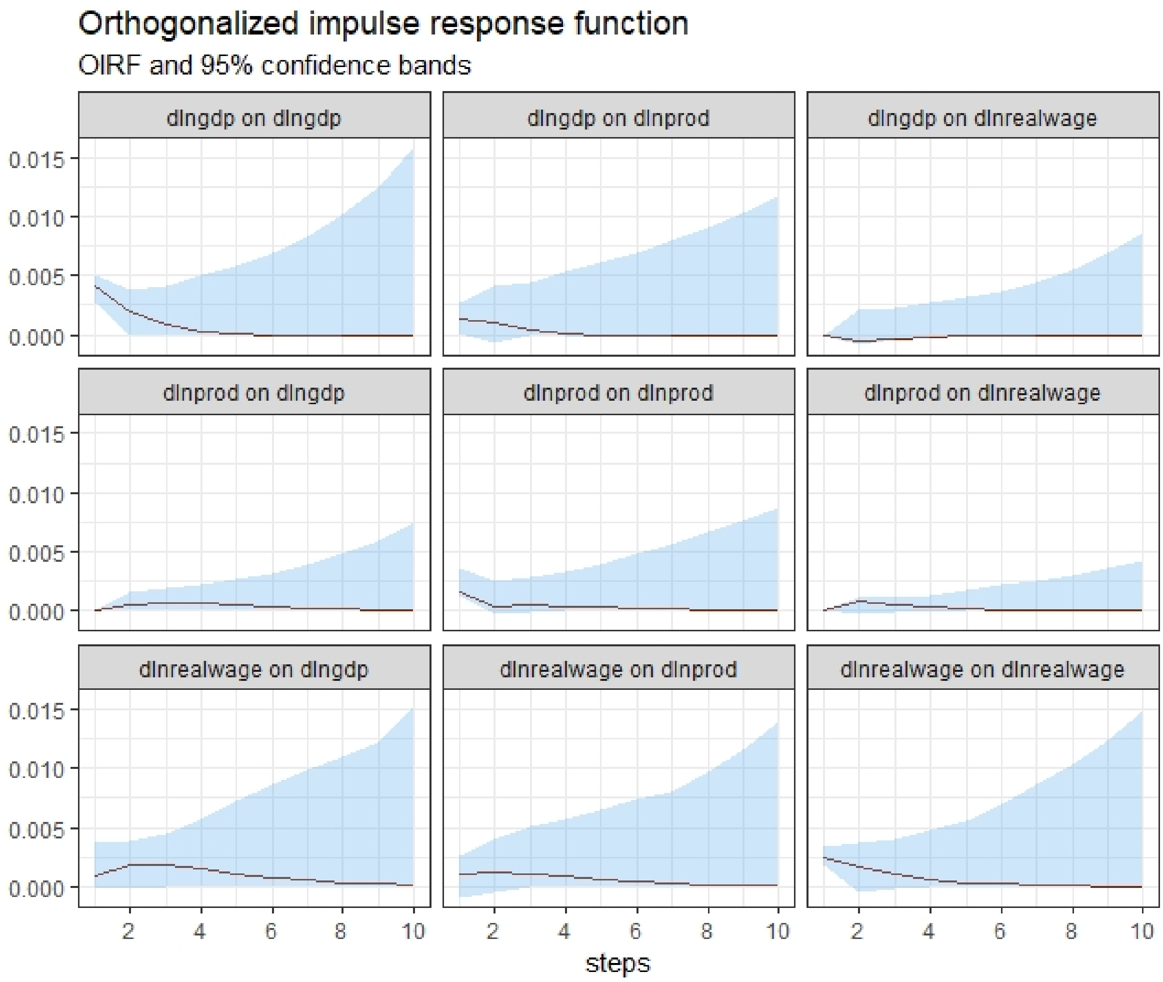
[35]One exception to this is that the effect of real GDP on the real wage rate at the five-year frequency. In orderings where real GDP comes first, it is found to have some positive effects on the real wage rate, along with some smaller lagged negative effects. In all other orderings, real GDP has only a negative impact on the real wage rate.

[36]However, the effect of real wage growth on GDP growth in Order 6 shows an initial negative effect before a larger lagged positive effect.

[37]Some positive effects of these variables are also found at the quarterly frequency. However, these effects are generally small relative to the effects of productivity growth on GDP growth (or the reverse, depending on the orderings). Furthermore, the effects of wage growth on productivity growth are negative in some specifications.

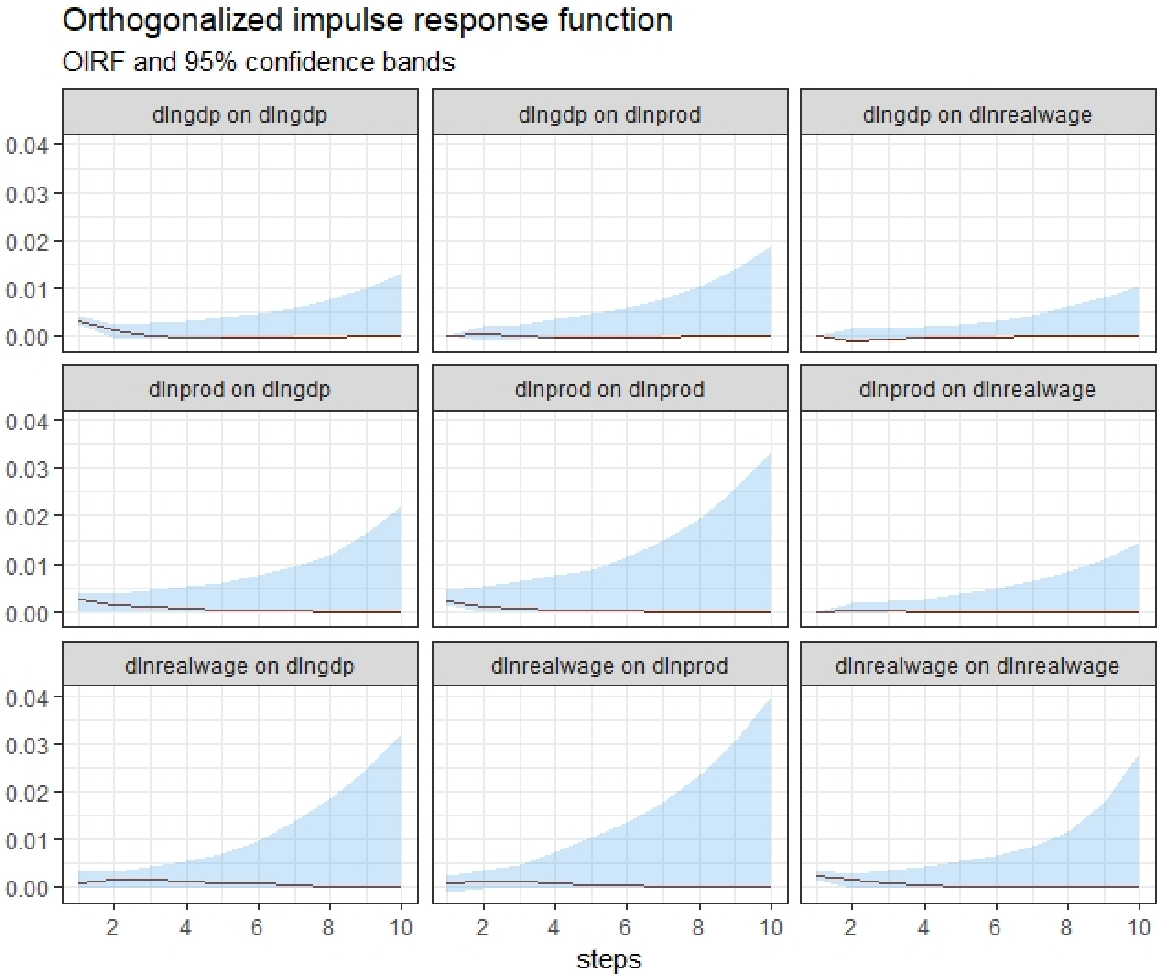
[38]The exceptions are the two orderings in which productivity comes first.



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln real wage, Δ ln GDP, Δ ln productivity
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure 3.11: Five-year IRFs for Wage Share Decomposition Model, Order 1

For example, the IRFs for Order 2 at the three-year frequency show that an innovation in wage growth leads to a contemporaneous increase of about 0.2 percentage points in both



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln real wage, Δ ln productivity, Δ ln GDP
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure 3.12: Five-year IRFs for Wage Share Decomposition Model, Order 2

productivity and output growth, while an innovation in productivity growth leads to a contemporaneous increase of .2 percentage points in output growth and a .1 percentage point increase in wage growth in the first quarter after the shock—as contemporaneous effects are ruled out by assumption—in addition to subsequent lagged effects in all of these cases.

The significance of the results follows a similar pattern in the annual estimates, where the effects of productivity growth on wage growth are significant only for orderings in which productivity growth precedes wage growth, and the effects in the other direction are significant only when the ordering of these two variables is reversed. In the annual estimates, the effects of productivity growth on output growth are significant for all orderings, and the effects of wage growth on output growth are significant in all but one case (the ordering in which productivity growth comes first and wage growth comes last).

Fewer statistically significant effects are found for the five-year estimates, likely because the smaller sample size leads to more noise. However, the positive effect of productivity growth on output growth is found to be significant at the 5% level for three of the six orderings, while the positive effect of wage growth on output growth is significant at this level in one case.[39] Unreported confidence intervals for the five-year frequency show that a few more effects are weakly significant at the 10% level. Using the two orderings in which wage growth comes first, the positive effect of wage growth on output growth is significant at the 10% level. Furthermore, the effects of productivity growth on output growth are significant for all possible orderings at this significance level. Although no significant effects between wage growth and productivity growth are found at the 5% level, the positive effect of wage growth on productivity growth is significant at the 10%

[39] The significance of these effects does not appear to follow any noticeable pattern based on ordering. Both productivity growth and wage growth have a significant effect on output growth when productivity comes first and wages last in the ordering, while the other significant productivity effects are found using the two orderings in which productivity comes second.

level when using the ordering in which wage growth comes first and productivity growth comes second.[40]

Although the estimates at these lower frequencies should be interpreted with a bit of caution because some significance levels are sensitive to variable ordering and data frequency, a clear pattern emerges when looking at the results. Positive and significant effects of productivity growth on output growth are found for all orderings at each of these three frequencies, and most specifications suggest that the positive effects of wage growth on output growth are at least weakly significant (although this finding is sensitive to ordering). Furthermore, a significant relationship between wage growth and productivity growth is found for each ordering at the annual and three-year frequencies.[41] Because significant effects are only ever found in one direction, the direction of causality is unclear, but the results suggest a positive relationship between these two components of the wage share.

If increases in either of these components leads to an increase in output growth, as most of the results suggest, then it is likely that an increase in either component of the wage share is likely to benefit the economy in the long run. Furthermore, the positive relationship between these two components found in all specifications at these lower frequencies (and found to be significant in many of them) suggests the possibility of virtuous circles, wherein increases in either of these components could lead not only to increases in output, but also increases in the other component that could bring further benefits. Because increases in the growth rate of the real wage rate increase the growth

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[40]Unreported results estimated at the five-year frequency show that the pattern found at lower frequencies when using the growth rate of real GDP is not found when using the output gap.

[41]Although these effects are generally insignificant at the five-year frequency, this could be due to greater noise in these estimates, for which the sample size is smaller.

rate of output more than the growth rate of productivity,[42] the concern that faster wage growth will reduce unemployment—as expressed by Storm and Naastepad (2017)—is not supported by the results.

These results also suggest that an examination of the effects of the wage share on output may not be meaningful, especially in the long run. Although the quarterly estimates of the wage share decomposition model are consistent with the findings of Chapter 1—suggesting a short-run cyclical relationship characterized by wage-led demand and procyclical productivity effects—estimates at lower frequencies suggest that the wage share may not be a strong determinant of output growth. Although researchers are interested in measuring the effect of a redistribution of income from capital to labor, or vice versa, on demand, they may be capturing a spurious relationship. If increases in productivity increase output, and the resulting increases in the wage rate are smaller than the increases in productivity, empirical estimates of the relationship between the wage share and demand will show this decrease in the wage share leading to higher demand. However, output did not increase because productivity grew faster than the wage rate—i.e. the wage share decreased—the increase in demand is simply the result of the positive productivity shock. Similarly, if increases in wages lead to increases in output, as well as smaller increases in productivity that result in a higher wage share, demand will appear wage-led even though the increase in output is simply the result of higher wages.

Because positive wage shocks increase output and also increase the wage share (assuming the increase in productivity that results from the shock is smaller than the increase in the wage share), and positive productivity shocks will increase output and decrease the wage share, estimates of the relationship between the wage share and output may simply reflect whether wage shocks or productivity shocks are more prevalent, and

[42]This result is robust to all orderings of the variables at the three and five-year frequencies. For the annual estimates the effects on productivity growth are larger than those on output growth for some orderings.

not whether output growth will be faster if productivity grows faster than the wage rate or vice versa.

These results suggest that it is the growth of wages and productivity, rather than the difference between them, that drives output growth, especially in the long run. This view is supported by the results of variance decomposition at the five-year frequency. Whereas the wage share explains less than 6% of the variation in real GDP at the 5-year frequency in the two variable PVAR (using the ordering in which the wage share comes first),[43] labor productivity and the real wage rate explain considerably more. The real wage explains as much as 34% (in Orders 1 and 2) of the variation in real GDP in some orderings, while productivity explains as much as 53% (in Orders 5 and 6).[44] Therefore, the evidence suggests that the components of the wage share are much stronger long-run determinants of output growth than the wage share itself.[45]

[43]Using the reverse ordering the real wage explains only about 2% of real GDP growth.

[44]These results are sensitive to ordering. For example, productivity growth explains only about 4% of real GDP growth in Order 4, while real wage growth explains only about 14% of real GDP growth in Order 6.

[45]This pattern is less clear-cut in the short-run. Forecast error variance decomposition at the quarterly frequency indicates that the wage share explains as much as 20% of the variation in real GDP growth (when using the ordering in which the wage share comes first, in the other ordering it explains only about 2%). However, these results appear to be capturing some of the effects of demand on productivity, as the cyclically adjusted wage share explains under 6% of the variation in the growth rate of GDP, using the same ordering. The components of the wage share seem to be weaker determinants of GDP growth at this frequency. Real wage growth explains 11% of the variation in real GDP growth in Orders 1 and 2, and 1% or less in the other orderings. Productivity growth explains 56-66% of real GDP growth in orderings where it comes before real GDP growth, but this is likely misinterpreting the procyclical effects of demand on productivity. In orderings where productivity growth comes after real GDP growth, it explains less than 1% of real GDP growth. Surprisingly, the wage share is found to be a stronger determinant of the output gap in the long run than in the short run. Using the alternative sample period and the ordering in which the wage share comes before the output gap, the wage share is found to explain roughly 17% of the variation in the output gap at the five-year frequency, but less than 1% at the quarterly frequency. Using the original sample period, the wage share explains roughly 5% of the variation in the output gap at the five-year frequency, and less than 1% at the quarterly frequency. The components of the wage share appear to be stronger determinants of the GDP growth rate than the output gap. At the five-year frequency, the growth rates of productivity and wages never explain more than 2% of the variation in the output gap (using either sample period). Using the original sample period, productivity and wage growth explain less than 1% of the variation in the output gap at the quarterly frequency in orderings where the output gap comes first or second. In orderings where the output gap comes last, whichever component of the wage share that comes first explains roughly 22% of the variation in the output gap, while the other

Therefore, it may be wise to reframe the wage-led vs. profit-led growth debate. Rather than asking whether a change in factor income shares will increase growth, it may be better to think of both the functional distribution of income and output growth as resulting from the same underlying shocks to wages and productivity in the medium to long run. Because increases in one are likely to lead to increases in the other, policies that increase either wages or productivity should benefit the economy. In other words, rather than viewing output growth as wage- or profit-led (i.e. wage share-led or profit share-led), it may be better to think of it as being productivity-led and real wage-led.

This is not meant to suggest that inequality in general has no effect on growth. However, more care should be taken to ensure that estimates of the relationship between the wage share and output growth are not capturing the underlying effects of the wage share's components. Future studies of the functional distribution should focus on more clearly modeling the complex relationship between wages, productivity, and output. This work should be complemented by further research on the relationships between the wage share, other dimensions of inequality, and macroeconomic outcomes.

Although the wage share may not be a strong determinant of output growth, it may still be a useful measure of the long-term health of an economy. The results for the wage share decomposition model at lower frequencies suggest that both supply-side factors (i.e. productivity growth) and demand-side factors (i.e. wage growth) are important for long-term growth. As such, policymakers should not ignore either, and should enact policies that both encourage innovation and lead to a distribution of income that does not suppress demand (e.g. by leading to low wage growth). Prioritizing one too much at the expense of the other will likely lead to slower growth. As such, the wage share

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explains less than 1%. Using the alternative sample period, wage growth never explains more than 2% of the variation in the output gap at the quarterly frequency, while productivity growth explains 10-12% of the variation in the output gap in orderings where productivity comes before the output gap, and less than 1% in other orderings.

may be able to indicate the balance of these two factors. A wage share with little long term trend indicates balanced growth of wages and productivity—a recipe for sustainable long-run growth. However, a wage share with a strong trend in either direction suggests weak growth in one of these factors. If this is the case, strong growth will likely not be sustainable, given the importance of both of these factors for stimulating growth and the virtuous cycle that may exist when wages and productivity are both growing.

3.5 Concluding Remarks

This chapter set out to test whether the relationship between the functional distribution of income and output differs in the short and longer run. Using a PVAR model with data measured at different frequencies, ranging from quarterly to five-year averages, find evidence in support of the hypothesis that demand is more wage-led in the longer run. Initial estimates do suggest that profit-led demand effects are weaker in the long-run. Estimates of the relationship between the wage share and the output gap find significant profit-led demand effects in the quarterly frequency, but no significant effects at higher frequencies. Furthermore, although the effects at higher frequencies are insignificant, they have a positive sign, suggesting wage-led demand. When using the growth rate of GDP in place of the output gap, demand is found to be profit-led at all frequencies, but these effects are only significant at the annual frequency. Furthermore, estimates become less profit-led as the frequency decreases. These findings suggest that profit-led demand is found only in the short run.

Furthermore, it appears that the significant effects found using higher frequency data are driven by a misinterpretation of the cyclical effects of output on productivity. Using a cyclically adjusted wage share measure, from which the cyclical variation in labor productivity has been removed, in order to adjust for the procyclical variation in productivity, no significant relationship between the wage share and output is found at any frequency. Furthermore, it appears that the initial finding of less profit-led demand at lower frequencies is due to lower levels of bias in lower frequency data, as demand is not found to be more wage-led at lower frequencies when using the cyclically adjusted wage share. Insignificant wage-led demand effects found at high frequencies using this measure become weaker at lower frequencies. Therefore, this chapter does not find the same clear pattern of more wage-led demand in the longer-run that Charpe et al. (2018) found using a measure of the wage share that does not adjust for cyclical variation in labor productivity.

Although the initial motivation for this chapter was to examine whether output becomes more wage-led in the longer run, its findings suggest that the wage share may not be a strong determinant of output at all, especially in the longer run. Models in which the wage share is split into its two components—the real wage rate and labor productivity—suggest relationships that are more complex than a simple wage-led or profit-led demand story based on relative income shares. Although models estimated at the quarterly frequency confirm the finding of Chapter 1 that the short-run relationship between these variables are indicative of wage-led demand and procyclical productivity dynamics, lower frequency estimates do not fit neatly into either the wage-led or profit-led categories. Instead, they suggest that real wage growth and productivity growth both increase output growth, even though they have opposite effects on the wage share. Furthermore, the growth of these two components is positively related, although the direction of causality is not clear due to the sensitivity of significance levels for these estimated effects to variable ordering. This positive relationship suggests the presence of a virtuous cycle, wherein growth in one of these components can increase output growth and growth in the other component, leading to further increases in growth. This finding suggests that any longer-run effects of the wage share on output growth are likely spurious. Moreover, forecast error variance decomposition suggests that the components of the wage share are much stronger determinants of long-run output growth than the wage share is.

Based on these results, it is argued that the way we think about the relationship between the functional distribution of income and demand needs to be reconsidered. Long-run output growth appears to be driven not by increases in either the wage share or the profit share, but by a combination of wage and productivity growth.

Together, the results of the three chapters of this dissertation have provided both some new insights into existing debates and some new questions to consider. As previous studies following the aggregative and structural approaches have generally found different results, there has been much debate about the cause of these differing results. This dissertation explored three potential explanations: bias in previous aggregative studies, bias in previous structural studies, and differing effects at different time horizons. Chapter 1 did find evidence that aggregative estimates will be biased towards more profit-led estimates if they do not account for the cyclical effects of demand on productivity. Evidence of wage-led demand was found when these cyclical productivity effects were accounted for. Similarly, although initial estimates (in both Chapters 1 and 3, along with the estimates in Chapter 2) indicate the presence of profit-squeeze effects, it appears that these estimates are really picking up effects of demand on productivity, as they generally disappear in specifications with more careful treatment of productivity effects. Chapter 2 explored whether structural estimates are biased towards more wage-led findings if they do not account for endogeneity of the wage share or the system dimension of models. It did not find evidence of such bias, as all three of the estimated models became more wage-led when estimated as systems. Together, the results of these two chapters point towards evidence that the true short-run relationship between the wage share and demand is wage-led. However, the results of this third chapter suggest that the relationship may not actually be that straightforward. Although it set out to test whether demand is more wage-led in the long run, it ultimately found that the wage share is not a strong determinant of long-run output growth. Instead, it appears that the long-run relationship is characterized by a more complex relationship, wherein output growth is actually driven by growth in the components of the wage share. As such, the framework of wage-led and profit-led demand regimes, as currently constituted, may not provide an adequate explanation of longer-run growth.

Of course, this dissertation does have some limitations. Most of the results pertain only to the U.S., or the U.S. and other advanced economies in the case of Chapter 3. It is possible that different relationships exist for other countries. Furthermore, the utilization rates used in Chapter 1 and the cyclically adjusted wage measures used in Chapters 1 and 3 depend on the use of filtering techniques that may not necessarily produce accurate measures. In Chapter 2, it is possible that the investment equations are misspecified, as they produce results that are the opposite of what theory predicts.

Much room for future research remains. As explained above, further exploration of the relationship between the wage share, its components, and macroeconomic outcomes is needed. Further exploration of the relationship between distribution and investment could also be beneficial. Studies using data on the output gap could benefit from the use of real-time data that do not get revised when new observations are added. While previous studies have examined how control factors, such as debt and wealth, affect the relationship between the wage share and demand, there is potential to explore these relationships further by examining the effects of these factors on the components of the wage share. Moreover, future studies could examine how the relationship between these variables has changed over time, with structural changes in the economy, such as globalization and financialization.

APPENDIX A

ADDITIONAL TABLES AND FIGURES FOR CHAPTER 1

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 output gap	1949 Q1-2016 Q4	Y	Reject 1%	Reject 1%	Fail to reject	Stationary
ln fed utilization	1967 Q1-2016 Q4	Y	Fail	Reject 5%	Fail	Stationary
ln production worker wage share	1964 Q1-2016 Q4	Y	Fail	Fail	Reject 1%	Difference

Continued on next page

Table A.1 – continued from previous page

Variables	Sample	Trend	ADF	PP	KPSS	Result
Δ ln production worker wage share	1964 Q2-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
ln corporate debt	1952 Q1-2016 Q4	Y	Fail	Fail	Reject 5%	Difference
Δ ln corporate debt	1952 Q2-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
ln household debt	1952 Q1-2016 Q4	Y	Fail	Reject 1%	Reject 5%	Difference
Δ ln household debt	1952 Q2-2016 Q4	N	Reject 10%	Reject 1%	Reject 10%	Stationary
ln wealth	1952 Q1-2016 Q4	Y	Fail	Fail	Reject 1%	Difference
Δ ln wealth	1952 Q2-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
ln exchange	1973 Q1-2016 Q4	N	Fail	Fail	Fail	Difference

Continued on next page

Table A.1 – continued from previous page

Variables	Sample	Trend	ADF	PP	KPSS	Result
Δ ln exchange	1973 Q2-2016 Q4	N	Fail	Reject 1%	Fail	Stationary
interest	1962 Q1-2016 Q4	Y	Reject 10%	Reject 5%	Reject 5%	Difference
Δ interest	1962 Q2-2016 Q4	N	Reject 1%	Reject 1%	Fail	Stationary
ln government spending	1962 Q1-2016 Q4	Y	Fail	Fail	Reject 5%	Difference
Δ ln government spending	1962 Q2-2016 Q4	N	Reject 1%	Reject 1%	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

Continued on next page

Table A.1 – continued from previous page

Variables	Sample	Trend	ADF	PP	KPSS	Result
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
Production worker wage share	Index of aggregate weekly payrolls of production and nonsupervisory workers in the total private sector / business sector output index	Index, 2009 = 100	BLS, Author's Calculations
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*
Output gap	100 * Real GDP / potential output	Percentage*100	Author's calculations
Nominal GDP	Nominal gross domestic product	Billions of dollars	BEA*

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Table A.2 – continued from previous page

Variable	Definition	Units	Source
Household debt	100 * Total liabilities of households and nonprofit organizations (in billions of dollars) / nominal GDP	Percentage*100	Federal Reserve*, Author's calculations
Corporate debt	100 * Total liabilities and equity of non-financial corporations (in billions of dollars) / nominal GDP	Percentage*100	Federal Reserve*, Author's calculations
Inflation Rate	Percent change in Consumer Price Index (2010=100), all consumers, all Items, seasonally adjusted, quarterly average of monthly data	Percentage	BLS*, Author's calculations
Interest Rate	100 * 10-Year Treasury Constant Maturity Rate - average inflation rate over past 10 years	Percentage*100	Federal Reserve*, Author's calculations
Exchange rate	Real trade weighted U.S. Dollar Index: Broad, quarterly average of monthly data	Index, 1973=100	Federal Reserve*
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

Continued on next page

Table A.2 – continued from previous page

Variable	Definition	Units	Source
Government spending	Government consumption expenditures and gross investment / nominal GDP	Percentage	BEA*, Author's calculations
Wealth	100 * Total assets of households and nonprofit organizations (in billions of dollars) / nominal GDP	Percentage*100	Federal Reserve*, Author's calculations

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

Construction of the Hamilton utilization rate, HP and Hamilton adjusted wage shares, and HP and Hamilton cyclical components of productivity are discussed in Section 1.3.2.

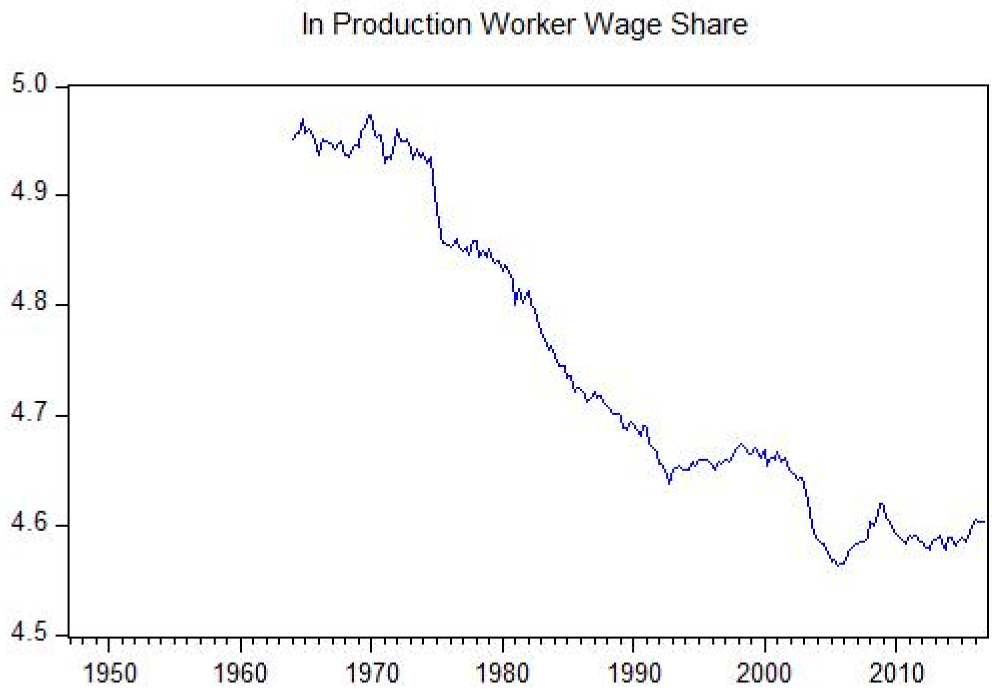
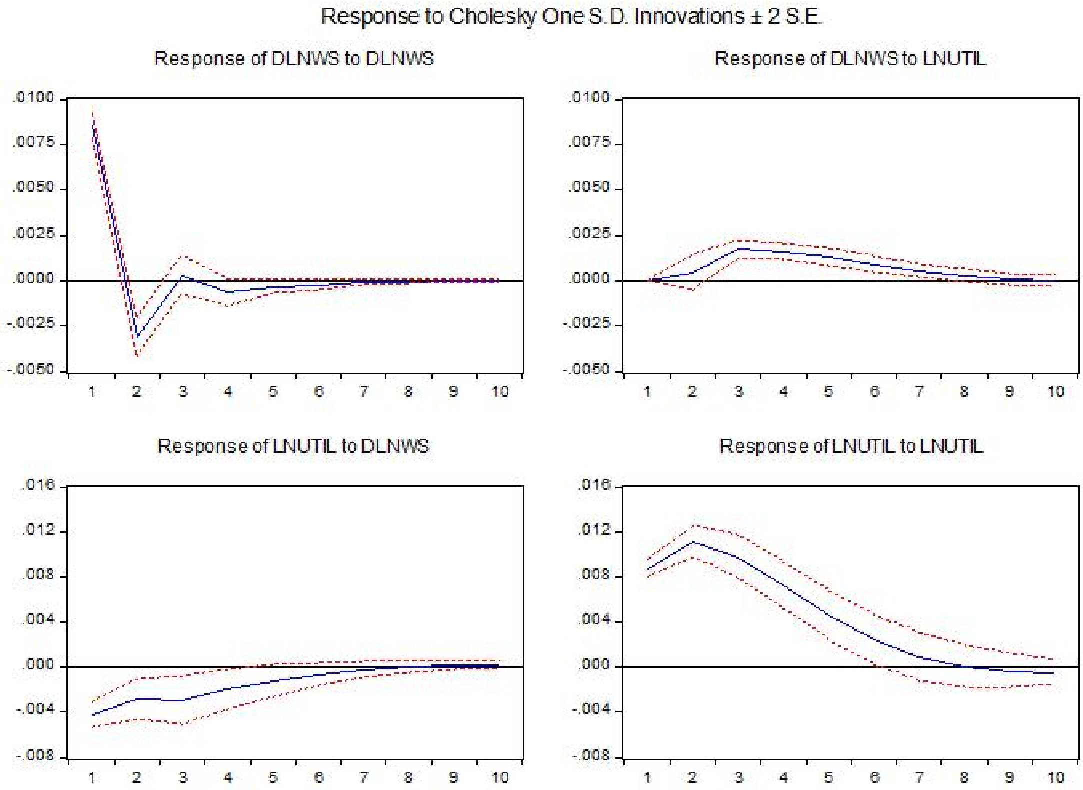


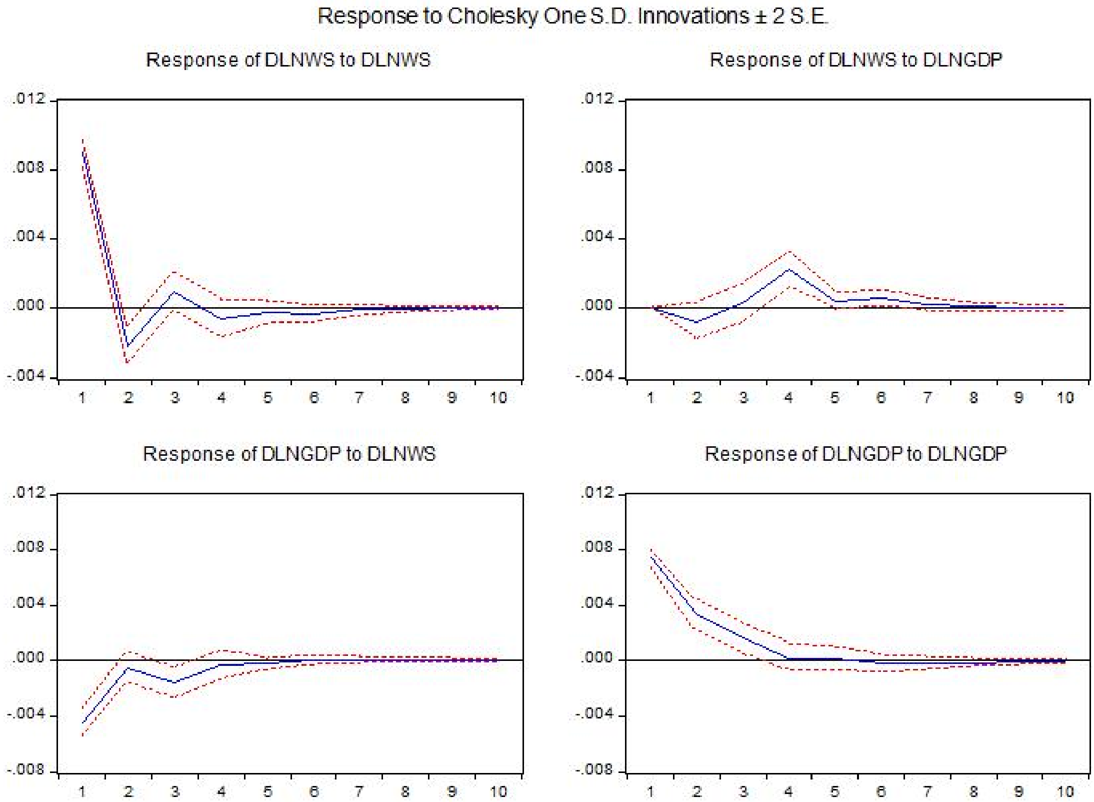
Figure A.1: ln Production Worker Wage Share Series, 1947-2016

Source: Refer to Table A.2



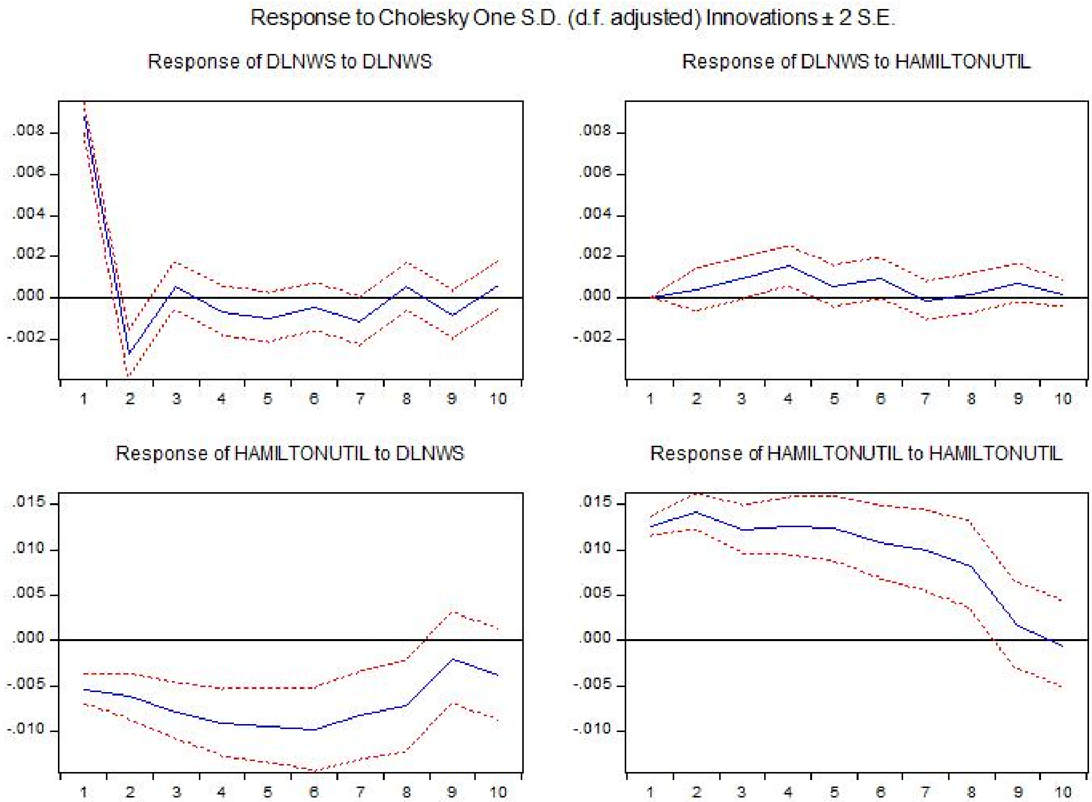
Sample period: 1947 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln HP utilization

Figure A.2: Complete IRFs for the Baseline Model



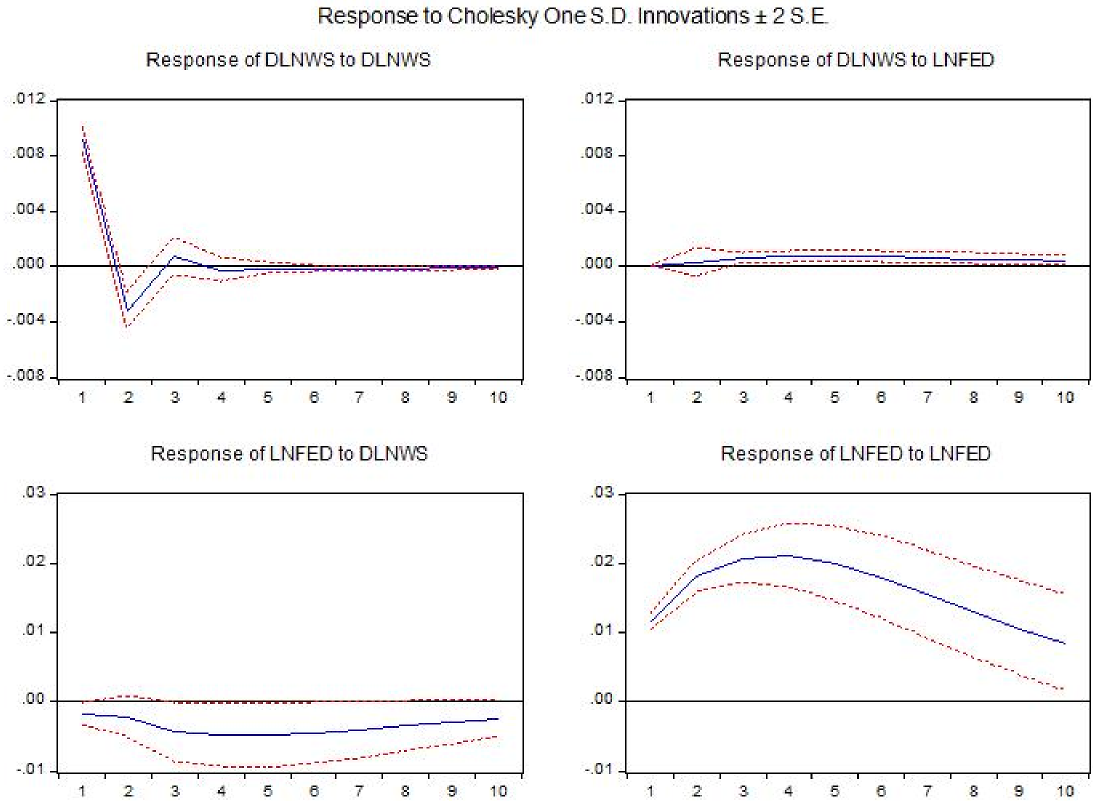
Sample period: 1948 Q1 - 2016 Q4
Model specification: 3 lags and constant term
Variable ordering: Δ ln wage share, Δ ln real GDP

Figure A.3: Complete IRFs for the Real GDP Model



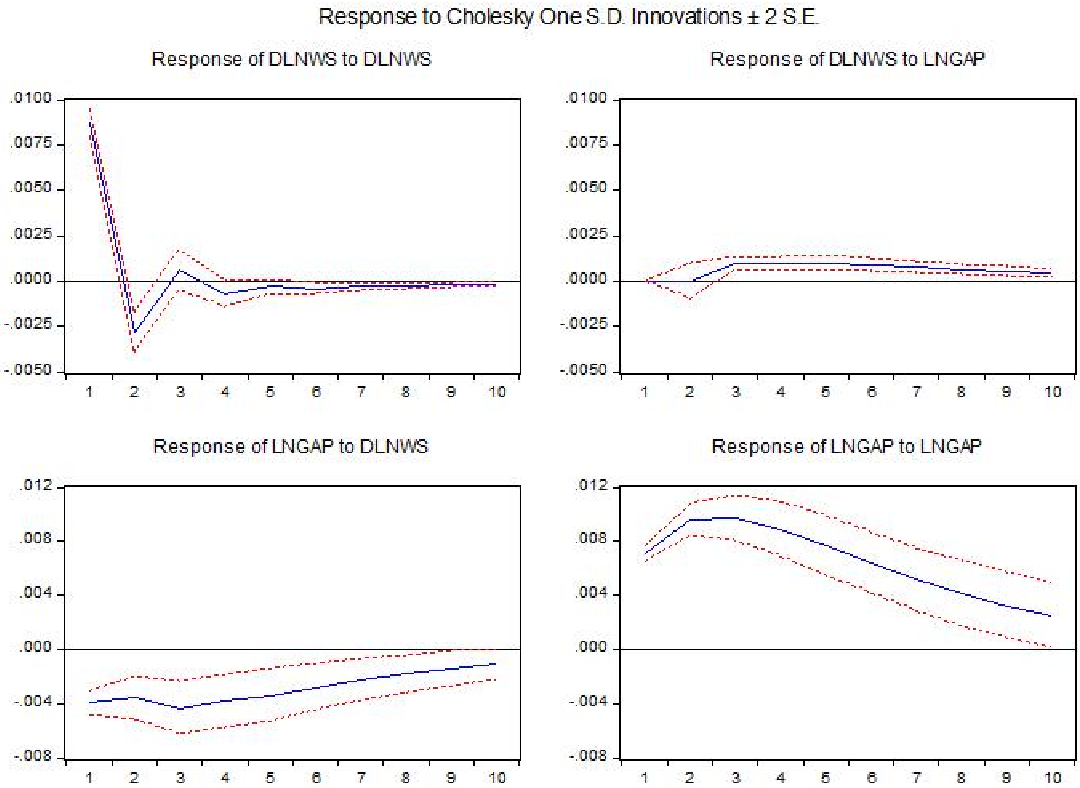
Sample period: 1952 Q1 - 2016 Q4
Model specification: 9 lags and constant term
Variable ordering: Δ ln wage share, Hamilton utilization

Figure A.4: Complete IRFs for the Hamilton Utilization Rate Model



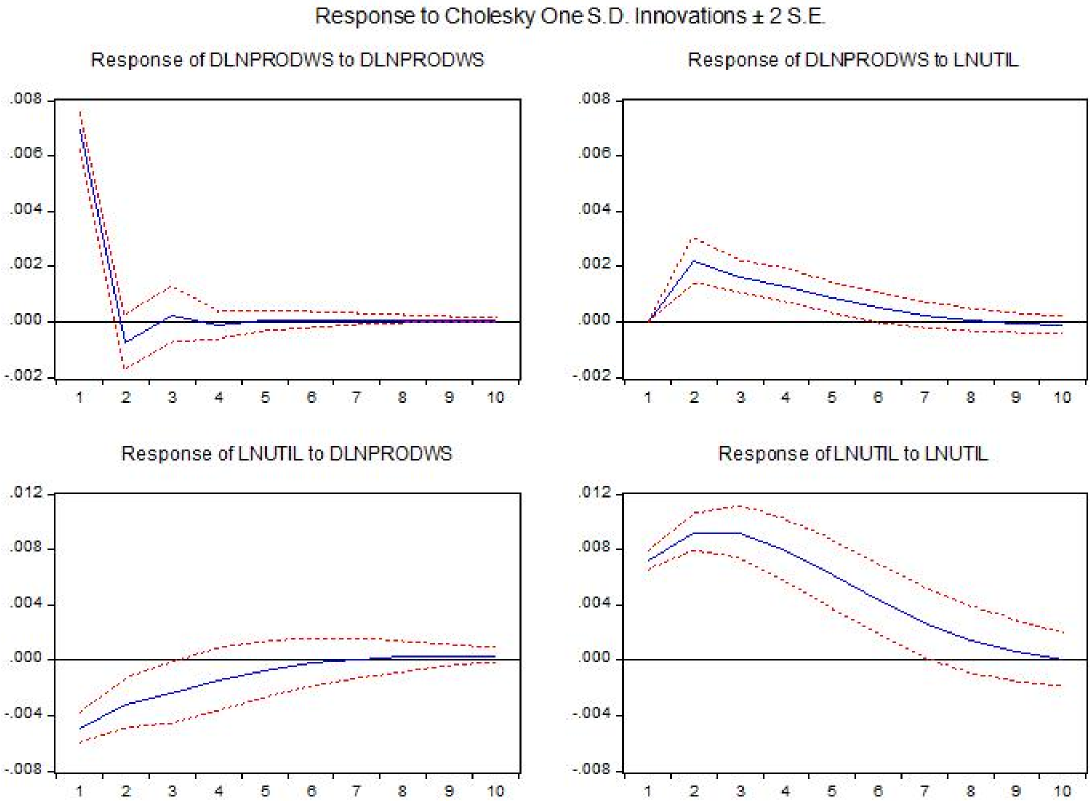
Sample period: 1967 Q3 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln Fed utilization

Figure A.5: Complete IRFs for the Federal Reserve Utilization Rate Model



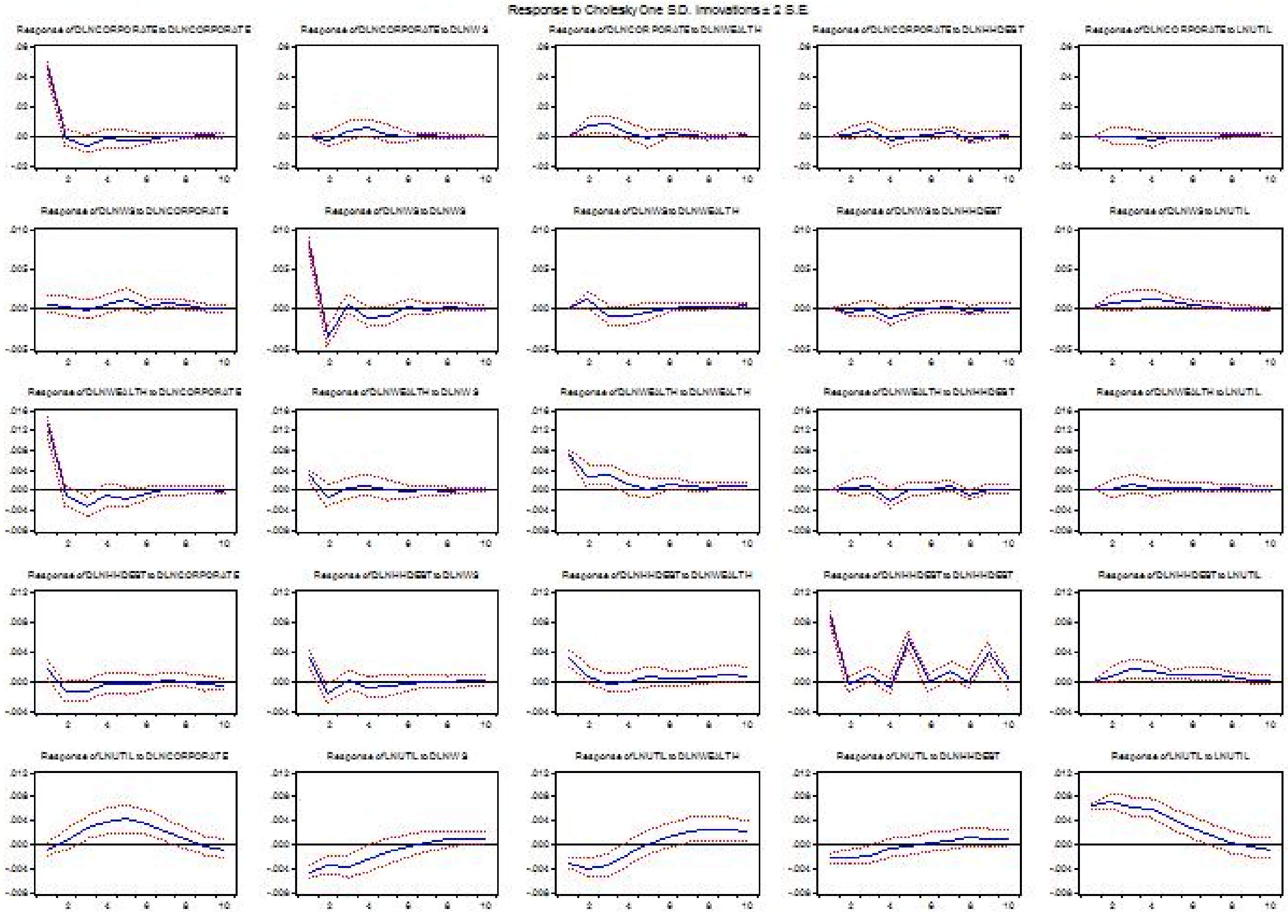
Sample period: 1949 Q3 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln wage share, ln output gap

Figure A.6: Complete IRFs for the Output Gap Model



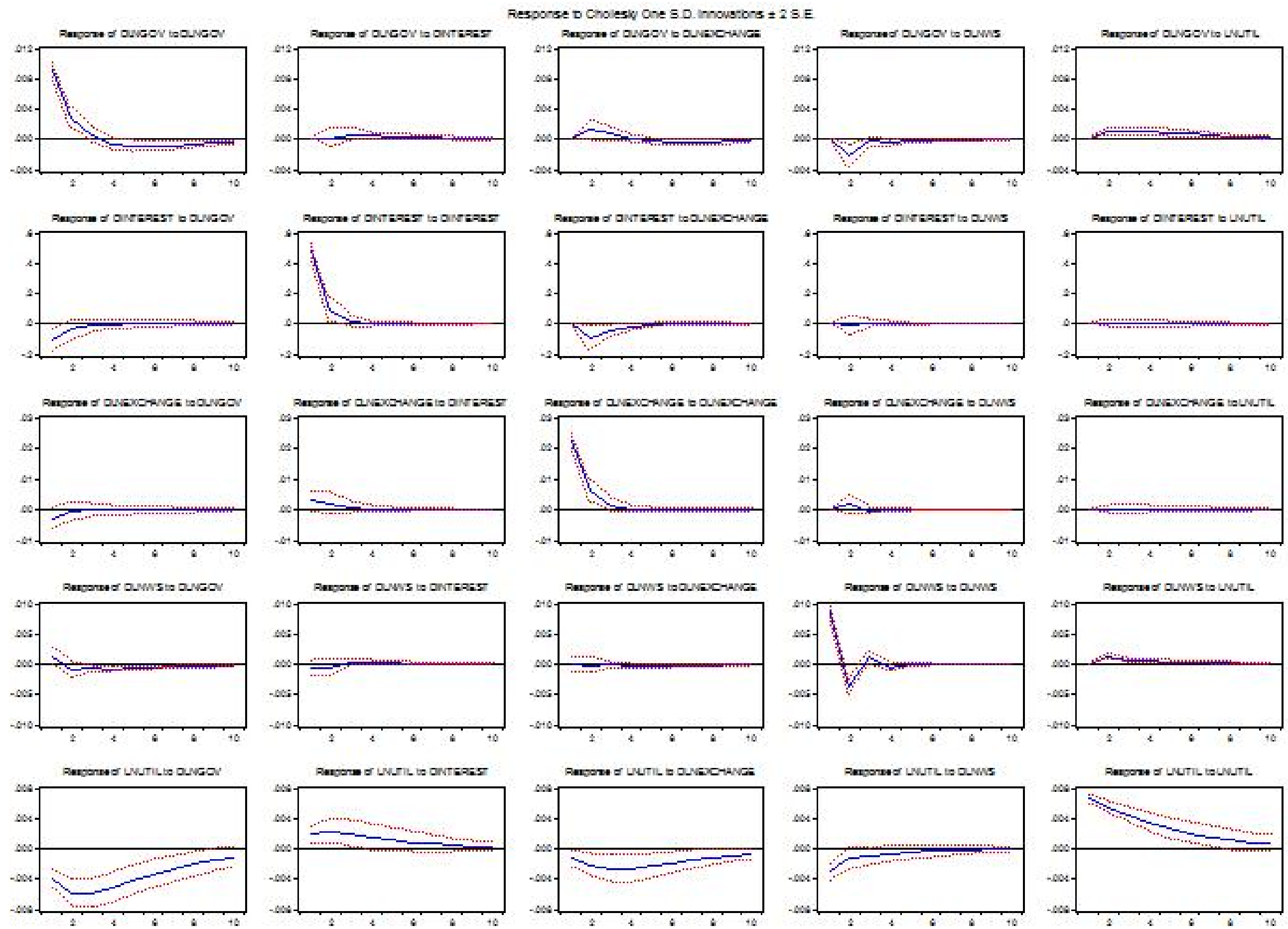
Sample period: 1964 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln production worker wage share, ln HP utilization

Figure A.7: Complete IRFs for the Production Worker Wage Share Model



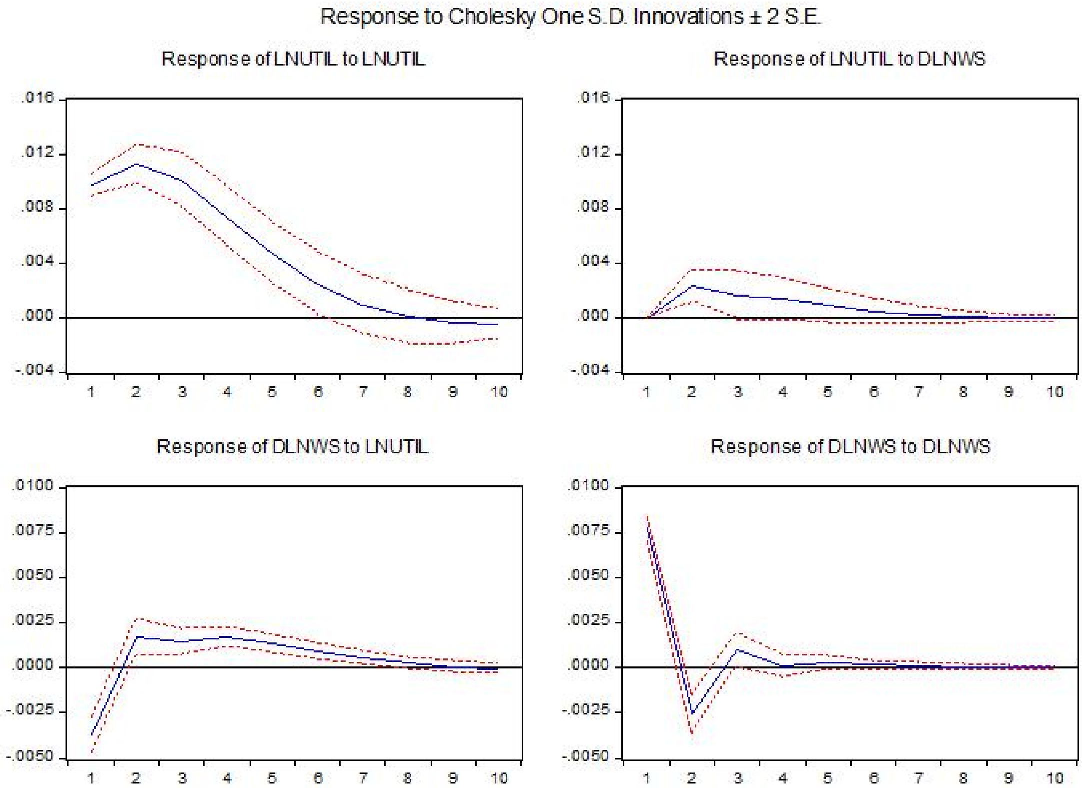
Sample period: 1953 Q2 - 2016 Q4; Model specification: 4 lags and constant term; Variable ordering: Δ ln corporate debt, Δ ln wage share, Δ ln wealth, Δ ln household debt, ln HP utilization

Figure A.8: Complete IRFs for Financial Control Variable Model



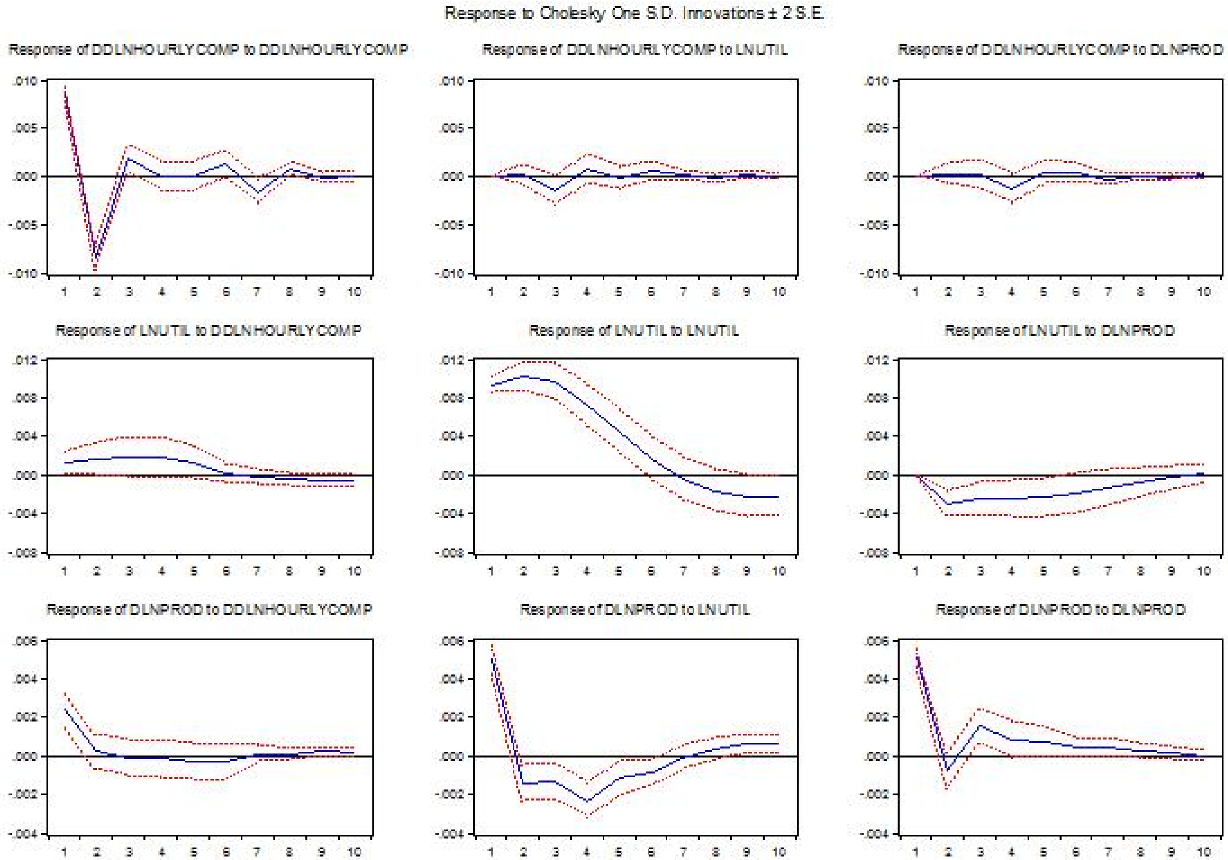
Sample period: 1973 Q3 - 2016 Q4; Model specification: 1 lag and constant term; Variable ordering: Δ ln government spending, Δ interest, Δ ln exchange, Δ ln wage share, ln HP utilization

Figure A.9: Selected IRFs for Macro Policy Control Variable Model



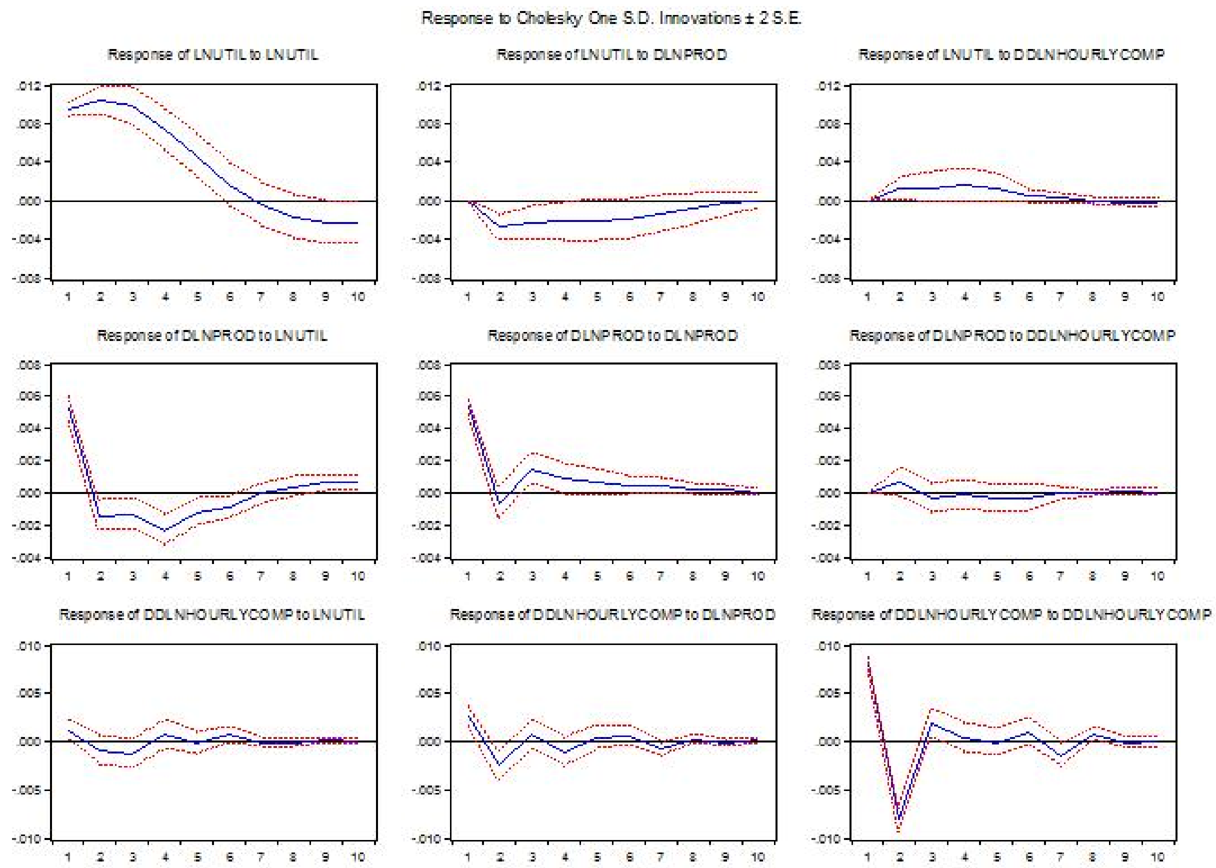
Sample period: 1947 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: ln HP utilization, Δ ln wage share

Figure A.10: Complete IRFs for Model with Reverse Ordering



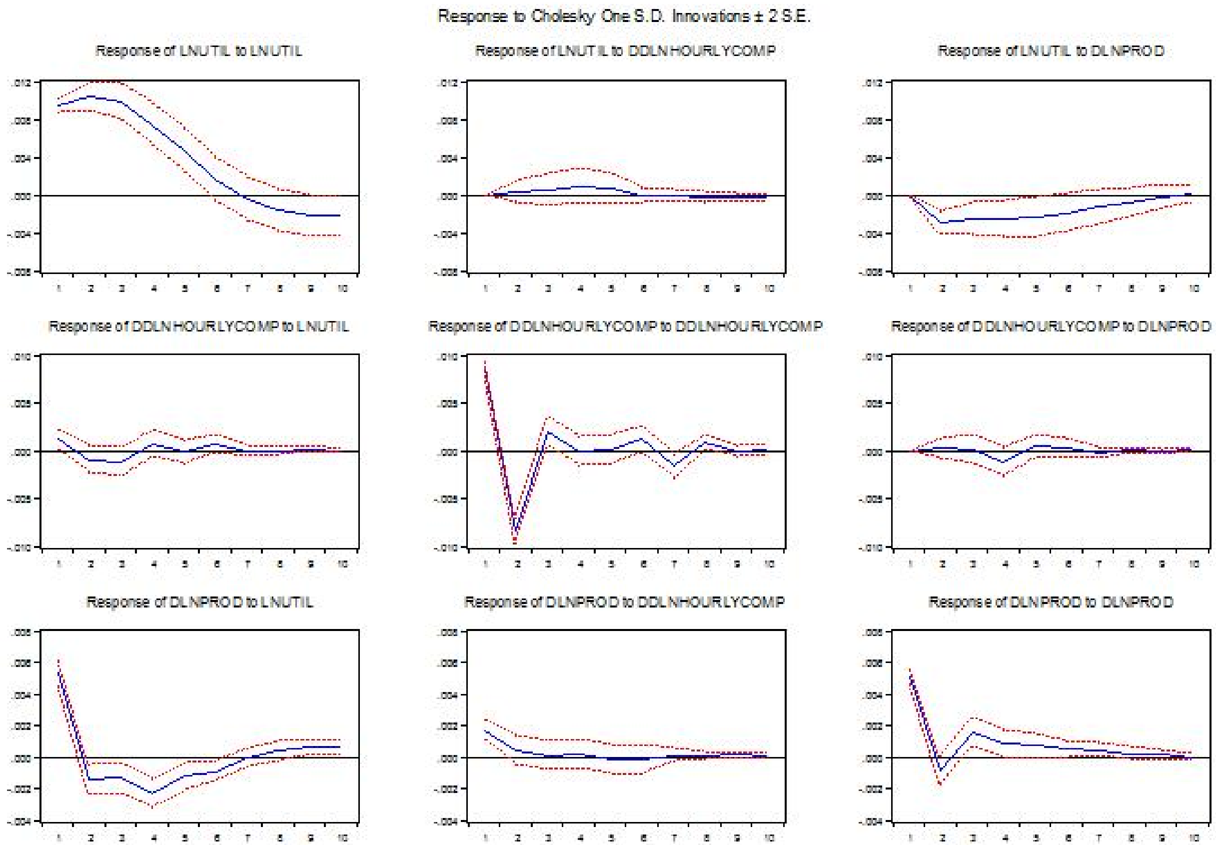
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term; Variable ordering: Δ Δ real hourly wage rate, ln HP utilization, Δ ln productivity

Figure A.11: Complete IRFs for Model Using Order 1



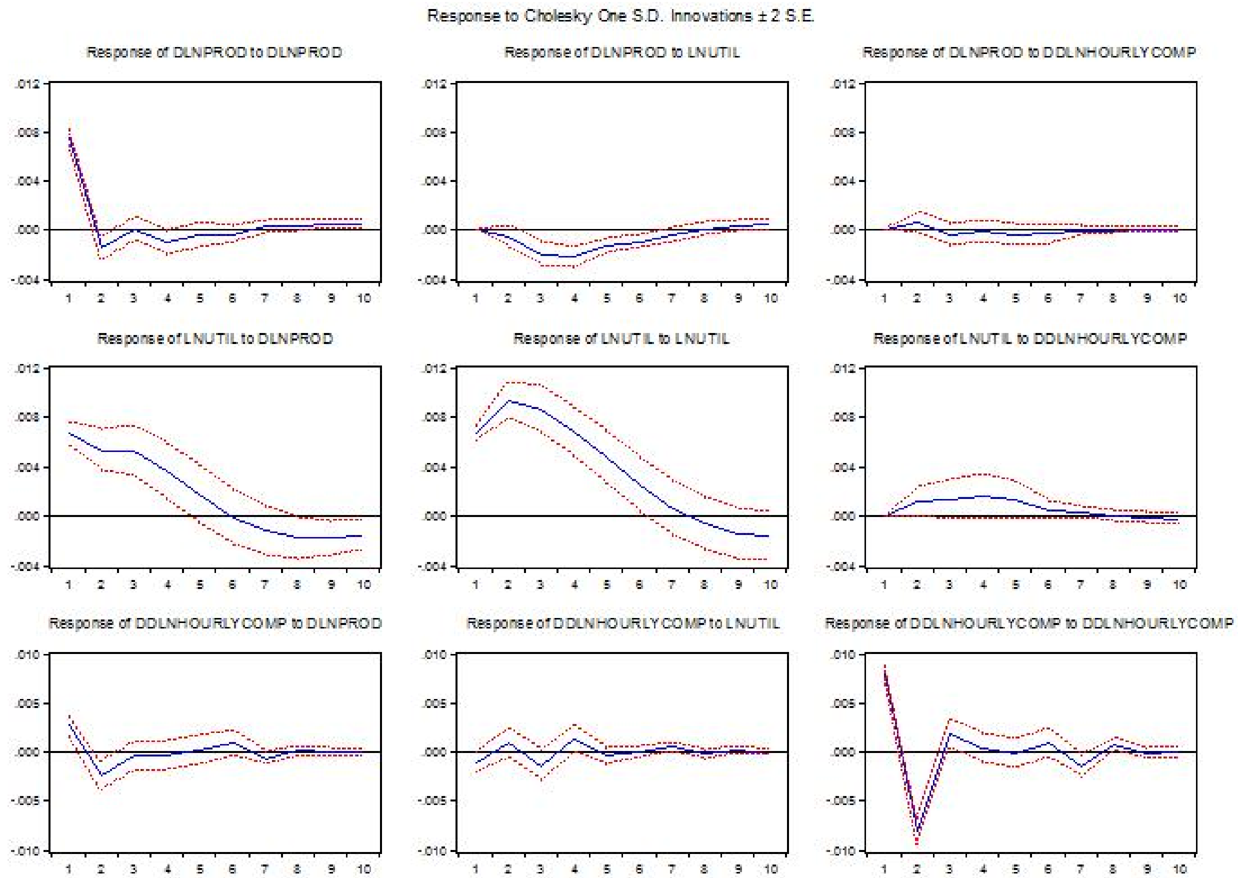
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term; Variable ordering: ln HP utilization, Δ ln productivity, Δ Δ real hourly wage rate

Figure A.12: Complete IRFs for Model Using Order 2



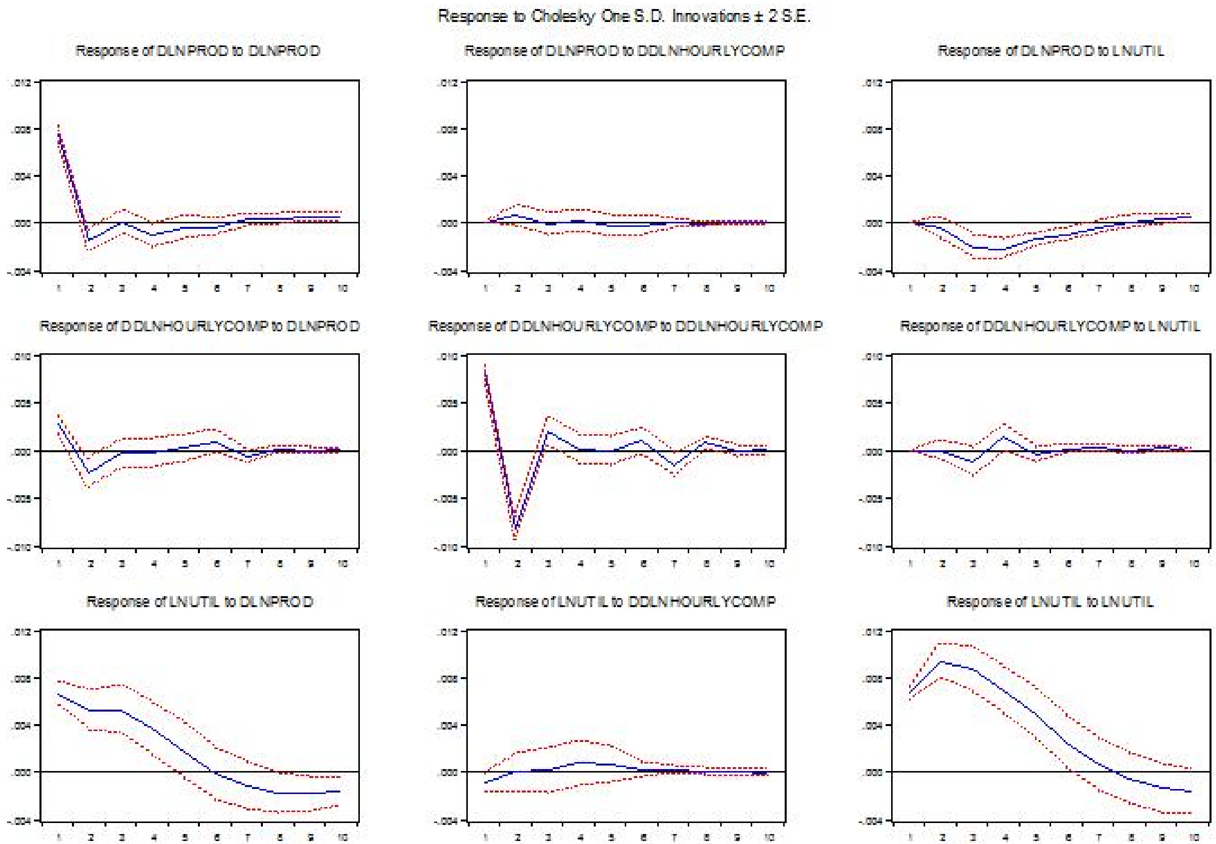
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term; Variable ordering: ln HP utilization, Δ Δ real hourly wage rate, Δ ln productivity

Figure A.13: Complete IRFs for Model Using Order 3



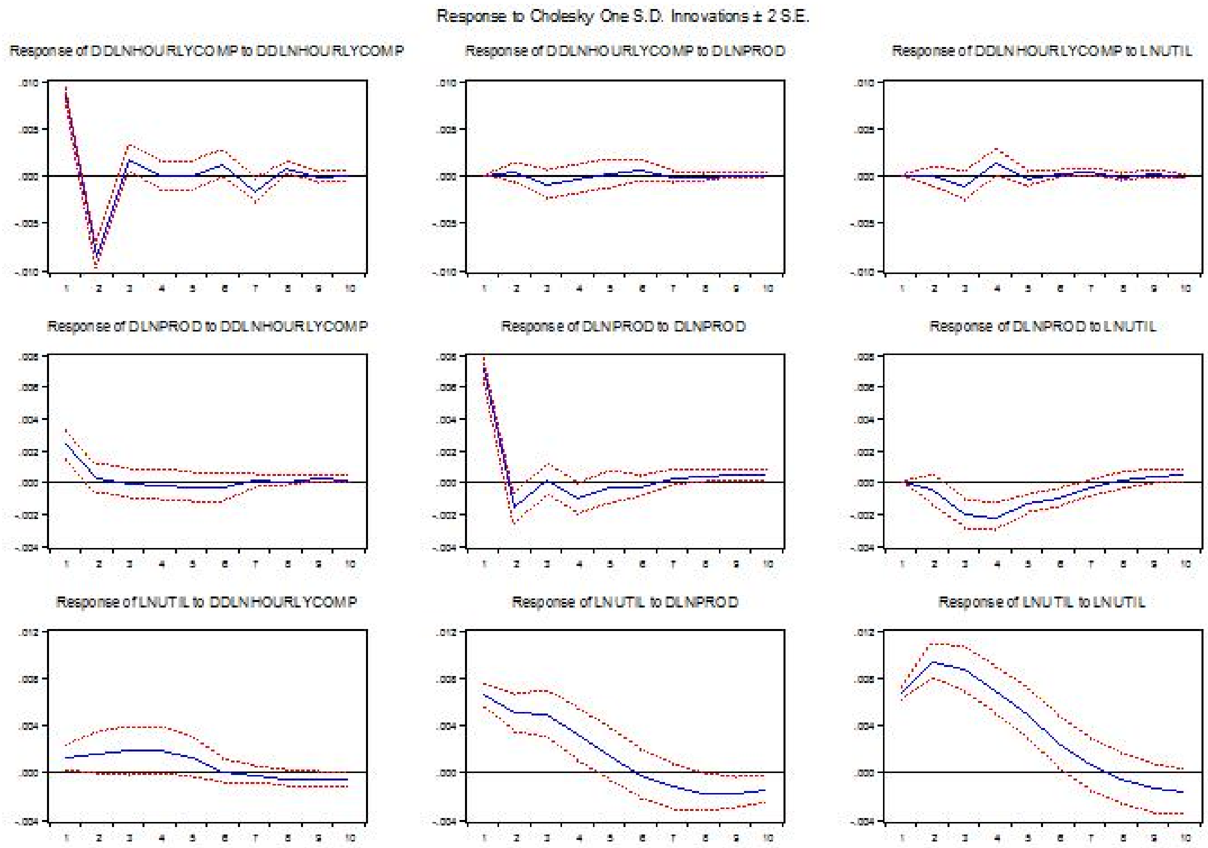
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term; Variable ordering: Δ ln productivity, ln HP utilization, Δ Δ real hourly wage rate

Figure A.14: Complete IRFs for Model Using Order 4



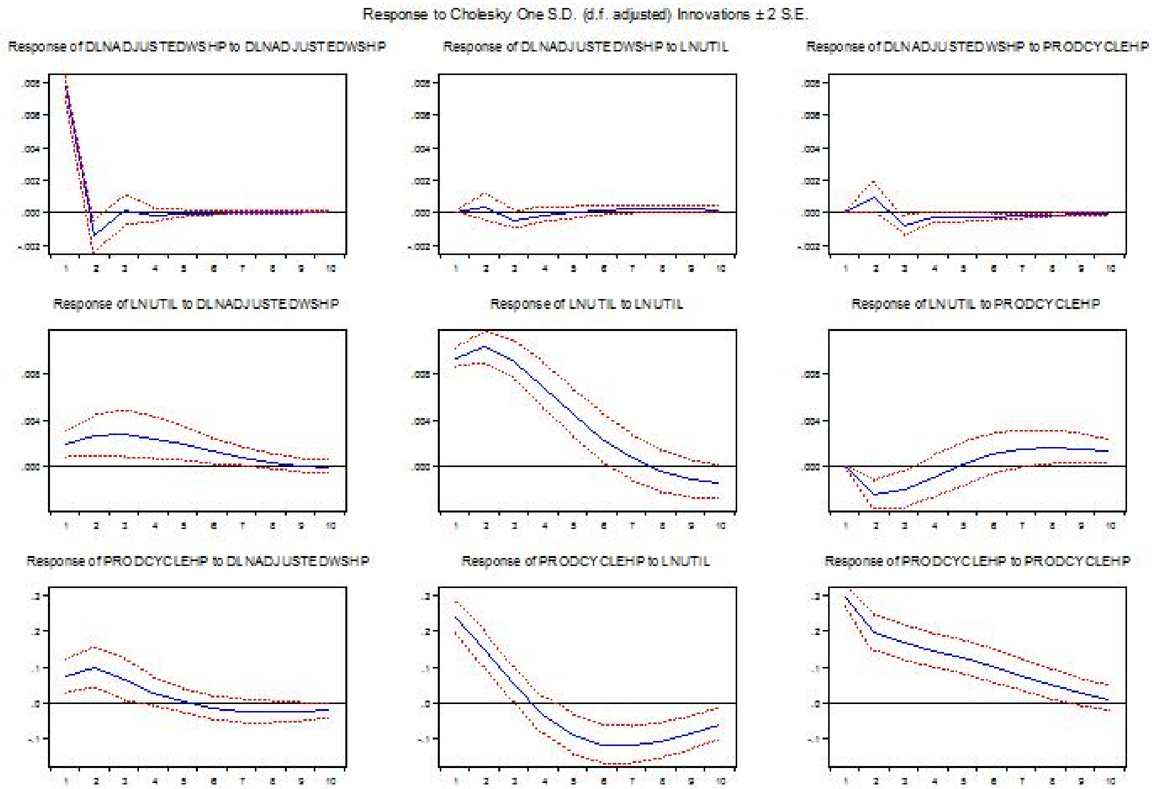
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term; Variable ordering: Δ ln productivity, Δ Δ real hourly wage rate, ln HP utilization

Figure A.15: Complete IRFs for Model Using Order 5



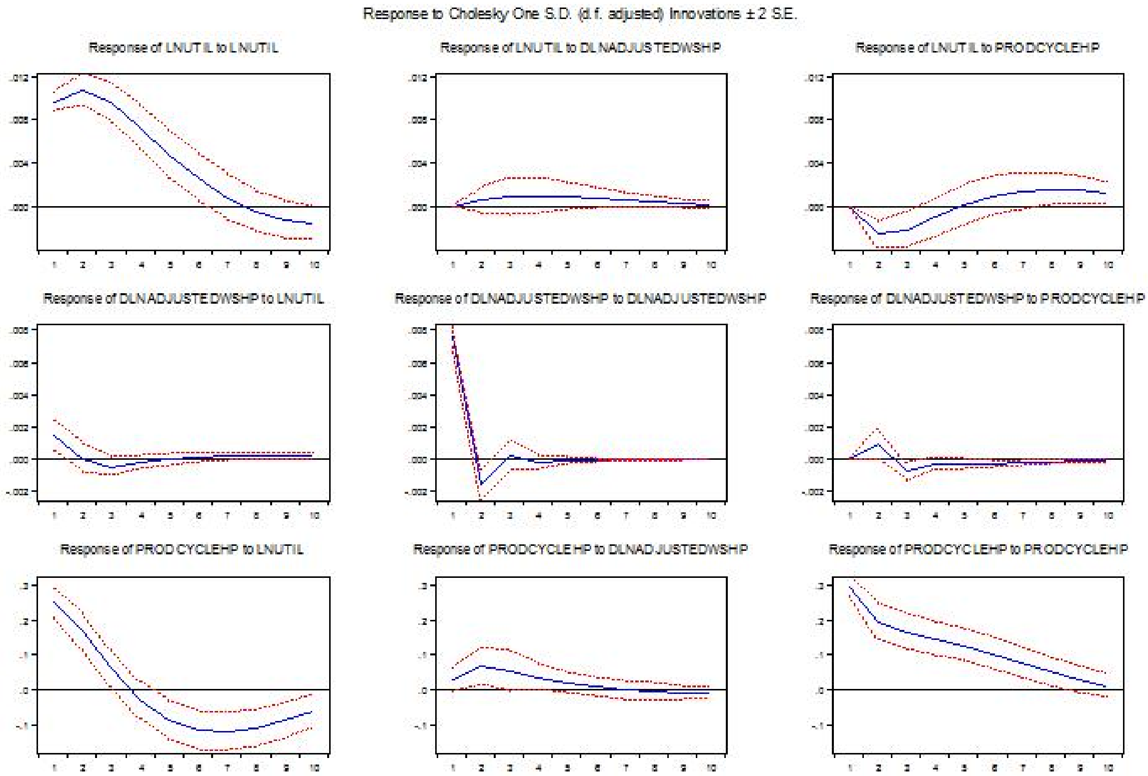
Sample period: 1948 Q3 - 2016 Q4; Model specification: 4 lags and constant term; Variable ordering: Δ Δ real hourly wage rate, Δ ln productivity, ln HP utilization

Figure A.16: Complete IRFs for Model Using Order 6



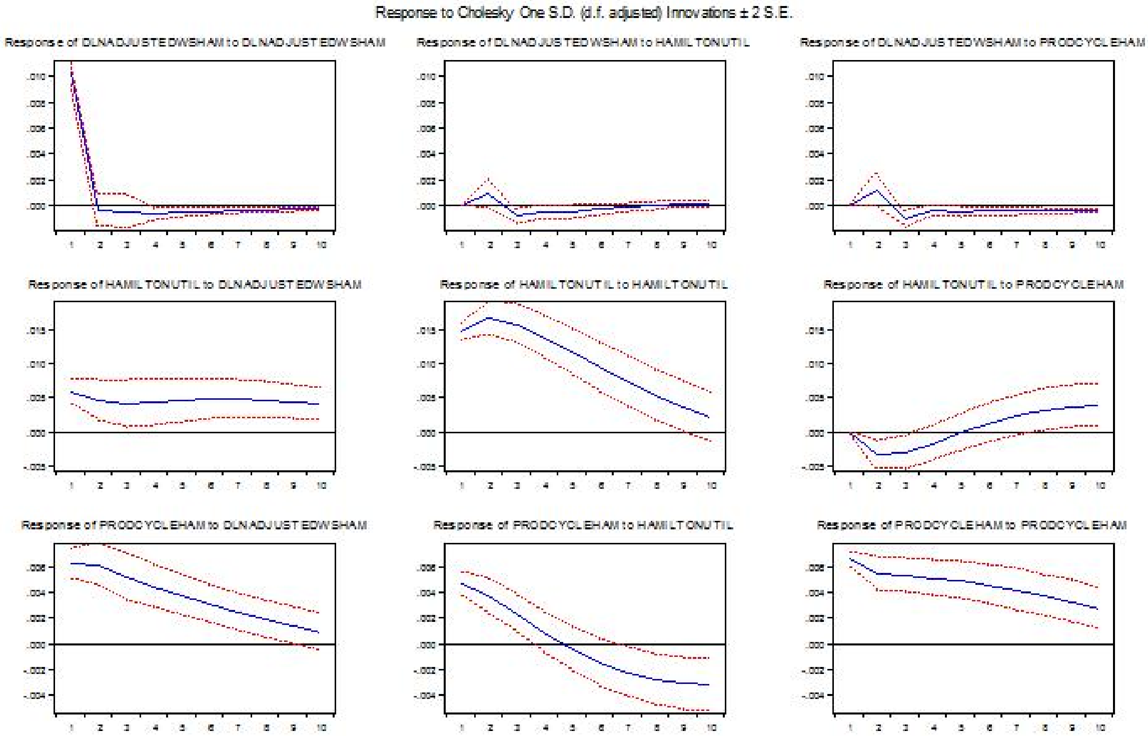
Sample period: 1947 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln HP adjusted wage share, ln HP utilization, HP cyclical component of productivity

Figure A.17: Complete IRFs for the HP Adjusted Wage Share Model



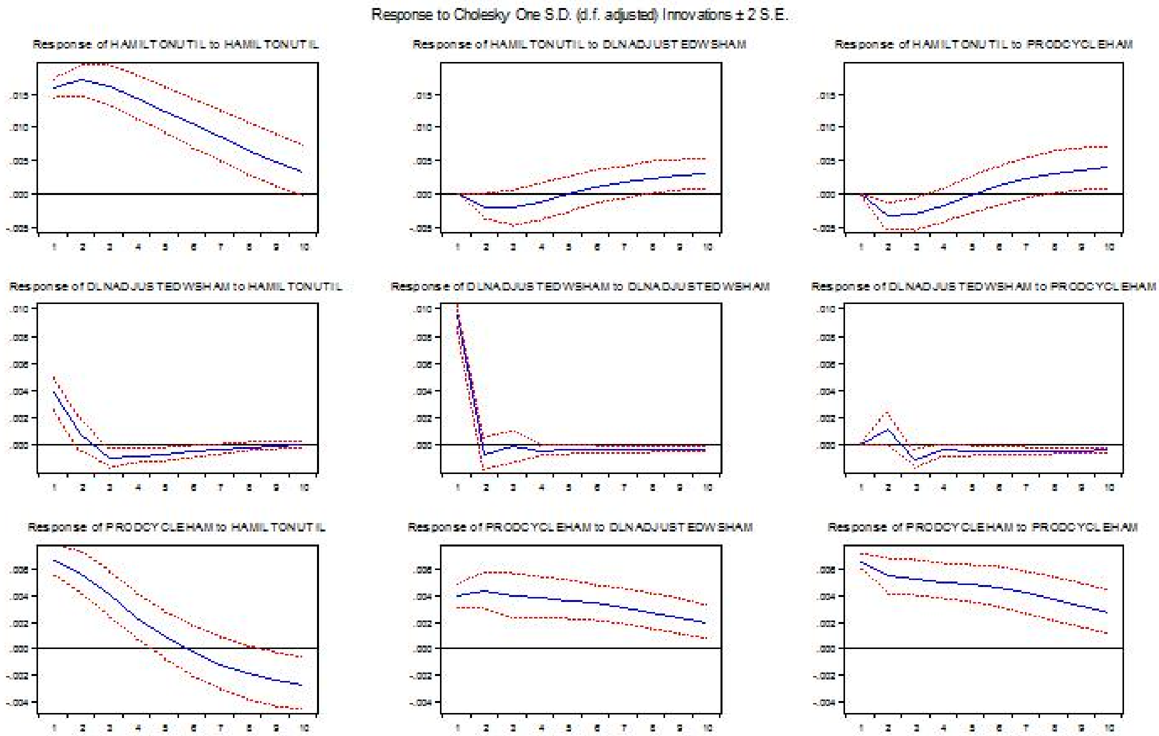
Sample period: 1947 Q4 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: ln HP utilization, Δ ln HP adjusted wage share, HP cyclical component of productivity

Figure A.18: Complete IRFs for the HP Adjusted Wage Share Model with Alternate Ordering



Sample period: 1950 Q3 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Δ ln Hamilton adjusted wage share, Hamilton utilization, Hamilton cyclical component of productivity

Figure A.19: Complete IRFs for the Hamilton Adjusted Wage Share Model



Sample period: 1950 Q3 - 2016 Q4
Model specification: 2 lags and constant term
Variable ordering: Hamilton utilization, Δ ln Hamilton adjusted wage share, Hamilton cyclical component of productivity

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

APPENDIX B

ADDITIONAL TABLES FOR CHAPTER 2

Table B.1: Selected Unit Root Test Results

Variables	Trend	ADF	PP	KPSS	Result
ln GDP	Y	Fail	Fail	Reject 5%	Difference
Δ ln GDP	N	Reject 1%	Reject 1%	Reject 5%	Stationary
ln consumption	Y	Fail	Fail	Reject 5%	Difference
Δ ln consumption	N	Reject 1%	Reject 1%	Reject 10%	Stationary
ln investment	Y	Fail	Fail	Fail	Difference
Δ ln investment	N	Reject 1%	Reject 1%	Fail	Stationary
ln exports	Y	Fail	Fail	Fail	Difference
Δ ln exports	N	Reject 1%	Reject 1%	Fail	Stationary
ln imports	Y	Fail	Fail	Fail	Difference
Δ ln imports	N	Reject 1%	Reject 1%	Fail	Stationary
Interest rate	Y	Fail	Reject 5%	Reject 10%	Stationary
ln corporate debt	Y	Fail	Fail	Reject 10%	Difference

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Table B.1 – continued from previous page

Variables	Trend	ADF	PP	KPSS	Result
Δ ln corporate debt	N	Reject 1%	Reject 1%	Fail	Stationary
ln household debt	Y	Fail	Fail	Reject 10%	Difference
Δ ln household debt	N	Reject 1%	Reject 1%	Fail	Stationary
ln wealth	Y	Fail	Fail	Reject 5%	Difference
Δ ln wealth	N	Reject 1%	Reject 1%	Fail	Stationary
ln wage share	Y	Fail	Fail	Fail	Difference
Δ ln wage share	N	Reject 1%	Reject 1%	Fail	Stationary
ln wages	Y	Fail	Fail	Reject 5%	Difference
Δ ln wages	N	Reject 1%	Reject 1%	Reject 10%	Stationary
ln profits	Y	Fail	Fail	Fail	Difference
Δ ln profits	N	Reject 1%	Reject 1%	Fail	Stationary

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Table B.1 – continued from previous page

Variables	Trend	ADF	PP	KPSS	Result
ln domestic prices	Y	Fail	Fail	Reject 1%	Difference
Δ ln domestic prices	N	Fail	Fail	Reject 10%	Difference
Δ Δ ln domestic prices	N	Reject 1%	Reject 1%	Fail	Stationary
ln export prices	Y	Fail	Fail	Reject 5%	Difference
Δ ln export prices	N	Fail	Reject 5%	Reject 10%	Stationary
ln import prices	Y	Fail	Fail	Reject 5%	Difference
Δ ln import prices	N	Fail	Reject 1%	Fail	Stationary
ln X/M price ratio	Y	Fail	Fail	Reject 5%	Difference

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Table B.1 – continued from previous page

Variables	Trend	ADF	PP	KPSS	Result
Δ ln X/M price ratio	N	Fail	Reject 1%	Fail	Stationary
ln P/M price ratio	N	Fail	Fail	Fail	Difference
Δ ln P/M price ratio	N	Fail	Reject 1%	Fail	Stationary
ln unit labor costs	Y	Fail	Fail	Reject 1%	Difference
Δ ln unit labor costs	Y	Reject 5%	Reject 10%	Reject 10%	Stationary
ln government investment	Y	Fail	Fail	Fail	Difference
Δ ln government investment	N	Reject 5%	Reject 10%	Fail	Stationary

Continued on next page

Table B.1 – continued from previous page

Variables	Trend	ADF	PP	KPSS	Result
ln foreign trade	Y	Fail	Fail	Fail	Difference
Δ ln foreign trade	N	Reject 1%	Reject 1%	Fail	Stationary
ln financial-ization	Y	Fail	Fail	Reject 10%	Difference
Δ ln financial-ization	N	Fail	Reject 1%	Fail	Stationary
ln markup	Y	Fail	Fail	Reject 5%	Difference
Δ ln markup	Y	Reject 1%	Reject 1%	Fail	Stationary
ln foreign income	Y	Fail	Fail	Reject 1%	Difference
Δ ln foreign income	N	Reject 1%	Reject 1%	Reject 1%	Stationary
ln top 5% income share	Y	Fail	Fail	Reject 5%	Difference

Continued on next page

Table B.1 – continued from previous page

Variables	Trend	ADF	PP	KPSS	Result
Δ ln top 5% income share	N	Reject 1%	Reject 1%	Reject 10%	Stationary
ln exchange rate	Y	Fail	Fail	Reject 5%	Difference
Δ ln exchange rate	N	Reject 5%	Reject 5%	Fail	Stationary
ln real exchange rate	Y	Fail	Fail	Fail	Difference
Δ ln real exchange rate	N	Reject 5%	Reject 5%	Fail	Stationary
ln capital intensity	Y	Fail	Fail	Reject 5%	Difference
Δ ln capital intensity	N	Reject 1%	Reject 5%	Fail	Stationary
ln union density	Y	Fail	Fail	Reject 5%	Difference

Continued on next page

Table B.1 – continued from previous page

Variables	Trend	ADF	PP	KPSS	Result
Δ ln union density	N	Reject 5%	Reject 1%	Fail	Stationary
ln credit	Y	Fail	Fail	Fail	Difference
Δ ln credit	N	Reject 1%	Reject 5%	Fail	Stationary
ln nonresidential investment	Y	Fail	Fail	Fail	Difference
Δ ln nonresidential investment	N	Reject 1%	Reject 1%	Fail	Stationary
ln residential investment	Y	Fail	Fail	Fail	Difference
Δ ln residential investment	N	Reject 1%	Reject 1%	Fail	Stationary

Continued on next page

Table B.1 – continued from previous page

Variables	Trend	ADF	PP	KPSS	Result
ln home prices	Y	Fail	Fail	Fail	Difference
Δ ln home prices	N	Reject 5%	Reject 5%	Fail	Stationary
ln business confi- dence	Y	Reject 1%	Reject 1%	Fail	Stationary

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

All unit root tests are conducted using a sample period of 1963-2014.

Table B.2: Variable Definitions and Data Sources

Variable	**Definition**	**Units**	**Source**
Real GDP	Real Gross Domestic Product	Billions of 2009 chained U.S. dollars	BEA*
Consumption	Real personal consumption expenditures	Billions of 2009 chained U.S. dollars	BEA*
Investment	Real gross private domestic investment	Billions of 2009 chained U.S. dollars	BEA*
Exports	Real exports of goods and services	Billions of 2009 chained U.S. dollars	BEA*
Imports	Real imports of goods and services	Billions of 2009 chained U.S. dollars	BEA*
Nominal exchange rate	Nominal effective exchange rate index (narrow-based)	Index, 2007=100	Darvas (2012)
Real exchange rate	Real effective exchange rate index (narrow-based)	Index, 2007=100	Darvas (2012)
Real interest rate	10-year constant maturity rate - average inflation (percentage change in CPI) over previous ten years	Percentage	Fed*, BLS, Author's calculations

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Table B.2 – continued from previous page

Variable	Definition	Units	Source
Corporate debt	Total liabilities and equity of nonfinancial corporate business as a percentage of nominal GDP	Percentage*100	Fed*, Author's calculations
Household debt	Total liabilities of households and nonprofit organizations as a percentage of nominal GDP	Percentage*100	Fed*, Author's calculations
Wealth	Total assets of households and nonprofit organizations as a percentage of nominal GDP	Percentage*100	Fed*, Author's calculations
Nominal GDP	Gross Domestic Product	Billions of Dollars	BEA*
Wages	Wages and salaries plus supplements to wages and salaries, paid, converted to real values using the GDP deflator	Billions of 2009 U.S. dollars	BEA NIPA Table 1.10, line 2
Wage share	100*wages / nominal GDP	Percentage*100	BEA, Author's calculations
Profits	Gross operating surplus; net operating surplus + private consumption of fixed capital, converted to real values using GDP deflator	Billions of 2009 U.S. dollars	NIPA table 1.10, lines 9 and 22, Author's calculations
Domestic price level	Implicit price deflator for Gross Domestic Product	Index, 2009=100	BEA NIPA 1.1.4, line 1
Import price level	Implicit price deflator for imports of goods and services	Index, 2009=100	BEA NIPA 1.1.4, line 16

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Table B.2 – continued from previous page

Variable	Definition	Units	Source
Export price level	Implicit price deflator for exports of goods and services	Index, 2009=100	BEA NIPA 1.1.4, line 19
X/M price ratio	Export price level / import price level	Index, 2009=100	BEA, Author's calculations
P/M price ratio	Domestic price level / import price level	Index, 2009=100	BEA, Author's calculations
Nominal unit labor costs	Wage share * domestic price level	Index	BEA, Author's calculations
Government investment	Gross government investment, converted to real values using the implicit price deflator for gross government investment	Billions of 2009 U.S. dollars	BEA NIPA Table 3.9.5 line 3, BEA NIPA Table 3.9.4 line 3, Author's calculations
Foreign income	OECD GDP - U.S. GDP (volume estimates, fixed PPPs), OECD's average of quarterly series	Millions of 2010 U.S. dollars	BEA, Author's calculations Author's calculations
Foreign trade	[(World GDP * World trade / World GDP) - (U.S. GDP * U.S. trade / U.S. GDP)] / (World GDP - U.S. GDP)	Percentage*100	World Bank, Author's calculations Author's calculations

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Table B.2 – continued from previous page

Variable	Definition	Units	Source
Size of financial sector	100*National income without capital consumption adjustment for FIRE industry / Nominal GDP	Percentage*100	BEA*, NIPA Table 6.1B Line 16, 6.1C Line 16, 6.1D Line 15, Author's calculations
Markup	Average markup, weighted by market share of sales	Percentage	De Loecker and Eeckhout (2017)
Top 5% income share	Share of pre-tax national income for 95th to 100th percentiles	Percentage	World Inequality Database
Capital Intensity	(1,000,000*Capital stock at constant national prices) / (1,000*annual average of civilian labor force)	2011 U.S. dollars per person	University of Groningen and University of California Davis*, BLS*, Author's calculations
Union density	100*Union members / Employees	Percentage*100	OECD Statistics

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Table B.2 – continued from previous page

Variable	Definition	Units	Source
Volume of banking credit	Bank credit at all commercial banks, annual average of monthly series, deflated using GDP deflator	Billions of 2009 U.S. dollars	Federal Reserve*
Residential investment	Private, fixed residential investment, deflated by price index for private, fixed residential investment	Billions of 2009 U.S. dollars	NIPA tables 5.3.4 and 5.3.5, line 20, Author's calculations
Nonresidential investment	Private, fixed nonresidential investment, deflated by price index for private, fixed nonresidential investment	Billions of 2009 U.S. dollars	NIPA tables 5.3.4 and 5.3.5, line 2, Author's calculations
Home prices	Residential property price index for new one-family houses, annual average of quarterly series, deflated with GDP deflator	Index, 2005=100 (new scale after deflating)	Bank for International Settlements, Author's calculations
Business confidence	Confidence indicator from business tendency surveys for manufacturing	Index, full series average = 100	OECD*

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

Table B.3: Sample Means Used to Calculate Marginal Effects

Series	**Sample Mean**
C/R	1.891
C/W	1.152
I/W	0.270
X/Y	0.073
M/Y	0.092
ψ	55.551
C/Y	0.638
I/Y	0.150
ULC/ψ	61.070
NI/W	0.196
RI/W	0.095
ULC	33.707

Table B.4: OG Model Export Price Cointegrating Regression Estimates

Dependent Variable: $ln\ Export\ Prices_t$

Variable	**Fully Modified Least Squares**
Constant	0.655***
	(0.101)
$ln\ ULC_t$	0.101***
	(0.023)
$\Delta\ ln\ Import\ Prices_t$	0.670***
	(0.022)
R^2	0.998
Adjusted R^2	0.998
N	52

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

Table B.5: Complete Wage Share Equation Estimates

Dependent Variable: $\Delta\ ln\ Wage\ Share_t$

Variable	**OLS**
Constant	1.273
	(0.897)
$\Delta\ ln\ Wage\ Share_{t-1}$	0.167
	(0.129)
$\Delta\ ln\ GDP_t$	-0.023
	(0.104)
$\Delta\ ln\ GDP_t t-1$	0.306***
	(0.069)
$\Delta\ ln\ Foreign\ Trade_t$	0.020
	(0.027)
$\Delta\ ln\ Foreign\ Trade_{t-1}$	-0.071**
	(0.029)
$\Delta\ ln\ Capital\ Intensity_t$	-0.591***
	(0.206)
$\Delta\ ln\ Capital\ Intensity_{t-1}$	0.535***
	(0.195)
$ln\ Business\ Confidence_t$	-0.278
	(0.195)
$\Delta\ ln\ Financialization_t$	-0.002
	(0.040)
$\Delta\ ln\ Union\ Density_t$	0.044
	(0.072)
$\Delta\ ln\ Real\ Exchange\ Rate_t$	0.015
	(0.034)
$\Delta\ ln\ Markup_t$	-0.084
	(0.077)
$\Delta\ ln\ Markup_{t-1}$	0.127*
	(0.074)
R^2	0.611
Adjusted R^2	0.474
Schwarz Criterion	-6.173
N	51
Maximum Lag Length	2

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

Table B.6: Complete ULC Equation Estimates

Dependent Variable: $\Delta\ ln\ ULC_t$

Variable	**OLS**
$\Delta\ ln\ ULC_{t-1}$	0.774***
	(0.062)
$\Delta\ ln\ GDP_t$	-0.150*
	(0.078)
$\Delta\ ln\ GDP_t t-1$	0.499***
	(0.070)
$\Delta\ ln\ Capital\ Intensity_t$	-0.605***
	(0.209)
$ln\ Business\ Confidence_t$	0.001
	(0.001)
$\Delta\ ln\ Financialization_t$	-0.015
	(0.044)
$\Delta\ ln\ Union\ Density_t$	0.001
	(0.079)
$\Delta\ ln\ Real\ Exchange\ Rate_t$	-0.072**
	(0.033)
$\Delta\ ln\ Foreign\ Trade_t$	0.159***
	(0.031)
R^2	0.872
Adjusted R^2	0.848
Schwarz Criterion	-6.000
N	52
Maximum Lag Length	2

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ Standard errors in parentheses

APPENDIX C

ADDITIONAL TABLES AND FIGURES FOR CHAPTER 3

Table C.1: Selected Unit Root Test Results

Variables	Trend	ADF	PP	KPSS	Result
Output gap	N	Reject 1%	Reject 1%	Reject 1%	Stationary
ln real GDP	Y	Fail	Fail	Fail	Difference
Δ ln real GDP	N	Reject 1%	Reject 1%	Reject 1%	Stationary
ln wage share	Y	Fail	Fail	Fail	Difference
ln wage share	N	Reject 5%	Reject 10%	Reject 5%	Stationary
Δ ln wage share	N	Reject 1%	Reject 1%	Reject 1%	Stationary
ln cyclically adjusted wage share	Y	Fail	Fail	Fail	Difference
ln cyclically adjusted wage share	N	Reject 1%	Reject 1%	Reject 1%	Stationary
Δ ln cyclically adjusted wage share	N	Reject 1%	Reject 1%	Reject 1%	Stationary
ln productivity	Y	Fail	Fail	Fail	Difference
Δ ln productivity	N	Reject 1%	Reject 1%	Reject 1%	Stationary
ln real wage	Y	Fail	Fail	Fail	Difference
Δ ln real wage	N	Reject 1%	Reject 1%	Reject 1%	Stationary

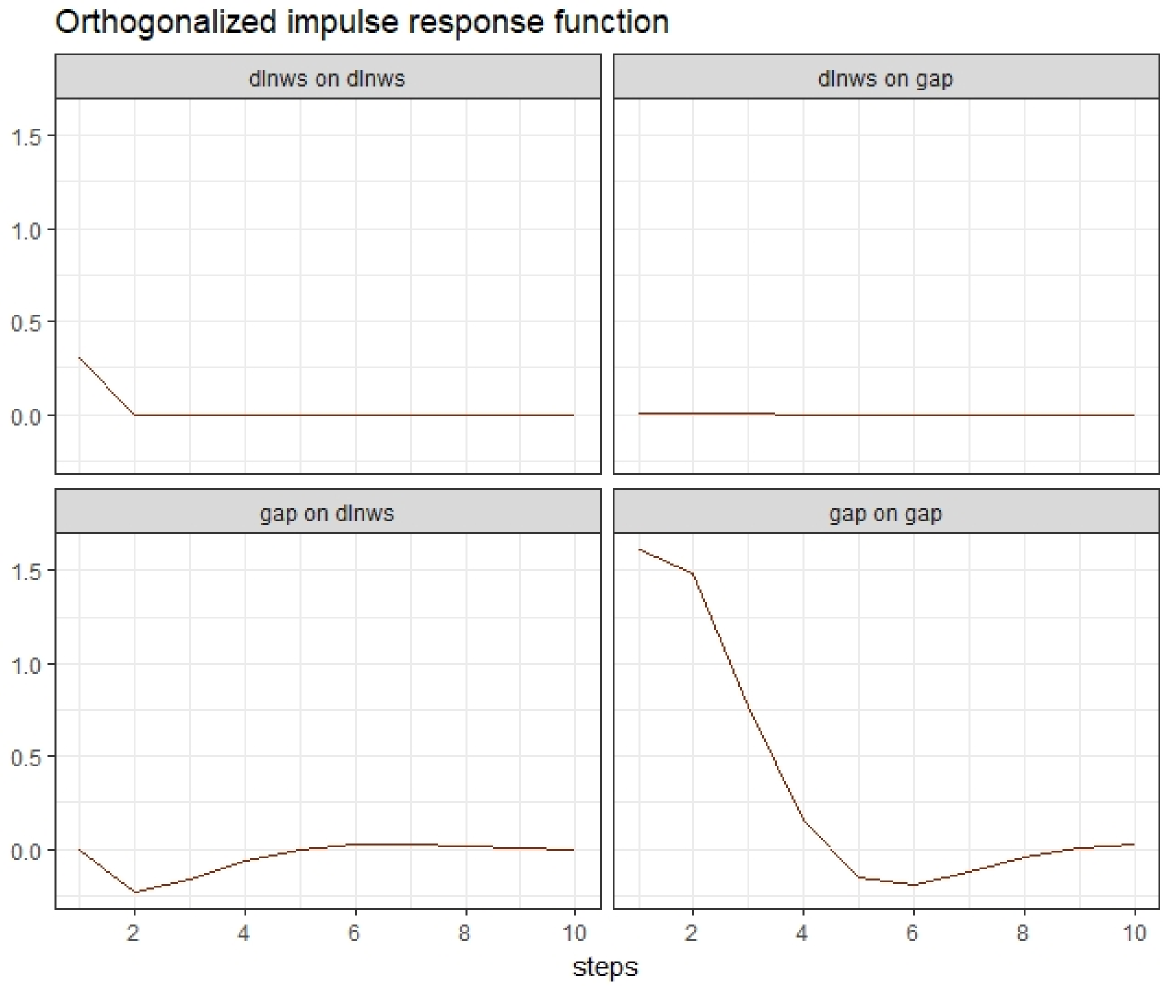
Null hypotheses: IPS Test – Unit Root, ADF Test – Unit Root, PP Test – Unit Root

All unit root tests are conducted on quarterly data for the period 1979 Q1 - 2013 Q4.

Table C.2: Variable Definitions and Data Sources

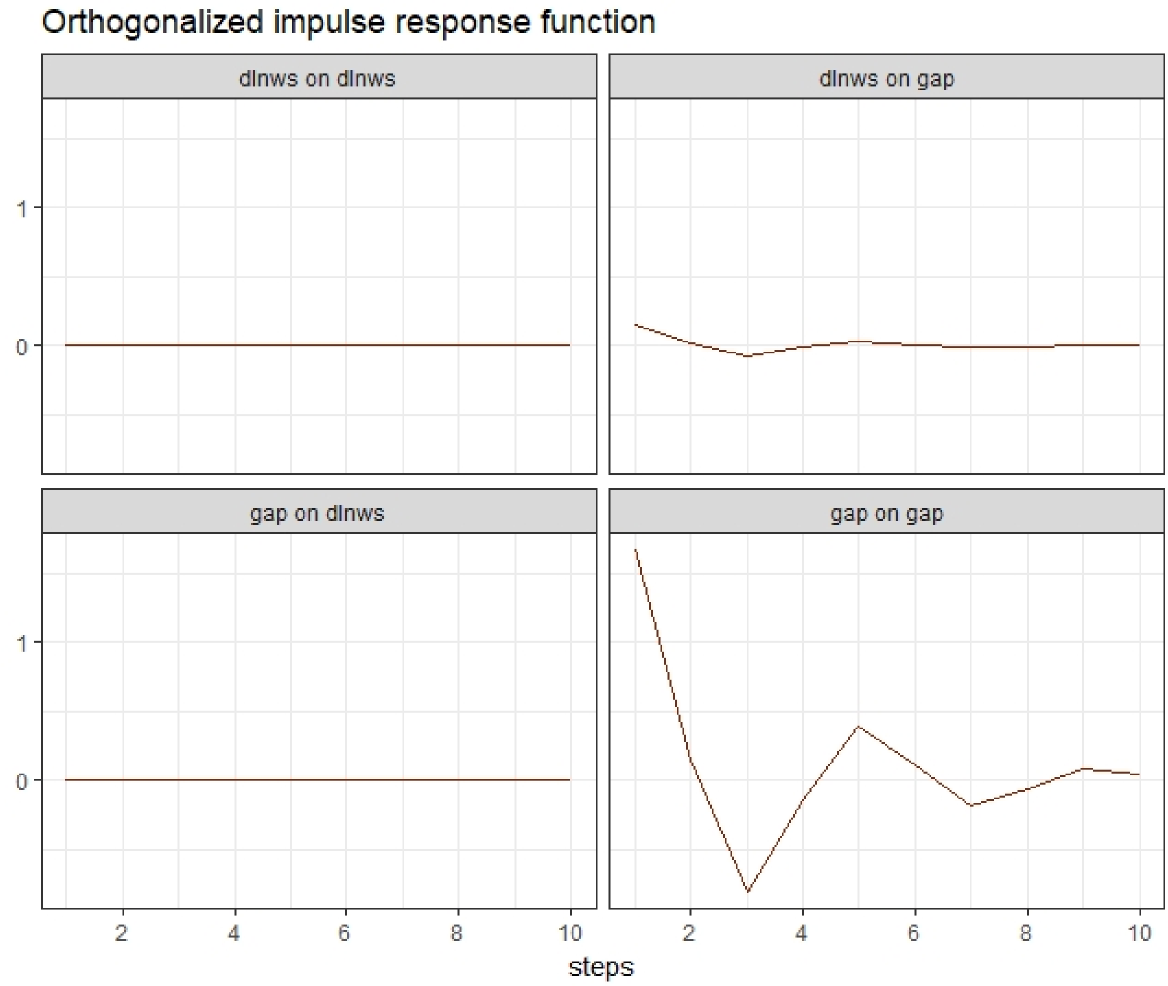
Variable	Definition	Units	Source
Output gap	(output - potential output) / potential output	Percentage	OECD iLibrary Economic Outlook No. 90 (Edition 2011/2)
Real GDP	GDP at constant prices, constant PPP	2010 U.S. Dollars	OECD iLibrary Economic Outlook No. 102 (Edition 2017/2)
Unit labor costs	Nominal unit labor costs	Index, 2010=1	OECD iLibrary Economic Outlook No. 102 (Edition 2017/2)
GDP deflator	GDP deflator at market prices	Index, 2010=1	OECD iLibrary Economic Outlook No. 102 (Edition 2017/2), rescaled by author
Wage share	Unit labor costs / GDP deflator	Index, 2010=1	OECD, author's calculations
Labor productivity	Real gross domestic product (volume, market prices) / total employment (national account basis)	Index, 2010=1	OECD iLibrary Economic Outlook No. 102 (Edition 2017/2)

Calculation of the cyclically adjusted wage share and real wage rate series are discussed in Section 3.3.1



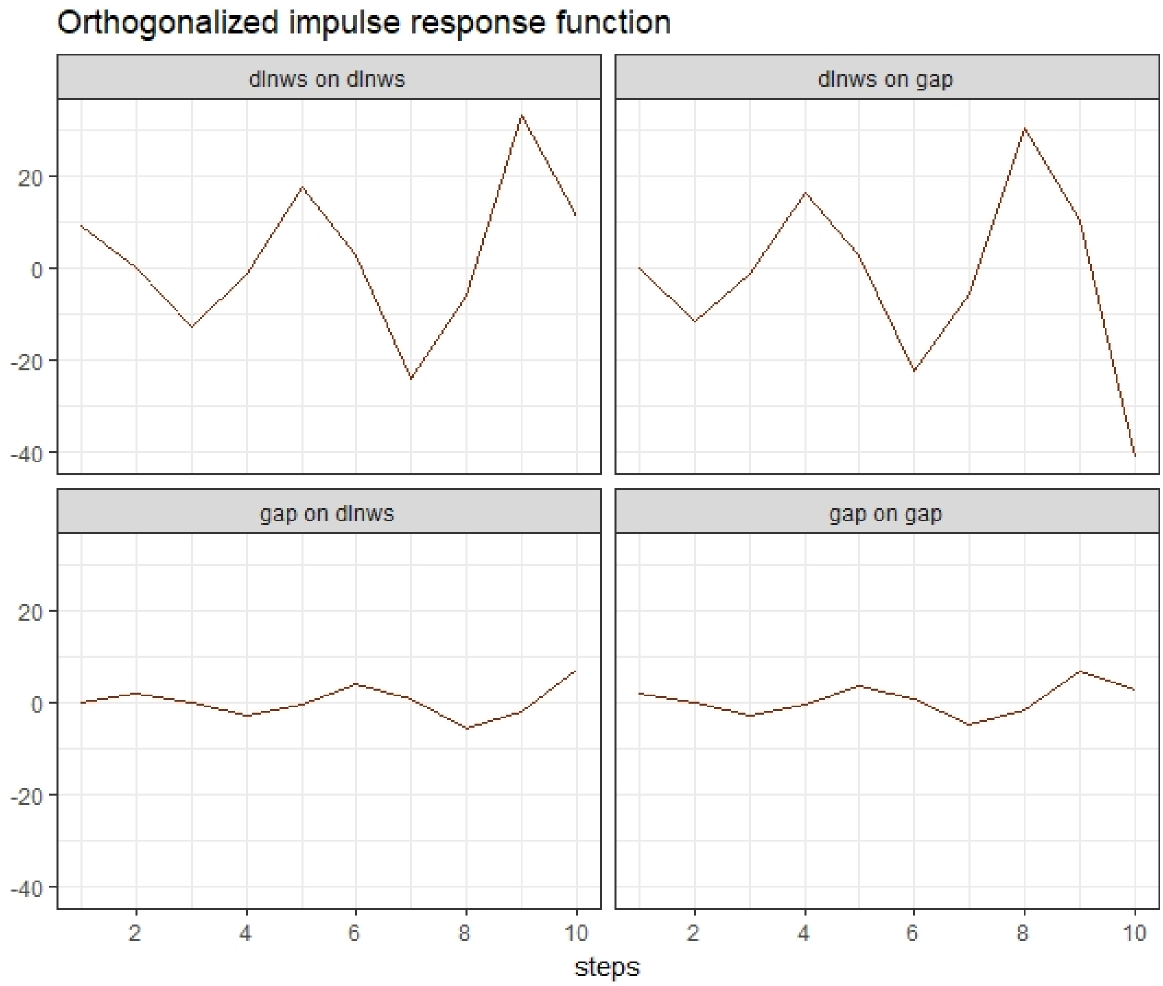
Sample period: 1979 Q1 - 2013 Q4
Lag length: 2
Variable ordering: Δ ln wage share, output gap
Frequency: Annual Maximum number of instruments: 10
Clockwise: Effect of Δ ln wage share on Δ ln wage share, effect of Δ ln wage share on output gap, effect of output gap on Δ ln wage share, effect of output gap on output gap

Figure C.1: Annual IRFs for the Wage Share - Output Gap Model



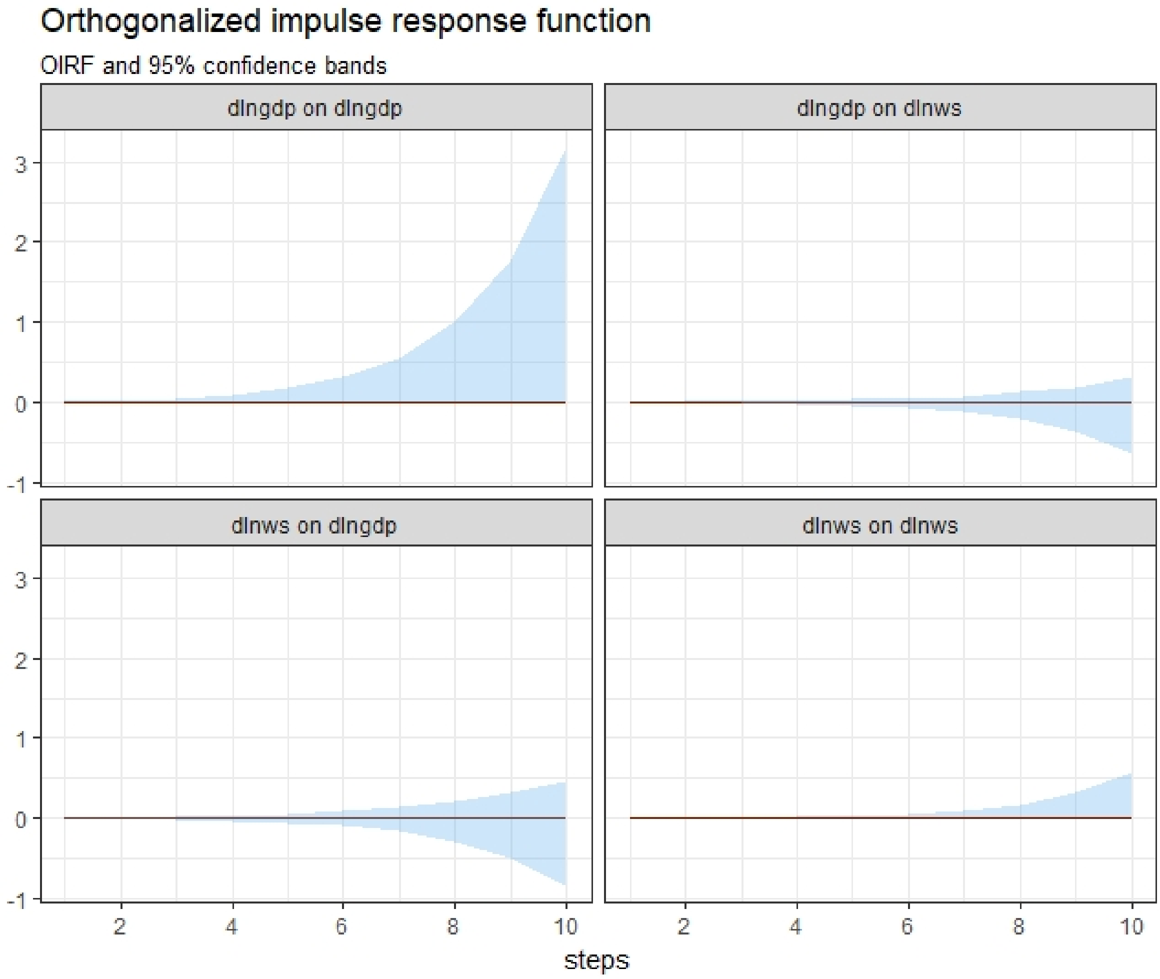
Sample period: 1979 Q1 - 2013 Q4
Lag length: 2
Variable ordering: Δ ln wage share, output gap
Frequency: Three-year averages
Maximum number of instruments: 5
Clockwise: Effect of Δ ln wage share on Δ ln wage share, effect of Δ ln wage share on output gap, effect of output gap on Δ ln wage share, effect of output gap on output gap

Figure C.2: Three-year IRFs for the Wage Share - Output Gap Model



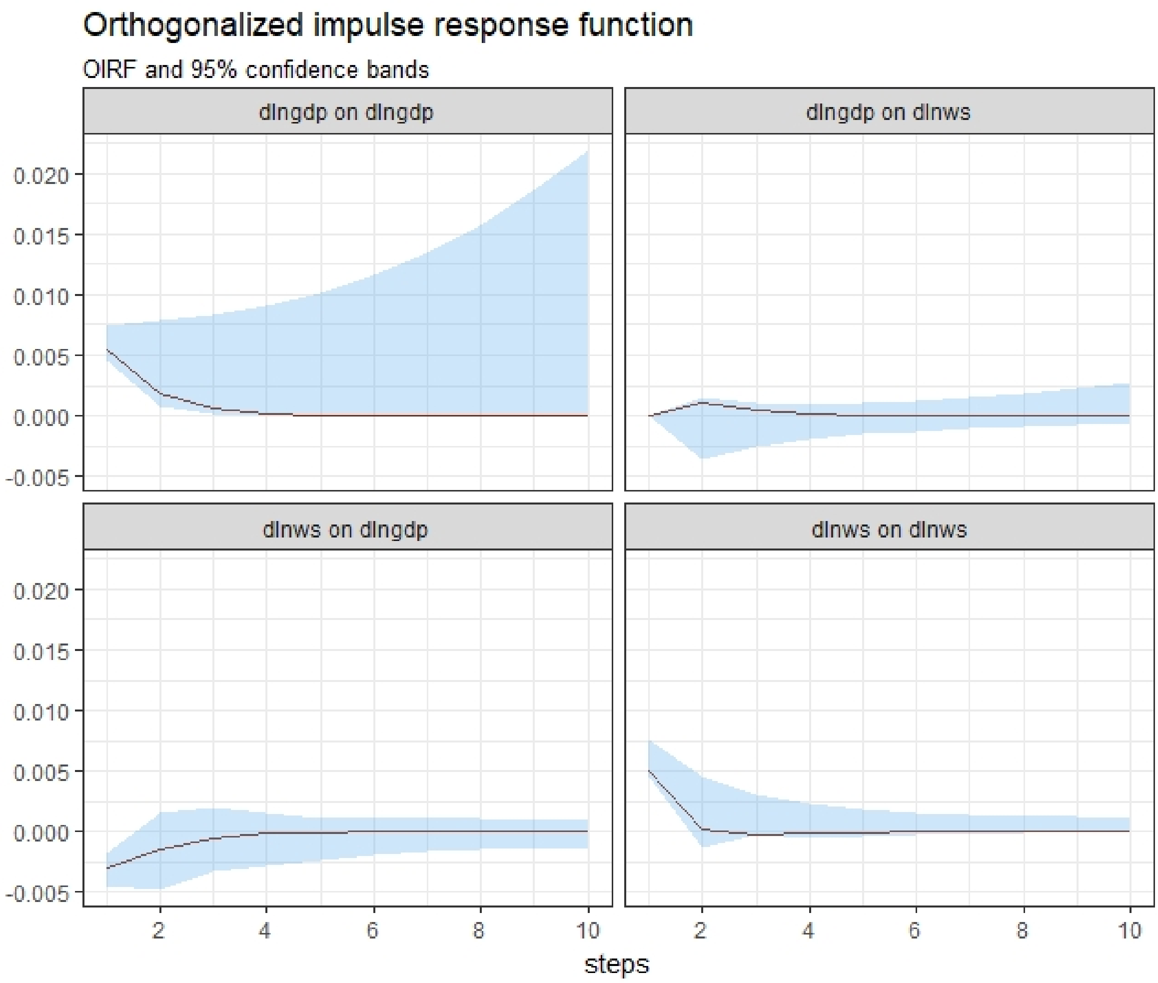
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln wage share, output gap
Frequency: Three-year averages
Maximum number of instruments: 10
Clockwise: Effect of Δ ln wage share on Δ ln wage share, effect of Δ ln wage share on output gap, effect of output gap on Δ ln wage share, effect of output gap on output gap

Figure C.3: Three-year IRFs for the Wage Share - Output Gap Model with More Instruments



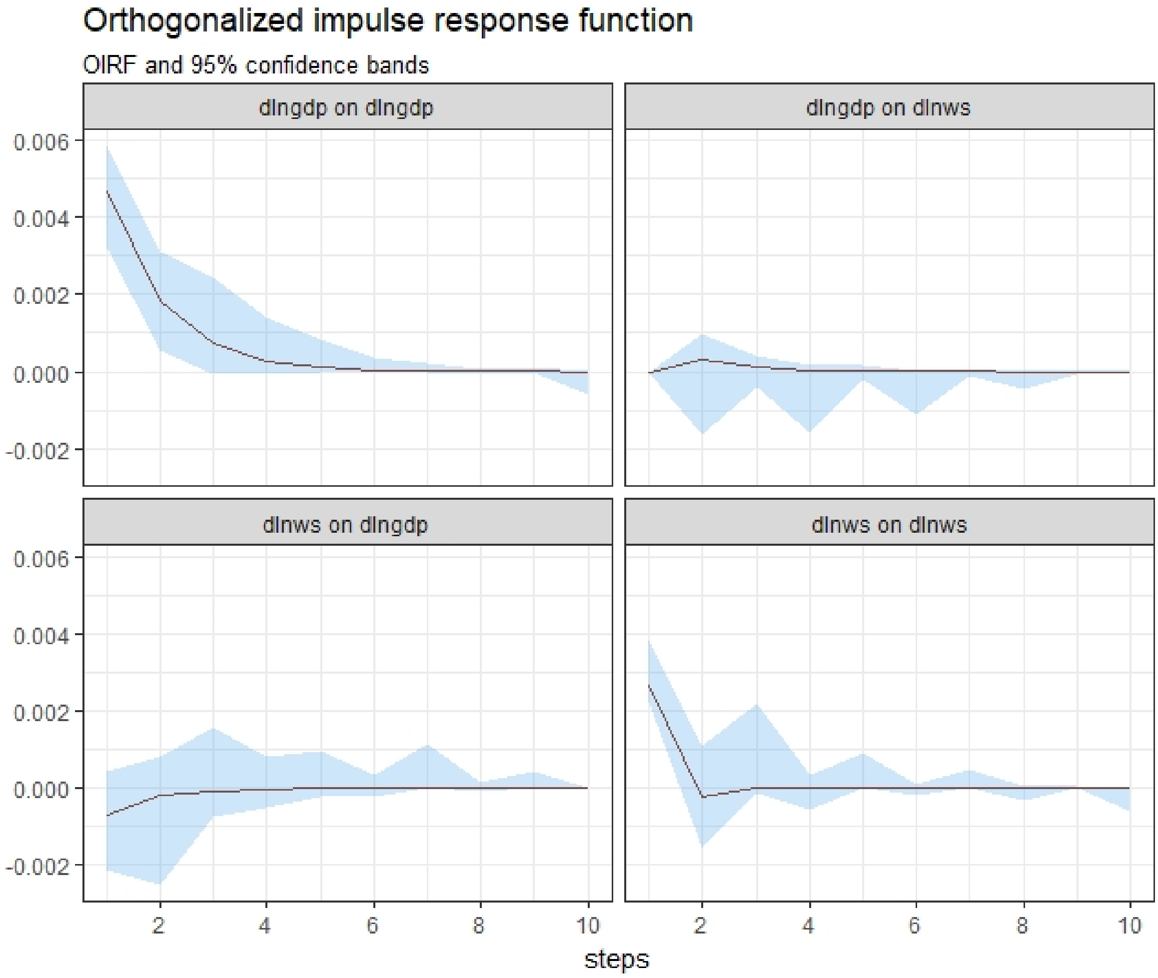
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln wage share, Δ ln GDP
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln wage share, effect of Δ ln wage share on Δ ln GDP, effect of Δ ln wage share on Δ ln wage share

Figure C.4: Quarterly IRFs for the Wage Share - Real GDP Growth Model with Confidence Intervals



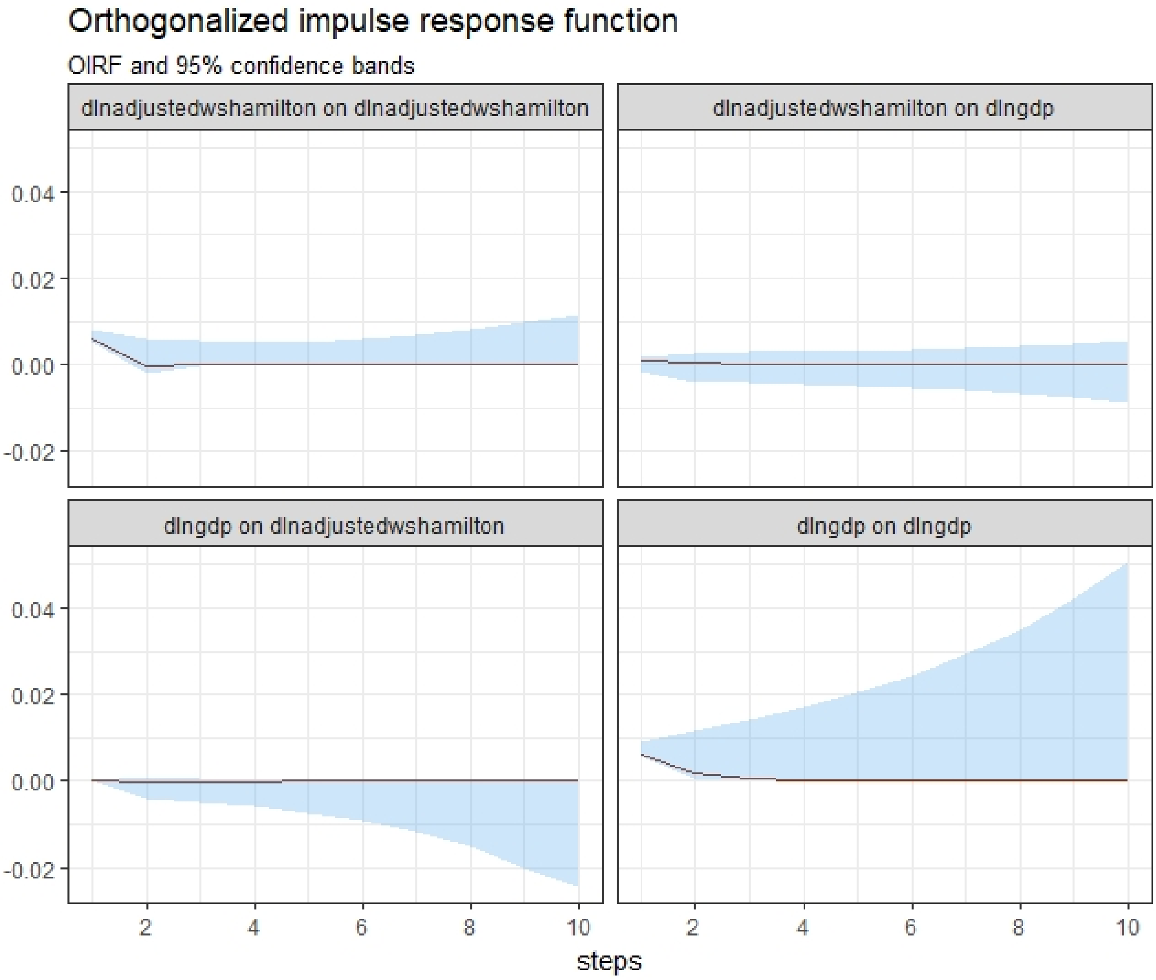
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln wage share, Δ ln GDP
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln wage share, effect of Δ ln wage share on Δ ln GDP, effect of Δ ln wage share on Δ ln wage share

Figure C.5: Annual IRFs for the Wage Share - Real GDP Growth Model



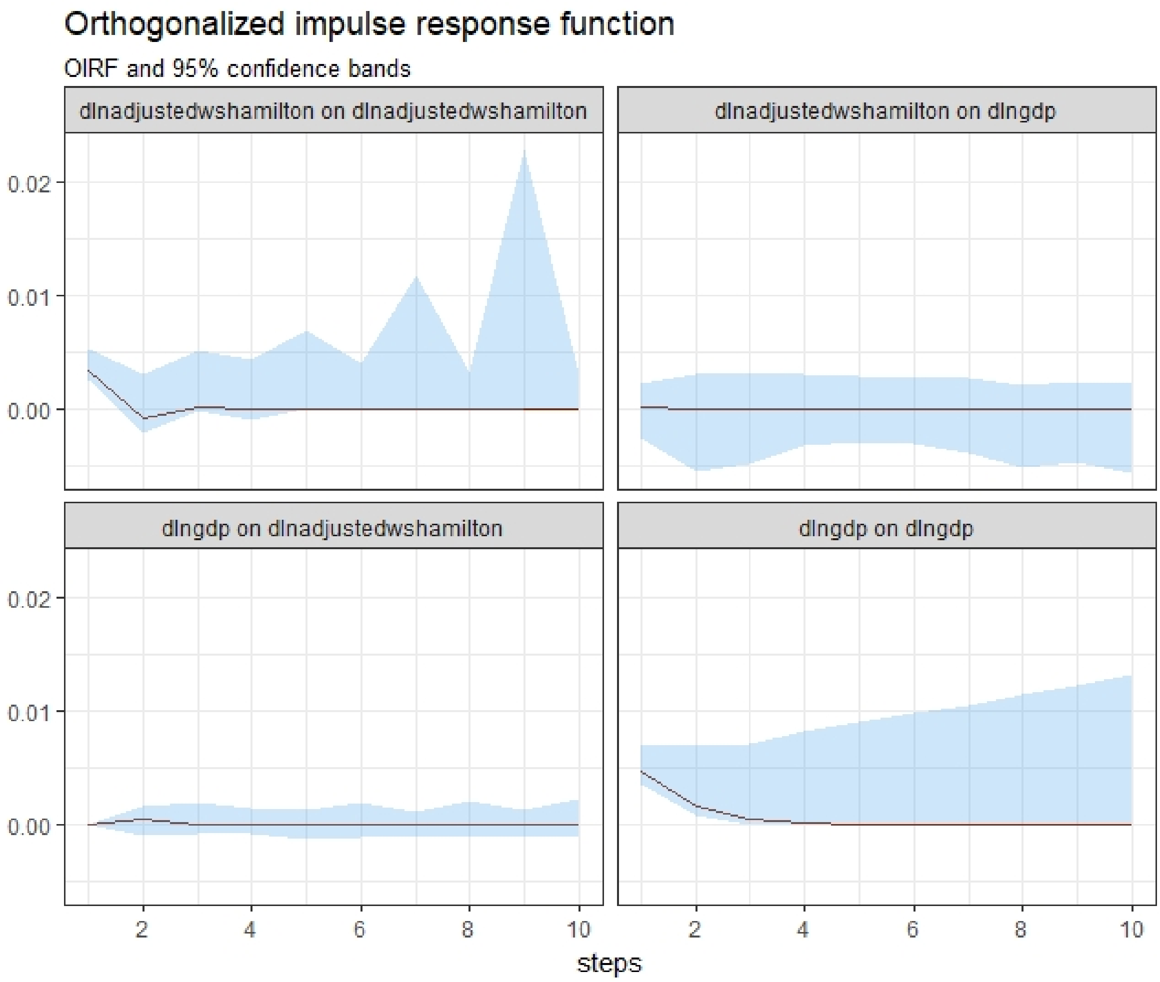
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln wage share, Δ ln GDP
Frequency: Three-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln wage share, effect of Δ ln wage share on Δ ln GDP, effect of Δ ln wage share on Δ ln wage share

Figure C.6: Three-year IRFs for the Wage Share - Real GDP Growth Model



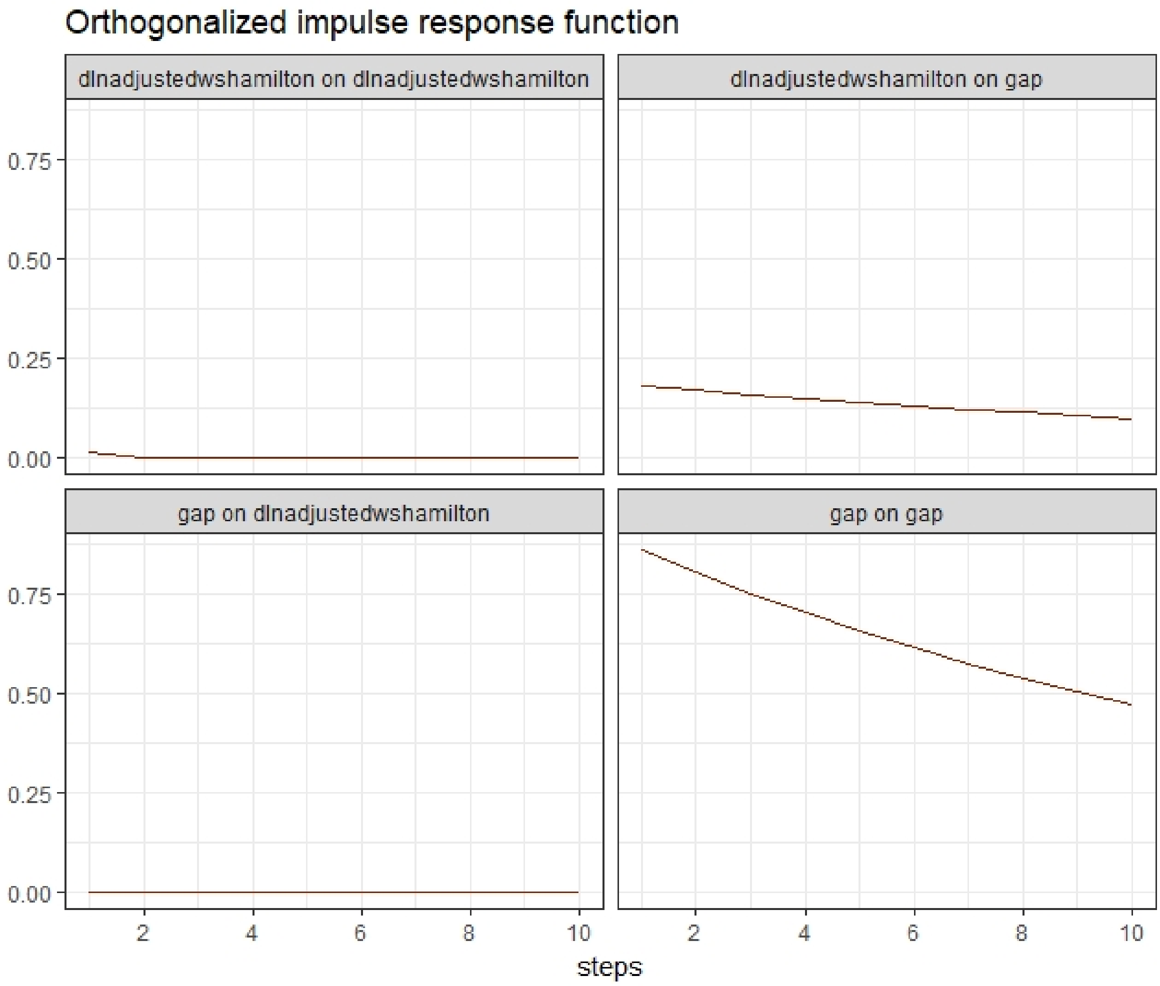
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, Δ ln GDP
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on Δ ln GDP, effect of Δ ln GDP on Δ ln adjusted wage share, effect of Δ ln GDP on Δ ln GDP

Figure C.7: Annual IRFs for Cyclically Adjusted Wage Share - Real GDP Growth Model



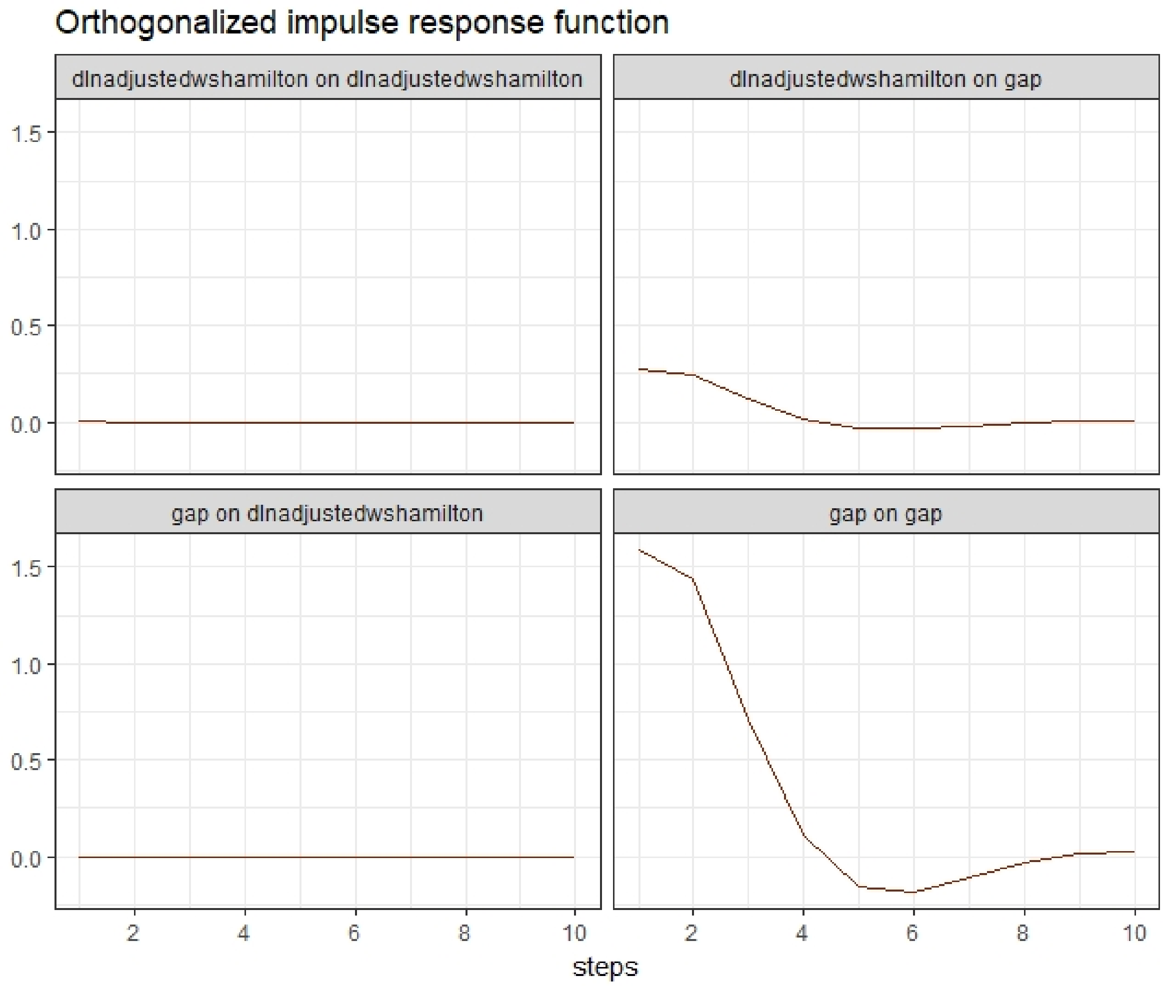
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, Δ ln GDP
Frequency: Three-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on Δ ln GDP, effect of Δ ln GDP on Δ ln adjusted wage share, effect of Δ ln GDP on Δ ln GDP

Figure C.8: Three-year IRFs for Cyclically Adjusted Wage Share - Real GDP Growth Model



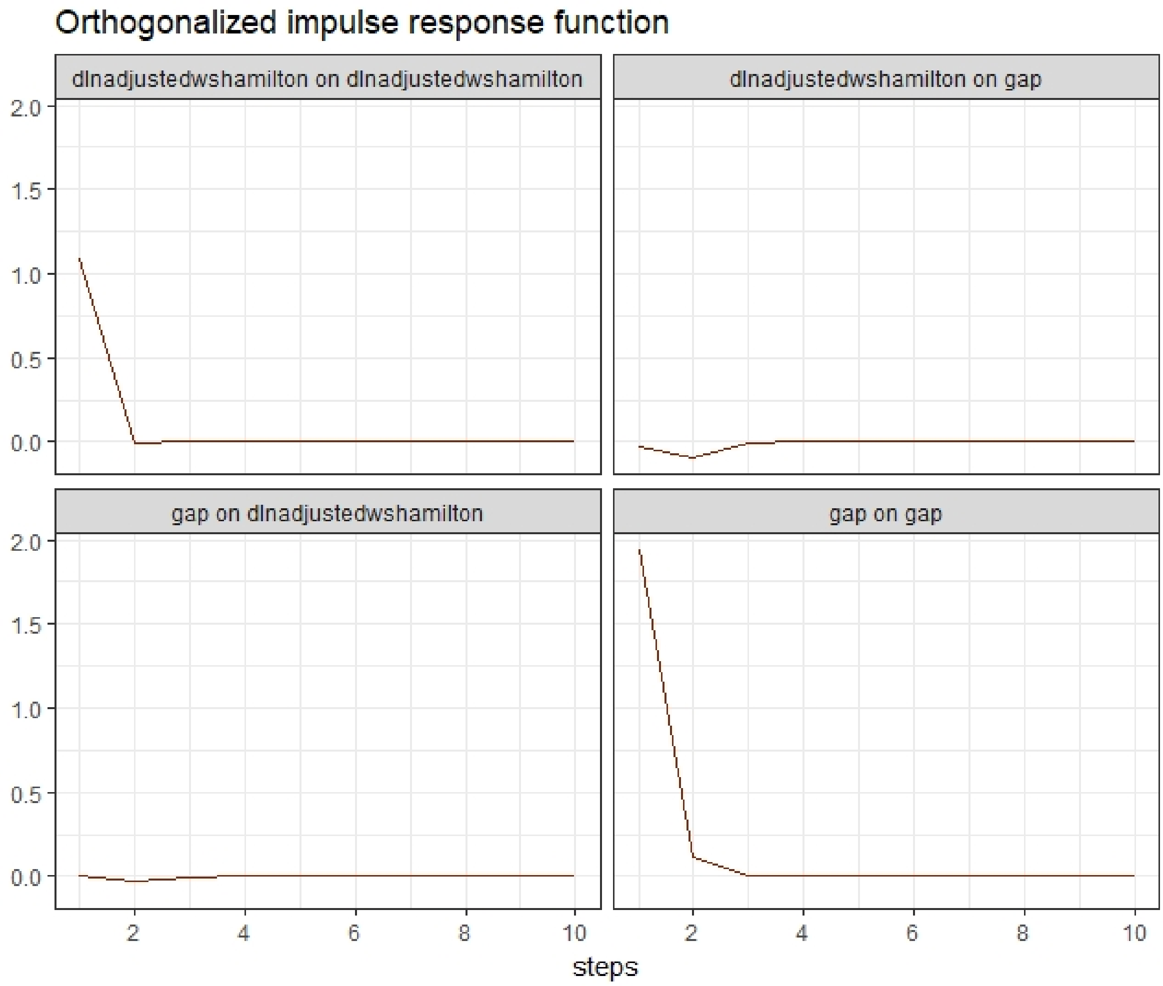
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, output gap
Frequency: Quarterly
Maximum number of instruments: 5
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on output gap, effect of output gap on Δ ln adjusted wage share, effect of output gap on output gap

Figure C.9: Quarterly IRFs for Cyclically Adjusted Wage Share - Output Gap Model



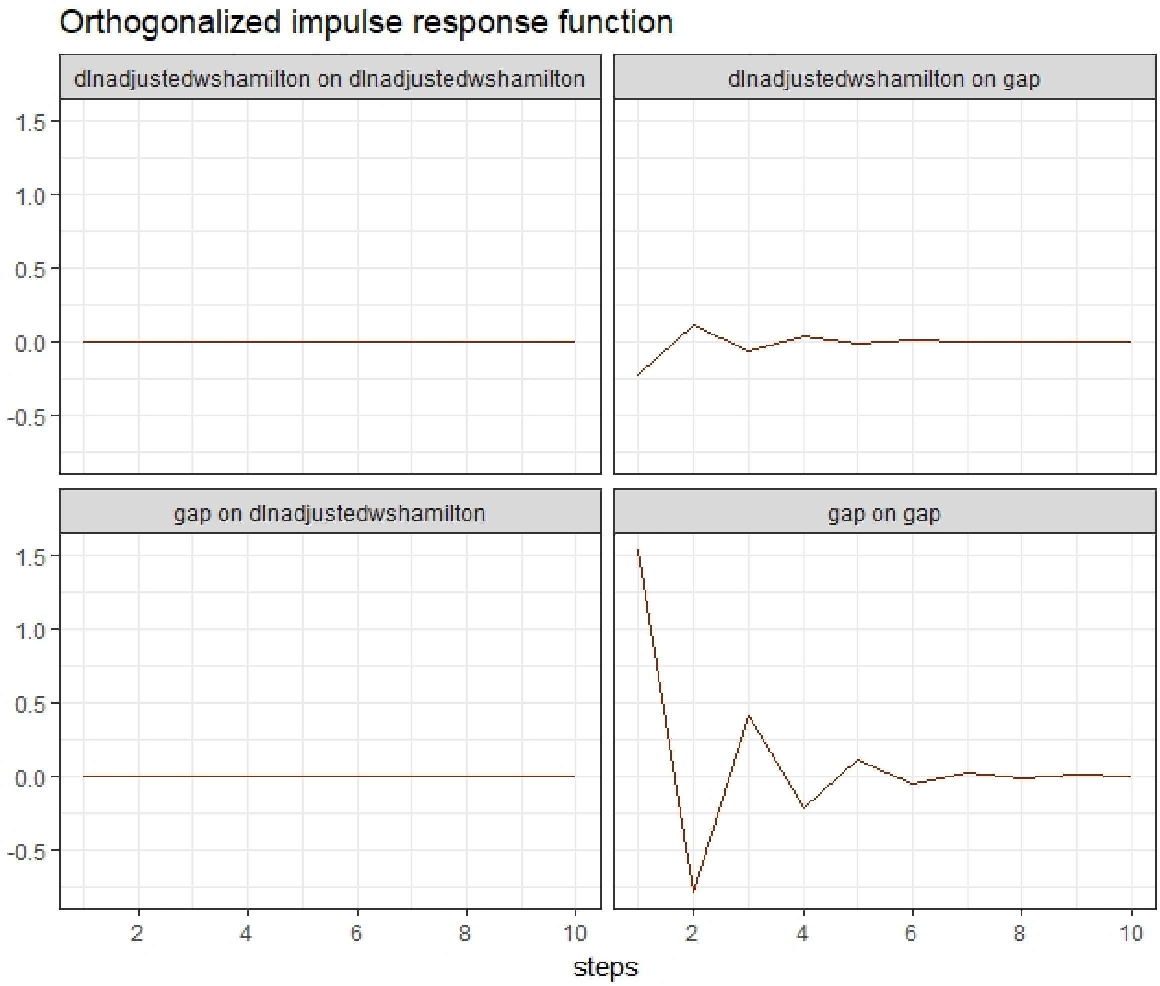
Sample period: 1979 Q1 - 2013 Q4
Lag length: 2
Variable ordering: Δ ln adjusted wage share, output gap
Frequency: Annual
Maximum number of instruments: 5
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on output gap, effect of output gap on Δ ln adjusted wage share, effect of output gap on output gap

Figure C.10: Annual IRFs for Cyclically Adjusted Wage Share - Output Gap Model



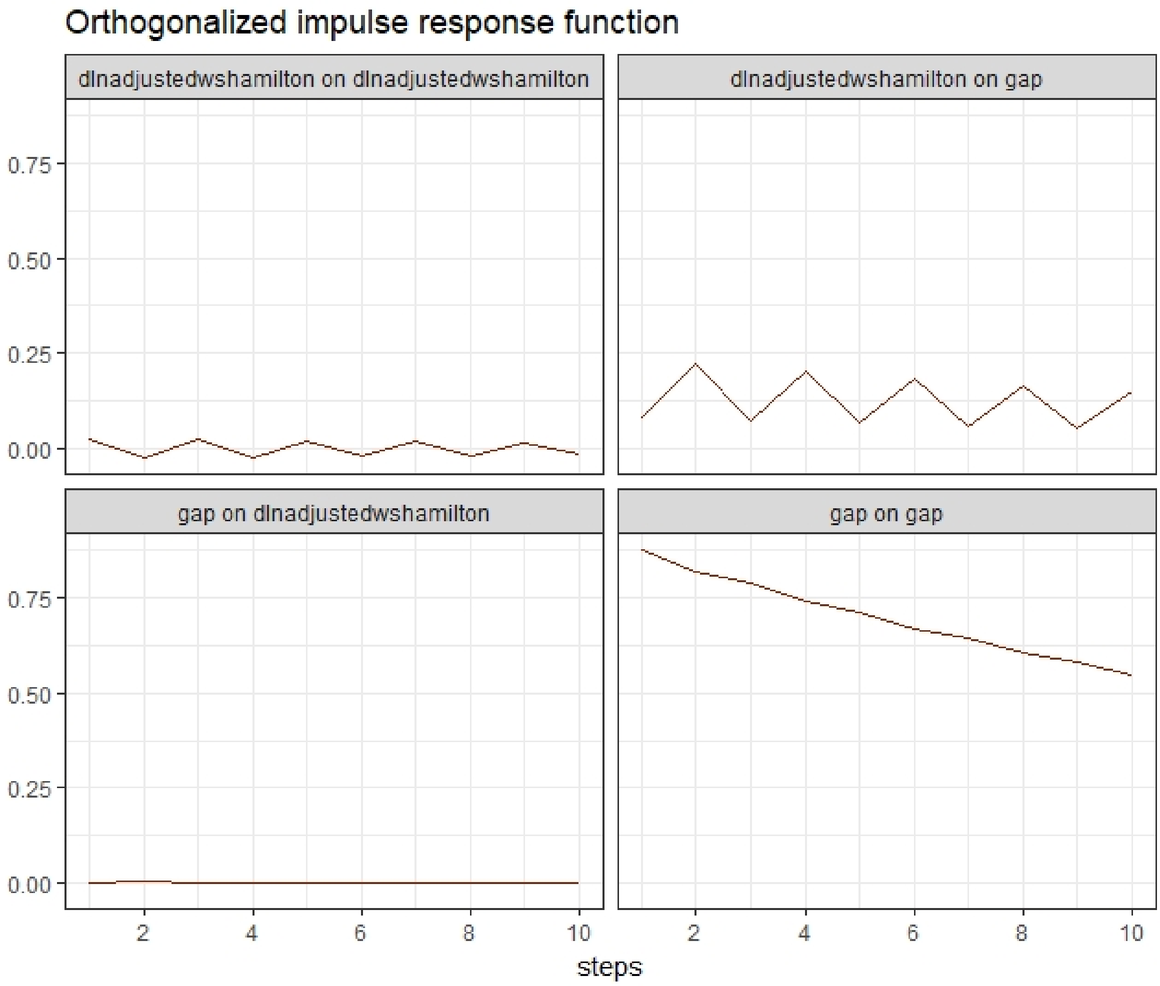
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, output gap
Frequency: Three-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on output gap, effect of output gap on Δ ln adjusted wage share, effect of output gap on output gap

Figure C.11: Three-year IRFs for Cyclically Adjusted Wage Share - Output Gap Model



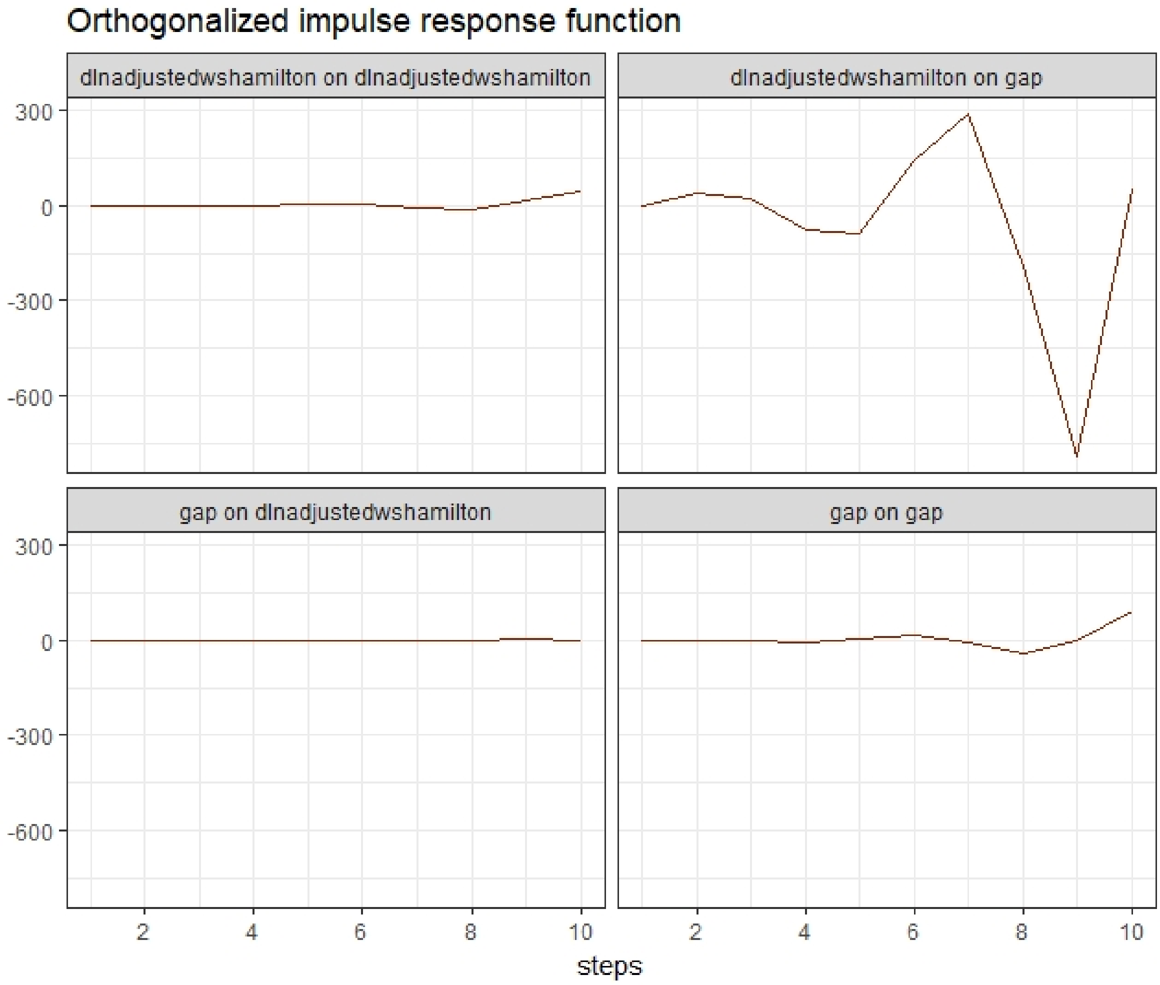
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, output gap
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on output gap, effect of output gap on Δ ln adjusted wage share, effect of output gap on output gap

Figure C.12: Five-year IRFs for Cyclically Adjusted Wage Share - Output Gap Model



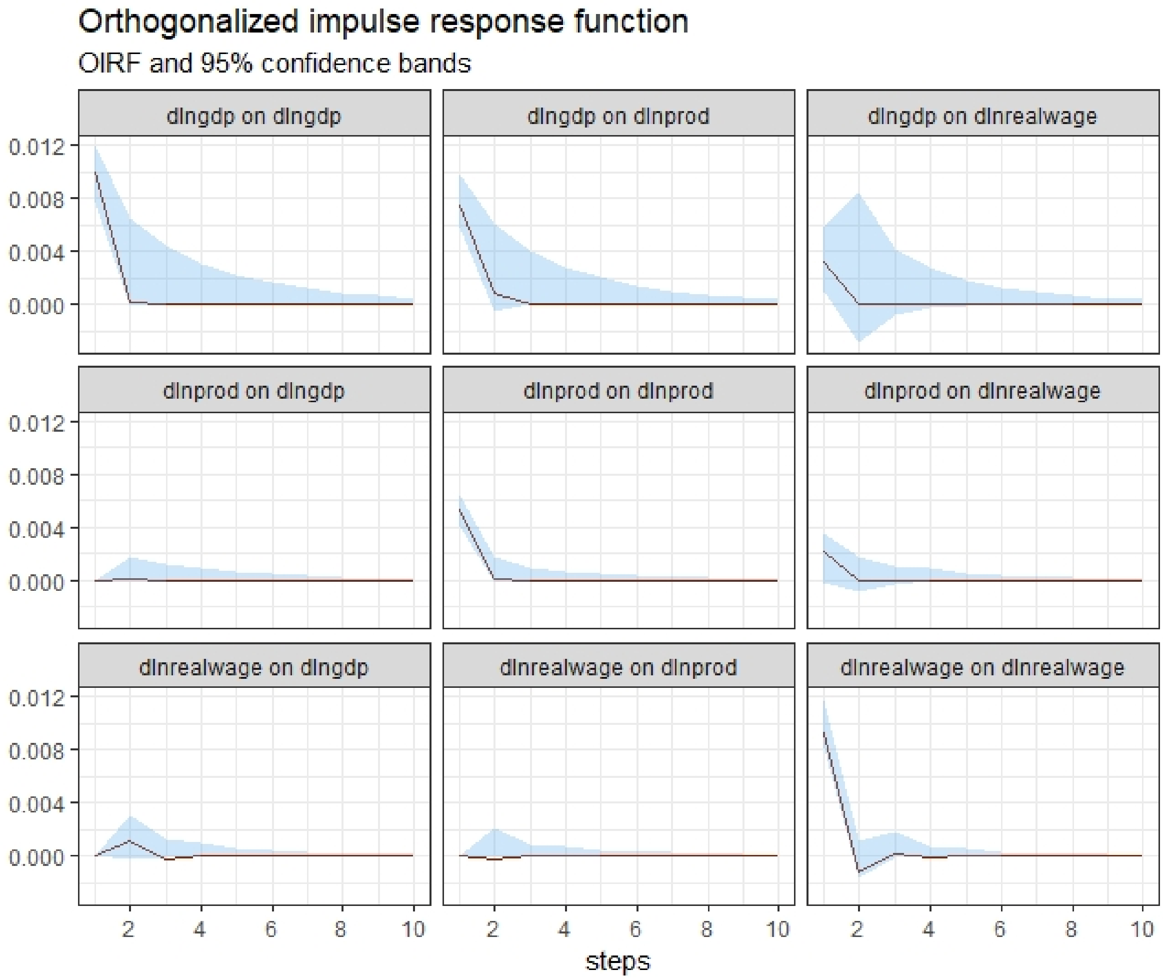
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, output gap
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on output gap, effect of output gap on Δ ln adjusted wage share, effect of output gap on output gap

Figure C.13: Quarterly IRFs for Cyclically Adjusted Wage Share - Output Gap Model with More Instruments



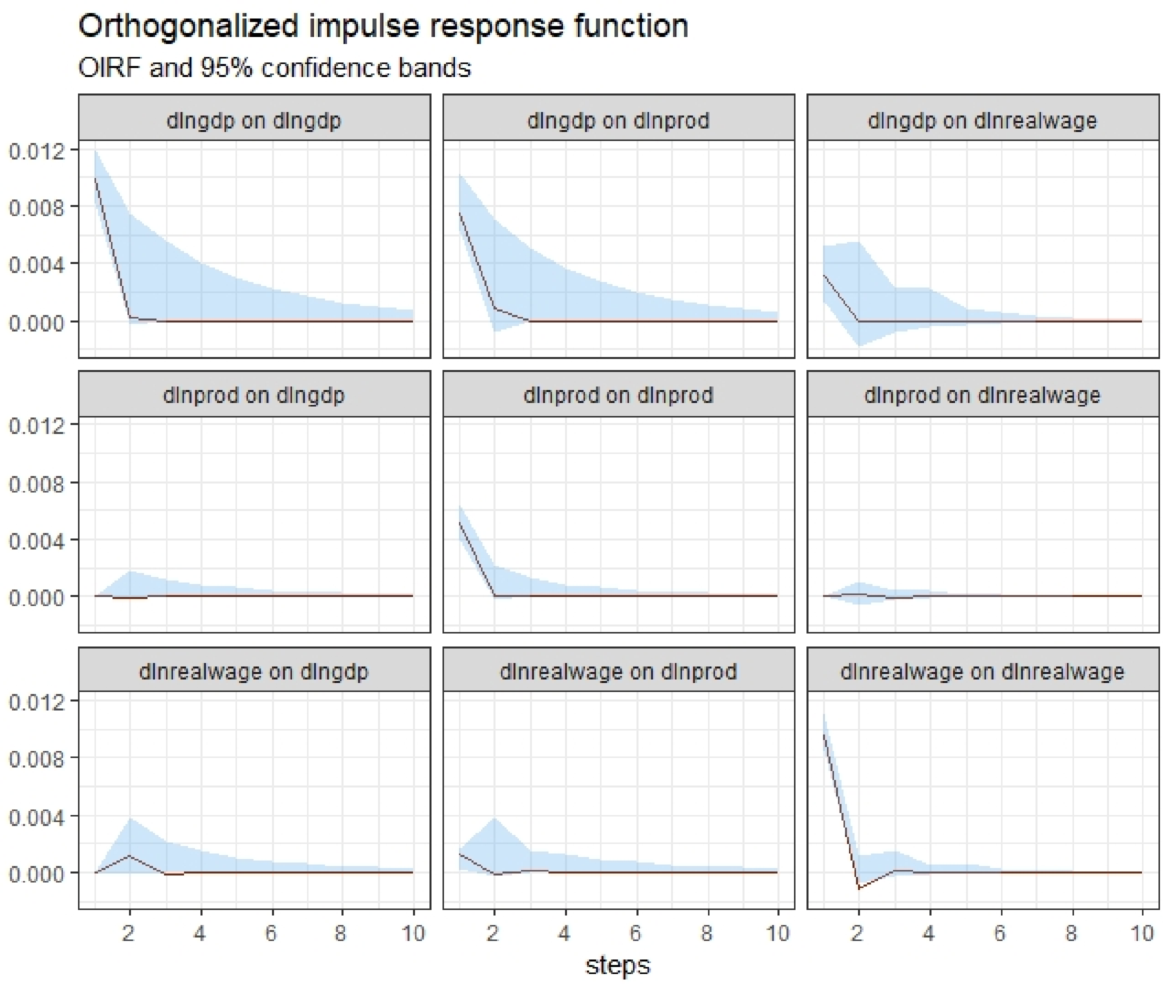
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln adjusted wage share, output gap
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln adjusted wage share on Δ ln adjusted wage share, effect of Δ ln adjusted wage share on output gap, effect of output gap on Δ ln adjusted wage share, effect of output gap on output gap

Figure C.14: Annual IRFs for Cyclically Adjusted Wage Share - Output Gap Model with More Instruments



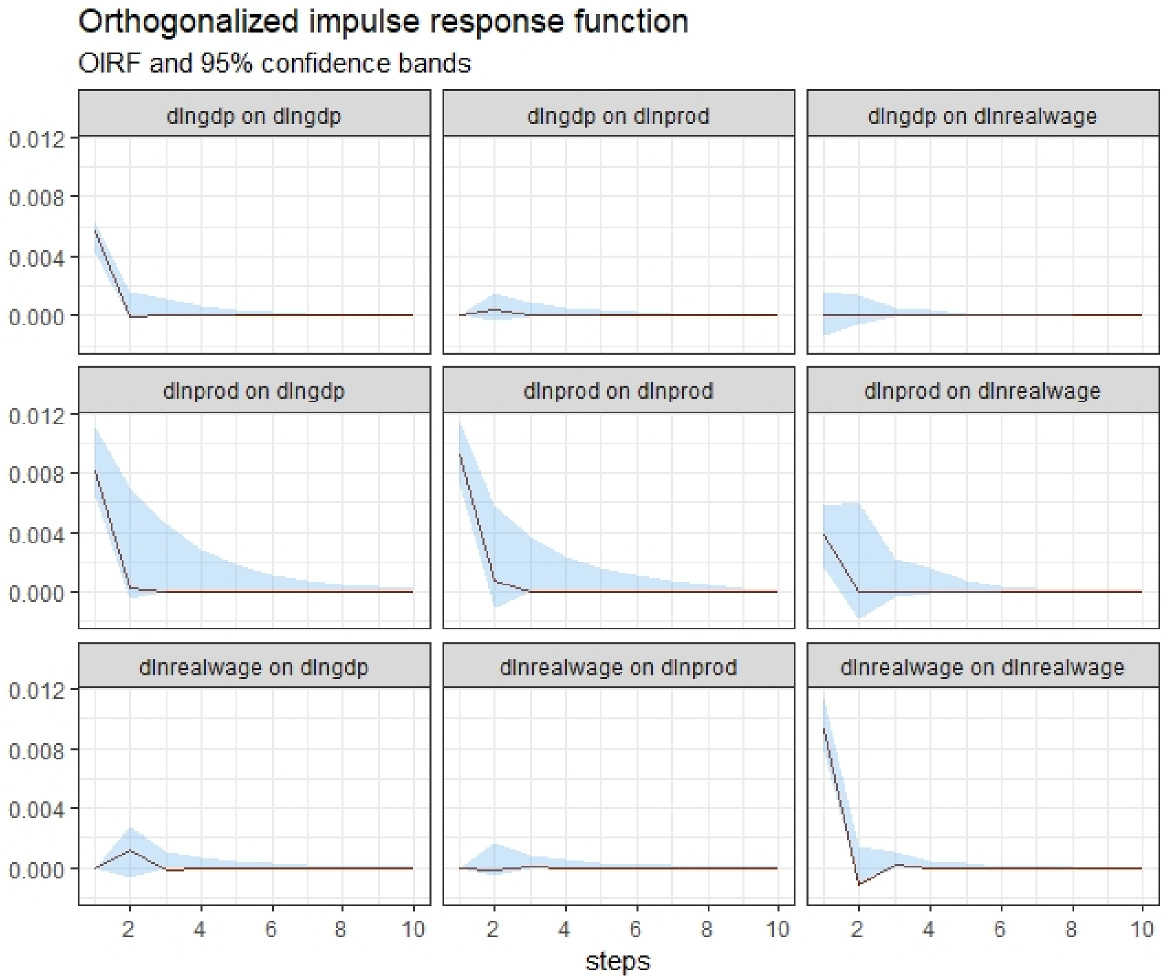
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln GDP, Δ ln productivity, Δ ln real wage
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.15: Quarterly IRFs for Wage Share Decomposition Model, Order 3



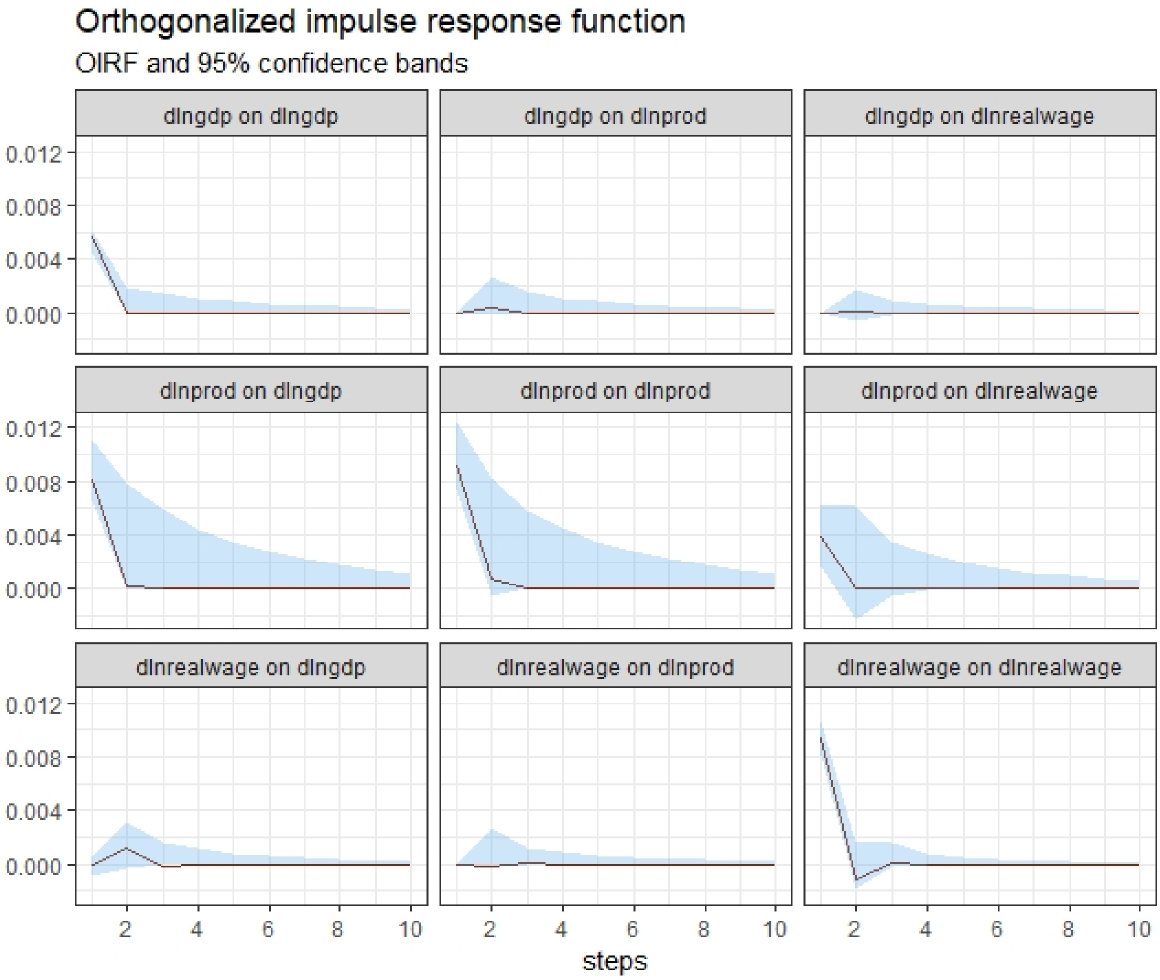
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln GDP, Δ ln real wage, Δ ln productivity
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.16: Quarterly IRFs for Wage Share Decomposition Model, Order 4



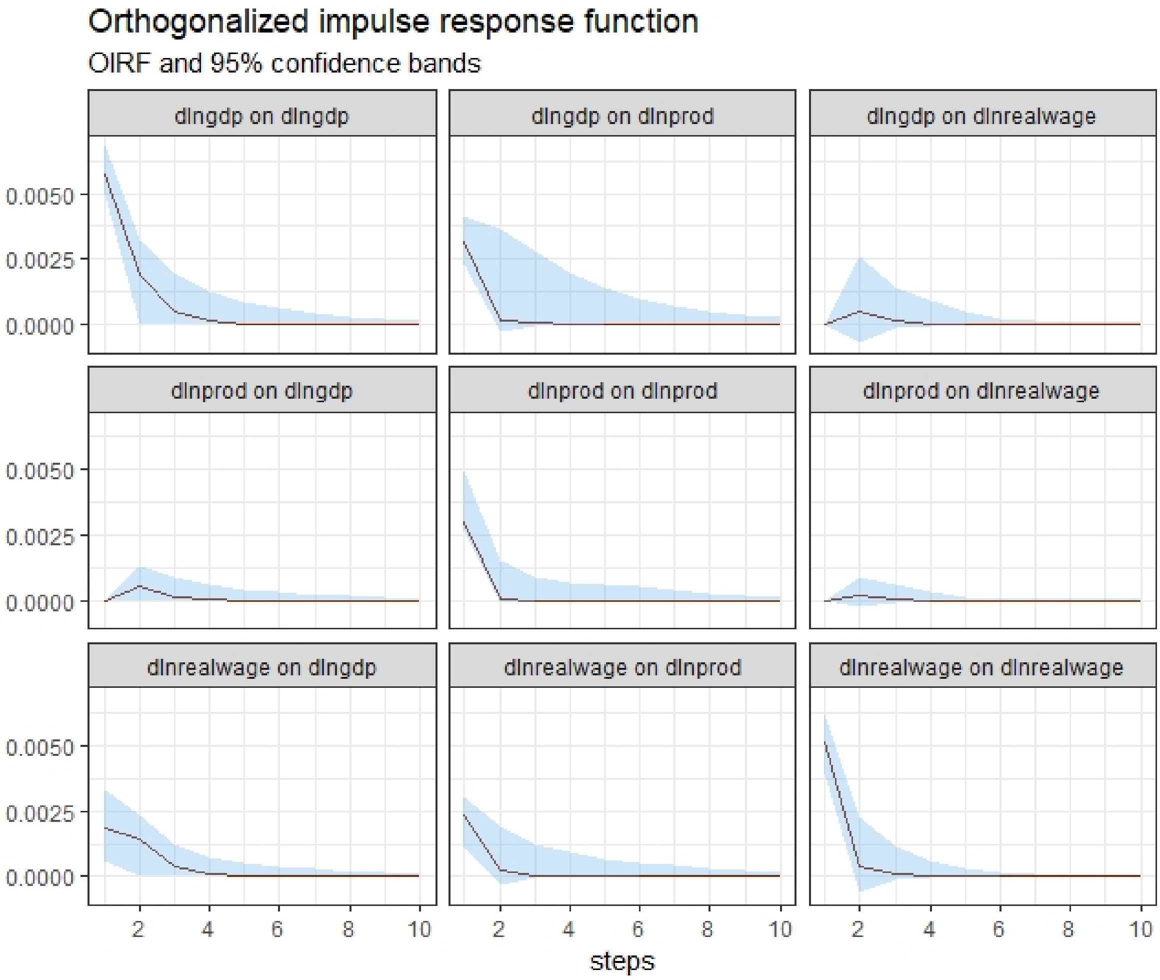
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln productivity, Δ ln GDP, Δ ln real wage
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.17: Quarterly IRFs for Wage Share Decomposition Model, Order 5



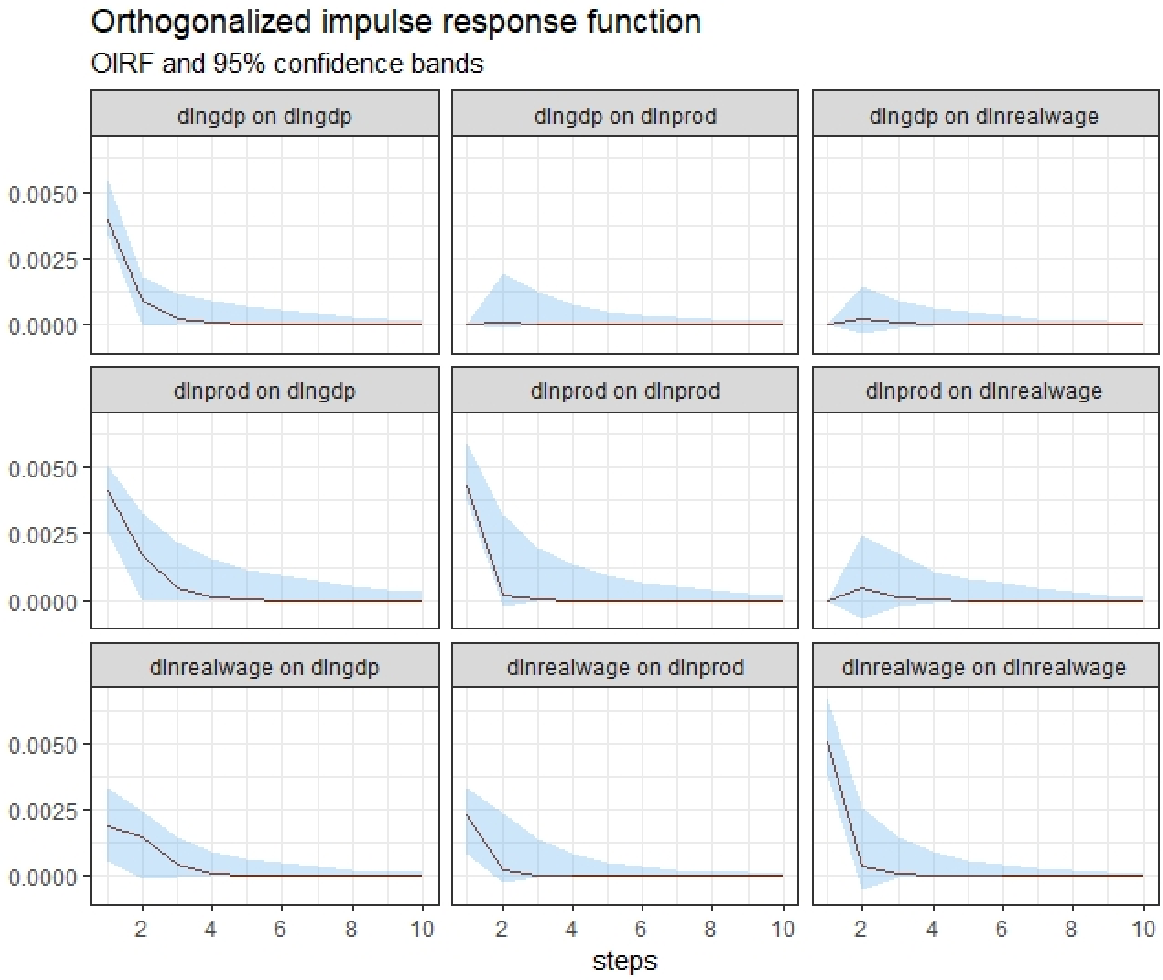
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln productivity, Δ ln real wage, Δ ln GDP
Frequency: Quarterly
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.18: Quarterly IRFs for Wage Share Decomposition Model, Order 6



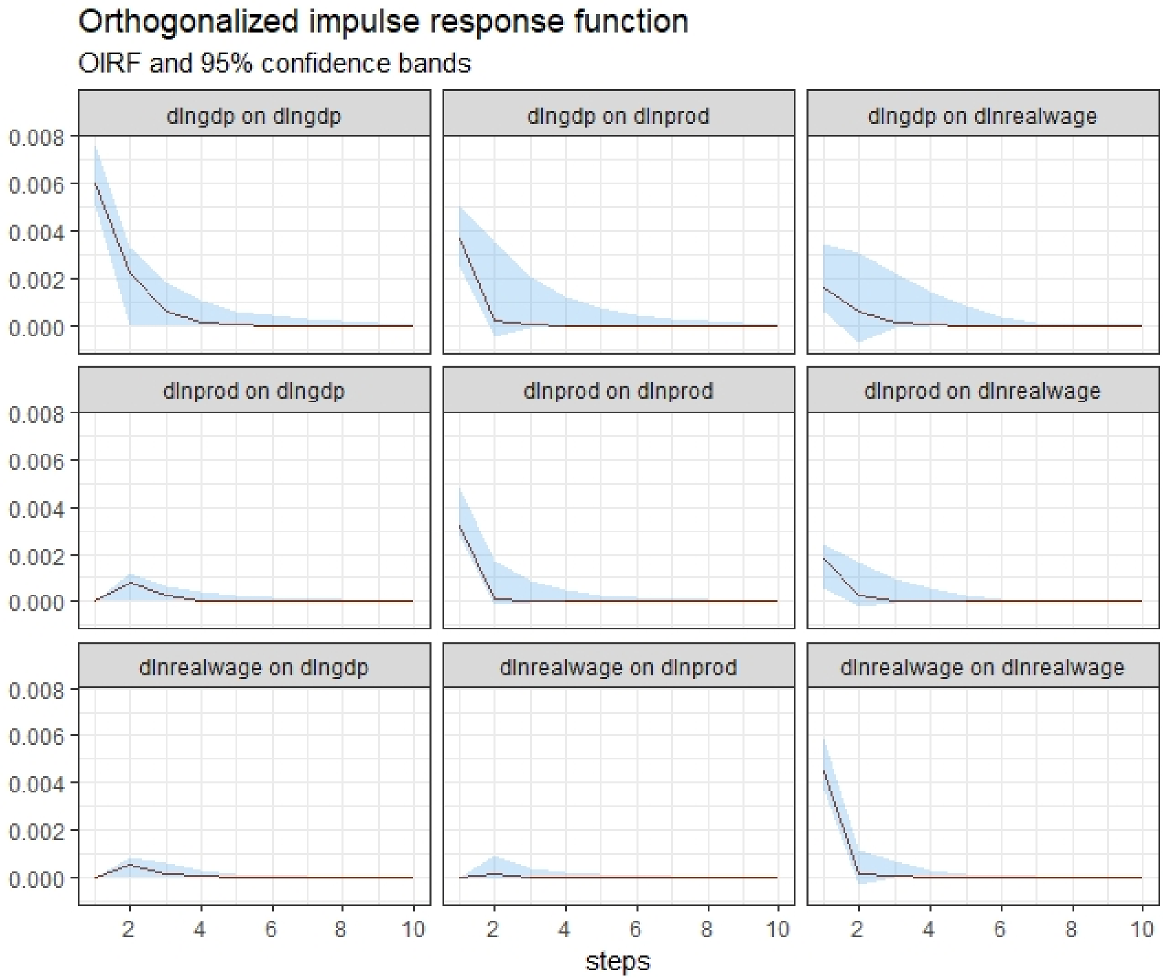
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln real wage, Δ ln GDP, Δ ln productivity
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.19: Annual IRFs for Wage Share Decomposition Model, Order 1



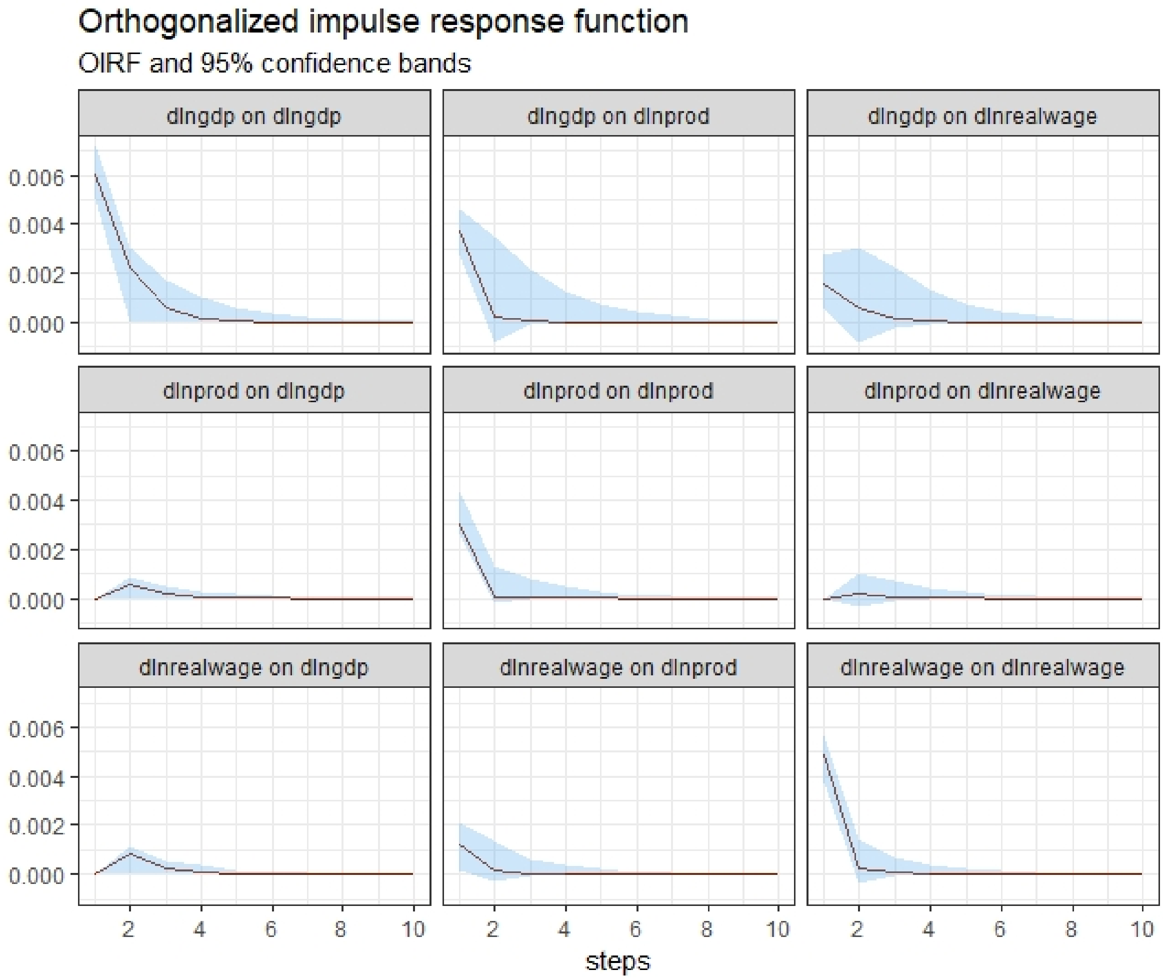
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln real wage, Δ ln productivity, Δ ln GDP
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.20: Annual IRFs for Wage Share Decomposition Model, Order 2



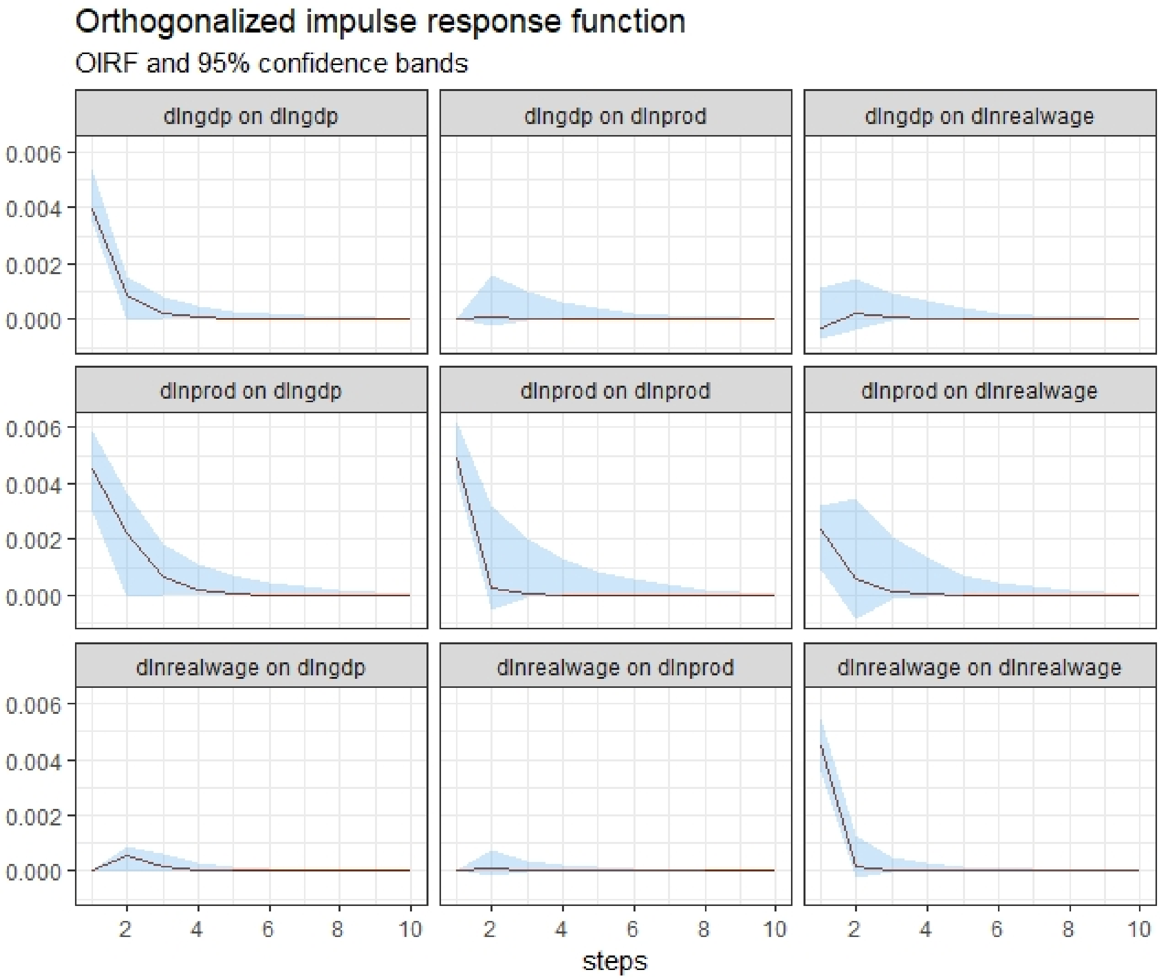
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln GDP, Δ ln productivity, Δ ln real wage
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.21: Annual IRFs for Wage Share Decomposition Model, Order 3



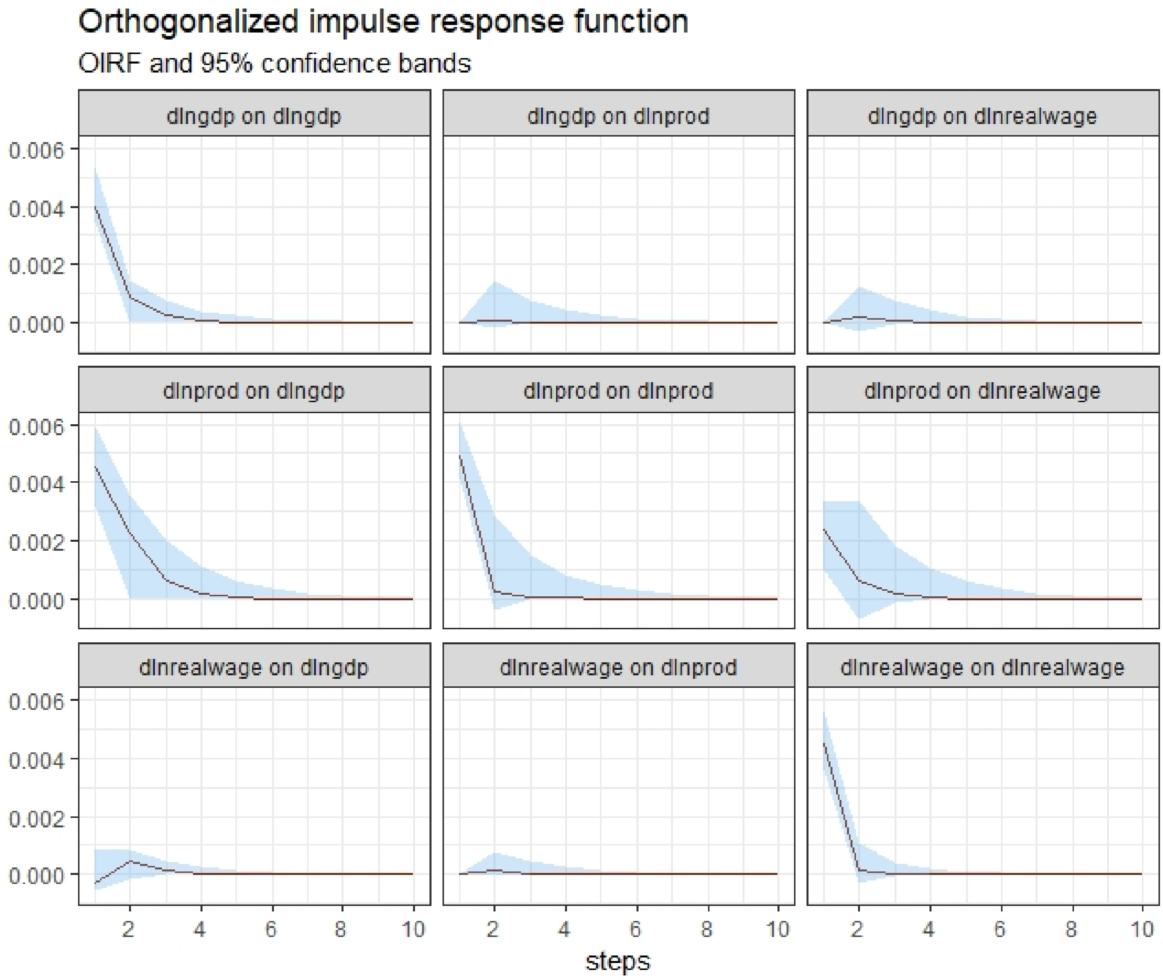
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln GDP, Δ ln real wage, Δ ln productivity
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.22: Annual IRFs for Wage Share Decomposition Model, Order 4



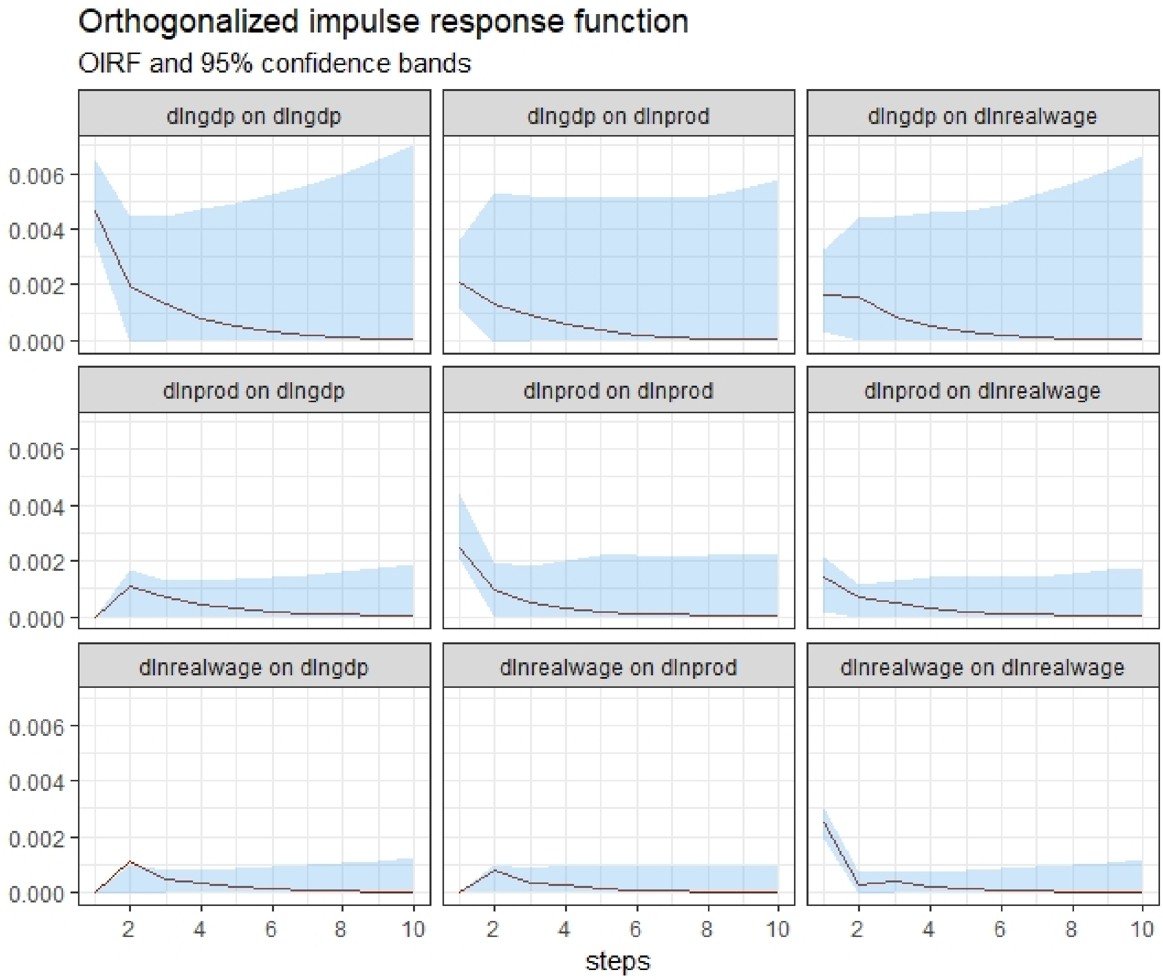
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln productivity, Δ ln GDP, Δ ln real wage
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.23: Annual IRFs for Wage Share Decomposition Model, Order 5



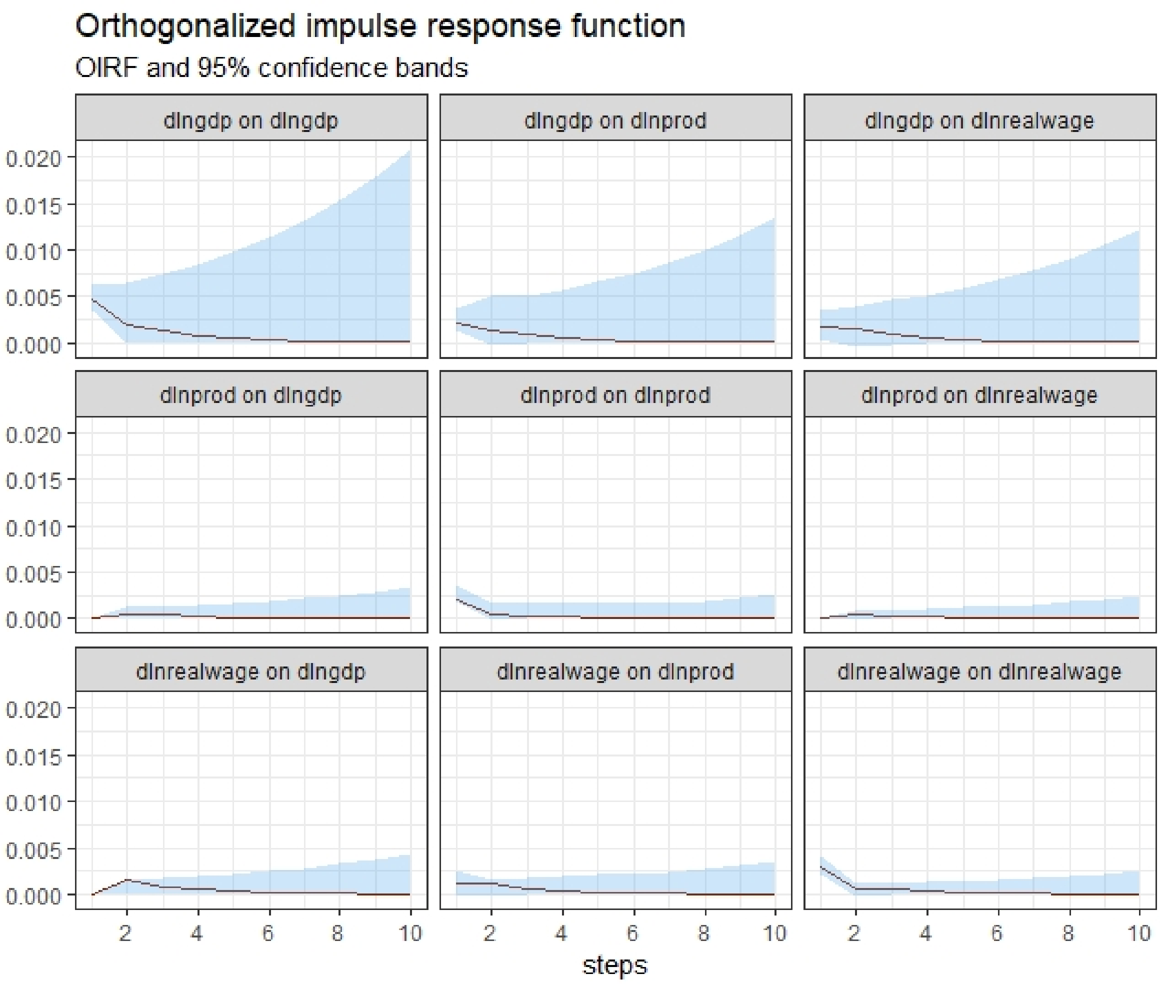
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln productivity, Δ ln real wage, Δ ln GDP
Frequency: Annual
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.24: Annual IRFs for Wage Share Decomposition Model, Order 6



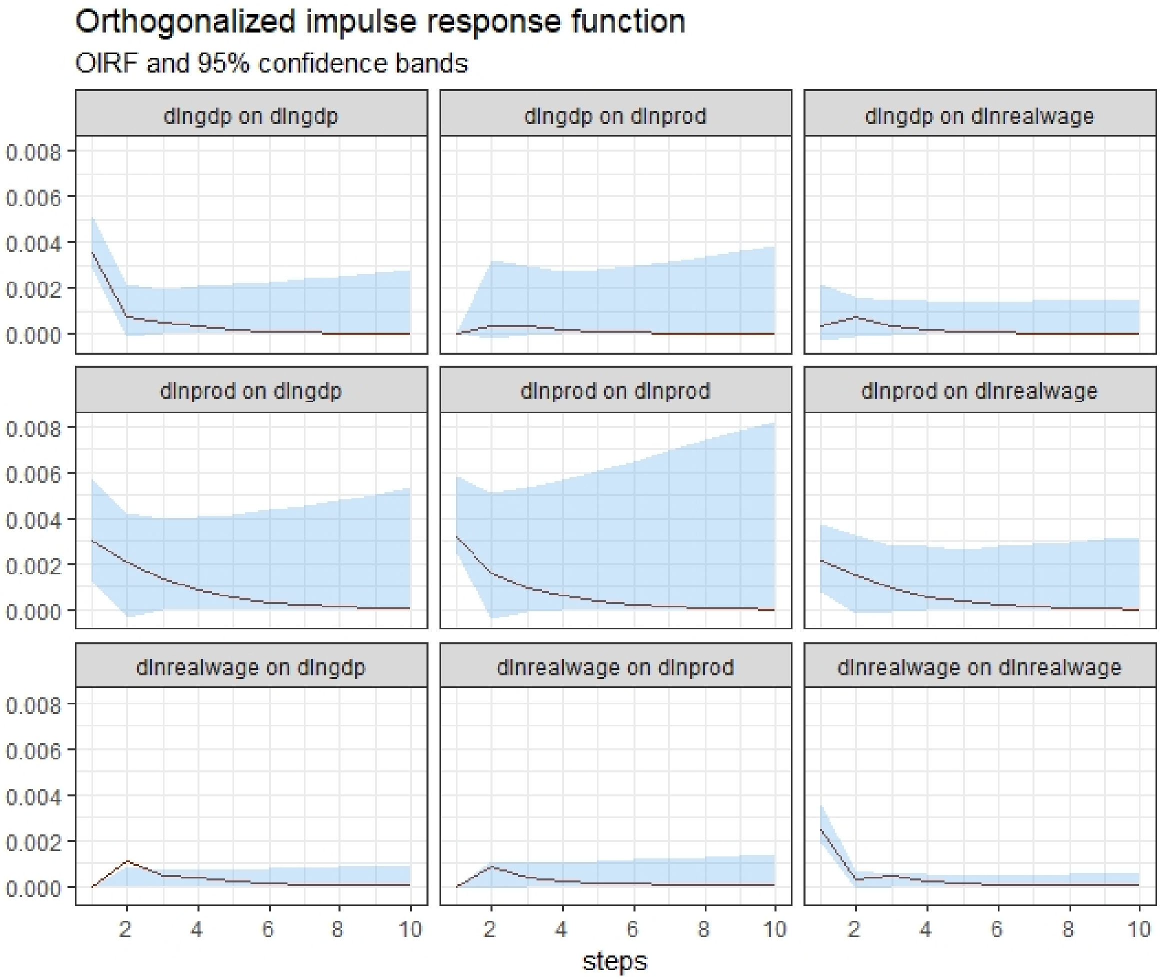
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln GDP, Δ ln productivity, Δ ln real wage
Frequency: Three-year
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.25: Three-year IRFs for Wage Share Decomposition Model, Order 3



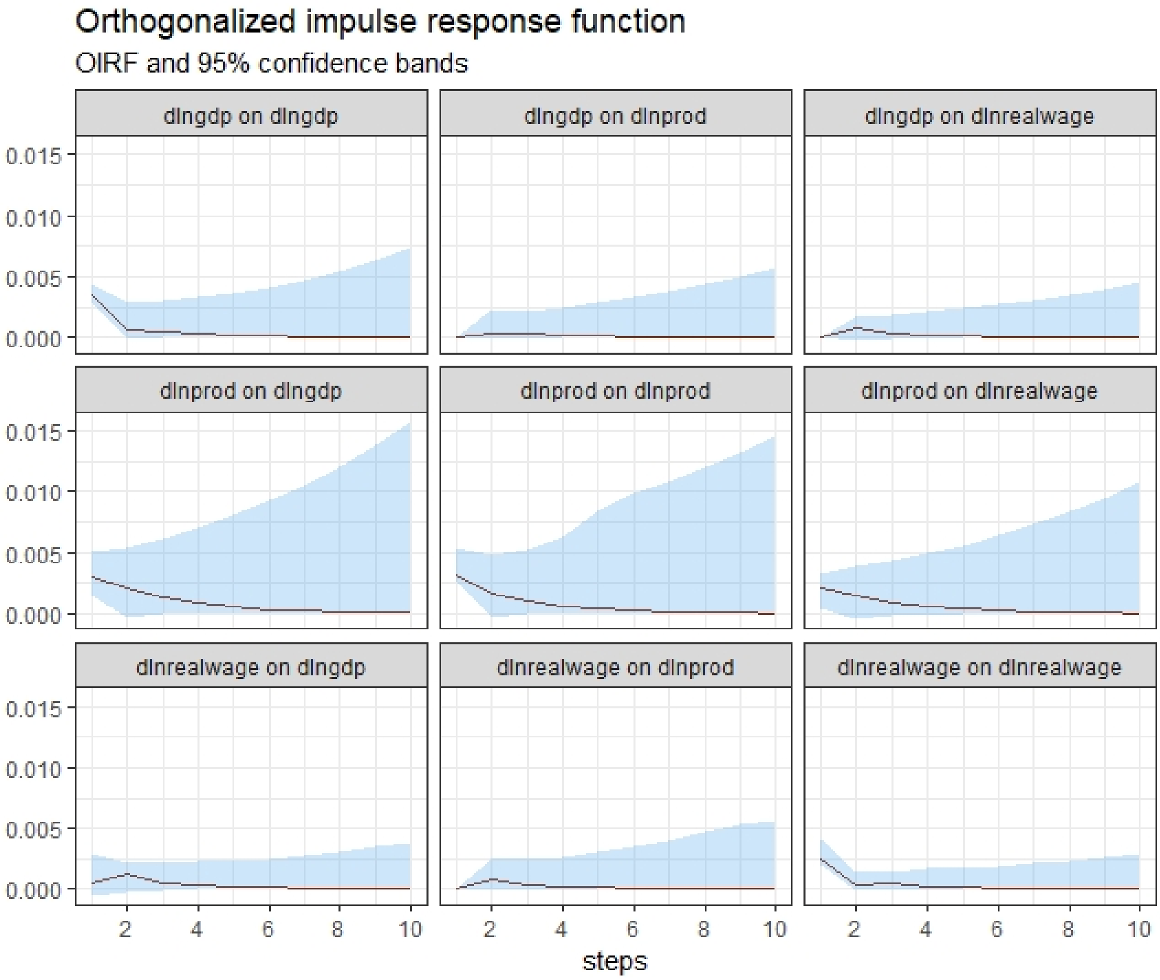
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln GDP, Δ ln real wage, Δ ln productivity
Frequency: Three-year
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.26: Three-year IRFs for Wage Share Decomposition Model, Order 4



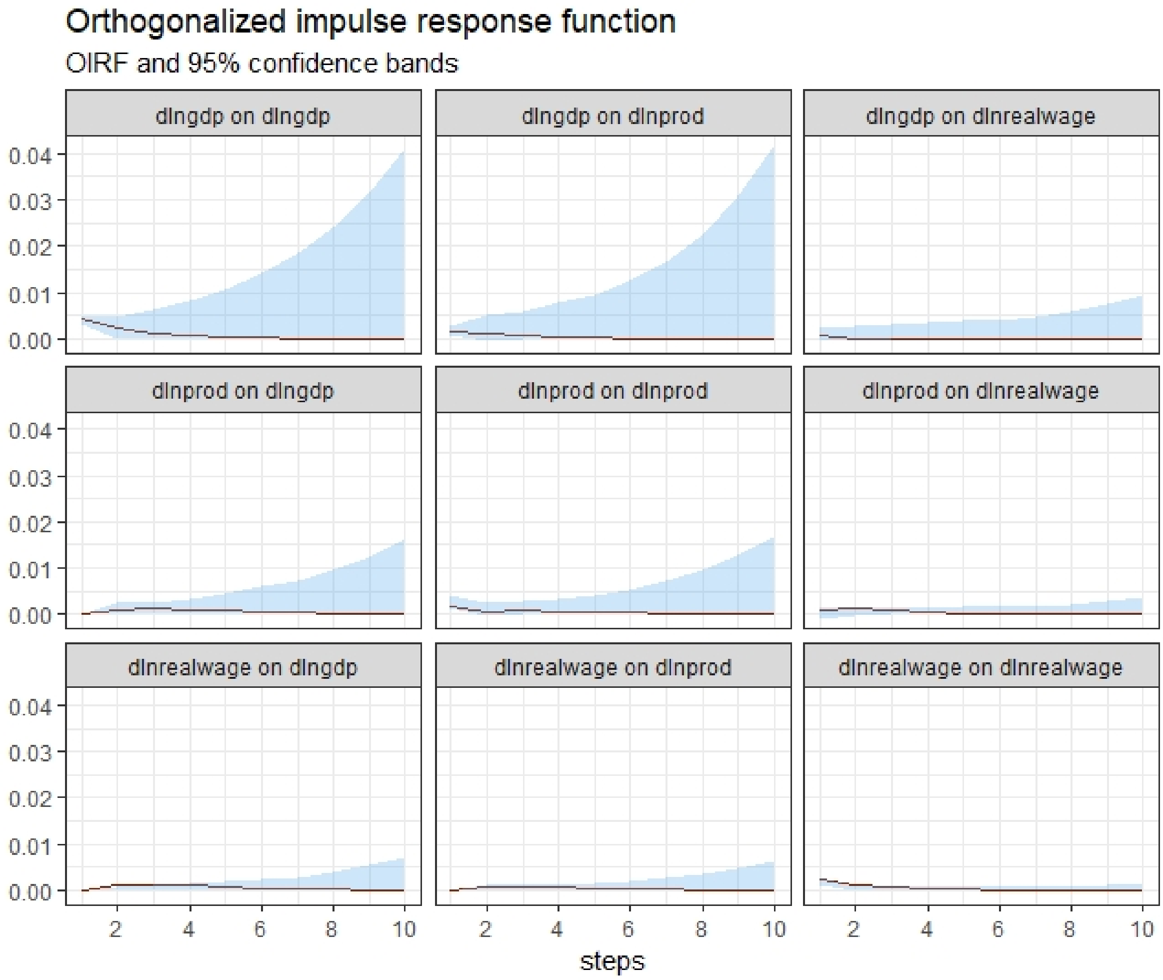
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln productivity, Δ ln GDP, Δ ln real wage
Frequency: Three-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.27: Three-year IRFs for Wage Share Decomposition Model, Order 5



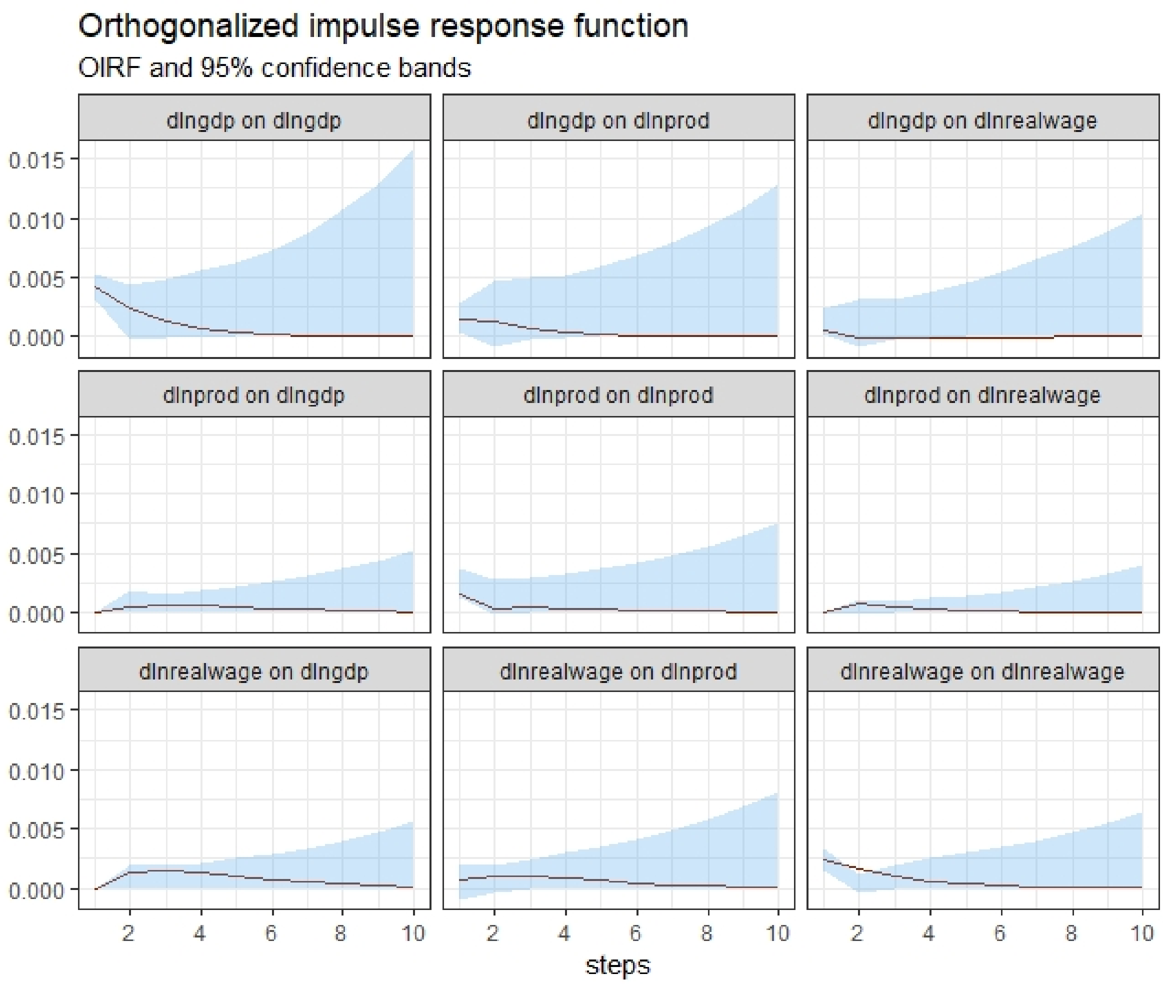
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln productivity, Δ ln real wage, Δ ln GDP
Frequency: Three-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.28: Three-year IRFs for Wage Share Decomposition Model, Order 6



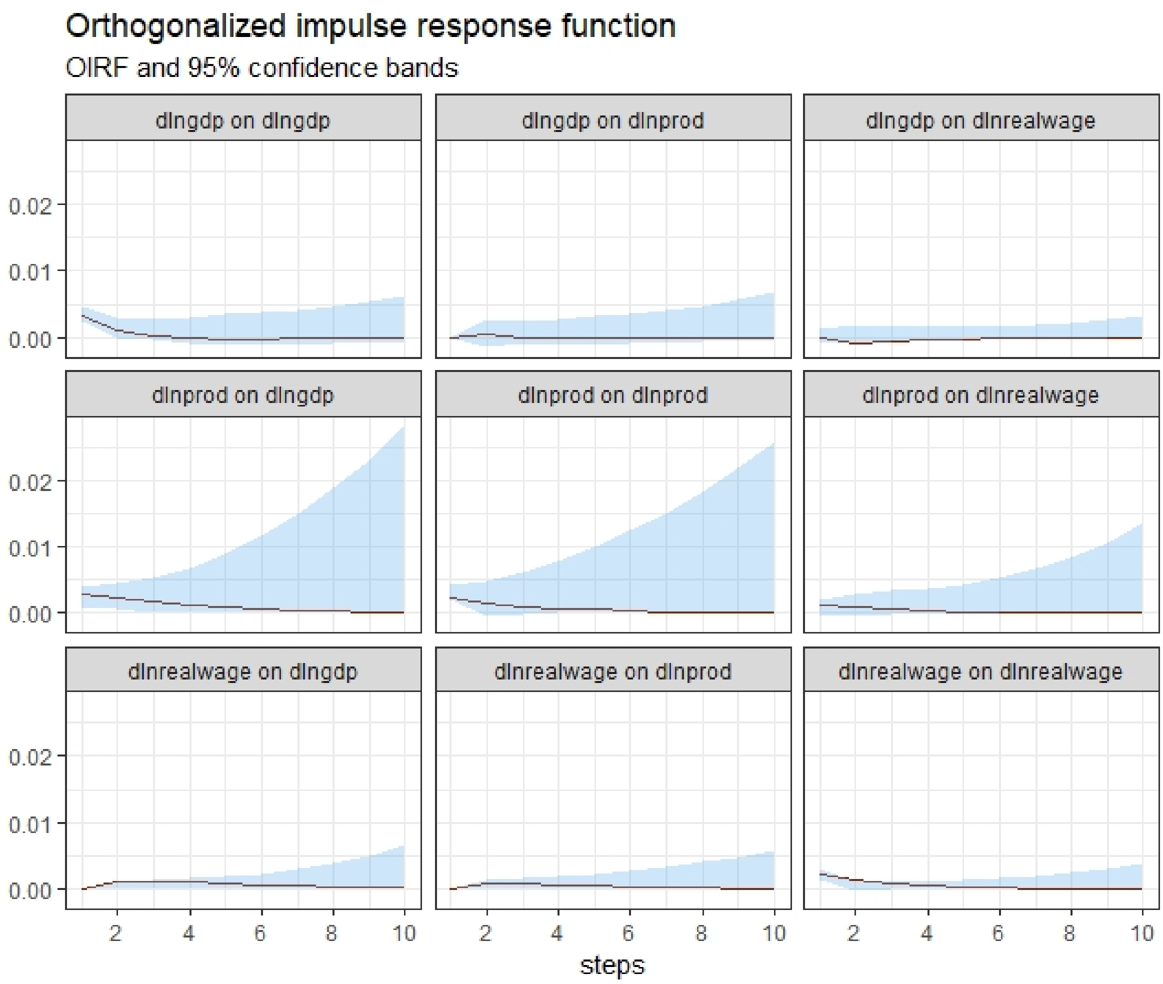
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln GDP, Δ ln productivity, Δ ln real wage
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.29: Five-year IRFs for Wage Share Decomposition Model, Order 3



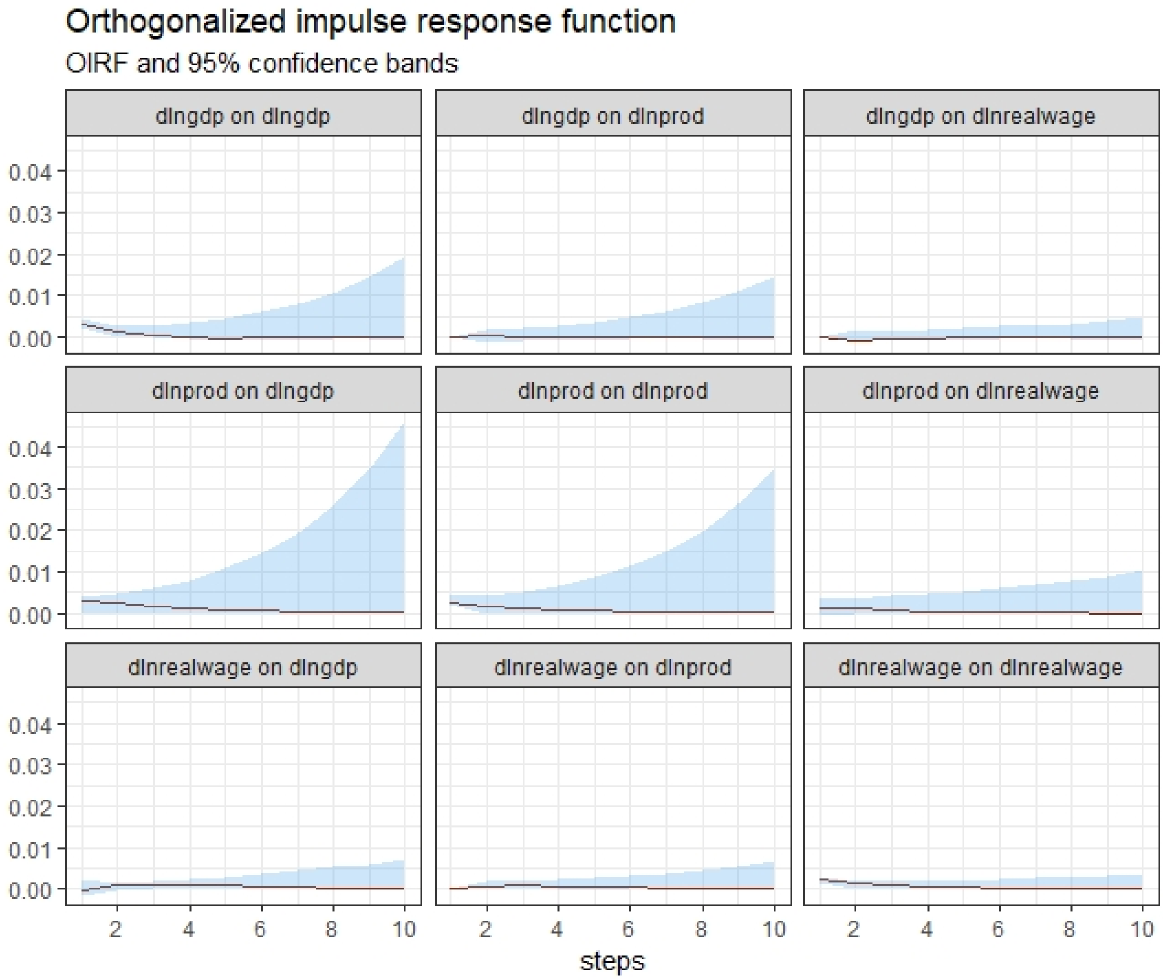
Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln GDP, Δ ln productivity, Δ ln real wage
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.30: Five-year IRFs for Wage Share Decomposition Model, Order 4



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln productivity, Δ ln GDP, Δ ln real wage
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.31: Five-year IRFs for Wage Share Decomposition Model, Order 5



Sample period: 1979 Q1 - 2013 Q4
Lag length: 1
Variable ordering: Δ ln productivity, Δ ln real wage, Δ ln GDP
Frequency: Five-year average
Maximum number of instruments: 10
Clockwise: Effect of Δ ln GDP on Δ ln GDP, effect of Δ ln GDP on Δ ln productivity, effect of Δ ln GDP on Δ ln real wage, effect of Δ ln productivity on Δ ln GDP, effect of Δ ln productivity on Δ ln productivity, effect of Δ ln productivity on Δ ln real wage, effect of Δ ln real wage on Δ ln GDP, effect of Δ ln real wage on Δ ln productivity, effect of Δ ln real wage on Δ ln real wage,

Figure C.32: Five-year IRFs for Wage Share Decomposition Model, Order 6

REFERENCES

Andrews, Donald W.K. and Biao Lu (2001). "Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models." *Journal of Econometrics* 101(1), 123–164.

Araujo, Ricardo Azevedo and Julio Fernando Costa Santos (2018). "Using non-linear estimation strategies to test an extended version of the Goodwin model to the US economy." Universidade de Brasilia, Brazil.

Arellano, Manuel and Olympia Bover (1995). "Another look at the instrumental variable estimation of error-components models." *Journal of Econometrics* 68(1), 29–51.

Arestis, Philip and Ana Rosa González-Martínez (2014). "Residential construction activity in OECD economies." *The Manchester School* 83(4), 451–474.

Barbosa-Filho, Nelson H. and Lance Taylor (2006). "Distributive and demand cycles in the US economy—a structuralist Goodwin model." *Metroeconomica* 57(3), 389–411.

Barrales, Jose and Rudiger von Arnim (2017). "Longer run distributive cycles: Wavelet decompositions for the US, 1948-2011." *Review of Keynesian Economics* 5(2), 196–217.

Basu, Susanto, John Fernald, and Miles Kimball (2004). "Are technology improvements contractionary?" Working Paper 10592, National Bureau of Economic Research. http://www.nber.org/papers/w10592.

Bhaduri, Amit and Stephen Marglin (1990). "Unemployment and the real wage: The economic basis for contesting political ideologies." *Cambridge Journal of Economics* 14(4), 375–393.

Blecker, Robert A. (1989). "International competition, income distribution and economic growth." *Cambridge Journal of Economics* 13(3), 395–412.

Blecker, Robert A. (2002). "Demand, distribution, and growth in neo-Kaleckian macro models." In Mark Setterfield, ed., *The Economics of Demand-Led Growth: Challenging the Supply-Side Vision of the Long Run*, pp. 129–152. Cheltenham: Edward Elgar.

Blecker, Robert A. (2016). "Wage-led versus profit-led demand regimes: The long and the short of it." *Review of Keynesian Economics* 4(4), 373–390.

Blecker, Robert A. (2017). "Long-term shifts in demand and distribution in Neo-Kaleckian models with and without short-run Goodwin cycles." Paper presented at the Eastern Economics Assoc. Meeting Feb. 2017.

Blundell, Richard and Stephen Bond (1998). "Initial conditions and moment restrictions in dynamic panel data models." *Journal of Econometrics* 87(1), 115–143.

Borio, Claudio, Piti Disyatat, and Mikael Juselius (2013). "Rethinking potential output: Embedding information about the financial cycle." Technical Report Working Paper No 404, Bank for International Settlements.

Bureau of Labor Statistics (2008). "Major sector productivity and costs." http://www.bls.gov/lpc/lpcmethods.pdf, accessed September 5, 2017.

Bureau of Labor Statistics (2016). "Employment, hours, and earnings from the establishment survey." http://www.bls.gov/opub/hom/pdf/homch2.pdf, accessed October 19, 2016.

Bureau of Labor Statistics (2017). "Estimating the U.S. labor share." Technical Report February 2017, Monthly Labor Review. https://www.bls.gov/opub/mlr/2017/article/estimating-the-us-labor-share.htm.

Caldentey, Esteban Pérez and Matías Vernengo (2013). "Wage and profit-led growth: The limits to neo-Kaleckian models and a Kaldorian proposal." Technical Report Working Paper No. 775, Levy Economics Institute.

Carvalho, Laura and Armon Rezai (2016). "Personal income inequality and aggregate demand." *Cambridge Journal of Economics* 40(2), 491–505.

Cerra, Valerie and Sweta C. Saxena (2017). "Booms, crises, and recoveries: A new paradigm of the business cycle and its policy implications." Technical Report WP/17/250, International Monetary Fund Working Paper.

Charpe, Matthieu, Slim Bridji, and Peter McAdam (2018). "Labor share and growth in the long run." Unpublished Manuscript, International Labour Organization and DG Research, European Central Bank, March 6.

Cogley, Timothy and James N. Nason (1995). "Effects of the Hodrick-Prescott filter on trend and difference stationary time series Implications for business cycle research." *Journal of Economic Dynamics and Control* 19(1-2), 253–278.

Cynamon, Barry Z. and Steven M. Fazzari (2016). "Inequality, the Great Recession and slow recovery." *Cambridge Journal of Economics* 40(2), 373–399.

Darvas, Zsolt (2012). "Real effective exchange rates for 178 countries: a new database." Working Paper 2012/06, Bruegel. http://bruegel.org/2012/03/real-effective-exchange-rates-for-178-countries-a-new-database/.

De Loecker, Jan and Jan Eeckhout (2017). "The rise of market power and the macroeconomic implications." Working Paper 23687, National Bureau of Economic Research. http://www.nber.org/papers/w23687.

Desai, Meghnad (1984). "An econometric model of the share of wages in national income: UK 1855– 1965." In Richard M. Goodwin, Michael Krüger, and Alessandro Vercelli, eds., *Nonlinear Models of Fluctuating Growth: An International Symposium Siena, Italy, March 24-27, 1983*, Berlin and Heidelberg, pp. 253–277. Springer Berlin Heidelberg.

Diallo, Mamadou Bobo, Peter Flaschel, Hans-Martin Krolzig, and Christian R. Proaño (2011). "Reconsidering the dynamic interaction between real wages and macroeconomic activity." *International Review of Applied Economics* 2(1), 77–93.

Dutt, Amitava Krishna (1984). "Stagnation, income distribution and monopoly power." *Cambridge Journal of Economics* 8(1), 25–40.

Dutt, Amitava Krishna (1987). "Alternative closures again: A comment on 'Growth, Distribution and Inflation'." *Cambridge Journal of Economics* 11(1), 75–82.

Enders, Walter (2014). *Applied Econometric Time Series* (4 ed.). Wiley.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer (2015). "The next generation of the penn world table." *American Economic Review* 105(10), 3150–3182. Available for download at www.ggdc.net/pwt.

Fernandez, Juan V. (2005). *Income Distribution and Aggregate Demand in the U.S. Economy: An Empirical Investigation.* Ph.D. thesis, American University, Washington, D.C.

Fiebiger, Brett (2018). "Semi-autonomous household expenditures as the causa causans of postwar US business cycles: the stability and instability of Luxemburg-type external markets." *Cambridge Journal of Economics* 42, 155–175. Advance Access publication April 15, 2017.

Goodwin, Richard M. (1967). "A growth cycle." In C.H. Feinstein, ed., *Socialism, Capitalism, and Economic Growth*, pp. 54–58. Cambridge: Cambridge University Press.

Gordon, Robert J. and Robert Krenn (2010). "The end of the Great Depression 1939-41: Policy contributions and fiscal multipliers." Working Paper 16380, National Bureau of Economic Research. http://www.nber.org/papers/w16380.

Gordon, Robert J. and Robert M. Solow (2003). "Are procyclical productivity fluctuations a figment of measurement error?" In *Productivity Growth, Inflation, and Unemployment: The Collected Essays of Robert J. Gordon*, pp. 239–272. Cambridge: Cambridge University Press. Cambridge Books Online.

Grasselli, Matheus R. and Aditya Maheshwari (2017). "A comment on 'Testing Goodwin: growth cycles in ten OECD countries'." *Cambridge Journal of Economics*. doi:10.1093/cje/bex018.

Greene, William H. (2011). "Econometric analysis. Chapter 13. Boston: Pearson.

Hahnel, Robin and Howard Sherman (1982). "The rate of profit over the business cycle." *Cambridge Journal of Economics* 6(2), 185–194.

Halter, Daniel, Manuel Oechslin, and Josef Zweimüller (2014). "Inequality and growth: the neglected time dimension." *Journal of Economic Growth* 19, 81–104.

Hamilton, James D. (2017). "Why you should never use the Hodrick-Prescott filter." *Review of Economics and Statistics*. Forthcoming.

Harvie, David (2000). "Testing Goodwin: growth cycles in ten OECD countries." *Cambridge Journal of Economics* 24(3), 349–376.

Hayakawa, Kazuhiko (2009). "First difference or forward orthogonal deviation - which transformation should be used in dynamic panel data models?: A simulation study." *Economics Bulletin* 29(3), 2008–2017.

Hein, Eckhard and Lena Vogel (2008). "Distribution and growth reconsidered: Empirical results for six OECD countries." *Cambridge Journal of Economics* 32(3), 479–511.

Hodrick, Robert J. and Edward C. Prescott (1997). "Postwar U.S. business cycles: An empirical investigation." *Journal of Money, Credit and Banking* 29(1), 1–16.

Ivanov, Ventzislav and Lutz Kilian (2005). "A practitioner's guide to lag order selection for VAR impulse response analysis." *Studies in Nonlinear Dynamics and Econometrics* 9(1), 2.

Kalecki, Michal (1954). *Theory of Economic Dynamics*. London: Unwin.

Kiefer, David and Codrina Rada (2015). "Profit maximising goes global: The race to the bottom." *Cambridge Journal of Economics* 39(5), 1333–1350.

Kim, Hyeongwoo (2013). "Generalized impulse response analysis: General or extreme?" *EconoQuantum* 10(2), 135–141.

Lavoie, Marc (2014). "The Kaleckian model with overhead costs." In *Post-Keynesian Economics: New Foundations*, pp. 322–339. Cheltenham, UK; Northampton, MA: Edward Elgar.

Lavoie, Marc (2017). "The origins and evolution of the debate on wage-led and profit-led regimes." *European Journal of Economics and Economic Policies: Intervention* 14(2), 200–221.

Loretan, Mico (2005, Winter). "Indexes of the foreign exchange value of the dollar." Technical report, Federal Reserve Bulletin.

Marglin, Stephen A. and Amit Bhaduri (1990). "Profit squeeze and Keynesian theory." In Stephen A. Marglin and Juliet B. Schor, eds., *The Golden Age of Capitalism*, pp. 153–186. Oxford: Oxford University Press.

Naastepad, C.W.M. and Servaas Storm (2006). "OECD demand regimes (1960-2000)." *Journal of Post Keynesian Economics* 29(2), 211–246.

Ng, Serena and Pierre Perron (2001). "Lag length selection and the construction of unit root tests with good size and power." *Econometrica* 69(6), 1519–1554.

Nikiforos, Michalis and Duncan K. Foley (2012). "Distribution and capacity utilization: Conceptual issues and empirical evidence." *Metroeconomica* 63(1), 200–229.

Obst, Thomas, Özlem Onaran, and Maria Nikolaidi (2017). "The effect of income distribution and fiscal policy on growth, investment, and budget balance: the case of Europe." Working Paper GPERC 43, GREENWICH POLITICAL ECONOMY RESEARCH CENTRE.

Onaran, Özlem and Giorgos Galanis (2012). "Is aggregate demand wage-led or profit-led? National and global effects." Working paper, International Labour Organization. http://econpapers.repec.org/paper/iloilowps/994786233402676.htm.

Onaran, Özlem and Thomas Obst (2016). "Wage-led growth in the EU15 member-states: the effects of income distribution on growth, investment, trade balance and inflation." *Cambridge Journal of Economics* 40(6), 1517–1551.

Onaran, Özlem, Engelbert Stockhammer, and Lucas Grafl (2011). "Financialisation, income distribution and aggregate demand in the USA." *Cambridge Journal of Economics* 35(4), 637–661.

Organisation for Economic Co-operation and Development (2018). "Oecd economic outlook database inventory.

Palley, Thomas I. (2017). "Wage- vs. profit-led growth: The role of the distribution of wages in determining regime character." *Cambridge Journal of Economics* 41(1), 49–61.

Rowthorn, Bob (1982). "Demand, real wages and economic growth." *Studi Economici* 18, 3–53.

Sánchez, Gustavo Vargas and Albino Luna (2014). "Slow growth in the Mexican economy." *Journal of Post Keynesian Economics* 37(1), 115–134.

Sherman, Howard J. and Gary R. Evans (1984). *Macro-Economics: Keynesian, Monetarist and Marxist Views.* New York: Harper Row.

Sigmund, Michael and Robert Ferstl (2017). “Panel vector autoregression in R with the package panelvar.” *SSRN*.

Silva de Jesus, Cleiton, Ricardo Azevedo Araujo, and Carlos Eduardo Drumond (2018). “An empirical test of the Post-Keynesian growth model applied to functional income distribution and the growth regime in Brazil.” *International Review of Applied Economics* 32(4), 428–449.

StataCorp (2017). “Stata statistical software: Release 15.” Technical report, StataCorp LLC, College Station, TX. https://www.stata.com/manuals13/rgmm.pdf.

Steindl, Josef (1952). *Maturity and Stagnation in American Capitalism*. Oxford: Blackwell. Reprinted New York: Monthly Review Press, 1976.

Stock, James H. and Mark W. Watson (2001). “Vector autoregressions.” *The Journal of Economic Perspectives* 15(4), 101–115.

Stockhammer, Engelbert (2017a). “Determinants of the wage share: A panel analysis of advanced and developing economies.” *British Journal of Industrial Relations* 55(1), 3–33.

Stockhammer, Engelbert (2017b). “Wage-led versus profit-led demand: what have we learned? A Kaleckian– Minskyan view.” *Review of Keynesian Economics* 5(1), 25–42.

Stockhammer, Engelbert, Eckhard Hein, and Lucas Grafl (2011). “Globalization and the effects of changes in functional income distribution on aggregate demand in Germany.” *International Review of Applied Economics* 25(1), 1–23.

Stockhammer, Engelbert and Jo Michell (2016). “Pseudo-Goodwin cycles in a Minsky model.” *Cambridge Journal of Economics* 41(1), 105–125.

Stockhammer, Englebert and Özlem Onaran (2004). “Accumulation, distribution and employment: a structural VAR approach to a Kaleckian macro model.” *Structural Change and Economic Dynamics* 15(4), 421–447.

Stockhammer, Engelbert, Özlem Onaran, and Stefan Ederer. (2009). “Functional income distribution and aggregate demand in the euro area.” *Cambridge Journal of Economics* 33(1), 139–159.

Stockhammer, Engelbert, Joel Rabinovich, and Niall Reddy (2018). “Distribution, wealth and demand regimes in historical perspective. USA, UK, France and Germany, 1855-2010.” Working Paper 1805, Post-Keynesian Economics Society.

Stockhammer, Engelbert and Robert Stehrer (2011). “Goodwin or Kalecki in demand? Functional income distribution and aggregate demand in the short run.” *Review of Radical Political Economics* 43(4), 506–522.

Stockhammer, Engelbert and Rafael Wildauer (2016). "Debt-driven growth? Wealth, distribution and demand in OECD countries." *Cambridge Journal of Economics* 40(6), 1609–1634.

Storm, Servaas and C.W.M. Naastepad (2017). "Bhaduri–Marglin meet Kaldor–Marx: wages, productivity and investment." *Review of Keynesian Economics* 5(1), 4–24.

Tavani, Daniele, Peter Flaschel, and Lance Taylor (2010). "Estimated non-linearities and multiple equilibria in a model of distributive-demand cycles." Technical Report 2010-6, Schwartz Center for Economic Analysis and Department of Economics, The New School for Social Research, Working Papers Series. http://www.economicpolicyresearch.org/media/k2/attachments/Taylor

Tavani, Daniele, Peter Flaschel, and Lance Taylor (2011). "Estimated non-linearities and multiple equilibria in a model of distributive-demand cycles." *International Review of Applied Economics* 25(5), 519–538.

Taylor, Lance (1983). *Structuralist Macroeconomics: Applicable Models for the Third World*. New York: Basic Books.

Taylor, Lance (1985). "A stagnationist model of economic growth." *Cambridge Journal of Economics* 9(4), 383–403.

Weisskopf, Thomas E. (1979). "Marxian crisis theory and the rate of profit in the postwar U.S. economy." *Cambridge Journal of Economics* 3(4), 341–378.