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Testing for Granger Causality in Quantiles Between the Wage Share and Capacity Utilization

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Abstract:

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Keywords: Granger causality in distribution; quantile regression; bootstrap resampling; wage share; capacity utilization.

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1 Introduction

Two of the most discussed stylized facts in macroeconomic circles in recent years are the declining trend of the wage share in aggregate income and the slow increase in economic activity in several advanced countries even long before the emergence of the COVID-19 pandemic.[1] Therefore, a

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[1]The decline in the wage share is documented and discussed, for instance, in Karabarbounis and Neiman (2014), ILO (2015) and Stockhammer (2017), while the slow increase in economic activity is discussed from different perspectives, for example, in Summers (2015), Blecker (2016b), Onaram (2016) and World Bank (2018).

relevant issue that arises in this regard and bears important theoretical and policy implications is whether these two recent stylized facts are possibly causally related.

Figure 1 plots *changes* in the cyclical components of the wage share and capacity utilization in the U.S. and Sweden in the 1963-2019 period as representative of similar patterns observed in other advanced economies, such as the U.K., the Netherlands, Italy, and Austria.[2] In these countries, changes in the wage share seem to be often associated with changes in the same direction in capacity utilization.[3] The pattern represented in Figure 1 suggests a potential cause-and-effect dynamic relationship between the wage share and capacity utilization, the possibility of which is worth exploring empirically.

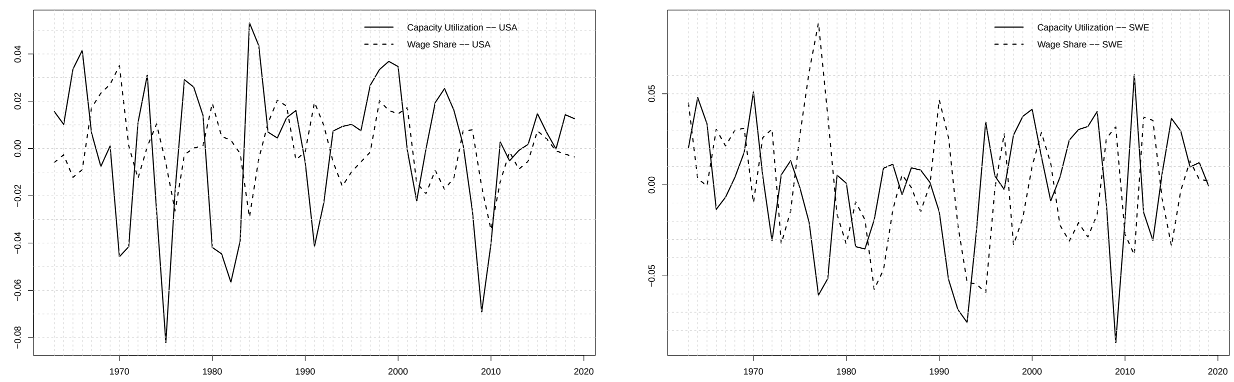

Figure 1: Comovement of the cyclical components of the wage share and capacity utilization in the U.S. and Sweden, 1963-2019.

In order to perform a broader and more robust evaluation of such a possibility, this paper uses bootstrap confidence intervals for testing Granger causality in quantiles between the wage share and capacity utilization in twelve advanced countries using annual data ranging from 1960 to 2019. We employ the notion of Granger causality in the conditional distribution (Granger, 1980; 1988) instead of Granger causality in the conditional mean, which fruitfully allows us to explore whether Granger causality is heterogeneous across different quantiles of the dependent variable. In effect, a single focus on the conditional mean may misrepresent the relationship between capacity utilization and the wage share if there are differences in such a relationship along the conditional distribution.

Dependence and predictability across macroeconomic variables may be state-dependent, implying that the sign and significance of the involved dynamic relationships may be different above and below the average. More broadly, the dynamic response of the dependent variable may be stronger or weaker, as well as statistically significant or not, depending on the specific quantiles range (for instance, at the upper or lower tail of the distribution). In fact, Nikiforos and Foley (2012) empirically identify a state-dependent relationship between capacity utilization and the wage share in the U.S. economy. At low levels of capacity utilization, the wage share falls as capacity utilization rises. In contrast, at high levels of capacity utilization, the wage share rises as

[2]The precise way the cyclical components of such variables is obtained is described in Section 3.

[3]The dual role of the wage as cost and demand factor, which we believe may underlie the potentially ambiguous relationship between the wage share (or unit labor cost) and capacity utilization, is elaborated, for instance, in Blecker (1989), Bhaduri and Marglin (1990), Nikiforos and Foley (2012), and Blecker and Setterfield (2019).

capacity utilization also rises. In order to deal with the issue of the likely simultaneous determination of capacity utilization and the functional distribution of income between wages and profits, and also identify possible non-linear relationships between such macroeconomic variables, Nikiforos and Foley (2012) use two-stage least squares. Blecker (2016a) also correctly notes there is likely to be simultaneous causality between the functional distribution of income (wage share) and aggregate demand (capacity utilization).

Although Nikiforos and Foley (2012) and Blecker (2016a) emphasize the state-dependent behavior of the functional distribution of income and capacity utilization, the conditional mean-regression analysis cannot properly detect causality under such circumstances. Therefore, we test for Granger causality in the full conditional distribution of the involved macroeconomic variables following the quantile regression approach (Gebka and Wohar, 2013; Baumöl and Lyócsa, 2017; Troster, 2018). Quantile regression methods offer the fruitful possibility of exploring how covariate effects influence the location, scale and possibly the shape of the conditional response distribution. Chuang et al. (2009) and Gebka and Wohar (2013) apply tests for Granger causality in the conditional distribution to fuller understand the dynamic relationship between stock returns and trading volume. Meanwhile, Troster (2018) proposes a parametric test of Granger causality in quantiles to investigate causal relationships between the gold price, oil price, and exchange rate. However, the test statistic proposed by Troster (2018) does not provide the sign and magnitude of the causal effects, but only their statistical significance. By employing impulse response functions, we can nonetheless overcome these limitations (see, for example, Granger et al. (2000)). In effect, the approach based on confidence intervals followed in this paper does not suffer from such limitations, as it provides the sign, magnitude, and significance of causal effects when they exist.

Blecker (2016a) argues that although an increase in the wage share may boost consumption and capacity utilization in the long term, an adverse effect on capacity utilization of such an increase is more likely to exist in the short term, in which higher labor costs may impair the international price competitiveness of the economy. Since we are using data describing only short-run cyclical movements, we could expect that a positive change in the wage share would negatively impact on the subsequent change in capacity utilization through cost effects. However, we could also expect that a positive change in capacity utilization is likely to positively impact on the subsequent change in the wage share due to effects operating through a tighter labor market leading to an increase in the bargaining power of workers. Therefore, the main ambition (and hence contribution) of this paper is to explore whether the dynamic behavior of the wage share (capacity utilization) can be fittingly used to Granger predict the dynamic behavior of capacity utilization (wage share) over a wide range of conditional quantiles of the dependent variable.

The remainder of this paper is organized as follows. Section 2 briefly describes the methodology and models used in the estimations. Section 3 reports the empirical results and discusses the main findings. Section 4 concludes the paper.

2 Methodology

2.1 Causality in distribution

Granger (1980; 1988) introduces the notion of causality in distribution. Specifically, we say that a random variable x does not Granger cause the random variable y in distribution if:

$$F_{y_t}(\eta|(Y,X)_{t-1}) = F_{y_t}(\eta|(Y)_{t-1}), \forall \eta \in \Re \quad (1)$$

holds almost surely, where $F_{y_t}(\cdot|\Im)$ is the conditional distribution of y_t, and $(Y,X)_{t-1}$ is the information set generated by y_i and x_i up to time $t-1$. This means that the past information of x does not alter the conditional distribution of y_t. Hence, we can infer that x causes y in conditional distribution when (1) fails to hold. Given that the distribution of random variables is fully determined by its quantiles, we can test for this proposition based on quantile regression methods.

The other notions of Granger "non-causality in risk" or Granger "non-causality in mean" are different and more stringent (see Troster (2018) for a more detailed discussion). Chuang et al. (2009) observe that failing to reject the null of "non-causality in mean" says nothing about the causality in other parts or characteristics of the distribution. The independent variables can affect features or parts of the distribution of a dependent variable other than its conditional mean, which can be well described by quantile regression estimates (Gebka and Wohar, 2013).

2.2 Econometric methodology

We estimate an unrestricted bivariate VAR(p) in conditional quantiles to test for Granger non-causality in the conditional distribution of the considered series. We employ quantile regression methods (Koenker and Bassett, 1978; Koenker, 2005) and hypothesis testing based on the confidence interval generated by bootstrap resampling designed to regression quantiles (Kocherginsky et al., 2005; Bose and Chatterjee, 2003). In the typical least-squares regression model approach to the relationship between capacity utilization and the wage share, the focus is on explaining such a relationship at the conditional mean. It is assumed that the marginal impact of the wage share on capacity utilization, for instance, does not change along the conditional capacity utilization distribution. In contrast, the quantile regression model introduced by Koenker and Bassett (1978) is less restrictive in such a modeling of capacity utilization in that the marginal impact of the wage share is permitted to vary at different points of the conditional distribution. Therefore, the quantile regression model allows better and more robustly quantifying the dynamic relationship between the wage share and capacity utilization over the business cycle and detecting the quantiles for which, if any, causality exists. We follow Chuang et al. (2009) and Gebka and Wohar (2013) in estimating the bivariate conditional quantile functions given by:

$$Q(\tau)_w(w_t|J_t') = \alpha_0(\tau) + \sum_{j=1}^{p} \gamma_j(\tau) w_{t-j} + \sum_{j=1}^{q} \beta_j(\tau) g_{t-j}, \tag{2}$$

$$Q(\tau)_g(g_t|J_t') = \xi_0(\tau) + \sum_{j=1}^{p} \zeta_j(\tau) g_{t-j} + \sum_{j=1}^{q} \delta_j(\tau) w_{t-j}, \tag{3}$$

where w_t refers to the wage share, g_t denotes capacity utilization, and J_t' includes past and current values of both w_t and g_t. The main parameters of interest $\beta_q(\tau)$ and $\delta_q(\tau)$ are quantile-dependent and can be different in sign, significance and magnitude across quantiles ($\tau \in (0,1)$). This flexible property of the quantile models make them suitable to describe potential asymmetric responses of the respective dependent variable during periods of higher and lower level of economic activity or wage share. The two null hypotheses to be tested are $\beta_1(\tau) = \ldots = \beta_q(\tau) = 0$ and $\delta_1(\tau) = \ldots = \delta_q(\tau) = 0$, $j = 1, \ldots, q$, in the models (2) and (3).

Our inference method is similar in spirit to the one adopted in Fallahi (2012), which constructs bootstrap confidence intervals for testing the null of unit root in consumption-income ratios in 23 OECD countries. Our inference method follows more closely the one adopted in Gebka and Wohar (2013), which uses bootstrapping confidence intervals for testing Granger causality in quantiles between trading volume and returns. As we are restricted to using a relatively small sample data set ($T < 100$), we conduct our hypothesis testing using a 10% significance level throughout the paper. Wooldridge (2020) provides further advice on choosing a suitable significance level for inference in small, medium, and large samples, with smaller sample sizes leading to less precise estimators. Due to its favorable performance in terms of speed, accuracy, and reliability, we adopt a bootstrap resampling method specifically designed for quantile regressions (Kocherginsky et al., 2005; Bose and Chatterjee, 2003).

Bootstrap confidence intervals have a great appeal because they are very informative, computationally easy to implement, and produce efficient and unbiased estimates even with the use of relatively small samples (Cho et al., 2015). We fail to reject the null hypothesis of Granger non-causality in distribution stated in (1) when the interval contains zero. We follow Chuang et al. (2009) and Gebka and Whoar (2013) and set $p = q$ in the models (2) and (3). We use the Akaike Information Criterion (AIC) for selecting the optimal lag length to obey the parsimony principle (Cho et al., 2015). Table 5 in the Appendix shows the values of minimum AIC and the corresponding number of the optimal lag length for each country in the sample.

3 Results and discussion

We use annual country-level data on the cyclical component of the wage share at factor cost and the cyclical component of the aggregate output for twelve advanced countries spanning from 1960 through 2019, a choice mostly based on data availability. We use both variables in the natural logarithm scale. The sample countries are the United States, Norway, Sweden, the Netherlands, the United Kingdom, Austria, Canada, Italy, Portugal, Ireland, Greece, and Spain. Therefore, our sample includes Eurozone countries (Portugal, Ireland, Italy, Greece, and Spain) where real unit labor costs fell, on average, by more than other Eurozone countries (Austria, the Netherlands, and Sweden) in the 1979-2012 period (Ordonez et al., 2015). We use data from AMECO, which is the annual macroeconomic database of the European Commission's Directorate General for Economic and Financial Affairs, and the Penn World Table (PWT). The AMECO database is freely available at `https://ec.europa.eu/`, and it does not provide data on the wage share for the considered countries for the years before 1960. The PWT 10.0 dataset is freely available at `https://www.rug.nl/ggdc/productivity/pwt/?lang=en`, and it provides data on the real GDP level at constant 2017 national prices (million 2017 USD) for the same countries until 2019. We follow Hamilton (2018) in using the cyclical component of the aggregate output as a measure of economic activity. Nikiforos and Foley (2012) also use the cyclical components of the wage share and aggregate output in their estimations and tests. We adopt the same procedure, but correct for problems of spurious dynamics by using the Hamilton filter instead of the Hodrick-Prescott filter.

We follow Rudd and Whelan (2005) and Stockhammer and Wildauer (2016) in using the wage share at factor cost to measure the functional distribution of income. Following Harvey et al. (2012) and Smeeks and Taylor (2012), we perform a bootstrap unit root test based on the union of rejections of tests with different deterministic components and different detrending methods. These tests are invariant to whether the linear time trend is present in the data or not, improve the power, and reduce the uncertainty about misspecification issues.

Tables 5 – 8 in Appendix A present the individual test results and summary statistics. Such tests reject the normality distribution for all variables. The standard deviation estimates suggest that the variables of interest are more volatile in Portugal, Ireland, and Greece. Moreover, we fail to reject the unit root hypothesis for the wage share in the U.K., Italy, and Portugal at the 10% level. The same is true for capacity utilization in the Netherlands, Portugal, and Greece. Except in these cases, we use all series of capacity utilization and the wage share in levels. We use the first difference of the variables when we fail to reject the unit root hypothesis.

We test for the null hypothesis of Granger non-causality based on 3000 bootstrap replications for standard errors associated with each parameter estimates ($\beta_j(\tau)$ and $\delta_j(\tau)$) for each quantile ($\tau = 0.05, 0.06, 0.07, ..., 0.95$). Thus, we inclusively specify 91 quantiles of the conditional distribution. The parameter estimates of interest $\beta_j(\tau)$ and $\delta_j(\tau)$ are quantile-specific, and may be different across quantiles, while their statistical significance is shown by the 90% confidence interval that excludes zero. In Figures 2–22 in Appendix C, we plot against τ (horizontal axis) the quantile regression estimates of $\beta_j(\tau)$ and $\delta_j(\tau)$ (dotted lines) in the vertical axis and their 90% confidence interval (shaded area) along with the least squares estimate (dashed line) and its bootstrapped 90% confidence interval (dotted lines).

Conveniently, the results referring to the quantile regressions estimates for the different quantiles provide a considerably fuller picture of causality in the whole distribution, in addition to the average. Our methods enable us to identify the significant quantiles, if any, for which causality exists. As there are many interesting results to be reported, we present them graphically in Appendix C and summarize the major findings in Tables 1 and 2.

We found significant positive Granger causality running from capacity utilization to the wage share in seven out of the twelve countries included in the sample, with the response of the wage share being stronger at more extreme quantiles. However, we did not find evidence of Granger causality in either direction between capacity utilization and the wage share in four countries: Norway, Canada, Ireland, and Portugal. We also found that the Granger causal response of the wage share to capacity utilization was heterogeneous across countries in both magnitude and conditional quantile. In the U.S., for instance, capacity utilization significantly positively Granger cause the wage share in almost all conditional quantiles. Meanwhile, in the Netherlands, a similar Granger causal effect was found only above the average. We obtained a different result for Spain, where the wage share significantly negatively Granger cause capacity utilization in all conditional quantiles. Therefore, while a positive and significant Granger causal effect running from capacity utilization to the wage share was found in most considered countries, a negative and significant Granger causal effect of the wage share on capacity utilization was detected only in Spain.

As can be observed in Figure 2, in the U.S., the response of the wage share (vertical axis) in lag one, $\beta_1(\tau)$, is considerably smaller at the lower tail of the distribution and larger at the upper tail. The least squares estimate could not capture this heterogeneous response since it yielded a uniform effect over the whole range of the distribution of about 0.30. Using the Wald test statistic based on Koenker and Bassett (1982), we could test the hypothesis that all the conditional quantile functions have the same slope parameters. The last column in Table 1 shows that in the U.S., Sweden, and the Netherlands, the data reject the joint equality of slopes at 5% level.

We take a step further by applying the Wald test statistic to check for the joint significance of the coefficients for a specific quantile. This joint significance test conveniently complement the confidence interval procedure for formal inference adopted to obtain the results reported above. Therefore, we apply these tests only to countries that presented significant causality in a given range of quantiles. Using conditional quantile functions, according to which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates, we could describe the conditional distribution of the realizations of the time series in three quartiles ($\tau = 0.25; \tau = 0.50; \tau = 0.75$) and the lower and upper tail ($\tau = 0.10; \tau = 0.90$) of the distribution. For the U.S., for example, the null hypothesis of non-causality from lagged capacity utilization to the wage share is $\beta_1(\tau) = \beta_2(\tau) = \beta_3(\tau) = 0$ for $\tau \in (0.10, 0.25, 0.50, 0.75, 0.90)$. These additional findings are reported in Tables 3 and 4.

Table 3 allows us to unambiguously conclude that there exists significant Granger causality running from capacity utilization to the wage share at the center and upper tail of the conditional distribution in six countries: the U.S., Sweden, the U.K., Austria, Italy, and Ireland. In particular, we have found significant joint causality running from capacity utilization to the wage share in all considered quantiles in the U.S., Sweden, and the U.K. (except in $\tau = 0.90$ in the U.K.). At the lower tail of the conditional distribution, it is only in Austria and Ireland that capacity utilization does not help to predict subsequent changes in the wage share. A similar result applies for Spain and the Netherlands at the center of the conditional distribution of the wage share.

Table 1: Granger causality **to** the wage share – Results: H_0: $\beta_j(\tau) = \ldots = \beta_q(\tau) = 0$ – Eq. (2).

Country	Sign	Significant quantiles range	Joint test for equality of slopes
1. *United States*	positive	[0.20;0.95]*	3.1337***
2. *Norway*	independence	—-	—-
3. *Sweden*	positive	[0.30;0.95]*	1.4670**
4. *Netherlands*	positive	[0.50;0.95]*	2.0255***
5. *United Kingdom*	positive	[0.05;0.80]*	1.0751
6. *Austria*	positive	[0.20;0.80]*	0.8279
7. *Canada*	independence	—-	—-
8. *Italy*	positive	[0.40;0.80]*	1.2226
9. *Portugal*	independence	—-	—-
10. *Ireland*	positive	[0.70;0.95]*	0.8817
11. *Greece*	independence	—-	—-
12. *Spain*	no effect	—-	—-

Note: * denotes significance at the 10% level for $\tau \in (0.05, 0.06, \ldots, 0.95)$. *** and ** denote significance at the 1% and 5% level for the F-statistic, respectively. When performing the Wald test statistic for equality of slopes, for computational convenience, we use $\tau \in (0.10, 0.20, \ldots, 0.90)$ and include only the countries with significant quantiles range. We identify these quantiles range for each country based on their statistical significance as indicated by the Granger causality results. "Independence" means no significant Granger causality in either direction between capacity utilization and the wage share.

Table 2: Granger causality **to** capacity utilization – Results: H_0: $\delta_j(\tau) = \ldots = \delta_q(\tau) = 0$ – Eq.(3).

Country	Sign	Significant quantiles range	Joint test for equality of slopes
1. *United States*	no effect	—-	—-
2. *Norway*	independence	—-	—-
3. *Sweden*	no effect	—-	—-
4. *Netherlands*	no effect	—-	—-
5. *United Kingdom*	no effect	—-	—-
6. *Austria*	no effect	—-	—-
7. *Canada*	independence	—-	—-
8. *Italy*	no effect	—-	—-
9. *Portugal*	independence	—-	—-
10. *Ireland*	no effect	—-	—-
11. *Greece*	independence	—-	—-
12. *Spain*	negative	[0.10;0.95]*	2.1847***

Note: * denotes significance at the 10% level for $\tau \in (0.05, 0.06, \ldots, 0.95)$. *** and ** denote significance at the 1% and 5% level for the F-statistic, respectively. When performing the Wald test statistic for equality of slopes, for computational convenience, we use $\tau \in (0.10, 0.20, \ldots, 0.90)$ and include only the countries with significant quantiles range. We identify these quantiles range for each country based on their statistical significance as indicated by the Granger causality results. "Independence" means no significant Granger causality in either direction between capacity utilization and the wage share.

Table 3: Wald test - joint significance: H_0: $\beta_i(\tau) = 0$, $i = 1,2,3$ for $\tau \in (0.10, 0.25, \ldots, 0.90)$.

Country	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
1. *United States*	3.5080**	10.5750***	12.0600***	16.6200***	63.5980***
2. *Sweden*	6.6796***	9.1433***	21.4040***	23.0880***	3.7378**
3. *Netherlands*	7.6556***	1.0868	2.3072	7.2753***	16.6810***
4. *United Kingdom*	9.8877***	5.7351***	10.3340***	14.6810***	0.0599
5. *Austria*	2.7456	12.6920***	22.0870***	5.4214**	1.4946
6. *Italy*	27.8980***	1.0945	6.5410***	6.3755***	51.8740***
7. *Ireland*	0.3322	2.5985*	6.1516***	4.5550***	4.1382**
8. *Spain*	10.4800***	6.8335***	0.9822	1.2081	3.4445**

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels for the F-statistic, respectively. We select the countries based on the statistical significance of the quantiles range as indicated by the Granger causality results.

Table 4: Wald test - joint significance: H_0: $\delta_i(\tau) = 0$, $i = 1,2,3$ for $\tau \in (0.10, 0.25, \ldots, 0.90)$.

Country	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
1. *United States*	2.6257*	0.2392	0.7684	0.4639	0.4243
2. *Sweden*	1.3188	0.6743	0.4672	0.5760	0.8068
3. *Netherlands*	1.3322	0.5215	0.9561	3.6992**	2.2480
4. *United Kingdom*	2.7268	3.1894*	1.4547	3.4728*	0.0090
5. *Austria*	0.4315	0.0000	2.7776	0.0075	1.7596
6. *Italy*	1.1324	1.4499	0.7482	3.7939**	1.8351
7. *Ireland*	0.2455	0.8672	1.5036	0.4886	2.0917
8. *Spain*	1.1033	9.4890***	6.3539***	23.1840***	12.1950***

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels for the F-statistic, respectively. We select the countries based on the statistical significance of the quantiles range as indicated by Granger causality results.

As clearly displayed in Table 4, there is no significant Granger causality from the wage share to capacity utilization in all considered quantiles in seven out of the eight countries in Table 3. In effect, it is only in Spain's case (and except at the lower tail of the conditional distribution) that there is significant negative Granger causality running from the wage share to capacity utilization. We also find weak and localized evidence of negative Granger causality running from the wage share to capacity utilization in the Netherlands and Italy operating at $\tau = 0.75$.

4 Conclusions

This paper tested for Granger causality in quantiles between the wage share and capacity utilization in twelve advanced countries in the long period from 1960 to 2019. Instead of focusing uniquely on the conditional mean, we tested for Granger causality in the entire conditional distribution of the variables under consideration. This allowed detecting Granger causal relations in both the mean and the entire conditional distribution, and therefore permitted a more thorough and comprehensive exploration of the dynamic relationship between capacity utilization and the wage share over the business cycle. Our inference strategy was based on confidence intervals generated by bootstrap resampling and the Wald test for joint significance.

Overall, our statistically significant results mainly indicate that the sample countries can be divided into three groups with respect to the dynamic relationship between capacity utilization and the wage share. The first group includes countries for which the only dynamic relation found features capacity utilization positively Granger causing the wage share (the United States, Sweden, the Netherlands, the United Kingdom, Austria, Italy, and Ireland). In these countries, the respective Granger causal effect is strong and heterogeneous across quantiles, it being larger for more extreme quantiles. The second group includes Spain, for which the only significant dynamic relation found has the wage share negatively Granger causing capacity utilization in most conditional quantiles. Lastly, no evidence of significant Granger causality in either direction between the variables of interest was found for Norway, Canada, Portugal, and Greece.

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Appendix A: Bootstrap Union Test for Unit Roots

Table 5: Bootstrap Union Test for Unit Roots — results.

	United States		*Norway*		*Sweden*	
	g_t	w_t	g_t	w_t	g_t	w_t
Level	(**0.0000**)	(**0.0000**)	(**0.0007**)	(**0.0000**)	(**0.0257**)	(**0.0013**)
First difference	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)
Median	0.0068	-0.0015	0.0030	0.0018	0.0048	-0.0015
SD	0.0292	0.0143	0.0230	0.0556	0.0319	0.0318
Maximum	0.0532	0.0350	0.0458	0.1243	0.0604	0.0890
Minimum	-0.0821	-0.0343	-0.0534	-0.1392	-0.0867	-0.0592
Skewness	-0.7486	0.0939	-0.3427	-0.3474	-0.6476	0.2341
Kurtosis	0.1430	-0.1266	0.1872	-0.1188	0.2630	-0.2523
KS normality test	**0.4788**	**0.4863**	**0.4817**	**0.4506**	**0.4759**	**0.4764**

Notes: In each test, the series has a unit root under the null hypothesis, where boldface values indicate rejection at the 5% level. The p-values are in brackets. We use modified AIC (MAIC) because Ng and Perron (2001) argue that standard information criteria should be modified to account for the presence of negative moving-average errors. w_t refers to the cyclical component of wage share at factor cost, and g_t is the cyclical component of output using Hamilton's (2018) procedure. We use the maximum number of lags given by $12(T/100)^{1/4}$. We obtain the p-values of the unit root test based on 3000 wild sieve bootstrap replications (Smeekes and Taylor, 2012). The Kolmogorov-Smirnov (KS) test has the normality under the null and can be applied to correlated data (Weiss, 1978).

Table 6: Bootstrap Union Test for Unit Roots — results.

	Netherlands		*United Kingdom*		*Austria*	
	g_t	w_t	g_t	w_t	g_t	w_t
Level	(0.2084)	(**0.0007**)	(**0.0000**)	(0.9226)	(**0.0120**)	(**0.0087**)
First difference	(**0.0003**)	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)
Median	0.0020	-0.0003	0.0080	0.0039	0.0022	-0.0031
SD	0.0288	0.0248	0.0321	0.0274	0.0239	0.0200
Maximum	0.0474	0.0440	0.0597	0.1072	0.0480	0.0519
Minimum	-0.0844	-0.0588	-0.0956	-0.0671	-0.0529	-0.0520
Skewness	-0.4413	-0.1461	-1.0285	0.5378	-0.2111	0.2314
Kurtosis	-0.1729	-0.6686	0.9170	3.0434	-0.6429	0.3481
KS normality test	**0.4811**	**0.4825**	**0.4762**	**0.4733**	**0.4809**	**0.4793**

Notes: In each test, the series has a unit root under the null hypothesis, where boldface values indicate rejection at the 5% level. The p-values are in brackets. We use modified AIC (MAIC) because Ng and Perron (2001) argue that standard information criteria should be modified to account for the presence of negative moving-average errors. w_t refers to the cyclical component of wage share at factor cost, and g_t is the cyclical component of output using Hamilton's (2018) procedure. We use the maximum number of lags given by $12(T/100)^{1/4}$. We obtain the p-values of the unit root test based on 3000 wild sieve bootstrap replications (Smeekes and Taylor, 2012). The Kolmogorov-Smirnov (KS) test has the normality under the null and can be applied to correlated data (Weiss, 1978).

Table 7: Bootstrap Union Test for Unit Roots — results.

	Canada		*Italy*		*Portugal*	
	g_t	w_t	g_t	w_t	g_t	w_t
Level	(**0.0000**)	(**0.0037**)	(**0.0010**)	(0.2297)	(0.6715)	(0.2347)
First difference	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0003**)
Median	0.0057	0.0031	0.0073	0.0016	0.0053	-0.0039
SD	0.0278	0.0242	0.0296	0.0215	0.0431	0.0612
Maximum	0.0514	0.0559	0.0769	0.0640	0.0818	0.2335
Minimum	-0.0759	-0.0440	-0.0714	-0.0593	-0.1319	-0.1896
Skewness	-1.0857	0.1303	-0.3409	0.1012	-0.5193	0.7236
Kurtosis	1.0199	-0.6938	0.0507	0.7595	0.2479	3.6627
KS normality test	**0.4795**	**0.4825**	**0.4715**	**0.4764**	**0.4674**	**0.4444**

Notes: In each test, the series has a unit root under the null hypothesis, where boldface values indicate rejection at the 5% level. The p-values are in brackets. We use modified AIC (MAIC) because Ng and Perron (2001) argue that standard information criteria should be modified to account for the presence of negative moving-average errors. w_t refers to the cyclical component of wage share at factor cost, and g_t is the cyclical component of output using Hamilton's (2018) procedure. We use the maximum number of lags given by $12(T/100)^{1/4}$. We obtain the p-values of the unit root test based on 3000 wild sieve bootstrap replications (Smeekes and Taylor, 2012). The Kolmogorov-Smirnov (KS) test has the normality under the null and can be applied to correlated data (Weiss, 1978).

Table 8: Bootstrap Union Test for Unit Roots — results.

	Ireland		*Greece*		*Spain*	
	g_t	w_t	g_t	w_t	g_t	w_t
Level	(**0.0127**)	(**0.0000**)	(0.1453)	(**0.0083**)	(**0.0138**)	(**0.0143**)
First difference	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)	(**0.0000**)
Median	-0.0032	-0.0019	0.0107	0.0061	0.0076	0.0012
SD	0.0630	0.0652	0.0549	0.0379	0.0330	0.0230
Maximum	0.2231	0.1363	0.1066	0.0551	0.0634	0.0492
Minimum	-0.1999	-0.2669	-0.1368	-0.1229	-0.0713	-0.0571
Skewness	0.3276	-1.3068	-0.4611	-0.7985	-0.3305	0.0527
Kurtosis	2.6606	4.5043	-0.2389	0.5611	-0.8235	0.0122
KS normality test	**0.4449**	**0.4458**	**0.4575**	**0.4780**	**0.4747**	**0.4804**

Notes: In each test, the series has a unit root under the null hypothesis, where boldface values indicate rejection at the 5% level. The p-values are in brackets. We use modified AIC (MAIC) because Ng and Perron (2001) argue that standard information criteria should be modified to account for the presence of negative moving-average errors. w_t refers to the cyclical component of wage share at factor cost, and g_t is the cyclical component of output using Hamilton's (2018) procedure. We use the maximum number of lags given by $12(T/100)^{1/4}$. We obtain the p-values of the unit root test based on 3000 wild sieve bootstrap replications (Smeekes and Taylor, 2012). The Kolmogorov-Smirnov (KS) test has the normality under the null and can be applied to correlated data (Weiss, 1978).

Appendix B: The best lag length

Table 9: Model selection by minimum AIC - results - Eqs. (2) and (3).

Country	*q**	*Minimum AIC*	*Maximum q*
1. United States	3	**-343.3174**	3
2. Norway	3	**-197.1498**	3
3. Sweden	3	**-270.1204**	3
4. Netherlands	2	**-258.5100**	3
5. United Kingdom	1	**-260.6397**	3
6. Austria	1	**-312.7517**	3
7. Canada	2	**-265.6436**	3
8. Italy	2	**-293.6259**	3
9. Portugal	3	**-180.5479**	3
10. Ireland	3	**-186.3657**	3
11. Greece	1	**-211.6189**	3
12. Spain	3	**-278.5650**	3

Appendix C: 90% confidence interval for a range of quantiles

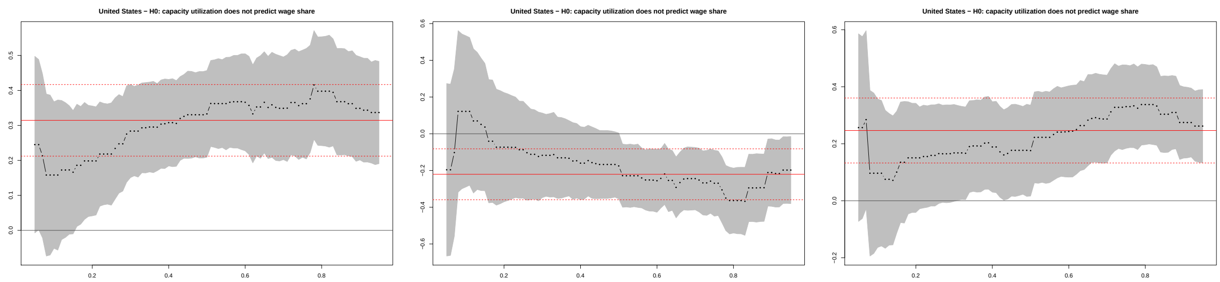

Figure 2: **United States** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

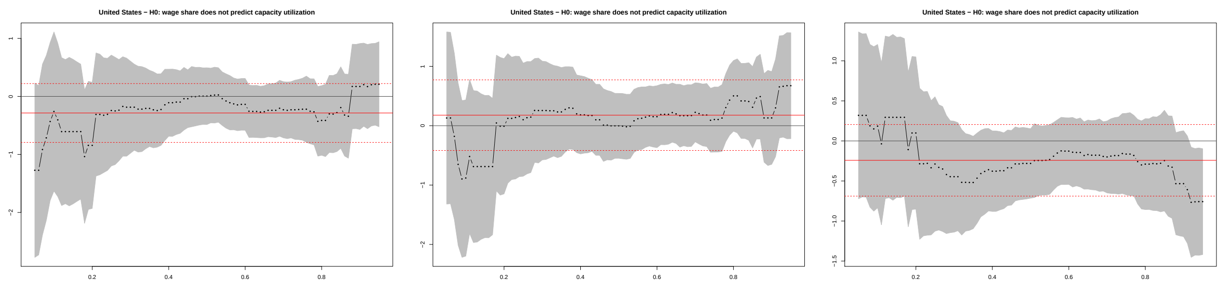

Figure 3: **United States** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.

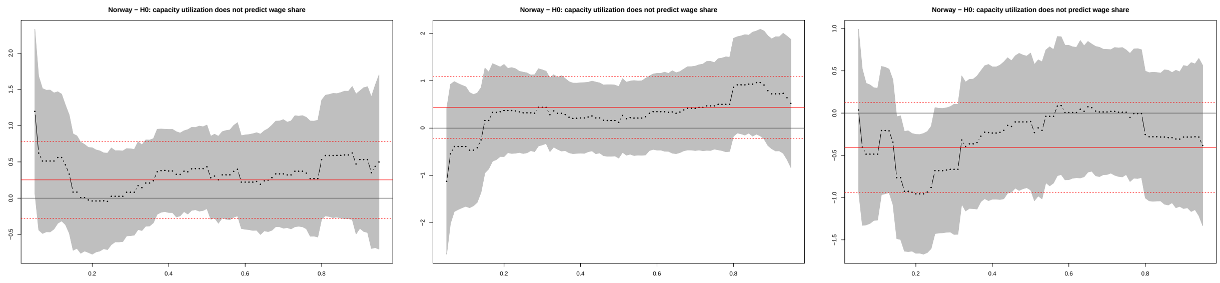

Figure 4: **Norway** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

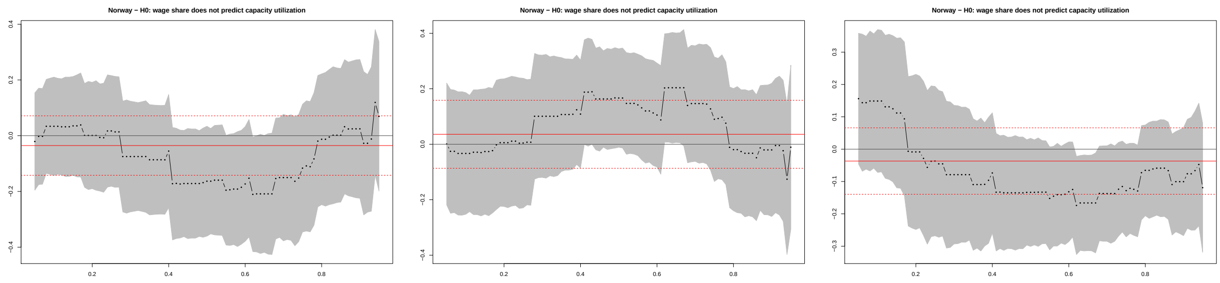

Figure 5: **Norway** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.

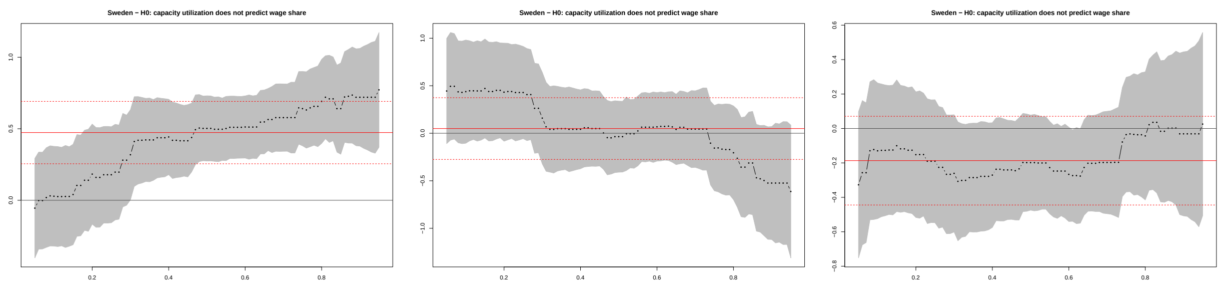

Figure 6: **Sweden** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

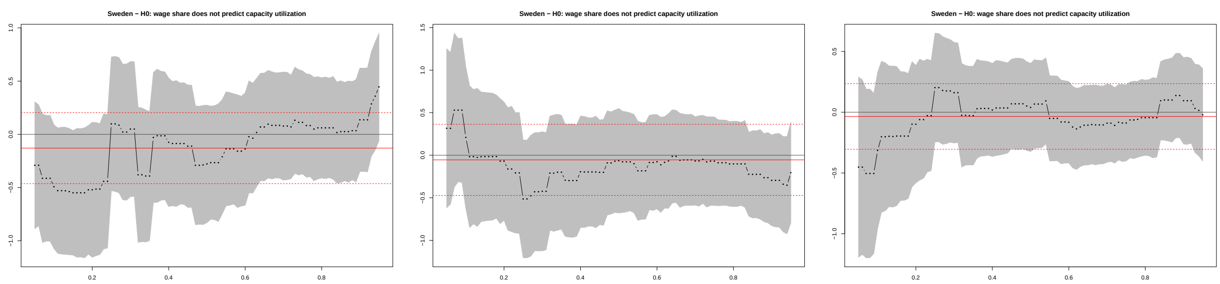

Figure 7: **Sweden** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.

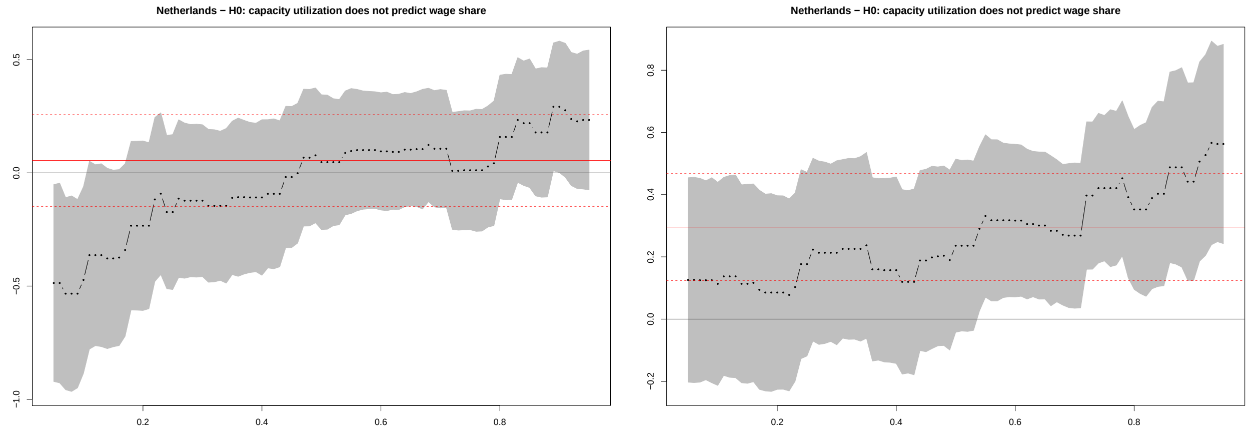

Figure 8: **Netherlands** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$.

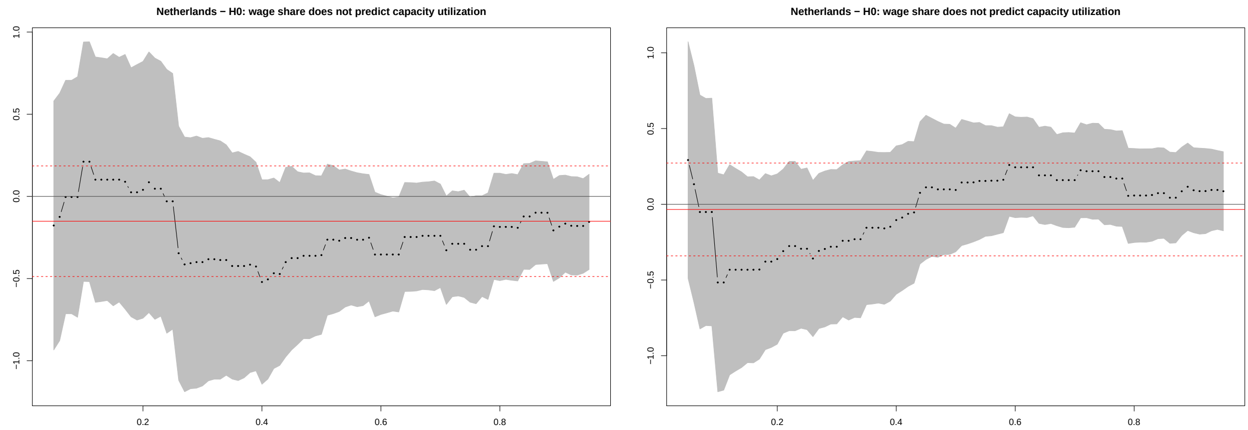

Figure 9: **Netherlands** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$.

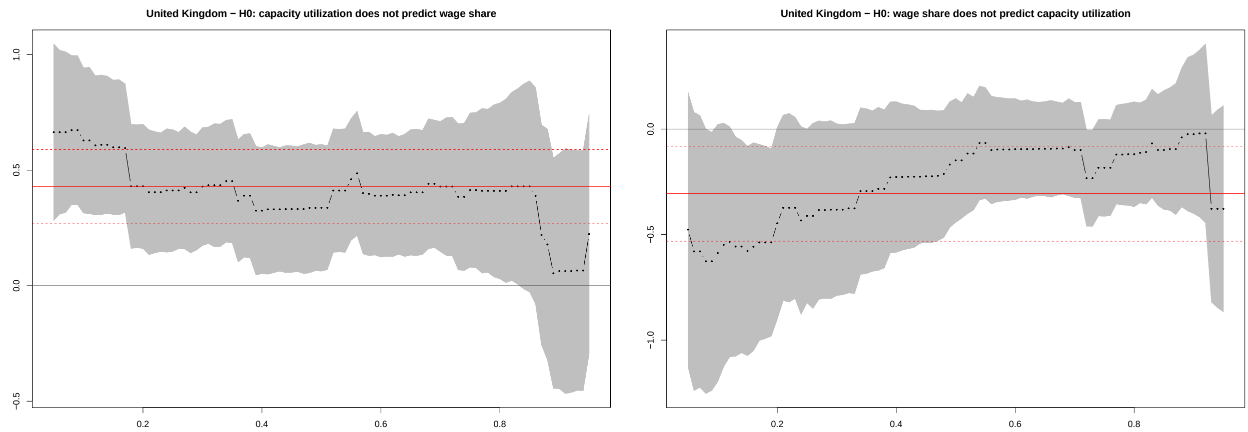

Figure 10: **United Kingdom** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$ and QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$.

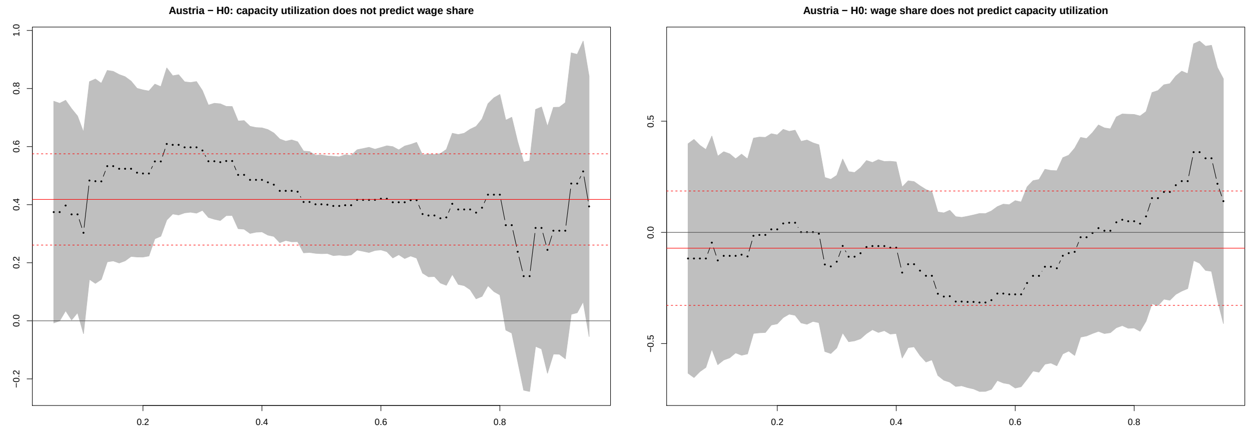

Figure 11: **Austria** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$ and QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$.

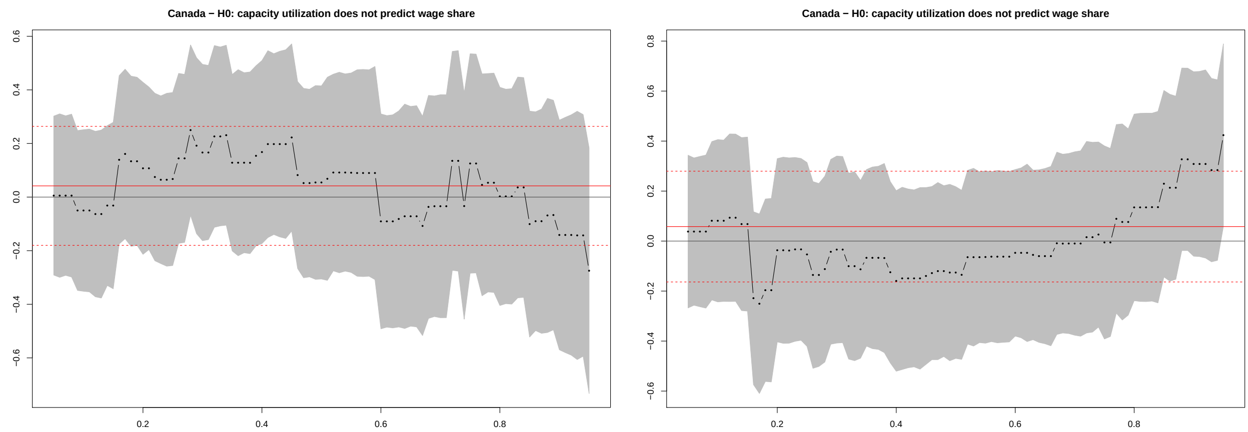

Figure 12: **Canada** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$.

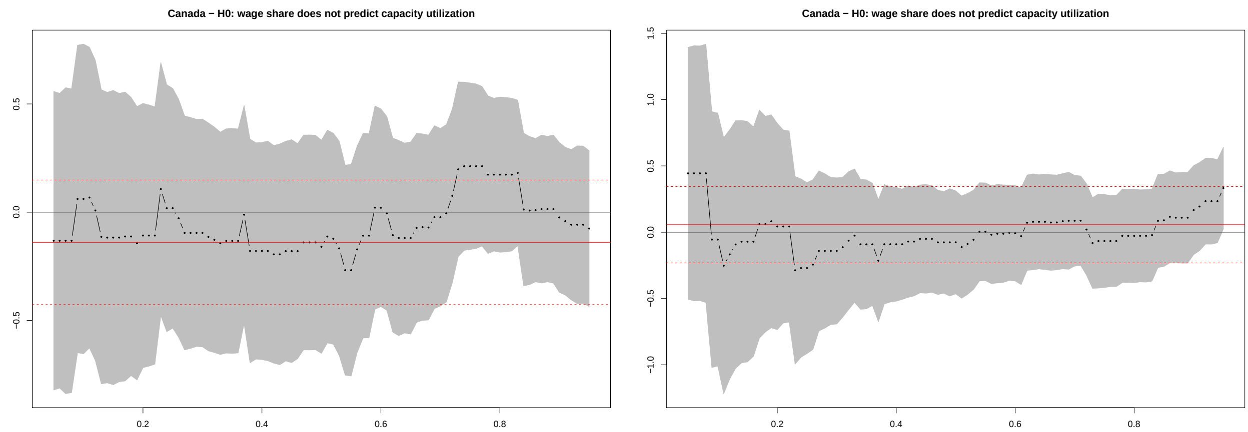

Figure 13: **Canada** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$.

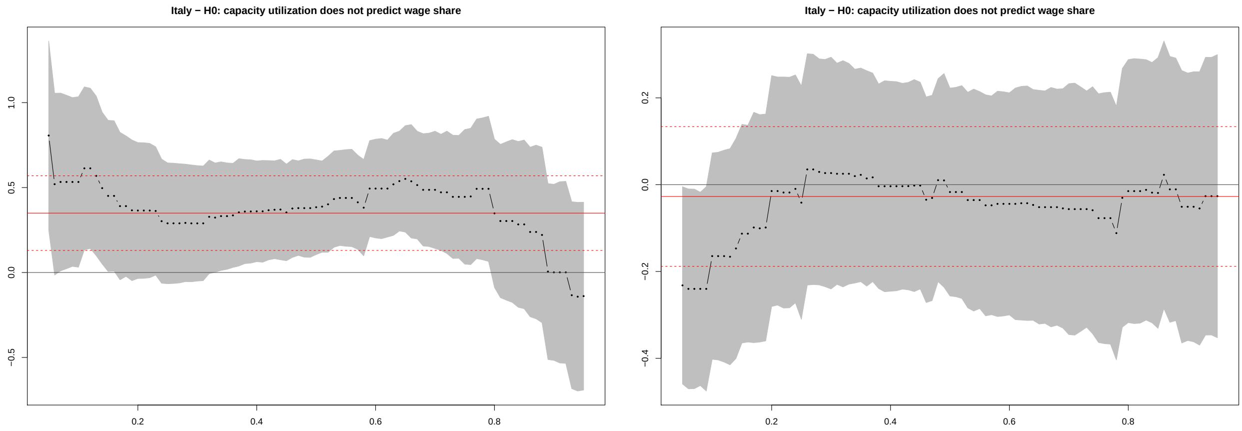

Figure 14: **Italy** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$.

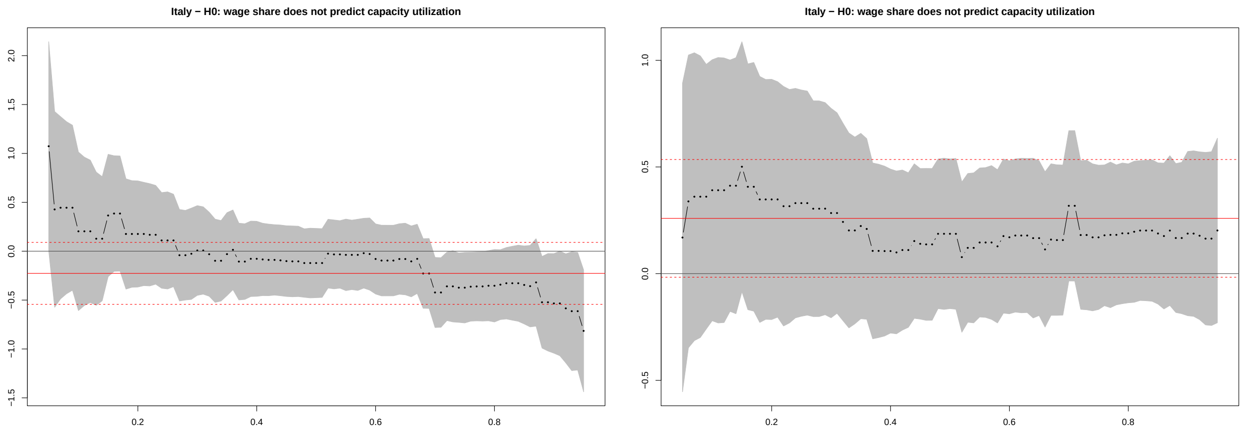

Figure 15: **Italy** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$.

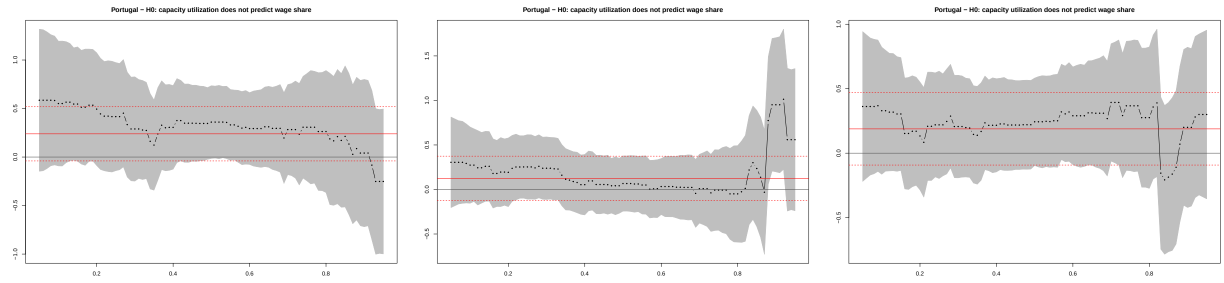

Figure 16: **Portugal** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

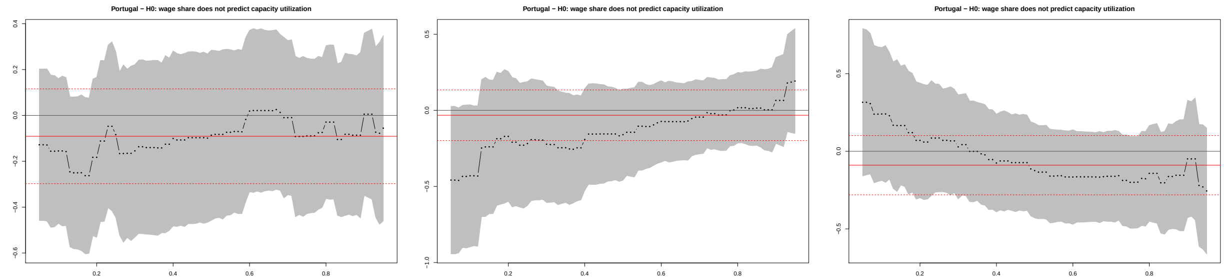

Figure 17: **Portugal** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.

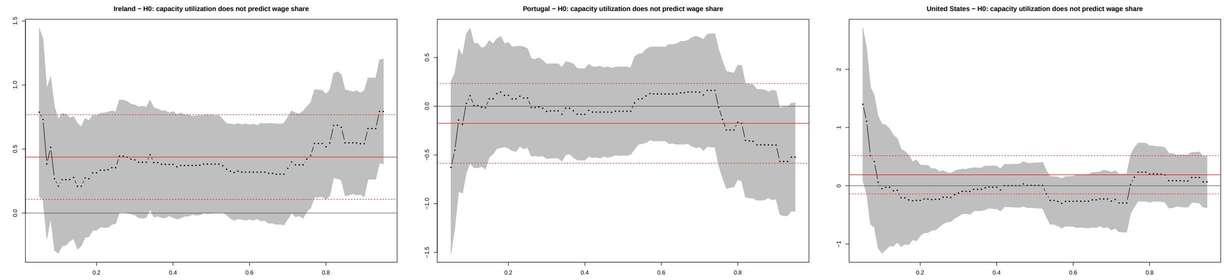

Figure 18: **Ireland** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

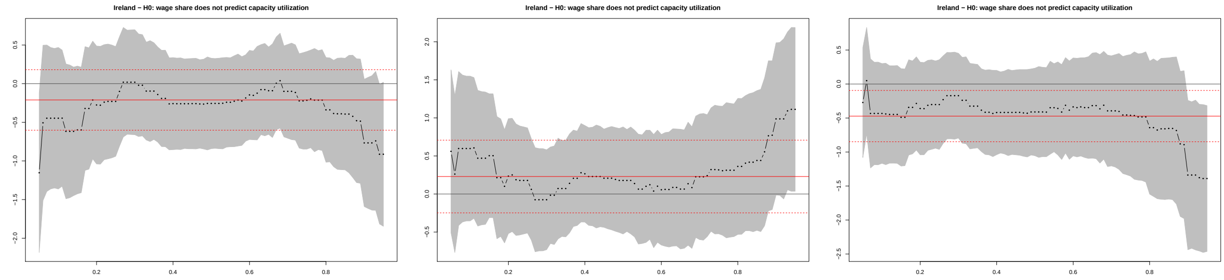

Figure 19: **Ireland** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.

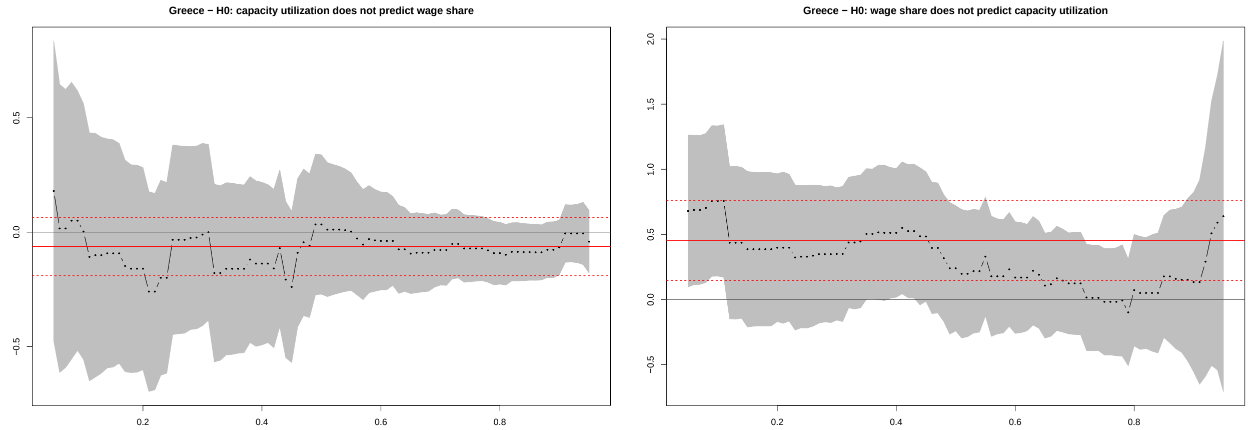

Figure 20: **Greece** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$ and QR and LS estimates of the causal *effects from wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$.

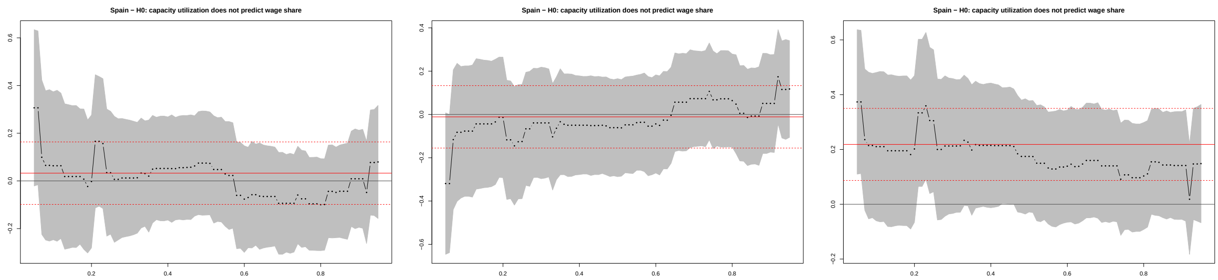

Figure 21: **Spain** – QR and LS estimates of the causal *effects from capacity utilization* **to** *the wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

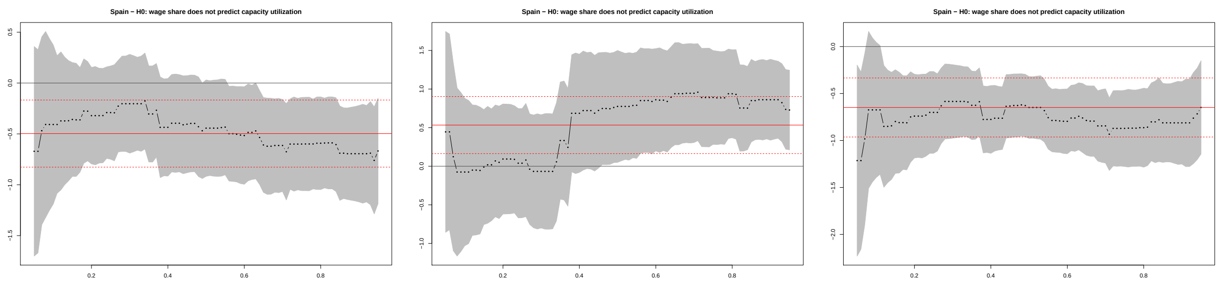

Figure 22: **Spain** – QR and LS estimates of the causal *effects from the wage share* **to** *capacity utilization*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.