Does the wage share drive capacity utilization? Testing for Granger-causality in quantiles

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This paper utilizes confidence intervals for testing Granger-causality relations in quantiles between the wage share and capacity utilization in six high-income countries using annual data ranging from 1960 to 2017. Instead of focusing on the conditional mean, we test for causality in the conditional distribution of the involved variables, which allows detecting causal relations not only in the mean, but also along the entire distribution of these variables. Based on confidence intervals generated by bootstrap resampling, we find evidence that capacity utilization positively drives the wage share in five out of the six countries under consideration. In the U.S., capacity utilization drives the wage share with a significant positive correlation in all conditional quantiles, while the negative cost effect of the wage share on capacity utilization is significant only when capacity utilization is above the average of the distribution. In Italy, capacity utilization positively drives the wage share only above the average of the distribution and at upper tail quantiles, while the adverse effect of the wage share on capacity utilization is significant only below the average of the distribution and at upper tail quantiles. We find no evidence of Granger-causality between capacity utilization and the wage share in the Netherlands in either direction.

Palavras-chave: Granger-causality in distribution; quantile regression; bootstrap resampling.
JEL Classification: C12; E32; E24.

Este artigo emprega intervalos de confiança para testar relações de causalidade de Granger em quantis entre a parcela dos salários na renda e a utilização da capacidade em seis países de alta renda, utilizando dados anuais de 1960 a 2017. Ao invés de focar na média condicional, testamos para causalidade na distribuição condicional das variáveis envolvidas, o que permite detectar relações causais não apenas na média, mas também ao longo de toda a distribuição dessas variáveis. Com base em intervalos de confiança gerados por reamostragem bootstrap, encontramos evidências de que a utilização da capacidade precede positivamente a parcela dos salários em cinco dos seis países analisados. Nos Estados Unidos, a utilização da capacidade precede a parcela dos salários com uma correlação positiva em todos os quantis condicionais, enquanto a parcela dos salários precede a utilização da capacidade com uma correlação negativa significativa apenas acima da média da distribuição. Na Itália, a utilização da capacidade precede positivamente a parcela dos salários apenas acima da média da distribuição e em quantis superiores, enquanto o efeito adverso da parcela dos salários sobre a utilização da capacidade é significativa apenas abaixo da média da distribuição e no quantil 0,90. Não

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encontramos evidência de relação de causalidade de Granger entre a parcela dos salários e a utilização da capacidade na Holanda, em nenhuma direção.

Keywords: Causalidade de Granger na distribuição; Regressão Quantílica; Reamostragem bootstrap.
Classificação JEL: C12; E32; E24.

Área ANPEC: **6 - Crescimento, Desenvolvimento Econômico e Instituições.**

1 Introduction

Two of the most discussed new stylized facts in macroeconomic circles as of late are the declining trend of the wage share in income and the slow recovery of economic activity in the U.S. and other high-income countries.[1] Therefore, a natural issue that arises in this context is to what extent these two new stylized facts are related, possibly in a causal way.

Figure 1 plots *changes* in the wage share (solid line – left scale) and capacity utilization (dotted line – right scale) in the U.S. and Sweden in the 1963-2017 period as examples of similar developments in other high-income economies, such as the U.K., the Netherlands, Italy, and Austria. For all these countries, changes in the wage share seem to be associated with changes in capacity utilization in the same direction.[2] The pattern represented in Figure 1 clearly suggests a possible cause-and-effect relationship between the wage share and capacity utilization. This study utilizes bootstrap confidence intervals for testing Granger-causality relations in quantiles between the wage share and capacity utilization in six high-income countries using annual data ranging from 1960 to 2017. We adopt the concept of causality in the conditional distribution (Granger, 1980; 1988), instead of the Granger-causality in the conditional mean. Interestingly, our approach allows us to investigate the possibility that Granger-causality is heterogeneous across different quantiles of the dependent variable.

Dependence and predictability across macroeconomic variables may be state-dependent, implying that the sign and significance of the dynamic relationships may be different above and below the average. In fact, Nikiforos and Foley (2012) empirically identified a (static) state-dependent relationship between capacity utilization and the wage share for the U.S. economy: at low capacity utilization levels, the wage share decreases as capacity utilization increases. In contrast, at high levels of capacity utilization, the wage share increases as capacity utilization increases. Nevertheless, the authors could not test for causality between the variables and observe that "there is no clear-cut causal relationship between them." Along similar lines, Blecker (2016, p. 376) observes that "there is likely to be simultaneous causality between distribution (wage share) and demand (capacity utilization)."

Therefore, Nikiforos and Foley (2012) and Blecker (2016) emphasize the state-dependent behavior of the functional distribution of income and aggregate effective demand. However, the conditional mean-regression analysis cannot detect causality under these circumstances (Troster, 2018; Baumöl and Lyócsa, 2017; Gebka and Wohar, 2013). Chuang et al. (2009) and Gebka and Wohar (2013) apply tests for Granger-causality in the conditional distribution to understand the dynamic relationship between stock returns and trading volume. Troster (2018) proposes a parametric test of Granger-causality in quantiles to investigate causal relationships between the gold price, oil price, and exchange rate.

[1]For instance, Summers (2015) and Eichengreen (2015) discuss the causes of the slow recovery of economic activity in high-income countries, while Basu and Stiglitz (2016), ILO (2015), and Hutchinson and Persyn (2012) discuss the potential causes of the declining trend of the wage share in income.

[2]The dual role of wages as cost and demand factor is elaborated, for instance, in Blecker (1989), Bhaduri and Marglin (1990), Bowles and Boyer (1995), Nikiforos and Foley (2012), and Blecker (2016).

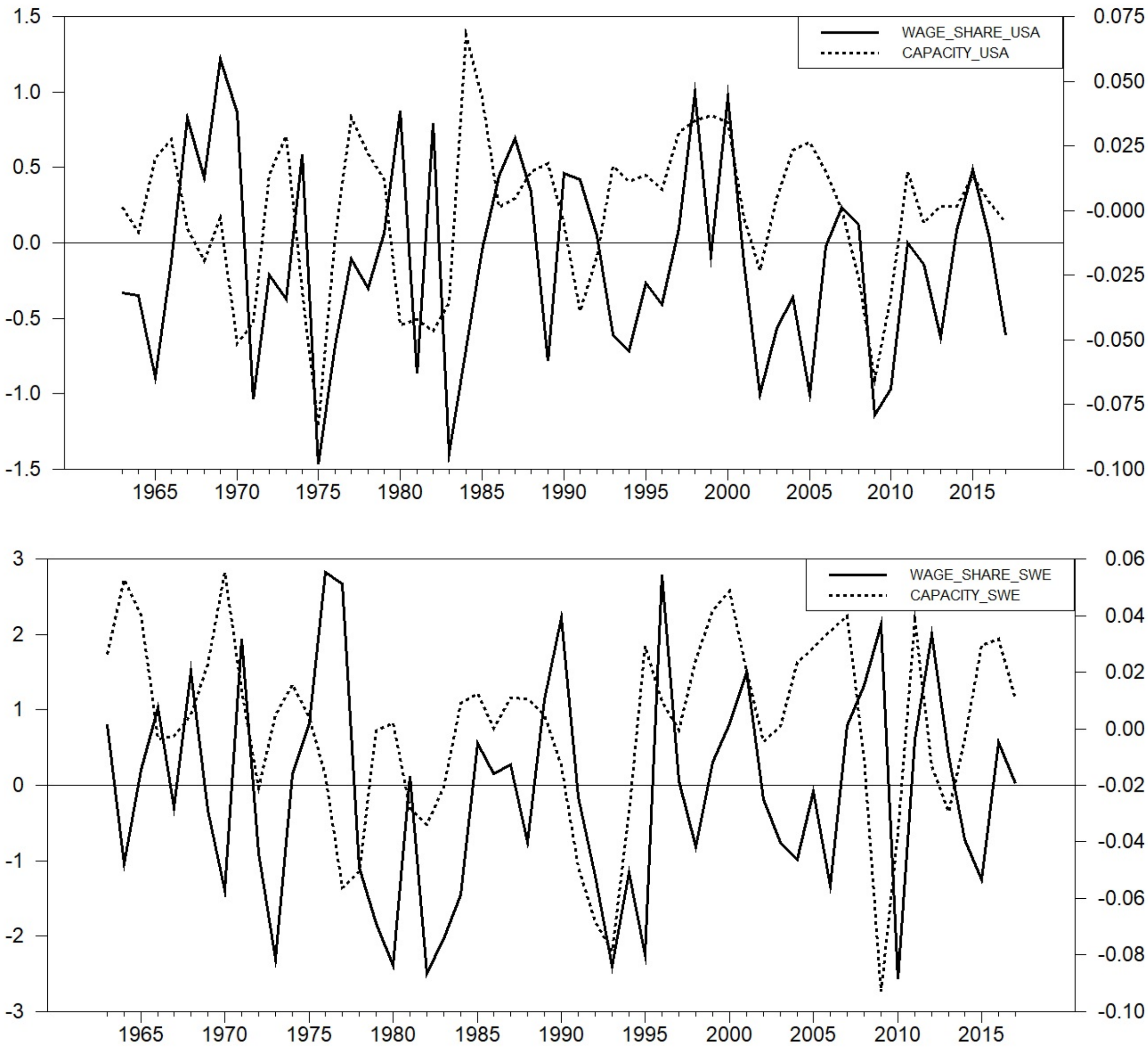

Figure 1: Comovement of the wage share and capacity utilization in the U.S. and Sweden, 1963-2017.

Blecker (2016) argues that while a rise in the wage share may boost consumption and capacity utilization in the long term, an adverse effect on capacity utilization of such a rise 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 that describe only short-run cyclical movements, we could expect a negative effect from the wage share to capacity utilization in the immediate future operating through cost effects. However, we could also expect that capacity utilization is more likely to feature a positive correlation with the wage share, for instance, due to effects operating through a tighter labor market leading to an increase in workers' bargaining power. In this context, the main question to be addressed in what follows regards whether the behavior of the wage share can be used to predict (forecast) the subsequent behavior of capacity utilization in conditional quantiles.

The paper is organized as follows. Section 2 briefly presents the methodology and describes the 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 concept of causality in distribution. We say that a random variable x does not Granger cause the random variable y in distribution if

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

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 may 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 concepts 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 series' conditional distribution. 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). Regression quantiles allow quantifying the dynamic relationship between the wage share and capacity utilization along the business cycle and detect for which quantiles (if any) causality exists. We follow Chuang et al. (2009) and Gebka and Wohar (2013) in estimating bivariate quantile functions given by:

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

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

where w_t refers to the wage share, g_t is the capacity utilization, and J_t' includes past and current values of both w_t and g_t. The 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 dependent variable during periods of expansion and contraction of economic activity. The two null hypotheses to be tested are $\beta_1(\tau) = \ldots = \beta_q(\tau) = 0$ and $\delta_1(\tau) = \ldots = \delta_q(\tau) = 0$.

Our method of inference is based on Fallahi (2012), in which bootstrapping confidence intervals are used to test for the unit root in consumption-income ratios in 23 OECD countries, and more closely on Gebka and Wohar (2013), who adopt bootstrapping confidence intervals for testing Granger-causality relations between trading volume and returns. Due to its favorable performance in terms speed, accuracy, and reliability, we adopt the bootstrap resampling method 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 small samples (Cho et al., 2015). We do not 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 optimal lag length in each country of the sample.

3 Results and discussion

We use annual country-level data on the wage share at factor cost and the cycle component of output for six OECD high-income countries spanning from 1960 through 2017, a choice based on availability of data. The AMECO database is freely available at `https://ec.europa.eu/`, and it does not provide data on the wage share for these countries for the years before 1960. The PWT 9.1 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 2011 national prices) for these countries until 2017. We follow Hamilton (2018) in using the cycle component of output as a measure of economic activity. This variable expresses the percentage difference between actual and potential gross domestic output as a measure of capacity utilization.

We follow Stockhammer and Wildauer (2016) and Rudd and Whelan (2005) in using the wage share at a factor cost to measure the functional distribution of income and average unit cost. Nikiforos and Foley (2012) and Blecker (2016) suggest that capacity utilization is a suitable measure of macroeconomic performance. Tables 3–6 (Appendix A) present the respective KPSS and ADF (MAIC) test results. These results indicate that we cannot reject the null of unit root at 10% level in all cases for the wage share. Hence, we use all series of capacity utilization in levels and the first difference for the wage share in our quantile regressions.[3].

We test for the null hypothesis of Granger-noncausality based on 3000 bootstrap replications for standard errors associated with each parameter estimates ($\beta_j(\tau)$ and $\delta_j(\tau)$) for each quantile ($\tau = 0.05, 0.06, 0.07, ..., 0.95$). Hence, we use 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, and their statistical significance is shown by the 95% confidence interval that excludes zero. In Figures 2-13 (in the Appendix) we plot against τ the QR estimates of $\beta_j(\tau)$ and $\delta_j(\tau)$ (dotted lines) and their 95% confidence interval (shaded area) with the Least Squares estimate (dashed line) and its bootstrapped 95% confidence interval (dotted lines).

The results from quantile regressions estimates for different quantiles provide a full picture of causality in the whole distribution, and not only its mean. As there is a large number of results to be reported, we present them graphically in Appendix C and provide a summary of general patterns in Tables 1 and 2. We find that the subsequent response of the wage share and capacity utilization is different across countries. For instance, in the U.S., capacity utilization drives the wage share with a significant positive correlation in all conditional quantiles, while the wage share only Granger causes a negative variation in capacity utilization above the average. This means that the adverse effect of the wage share on capacity utilization (possibly due to cost reasons) is significant only when capacity utilization is above the average.

We obtain a different result for Italy, in which capacity utilization drives the wage share with positive correlation only above the average and at upper tail quantiles, while the adverse effect of

[3]As we do not reject the stationarity for w_t in the U.K. at the 1% level, we reject the null of the unit root by applying the Phillips and Perron (1988) at the 1% (-10.0634) level.

the wage share on capacity utilization is significant only below the average. We find no evidence of Granger-causality between the wage share and capacity utilization in either direction for the Netherlands.

For Sweden, similarly to the U.S., we find that capacity utilization leads the wage share with a significant positive correlation in all conditional quantiles. We also find that a positive correlation running from capacity utilization to the wage share for the U.K. (below the average) and Austria (above the average) is present in a more specific range of quantiles.

While the positive and significant effect running from capacity utilization to subsequent values of the wage share seems to be a common phenomenon in our sample, the negative effect of the wage share on capacity utilization (possibly due to a cost channel) is not significant in all countries. While we cannot detect a negative causal cost effect running from the wage share to capacity utilization in the U.K., the wage share predicts positive variation of capacity utilization in Austria at the extreme lower and upper tail quantiles.

Based on these findings, our main conclusions are the following. First, capacity utilization drives the wage share with a positive correlation in five out of the six countries under consideration in most conditional quantiles. Second, we find a negative significant Granger causal effect of the wage share on subsequent capacity utilization only when the latter is above the average in the U.S. and below the average in Italy.

Table 1: Granger-causality to wage share – Results: H0: $\beta_j(\tau) = \ldots = \beta_q(\tau) = 0$ based on Eq.(2).

Country	τ	lag 1	lag 2	lag 3
1. *United States*	[0.05;0.50]	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) < 0$	$\beta_3^{**}(\cdot) > 0$
	[0.50;0.80]	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) < 0$	$\beta_3^{**}(\cdot) > 0$
	0.10	$\beta_1^{**}(\cdot) > 0$	$\beta_2^{**}(\cdot) < 0$	$\beta_3^{**}(\cdot) > 0$
	0.90	$\beta_1(\cdot) > 0$	$\beta_2(\cdot) < 0$	$\beta_3^{**}(\cdot) > 0$
2. *Italy*	[0.05;0.50]	$\beta_1(\cdot) > 0$	—	—
	[0.50;0.95]	$\beta_1^{**}(\cdot) > 0$	—	—
	0.10	$\beta_1^{**}(\cdot) > 0$	—	—
	0.90	$\beta_1^{**}(\cdot) > 0$	—	—
3. *Sweden*	[0.30;0.50]	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) > 0$	$\beta_3(\cdot) < 0$
	[0.50;0.95]	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) < 0$	$\beta_3(\cdot) > 0$
	0.10	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) < 0$	$\beta_3(\cdot) < 0$
	0.90	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) > 0$	$\beta_3(\cdot) > 0$
4. *Netherlands*	[0.05;0.50]	$\beta_1(\cdot) > 0$	$\beta_2(\cdot) < 0$	$\delta_3(\cdot) > 0$
	[0.50;0.95]	$\beta_1(\cdot) > 0$	$\beta_2(\cdot) > 0$	$\beta_3(\cdot) < 0$
	0.10	$\beta_1(\cdot) > 0$	$\beta_2(\cdot) < 0$	$\beta_3(\cdot) > 0$
	0.90	$\beta_1(\cdot) > 0$	$\beta_2(\cdot) > 0$	$\beta_3(\cdot) < 0$
5. *United Kingdom*	[0.05;0.50]	$\beta_1(\cdot) > 0$	$\beta_2^{**}(\cdot) > 0$	$\beta_3(\cdot) > 0$
	[0.50;0.95]	$\beta_1(\cdot) > 0$	$\beta_2(\cdot) > 0$	$\beta_3(\cdot) < 0$
	0.10	$\beta_1^{**}(\cdot) < 0$	$\beta_2(\cdot) > 0$	$\beta_3(\cdot) < 0$
	0.90	$\beta_1(\cdot) > 0$	$\beta_2^{**}(\cdot) > 0$	$\beta_3(\cdot) > 0$
6. *Austria*	[0.05;0.50]	$\beta_1(\cdot) > 0$	$\beta_2(\cdot) > 0$	—
	[0.50;0.95]	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) > 0$	—
	0.10	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) > 0$	—
	0.90	$\beta_1^{**}(\cdot) > 0$	$\beta_2(\cdot) > 0$	—

Note: ** denotes significance at the 5% level for $\tau \in (0.05, 0.06, \ldots, 0.95)$.

Table 2: Granger-causality to output – Results: H0: $\delta_j(\tau) = \ldots = \delta_q(\tau) = 0$ based on Eq.(3).

Country	τ	lag 1	lag 2	lag 3
1. *United States*	[0.05;0.50]	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) < 0$	$\delta_3(\cdot) < 0$
	[0.50;0.95]	$\delta_1^{**}(\cdot) < 0$	$\delta_2(\cdot) < 0$	$\delta_3(\cdot) < 0$
	0.10	$\delta_1^{**}(\cdot) < 0$	$\delta_2(\cdot) < 0$	$\delta_3(\cdot) < 0$
	0.90	$\delta_1^{**}(\cdot) < 0$	$\delta_2(\cdot) < 0$	$\delta_3^{**}(\cdot) < 0$
2. *Italy*	[0.05;0.50]	$\delta_1^{**}(\cdot) < 0$	—	—
	[0.50;0.95]	$\delta_1(\cdot) < 0$	—	—
	0.10	$\delta_1^{**}(\cdot) < 0$	—	—
	0.90	$\delta_1^{**}(\cdot) < 0$	—	—
3. *Sweden*	[0.05;0.50]	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
	[0.50;0.95]	$\delta_1(\cdot) > 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
	0.10	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
	0.90	$\delta_1(\cdot) > 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
4. *Netherlands*	[0.05;0.50]	$\delta_1(\cdot) > 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
	[0.50;0.95]	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) > 0$
	0.10	$\delta_1(\cdot) > 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
	0.90	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) > 0$
5. *United Kingdom*	[0.05;0.50]	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
	[0.50;0.95]	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
	0.10	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) > 0$	$\delta_3(\cdot) < 0$
	0.90	$\delta_1(\cdot) < 0$	$\delta_2(\cdot) > 0$	$\delta_3^{**}(\cdot) < 0$
6. *Austria*	[0.05;0.50]	$\delta_1(\cdot) < 0$	$\delta_2^{(}\cdot) > 0$	—
	[0.50;0.80]	$\delta_1(\cdot) > 0$	$\delta_2^{**}(\cdot) > 0$	—
	0.10	$\delta_1(\cdot) < 0$	$\delta_2^{**}(\cdot) > 0$	—
	0.90	$\delta_1^{**}(\cdot) > 0$	$\delta_2(\cdot) > 0$	—

Note: ** denotes significance at the 5% level for $\tau \in (0.05, 0.06, \ldots, 0.95)$.

4 Conclusions

This paper applies quantile regression methods to investigate Granger-causality relations between the wage share and capacity utilization in six high-income countries using annual data ranging from 1960 to 2017. Instead of focusing on the conditional mean, we test for causality relations between the wage share and capacity utilization in the conditional distribution, thus providing a full picture of the dynamics of these variables.

Based on confidence intervals generated by bootstrap resampling, we found that capacity utilization drives the wage share with a positive correlation in the U.S., Italy, Sweden, the U.K., and Austria. The causal effect of the wage share on capacity utilization is heterogeneous across countries and along conditional quantiles. We found a negative significant Granger causal effect of the wage share on subsequent capacity utilization only when the latter is above the average in the U.S. and below the average in Italy.

While we found that capacity utilization drives the wage share with positive correlation, we found positive and negative effects when the wage share drives capacity utilization at several quantiles. This result suggests that the sensitivity of capacity utilization to the wage share depends on the phase of the business cycle the economy happens to be in.

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5 Appendix A: ADF (MAIC) and KPSS Unit Root Tests

Table 3: ADF (MAIC) unit root tests — results.

	United States		*Italy*		*Sweden*	
	g_t	w_t	g_t	w_t	g_t	w_t
Level (c)	-4.2793***	-0.2517	-3.4170**	-1.2362	-2.8325*	-1.6689
	(0.0013)	(0.9244)	(0.0149)	(0.6516)	(0.0610)	(0.4405)
First difference (c)	-6.4362***	-6.3522***	-7.7884***	-6.1788**	-5.9246***	-5.7681**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: 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. This table presents the t-statistics and p-values of ADF unit root tests, where ***, ** and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. (c) indicate the deterministic component included in the model. w_t refers to the wage share at factor cost, and g_t is the capacity utilization (cycle component of output as a share of potential GNP) using Hamilton's procedure. The p-values are into brackets. Four maximum number of lags were selected to adjust for autocorrelation. For the level and first differenced data and we allow only for a constant (c).

Table 4: ADF (MAIC) unit root tests — results.

	Netherlands		*United Kingdom*		*Austria*	
	g_t	w_t	g_t	w_t	g_t	w_t
Level (c)	-2.7665*	-0.9632	-4.3338***	-1.6625	-3.8311***	-1.0040
	(0.0704)	(0.7593)	(0.0011)	(0.4438)	(0.0048)	(0.7450)
First difference (c)	-6.7084***	-2.5891*	-6.6661***	-5.4481***	-6.4304***	-3.6269**
	(0.0000)	(0.1020)	(0.0000)	(0.0000)	(0.0000)	(0.0086)

Notes: 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. This table presents the t-statistics and p-values of ADF unit root tests, where ***, ** and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. (c) indicate the deterministic component included in the model. w_t refers to the wage share at factor cost, and g_t is the capacity utilization (cycle component of output as a share of potential GNP) using Hamilton's procedure. The p-values are into brackets. Four maximum number of lags were selected to adjust for autocorrelation. For the level and first differenced data and we allow only for a constant (c).

Table 5: KPSS unit root test — results.

	United States		*Italy*		*Sweden*	
	g_t	w_t	g_t	w_t	g_t	w_t
Level (c)	0.1414	1.2102***	0.1826	1.2866***	0.1082	1.0047***
First difference (c)	0.0341	0.0967	0.0777	0.0973	0.0541	0.0672

Notes: The critical values of the KPSS test are 0.739 (1%), 0.463 (5%), and 0.347 (10%). We set the number of lags to $\sqrt[4]{4 \times (n/100)}$. The symbols ***, ** and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. (c) indicate the deterministic component included in the model. w_t refers to the wage share at factor cost, and g_t is the capacity utilization (cycle component of output as a share of potential GNP) using Hamilton's procedure. For the level and first differenced data and we allow only for a constant (c).

Table 6: KPSS unit root test — results.

	Netherlands		*United Kingdom*		*Austria*	
	g_t	w_t	g_t	w_t	g_t	w_t
Level (c)	0.1074	1.0364***	0.1207	0.2696	0.1013	1.3491***
First difference (c)	0.0500	0.2159	0.0349	0.0930	0.0697	0.0794

Notes: The critical values of the KPSS test are 0.739 (1%), 0.463 (5%), and 0.347 (10%). We set the number of lags to $\sqrt[4]{4 \times (n/100)}$. The symbols ***, ** and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. (c) indicate the deterministic component included in the model. w_t refers to the wage share at factor cost, and g_t is the capacity utilization (cycle component of output as a share of potential GNP) using Hamilton's procedure. For the level and first differenced data and we allow only for a constant (c).

6 Appendix B: The best lag length

Table 7: Model selection by minimum AIC - results - Eqns. (2) and (3).

Country	q^*	*Minimum AIC*	*Maximum q*
1. United States	3	**97.14084**	3
2. Italy	1	**143.1898**	3
3. Sweden	3	**169.0977**	3
4. Netherlands	3	**169.6207**	3
5. United Kingdom	3	**160.9540**	3
6. Austria	2	**148.3238**	3

7 Appendix C: 95% Confidence Interval for Specific Quantiles

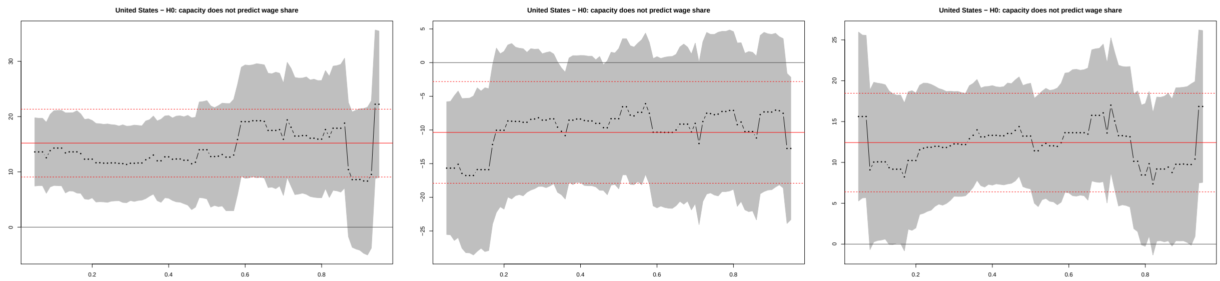

Figure 2: **United States** – QR and LS estimates of the causal *effects of capacity* **on** *wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

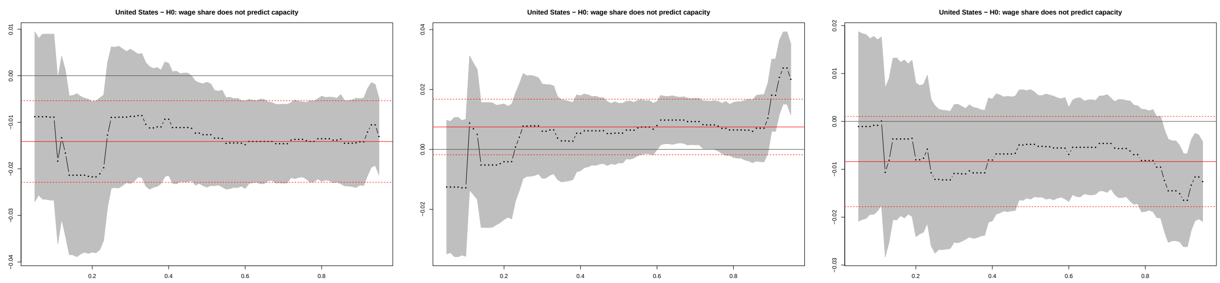

Figure 3: **United States** – QR and LS estimates of the causal *effects of wage share* **on** *capacity*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.

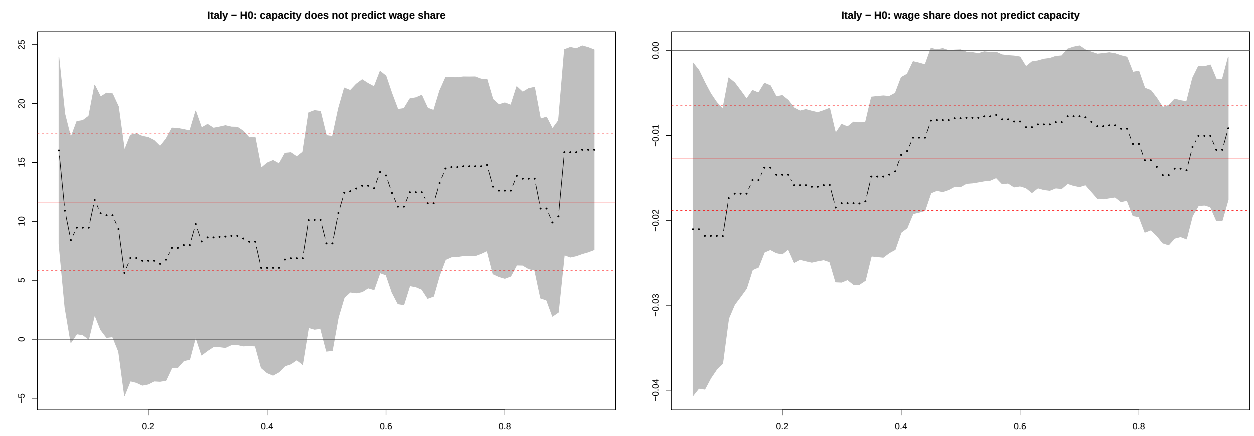

Figure 4: **Italy** – QR and LS estimates of the causal *effects of capacity* **on** *wage share* $\hat{\beta}_1(\tau)$ and the causal *effects of wage share* **on** *capacity* $\hat{\delta}_1(\tau)$.

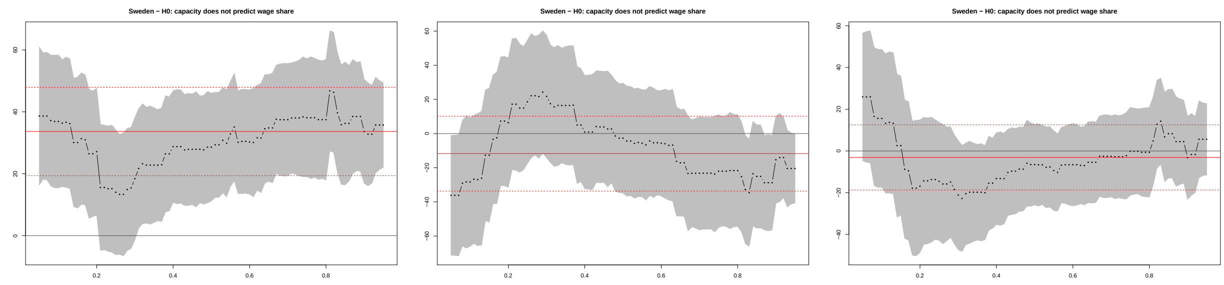

Figure 5: **Sweden** – QR and LS estimates of the causal *effects of capacity* **on** *wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

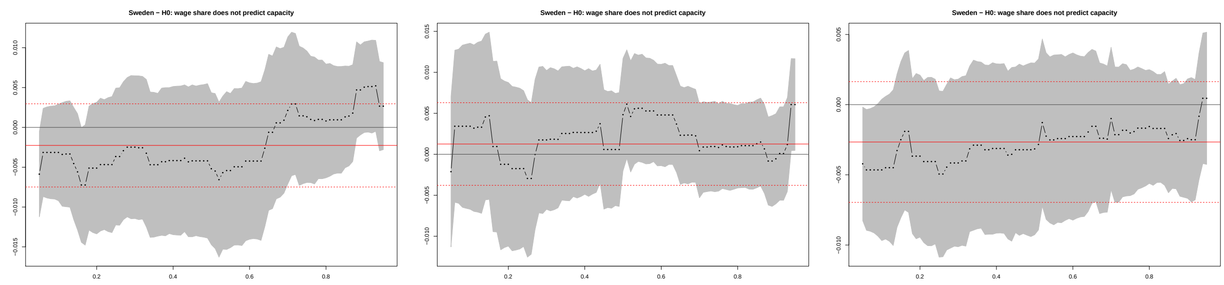

Figure 6: **Sweden** – QR and LS estimates of the causal *effects of wage share* **on** *capacity*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.

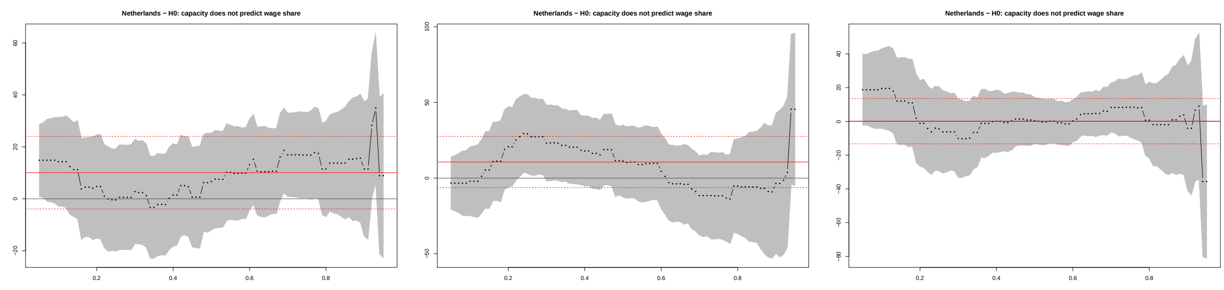

Figure 7: **Netherlands** – QR and LS estimates of the causal *effects of capacity* **on** *wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$, $\hat{\beta}_3(\tau)$.

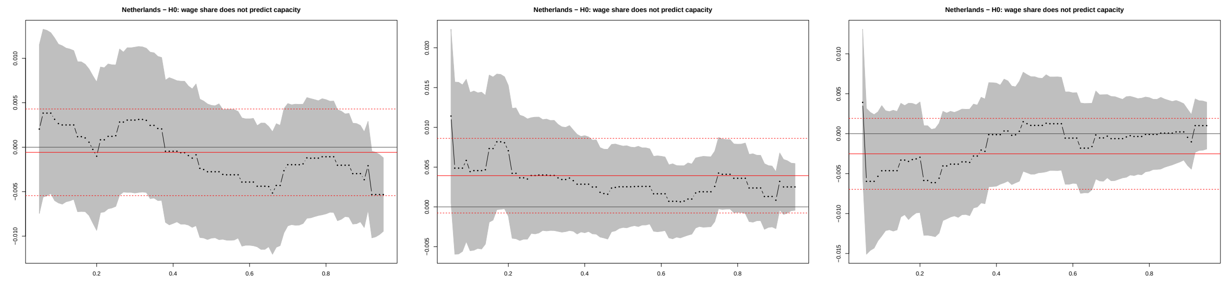

Figure 8: **Netherlands** – QR and LS estimates of the causal *effects of wage share* **on** *capacity*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$, $\hat{\delta}_3(\tau)$.

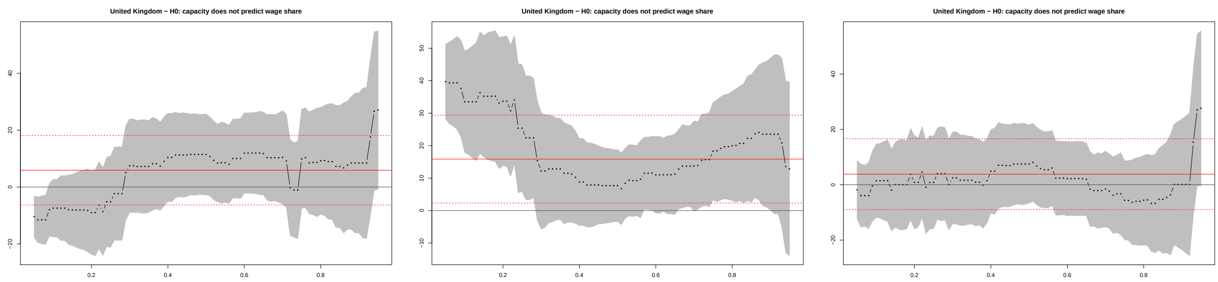

Figure 9: **United Kingdom** – QR and LS estimates of the causal *effects of capacity* **on** *wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$.

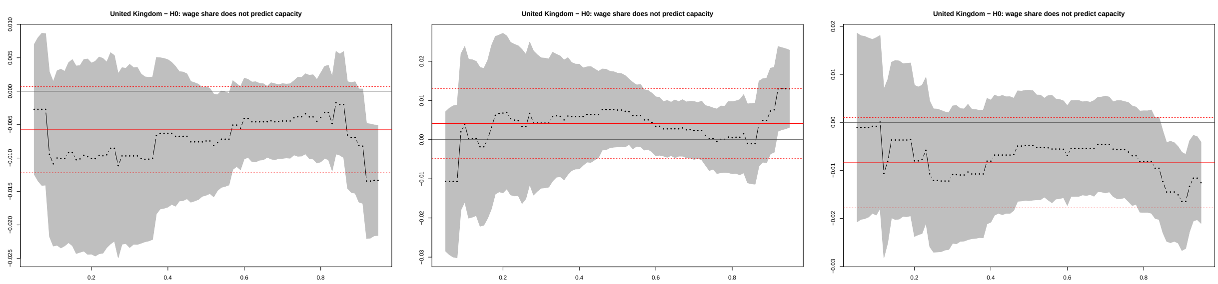

Figure 10: **United Kingdom** – QR and LS estimates of the causal *effects of wage share* **on** *capacity*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$.

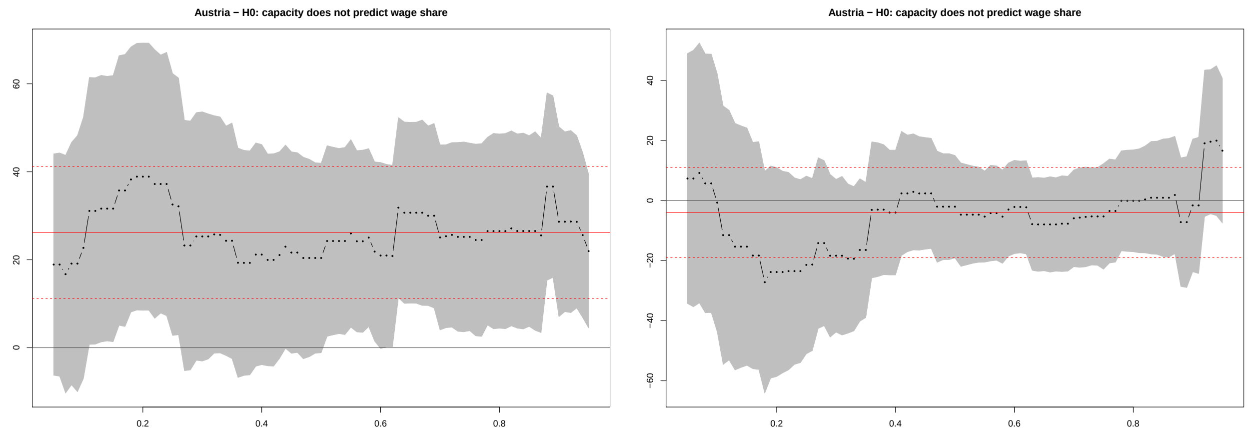

Figure 11: **Austria** – QR and LS estimates of the causal *effects of capacity* **on** *wage share*: $\hat{\beta}_1(\tau)$, $\hat{\beta}_2(\tau)$.

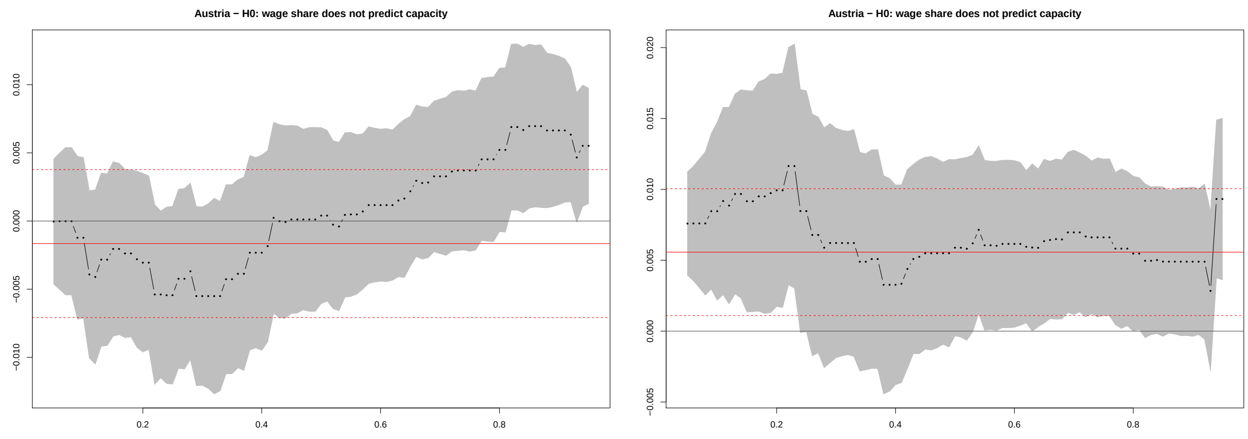

Figure 12: **Austria** – QR and LS estimates of the causal *effects of wage share* **on** *capacity*: $\hat{\delta}_1(\tau)$, $\hat{\delta}_2(\tau)$.