Time-Varying Predictability of Labor Productivity on Inequality in United Kingdom[#]

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Abstract

In this paper, we analyze time-varying predictability of labor productivity for growth in income (and consumption) inequality of the United Kingdom (UK) based on a high-frequency (quarterly) data set over 1975:Q1 to 2016:Q1. Results indicate that the growth rate of an index of labor productivity has a strong predictive power on growth rate of income (and consumption) inequality in the UK. Interestingly, the strength of the predictive power is found to be higher towards the end of the sample period in the wake of the global financial crisis. In addition, based on time-varying impulse response function analysis, we find that inequality and labor productivity growth rates are in general negatively associated over our sample period, barring a short-lived positive impact initially.

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1. Introduction

Although the association between weak productivity growth and increase in inequality can be traced to before the Global Financial Crisis and the subsequent Great Recession, the situation has been exacerbated globally in the wake of these two extreme events (Patterson, 2012; Haldane, 2018; Ravallion, 2018; Tenreyro, 2018). Intuitively, productivity growth is the key determinant of how demand can grow without inflation, and therefore reducing inequality of income, wealth and opportunity. Given this, quite a few studies have found increases in productivity to be a significant factor in terms of reducing inequality (see for example, Blundell et al., (2013), Disney et al., (2013), Castle and Hendry (2014), Haldane (2017, 2018), Tenreyro (2018)). At the same time, some authors have indicated that productivity increases associated with innovation and technological progress are leading to inequality by displacing low-skilled workers and creating demand for those with better education (Rifkin, 1995; Lanier, 2013). In other words, productivity increases can either cause a rise or decline in inequality, but with the possibility that the former effect dominates in the short-run, and the latter in the medium to longer-run (Arestis, 2018; 2020).

We contribute to this line of research by exploring the time-varying predictive power of growth in labor productivity for growth in income (and consumption) inequality in the United Kingdom (UK) over the quarterly period of 1975:2 to 2016:1. Unlike the existing literature, which rely on constant parameter models based on low-frequency (annual) data, we conduct a time-varying, i.e., state-dependent analysis which allows us to accommodate for regime-changes, using relatively high-frequency (quarterly) data. These issues are important since accurate prediction of inequality, which accounts for structural breaks, is conducted at a higher frequency, which in turn should be more relevant to policymakers than at the lower annual frequency. It is this availability of quarterly measures of inequality that motivates us to consider the UK in our study. In addition, in the last four decades the UK has experienced dramatic increases in income inequality (Mumtaz and Theophilopoulou (2017)) and is considered to be an outlier of extreme inequality in the European context (Dorling, 2015). Simultaneously, the UK has also witnessed a large and persistent fall in labor productivity, with Felstead et al., (2018) pointing out that the UK has a longstanding labor productivity gap with its international competitors. In addition, Mason et al., (2018) suggested that the 2008-2009 recession worsened the situation, with workers in France, Germany and the United States (US) producing on average as much in four days as UK workers did in five. Further evidence in this regard can also be found in Barnett et al., (2014), Haldane (2017, 2018), and McCafferty (2018).

To the best of our knowledge, this paper is the first study to analyze time-varying predictability of (country-level) labor productivity, as captured by an index of total labor productivity, for growth in income (and consumption) inequality based on a high-frequency data set. In this regard, from an econometric perspective, we use the recently proposed (multivariate) test of time-varying causality in a vector autoregressive (VAR) framework by Rossi and Wang (2019), which is robust to the presence of instabilities. In addition, though the time-varying predictability is the primary focus of our paper, since causality tests are silent about the sign of the impact (if any), we use time-varying impulse response function to analyze the effect of a shock to the growth in labor productivity on the growth of inequality in a time-varying parameter VAR model of Primiceri (2005).

To preview, results indicate that the labor productivity growth has strong predictive power on growth in income (and consumption) inequality in the UK, with the strength of the effect being indeed time-varying and increasing in the wake of the Global Financial Crisis of 2007-2009. Moreover, the time-varying impulse response function in general reveals a negative association between inequality and labor productivity growth rates, following a short-lived positive impact initially, over the four decades of our sample period. The rest of the paper proceeds as follows: Section 2 discusses the data and the methodology, Section 3 presents the empirical results, and Section 4 concludes.

2. Data and Methodology

2.1. Data

We use quarterly data from 1975:Q1 to 2016:Q1, based on availability of measures of inequality. The income inequality data is taken from Mumtaz and Theophilopoulou (2017). To construct income inequality measures they use income equivalized by dividing with the square root of the number of people in a household. The inequality measures are computed using survey data on income and consumption from the family expenditure survey (FES).[1] Mumtaz and Theophilopoulou (2017) provide an extensive documentation of the construction of the data and the survey. Note that, while the surveys are recorded at an annual frequency, Mumtaz and Theophilopoulou (2017) assign households to different quarters within a year based on the date of the survey interviews, which, in turn, allows them to calculate the measures of inequality at a quarterly frequency. Note that, these authors remove any households reporting zero or negative income, when constructing the income-based measures of inequality.[2] In our main analysis, we consider the Gini coefficient of income inequality. However, as part of additional analyses, we also present the results involving the Gini coefficient of consumption inequality (for total consumption per capita of a household), as well as, the standard deviation (of the data in natural logs), and the difference between the 90th and 10th percentile (with the data in natural logs) associated with both income and consumption. These five additional measures of inequality is also sourced from Mumtaz and Theophilopoulou (2017).

As far as the labor productivity data is concerned, we derive it from the FRED database of the Federal Reserve Bank of St. Louis,[3] and corresponds to an index (with a base year of 2015) available as part of early estimate of quarterly unit labor cost indicators of the UK. Given that developments in unemployment and income taxation is likely to affect both income (consumption) inequality and labor productivity (Berg and Ostry, 2011; Korinek and Kreamer, 2013; Piketty, 2014; Atkinson, 2015), we also consider the change in the unemployment rate and growth of the income tax to Gross Domestic Product (GDP) ratio (to ensure stationarity) for the UK as additional controls in our VAR model as part of robustness checks. The data source used to derive the two controls is the Main Economic Indicators database of the Organisation for Economic Co-operation and Development (OECD). All variables, if not available in seasonally-adjusted form, have been done so using the X-13 approach of the Census Bureau of the US.

Since our econometric approach, which we describe below requires us to work with stationary data, we convert the inequality and index of labor productivity into their corresponding growth rates,[4] but unemployment rate and the ratio of income tax to nominal GDP is in levels due to their underlying

[1] The data is downloadable from: https://discover.ukdataservice.ac.uk/series/?sn=200016 and https://discover.ukdataservice.ac.uk/series/?sn=2000028.

[2] We would like to thank Professor Haroon Mumtaz for kindly sharing the inequality data.

[3] The data is available for download from: https://fred.stlouisfed.org/series/ULQELP01GBQ661S.

[4] Complete details of the various unit root tests (ADF (Dickey and Fuller, 1979), PP (Phillips and Perron, 1988), Kwiatkowski et al. (KPSS, 1992), Elliot et al. (ERS, 1996), Ng and Perron (NP, 2001)) have been presented in Table A1 in the Appendix of the paper.

mean-reverting property. We depict the variables in our model as: GI*j*, *j*=1..6, corresponding to the growth rates of the six measures of income and consumption inequalities (Gini coefficient, the standard deviation, and the difference between the 90th and 10th percentile) respectively; GLP: growth of labor productivity; DUR: change in unemployment rate, and; GITGDP: growth of the ratio of income tax to GDP. Due to the transformations, our effective sample starts from 1975:Q2 to 2016:Q1, giving us a total of 164 observations. All variables have been plotted in Figure A1 in the Appendix of the paper.

2.2. Methodology

Given that we use four decades of quarterly data on, which is likely to be (and as we show below that it indeed is) associated with structural breaks in their relationship, we use the recently proposed full-fledged time-varying Granger causality test of Rossi and Wang (2019). This approach analyzes the time-varying impact of GLP on GI*j*, *j*=1,…,6, and hence, provide a more appropriate inference of the effect rather than a constant parameter Granger causality method. Besides, understandably, the time-varying approach helps us to depict the time-variation in the strength of predictability.

In this study, we consider the following VAR model with time-varying parameters:

$$y_t = \Psi_{1,t}y_{t-1} + \Psi_{2,t}y_{t-2} + \cdots + \Psi_{p,t}y_{t-p} + \varepsilon_t \quad (1)$$

where $\Psi_{j,t}$, $j = 1, \dots p$ are functions of time varying coefficient matrices, $y_t = [y_{1,t}, y_{2,t}, \dots, y_{n,t}]'$ is an (n×1) vector, and the idiosyncratic shocks ε_t are assumed to be heteroscedastic and serially correlated.

The variables included in our VAR constitutes of two endogenous variables namely, GI*j*, *j*=1,…,6, and GLP in a bivariate set-up, and then later DUR and ITGDP as controls in the multivariate (four variables) model. We test the null hypothesis that GLP does not Granger cause GI*j* for all *t*, where the null hypothesis is $H_0: \phi_t = 0 \text{ for all t} = 1,2, \dots, T$, given that ϕ_t is appropriate subset of $vec\ (\Psi_{1,t}, \Psi_{2,t}, \dots, \Psi_{p,t})$. To this end, Rossi and Wang (2019) suggest four alternative test statistics namely: the exponential Wald (*ExpW*), mean Wald (*MeanW*), Nyblom (*Nybolm*) and Quandt Likelihood Ratio (*SupLR*) tests. Based on the Schwarz Information Criterion (SIC), the VAR model is estimated using 2 lags. We use an end-point trimming of 5% in the bivariate set-up, which in turn amounts us to losing 8 observations from both ends. But a trimming of 10%, i.e., loss of 16 observations from both ends of the sample, is required in the four-variable system.

3. Results

In Table 1, to analyze the predictive ability of LPG on GI1, we first started with the standard constant parameter Granger causality test and found that LPG does not Granger cause GI1 even at the 10% level of significance. However, based on the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), used to detect 1 to *M* structural breaks in the GI1 equation of the VAR(2) model, allowing for heterogenous error distributions across the breaks and 5% trimming, yielded 2 break points at: 1985:Q1 and 1987:Q1, possibly due to the so-called "Thatcherite Revolution" which involved a host of supply-side reforms such as, privatization, reduction in the power of trade unions, deregulation, and lower income tax rates. Given this evidence of instability, the results from the constant parameter model is not robust, and hence to obtain reliable inference, we look at the *ExpW*, *MeanW*, *Nyblom*, and *SupLR* tests of Rossi and Wang (2019) based on the time-varying VAR also reported in Table 1. As can be seen, the null of no-Granger causality from GLP to GI1 is overwhelmingly rejected at the highest possible level of significance for three (*ExpW*, *MeanW*, and *SupLR*) of the four tests, and at the conventional 5% level under the *Nybolm* test statistic. In other words, the predictive ability of LGP for GI1 is in fact time-varying and exceptionally strong, even though no evidence of predictability can be derived from the constant parameter model.

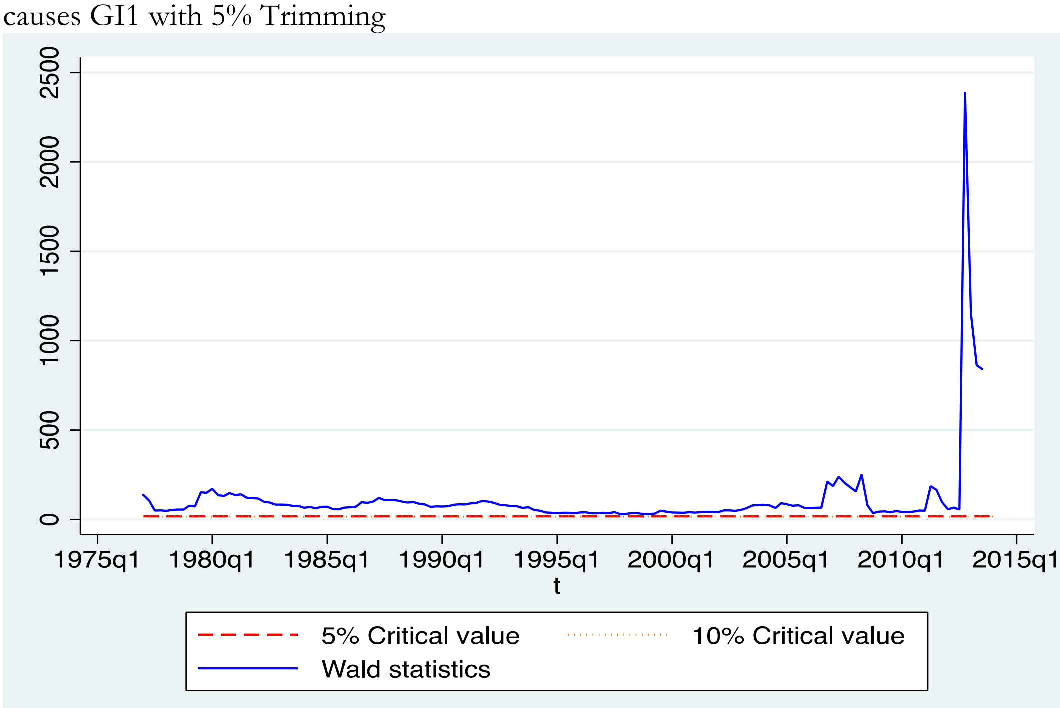
Table 1. Constant parameter and time-varying parameter Granger causality tests

	$\chi^2(2)$	*ExpW*	*MeanW*	*Nyblom*	*SupLR*
Test Statistic	4.290	555.176	112.878	3.813	2390.887
p-value	0.117	0.000	0.000	0.038	0.000

Note: Null hypothesis is GLP does not Granger cause GI1 in a constant or time-varying VAR(2). GI1: growth of Gini coefficient corresponding to income inequality; GLP: growth of labor productivity.

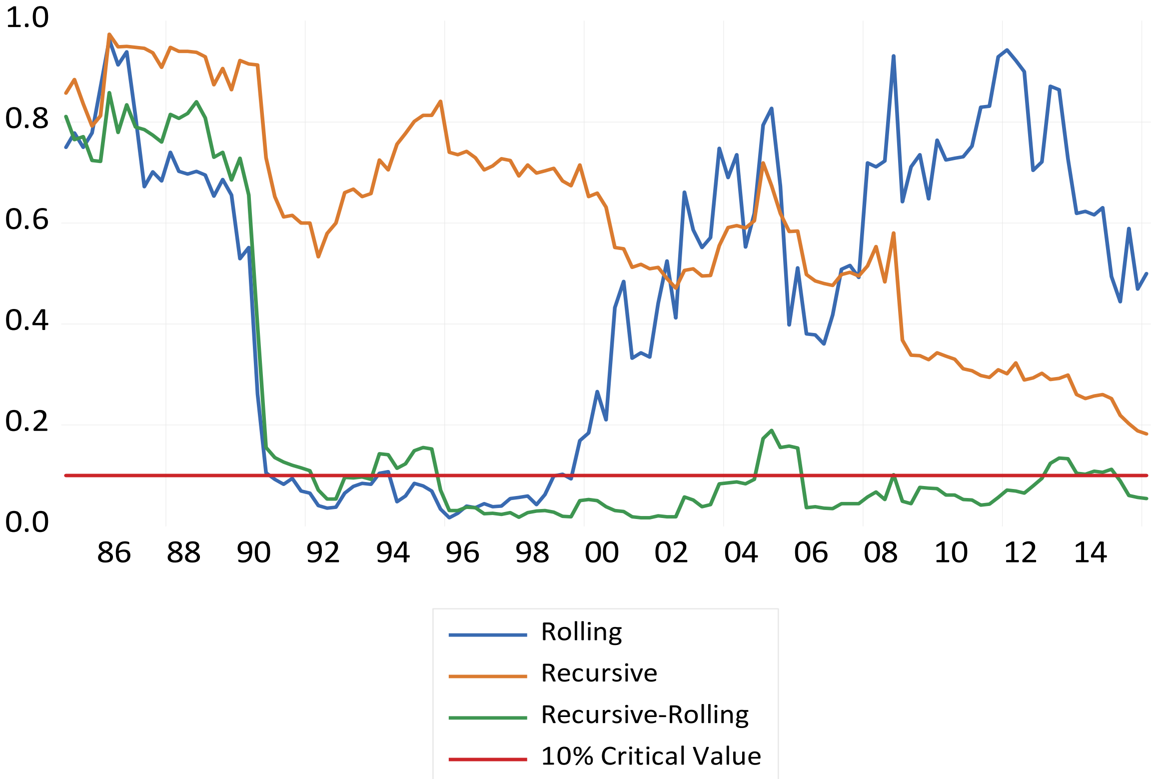
Next, in Figure 1(a), we present the whole sequence of the Wald statistics across time, which gives more information on when the Granger-causality occurs. As can be seen, GLP consistently predicts GI1, with the effects being particularly strong during and post the global financial crisis. Now since 5% trimming implies losing information on the time-varying statistic for 8 observations from both ends of the sample, we also conducted the rolling, recursive and recursive-rolling tests of Shi et al., (2018, 2020) reported in Figure 1(b). While the 10-year window (chosen to match-up with the first break point date) could not account for the issue regarding the lack of information on predictability at the beginning of the sample period, the recursive-rolling test did indeed pick-up evidence of causality in general from GLP to GI1 over the period of 1992:Q1 till 2016:Q1, at least at the recommended 10% level of significance with 1000 bootstrap replications.

Figure 1(a). Time-varying Wald statistics with VAR(2) under SIC, testing whether GLP Granger-causes GI1 with 5% Trimming



Note: See Notes to Table 1; t: corresponds to quarterly data; and the vertical axis measure the test statistic.

Figure 1(b). Rolling, Recursive, Recursive-Rolling Tests *p*-values with VAR(2) under SIC, testing whether GLP Granger-causes GI1 with a Window of 40 Quarters



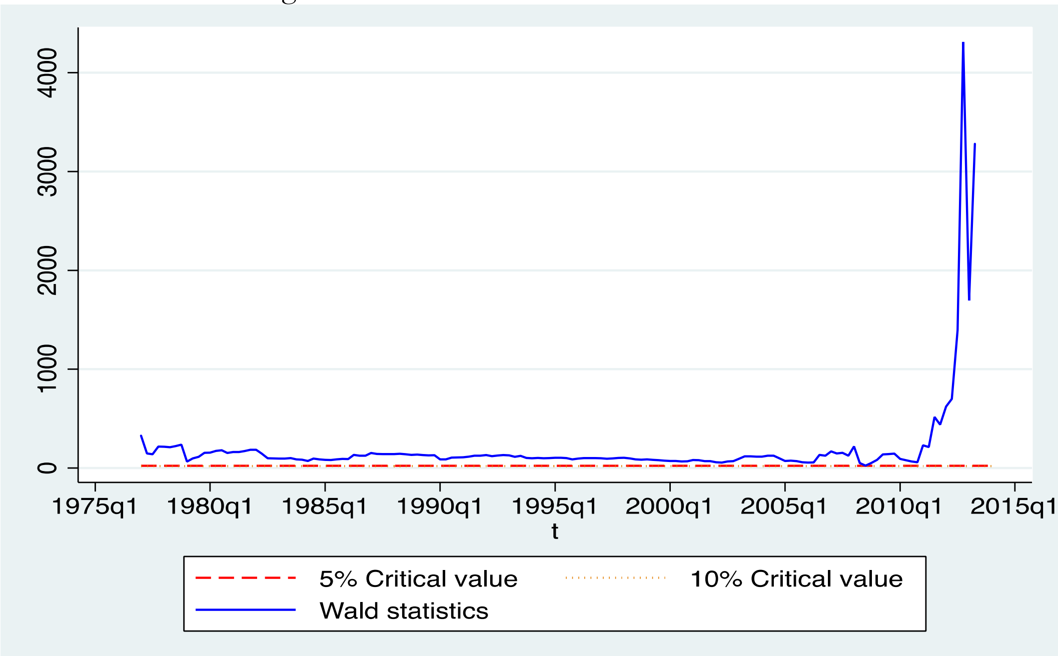
Note: See Notes to Table 1; horizontal axis corresponds to the sample period; and the vertical axis measure the p-values of the three test statistics.

Given that some studies have found that inequality can predict productivity (see for example, Hayes et al., (1994), Mo (2000), Lloyd-Ellis (2003), Ramos (2014), OECD (2015)), in Figure A2 in the Appendix of the paper, we plot the time-varying Wald statistics of GI1 Granger causing GLP. A similar story to the effect of GLP on GI1 emerges ever since the global financial crisis, with causality consistently running from GI1 to GLP, and being particularly strong for the start of the sample period to late 1980s.[5] Furthermore in Figures A3 to A7, we provide the evolution of the Wald statistics over time based on a VAR(2) model with 5% trimming, whereby we test the time-varying causality from GLP to GI*j*, *j*=2,..6. As can be seen from the figures, GLP consistently causes the alternative measures of income inequalities over the entire sample period.

As is well-known, causality tests are sensitive to the lag-length, so we revisit our results by re-conducting the Rossi and Wang (2019) test by using a VAR(3) model as suggested by the Akaike Information Criterion (AIC), with the 5% trimming used above. As can be seen from Figure 2, we are able to replicate the results observed in Figure 1 under the VAR(2) model, implying that our results are robust to alternative optimal lag-lengths derived using information criteria.

[5] Again, the constant parameter-based Granger causality test could not detect causality running from GI1 to GLP even at the 10% level of significance, though *ExpW*, *MeanW*, and *SupLR* tests all overwhelmingly rejected the null of no time-varying predictability at the highest level of significance, but the *Nyblom* test statistic could not do so event at the 10% level of significance. Complete details of these results are available upon request from the authors.

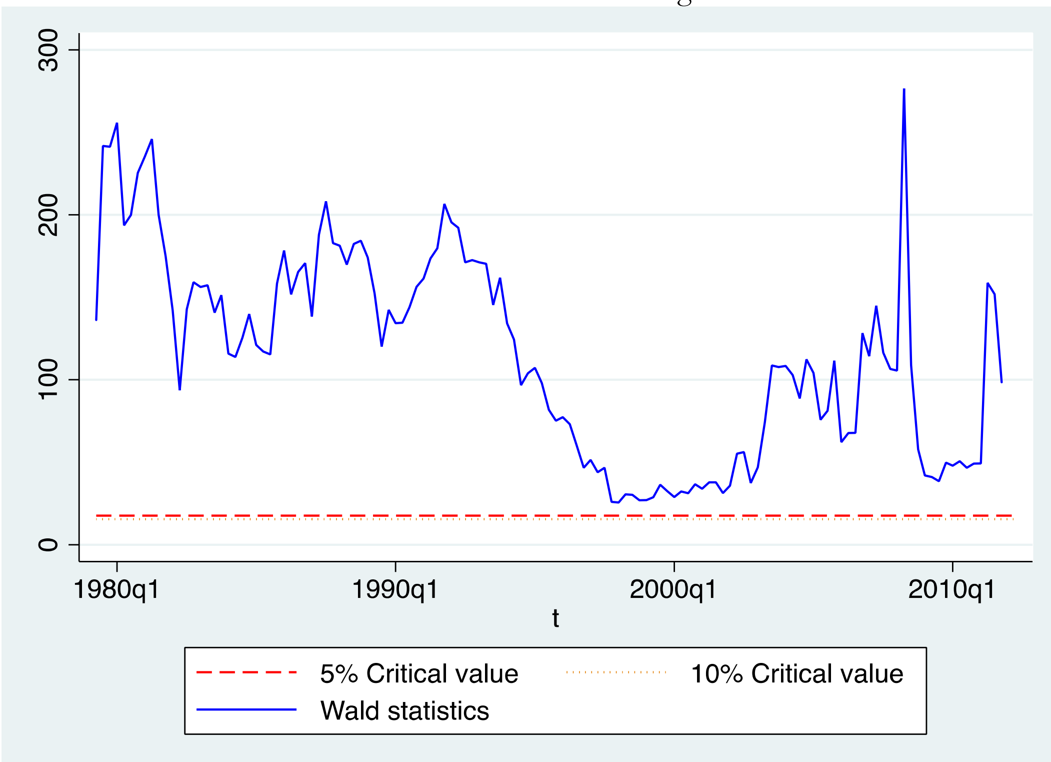
Figure 2. Time-varying Wald statistics with VAR(3) under AIC, testing whether GLP Granger-causes GI1 with 5% Trimming



Note: See Notes to Table 1 and Figure 1

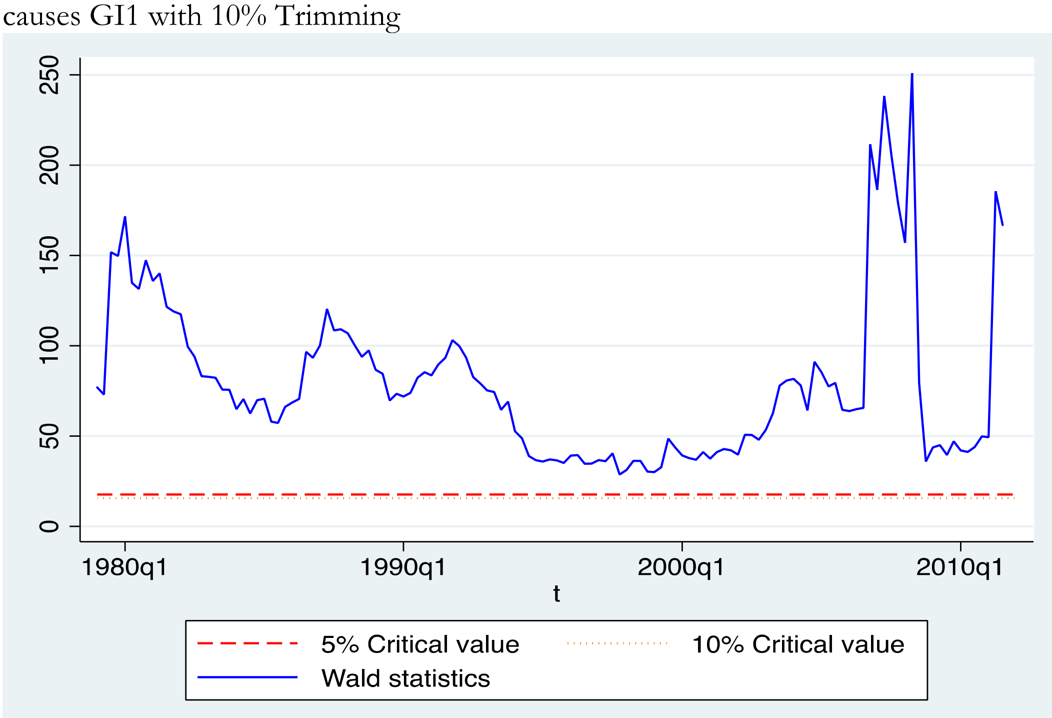
As a further robustness check, we extend our bivariate model to include DUR and GITGDP to control for possible omitted variables, and revisit the causality from GLP to GI1 in Figure 3(a). Using a VAR(2) model with a trimming of 10% required to accommodate the four variables, we find that the pattern of results derived under the bivariate model continues to hold in the extended model in terms of causality over the entire sample period, with increased predictability following the global financial crisis. But now, we also observe strong causal evidence from GLP to GI1 at the beginning of the sample. In other words, our two-variable model does not suffer from omitted variables bias, and GLP indeed causes GI1 over the entire sample period in a time-varying manner. To further vindicate this issue and provide one-to-one correspondence, we also report in Figure 3(b) the time-varying Wald statistics for the bivariate model, but now with 10% rater than 5% trimming. The pattern of the time-varying causality is in line with Figure 3(a) reporting the four variable case.

Figure 3(a). Time-varying Wald statistics with VAR(2) under SIC, testing whether GLP Granger-causes GI1 with additional controls and 10% Trimming



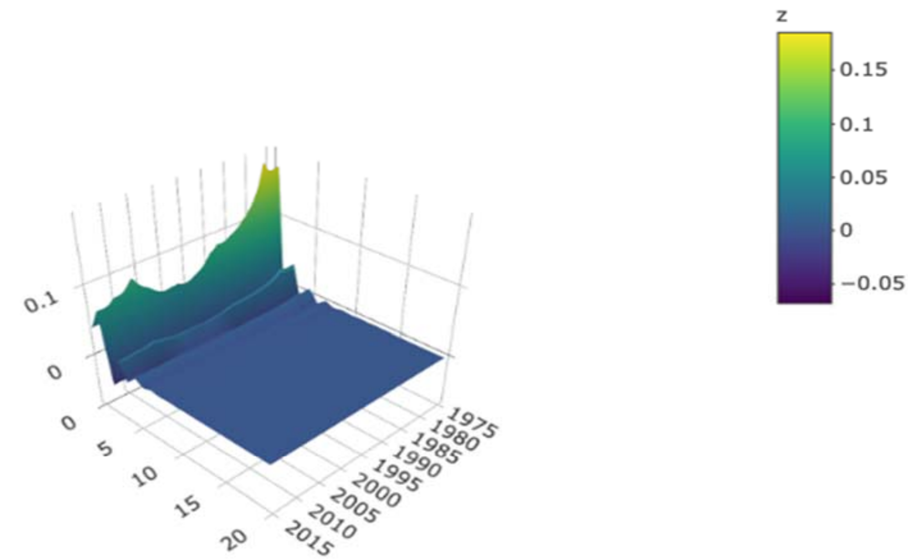
Note: See Notes to Table 1 and Figure 1; the two additional controls are: DUR: Change in Unemployment Rate, and GITGDP: Growth of Income Tax to GDP ratio.

Figure 3(b). Time-varying Wald statistics with VAR(2) under SIC, testing whether GLP Granger-causes GI1 with 10% Trimming



Note: See Notes to Table 1 and Figure 1.

Figure 4. Response of GI1 to a one standard deviation GLP shock in the TVP-VAR model



Note: See Notes to Table 1 and Figure 1

While the time-varying predictive analysis is the focus of our paper, causality tests are silent about the sign of the impact of GLP on GI1. Given this, as a final part of the analysis, we estimate a time-varying parameter VAR model with stochastic volatility (TVP-VAR-SV) as developed by Primiceri (2005), and Del Negro and Primiceri (2015) with 2 lags, and analyze the time-varying impact on GI1 following a shock to GLP. Given the evidence of bi-directional causality, we rely on generalized impulse response functions (GIRFs). The TVP-VAR model is estimated using Markov-Chain Monte-Carlo (MCMC) methods with Bayesian inference, based on 40,000 draws after an initial burn-in of 40,000 (i.e., we use a total of 80,000 iterations). The MCMC method assesses the joint posterior distributions of the parameters of interest based on certain prior probability densities that we set in advance, which in turn, are identical to those used in Primiceri (2005), Del Negro and Primiceri (2015). Once the model is estimated, we can produce time-varying impulse response functions of the variables in the model following the one standard deviation of the GLP shock. In Figure 4, we present the time-varying response of GI1 over a horizon of 20 quarters. In essence, the impact is initially positive but short-lived as it is restricted to basically one-quarter-ahead. The size of this positive effects has also seemed to decline over time, but beyond the first period following the shock, the effect is strongly negative. While the magnitude of the negative impact from three-quarter-ahead declines, with evidence of recovery in the impulse response function, the effect is consistently negative over the remaining quarters of the forecast horizon. This result is in line with our initial understanding that while higher productivity growth can increase inequality in the short-run, the effect is likely to be negative beyond that in medium- and long-runs.[6]

[6] This line of reasoning is further corroborated by the Bayesian Markov-switching quantile regression model (see, Yamaka et al., (2019) for further technical details) in Table A2 in the Appendix of the paper, with the results highlighting the importance of accounting for regime-changes in standard quantile regression models, when trying to deduce the correct

In sum, GLP has a robust time-varying predictive content for GI1, with the sign of the relationship being negative in general.

4. Conclusion

Existing empirical evidence suggests that productivity can act as driver of inequality. Consequently, in this study we explore the time-varying predictive power of the growth rate of an index of labor productivity for growth in income (and consumption) inequality in the UK. We focus on the UK since income (and consumption) inequality data are available at a high frequency, i.e., on a quarterly basis for over 40 years (1975:Q1 to 2016:Q1). Given that inequality is not only a problem in itself, but it also has negative economic, social, and health implications (Pierdzioch et al., 2019), we consider the usage of quarterly data to be of tremendous importance, since accurate prediction of inequality at a higher frequency should be more relevant to policymakers in designing appropriate policies to circumvent the wide-ranging negative impacts of inequality, compared to when predictions are only available at the lower annual frequency.

Our findings point that growth in productivity is generally associated with decreases in the growth of inequality at medium- to longer-runs, with the index of labor productivity containing important information in predicting growth in income inequality. Further, the strength of the predictive power is high post the period of the Global Financial Crisis, which is known to have been associated with global decline in productivity and heightened inequality. We believe these findings highlight an important role of productivity for inequality – an area of investigation that has in general remained untouched in a time-varying manner at high-frequency. In line with Arestis (2020), our results highlight the paramount importance of distributional policies, particularly fiscal policies along with (minimum) wage policies (and a code of practice for pay above the minimum), to enhance productivity that took a knock during the Global Financial Crisis, so as to ensure declines in the growth of inequality.

As part of future research, it would be interesting to extend our analysis to other developed and emerging economies around the world, but this is likely to involve the usage of low frequency, i.e., annual data only. But, if productivity data is available at a higher frequency, we could resort to mixed data sampling (MIDAS) techniques to predict the movements of annual inequality growth rates. Furthermore, other approaches like cointegration (Johansen, 1996) or even fractional cointegration-based (to account for long-memory in the data) VAR (FCVAR, Johansen, 2008; Johansen and Nielsen, 2010, 2012), can be used to analyze the relationship between the variables in levels to ensure that transformation of the data does not affect the robustness of our conclusions.

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inference, i.e., the negative relationship between GI1 and GLP, especially when inequality growth is conditionally high. Note the quantile regression model involves two lags of GLP with and without regime-switching across two states of low (indicated by regime-0) and high (indicated by regime-1)-GI1 states.

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APPENDIX:

Figure A1. Data Plots

Note: GI*j*, *j*=1,..6, corresponds to the growth rate six measures of income and consumption inequality (Gini coefficient, the standard deviation, and the difference between the 90th and 10th percentile) respectively; GLP: growth of labor productivity index; DUR: change in unemployment rate; GITGDP: growth of income tax to nominal GDP ratio.

Table A1. Unit Root Results

Levels		ADF	DF-GLS	PP	KPSS	ERS	NG-Perron			
							MZa	MZt	MSB	MPT
Gini_Income Inequality	Intercept	-1.779	-0.438	-2.127	0.695**	48.880	-0.495	-0.438	0.884	39.829
	Intercept + Trend	-0.847	-0.543	-2.192	0.386***	56.619	-1.040	-0.507	0.488	50.611
	None	0.541	-	0.522	-	-	-	-	-	-
SD_Income Inequality	Intercept	-1.921	-0.197	-1.929	0.876***	70.380	-0.236	-0.244	1.035	55.934
	Intercept + Trend	-0.749	-0.560	-1.376	0.376***	62.065	-0.730	-0.371	0.509	56.185
	None	0.923	-	0.561	-	-	-	-	-	-
Difference between the 90 and 10th percentile_Income Inequality	Intercept	-1.761	-0.368	-1.843	0.658**	62.145	-0.364	-0.364	0.998	50.688
	Intercept + Trend	-0.694	-0.431	-1.317	0.365***	78.531	-0.552	-0.319	0.579	70.179
	None	0.707	-	0.410	-	-	-	-	-	-
Gini_Consumption Inequality	Intercept	-2.231	-0.771	-3.016**	0.817***	16.984	-1.509	-0.778	0.515	14.388
	Intercept + Trend	-1.545	-1.835	-4.094***	0.361***	32.852	-5.881	-1.646	0.280	15.410
	None	0.986	-	0.582	-	-	-	-	-	-
SD_Consumption Inequality	Intercept	-1.988	-0.052	-2.226	1.064***	59.020	-0.086	-0.079	0.916	47.120
	Intercept + Trend	-1.317	-1.102	-3.073	0.374***	34.436	-2.376	-0.948	0.399	32.534
	None	1.214	-	0.923	-	-	-	-	-	-

Difference between the 90 and 10th percentile_Consumption Inequality	Intercept	-2.152	-0.349	-2.677*	1.049***	70.453	-0.543	-0.368	0.678	26.004
	Intercept + Trend	-1.223	-1.601	-3.755**	0.378***	43.588	-4.880	-1.471	0.302	18.195
	None	1.300	-	0.841	-	-	-	-	-	-
Income Tax to GDP	Intercept	-3.901***	0.216	-3.421**	0.545**	71.992	0.118	0.116	0.981	55.667
	Intercept + Trend	-3.143*	-0.730	-2.917	0.306***	52.427	-1.83	-0.891	0.487	45.185
	None	1.556	-	1.152	-	-	-	-	-	-
Labor Productivity	Intercept	-1.377	1.855	-1.090	1.590***	603.327	1.182	2.190	1.853	231.622
	Intercept + Trend	-0.866	-1.303	-0.698	0.222***	19.276	-4.752	-1.361	0.286	18.121
	None	3.577	-	4.908	-	-	-	-	-	-
Unemployment Rate	Intercept	-2.322	-1.516	-2.011	0.363*	6.313	-4.617	-1.519	0.329	5.308
	Intercept + Trend	-2.692	-1.802	-2.433	0.156**	17.938	-7.143	-1.840	0.258	12.842
	None	-0.712	-	-0.439	-	-	-	-	-	-
First-Differences		ADF	DF-GLS	PP	KPSS	ERS	NG-Perron			
							MZa	MZt	MSB	MPT
GI1	Intercept	-14.029***	-13.963***	-22.571***	0.529**	0.204***	-42.361***	-4.602***	0.109***	0.578***
	Intercept + Trend	-14.349***	-14.363***	-25.789***	0.072	0.734***	-38.107***	-4.365***	0.115***	2.394***
	None	-14.025***	-	-21.772***	-	-	-	-	-	-
GI2	Intercept	-13.910***	-1.866*	-24.838***	0.485**	0.358***	-32.330***	-3.978***	0.123***	0.888***
	Intercept + Trend	-14.248***	-2.637	-23.423***	0.054	1.144***	-31.458***	-3.902***	0.124***	3.263***
	None	-13.831***	-	-24.302***	-	-	-	-	-	-
GI3	Intercept	-14.158***	-1.340	-20.414***	0.426**	0.297***	-32.429***	-4.026***	0.124***	0.759***
	Intercept + Trend	-14.548***	-2.681	-21.695***	0.073	0.844***	-35.246***	-4.191***	0.119***	2.623***
	None	-14.127***	-	-20.136***	-	-	-	-	-	-
GI4	Intercept	-10.272***	-0.343	-37.650***	0.222	0.445	-19.258***	-3.096***	0.161***	1.300***
	Intercept + Trend	-10.446***	-1.390	-50.089***	0.113*	1.598***	-26.474***	-3.578***	0.135***	3.802***
	None	-15.200***	-	-26.473***	-	-	-	-	-	-
GI5	Intercept	-12.346***	-0.360	-28.428***	0.279	0.0003***	-17.173***	-2.922***	0.170***	1.459***
	Intercept + Trend	-12.508***	-1.352	-34.713***	0.092	0.001***	-22.004**	-3.257**	0.148**	4.509**

	None	-12.213***	-	-26.423***	-	-	-	-	-	-
GI6	Intercept	-16.806***	-0.476	-30.606***	0.245	0.235***	-17.808***	-2.984***	0.168***	1.376***
	Intercept + Trend	-10.972***	-1.527	-52.251***	0.109	2.868***	-21.385**	-3.249**	0.152**	4.392**
	None	-16.762***	-	-27.876***	-	-	-	-	-	-
GITGDP	Intercept	-20.909***	-2.531**	-19.227***	0.380*	0.315***	-91.641***	-6.752***	0.074***	0.302***
	Intercept + Trend	-21.339***	-7.585***	-19.966***	0.120*	1.154***	-80.482***	-6.339***	0.078***	1.151***
	None	-20.707***	-	-18.951***	-	-	-	-	-	-
GLP	Intercept	-7.303***	-1.778*	-12.471***	0.459*	2.451**	-19.076***	-3.072***	0.161***	1.344***
	Intercept + Trend	-7.788***	-2.864*	-12.768***	0.112	3.967***	-37.428***	-4.313***	0.115***	2.507***
	None	-5.407***	-	-11.130***	-	-	-	-	-	-
DUR	Intercept	-4.306***	-2.921***	-4.157***	0.190	2.245**	-13.428**	-2.566**	0.191**	1.922**
	Intercept + Trend	-4.347***	-4.029***	-4.204***	0.084	3.903***	-24.399***	-3.482***	0.143***	3.798***
	None	-4.322***	-	-4.175***	-	-	-	-	-	-

Note: See Notes to Figure A1.

Table A2(a). The estimation results for the quantile regression model

Parameter	τ =0.25	τ =0.50	τ =0.75
α^{τ}	-2.072*** (0.107)	0.0288*** (0.042)	1.759*** (0.044)
β^{τ} (lag1)	0.672*** (0.098)	-0.408*** (0.030)	0.013 (0.042)
β^{τ} (lag2)	-0.008 (0.052)	0.036 (0.032)	-0.053 (0.052)
σ^{τ}	0.846*** (0.066)	1.056*** (0.082)	0.844*** (0.066)
SIC	842.717	820.21	842.021

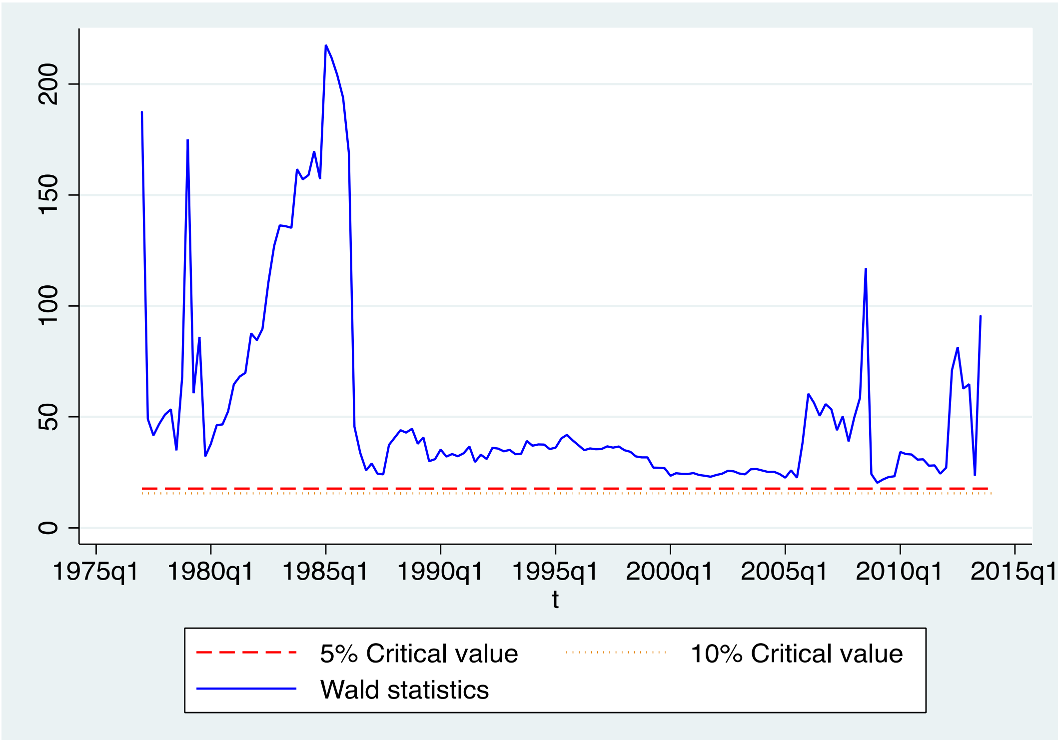
Note: *** indicate significance at 1% level.

Table A2(b). The estimation results for the Markov-switching quantile regression model

Parameter	τ =0.25	τ =0.50	τ =0.75
$\alpha^{\tau}(s_t = 0)$	-3.411***	0.218***	0.611***
	(0.241)	(0.055)	(0.031)
$\beta^{\tau}(s_t = 0)$ (lag1)	0.562***	-0.422***	0.867***
	(0.050)	(0.034)	(0.029)
$\beta^{\tau}(s_t = 0)$ (lag2)	0.157	0.018	0.399***
	(0.246)	(0.031)	(0.026)
$\alpha^{\tau}(s_t = 1)$	0.296***	0.283	2.952***
	(0.025)	(0.150)	(0.027)
$\beta^{\tau}(s_t = 1)$ (lag1)	-0.462***	-0.385***	-0.626***
	(0.111)	(0.056)	(0.017)
$\beta^{\tau}(s_t = 1)$ (lag2)	-0.001	0.052	-0.270***
	(0.097)	(0.108)	(0.016)
$\sigma^{\tau}(s_t = 0)$	0.644***	1.062***	0.721***
	(0.086)	(0.165)	(0.109)
$\sigma^{\tau}(s_t = 1)$	0.525***	1.059***	0.579***
	(0.061)	(0.156)	(0.072)
$p_{11}^{\tau}(s_t = 0)$	0.356***	0.873***	0.370**
	(0.072)	(0.023)	(0.158)
$p_{22}^{\tau}(s_t = 0)$	0.089	0.882***	0.145***
	(0.077)	(0.034)	(0.097)
SIC	819.249	817.889	831.103

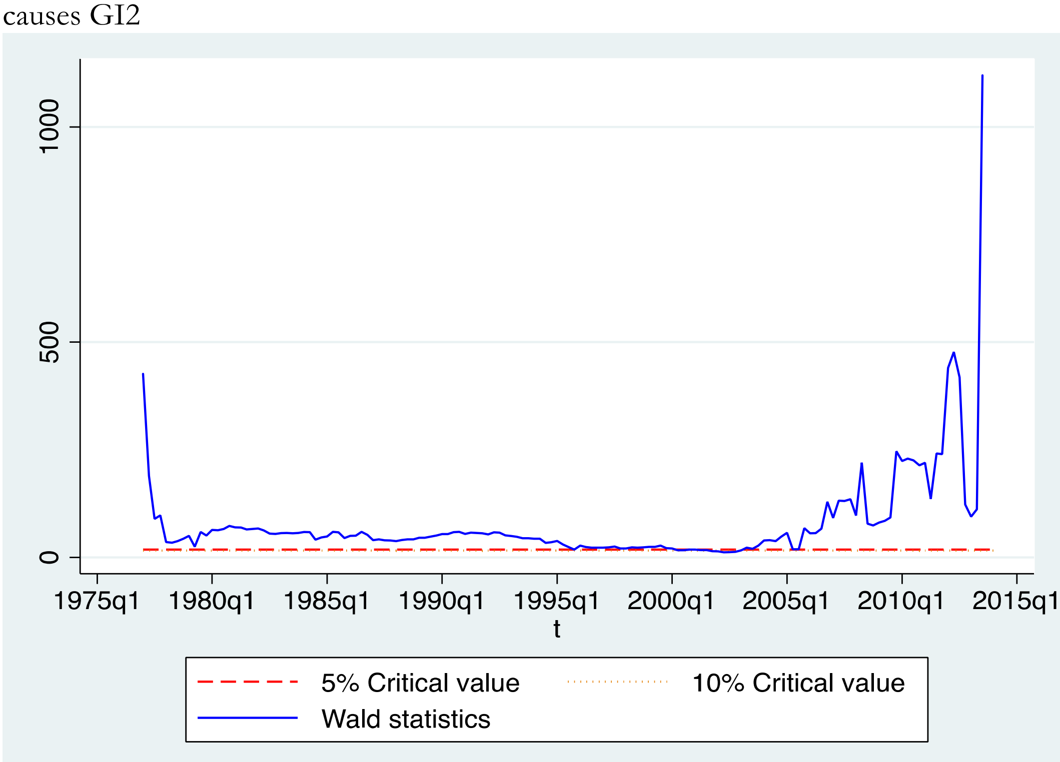
Note: *** indicate significance at 1% level.

Figure A2. Time-varying Wald statistics with VAR(2) under SIC, testing whether GI1 Granger-causes GLP



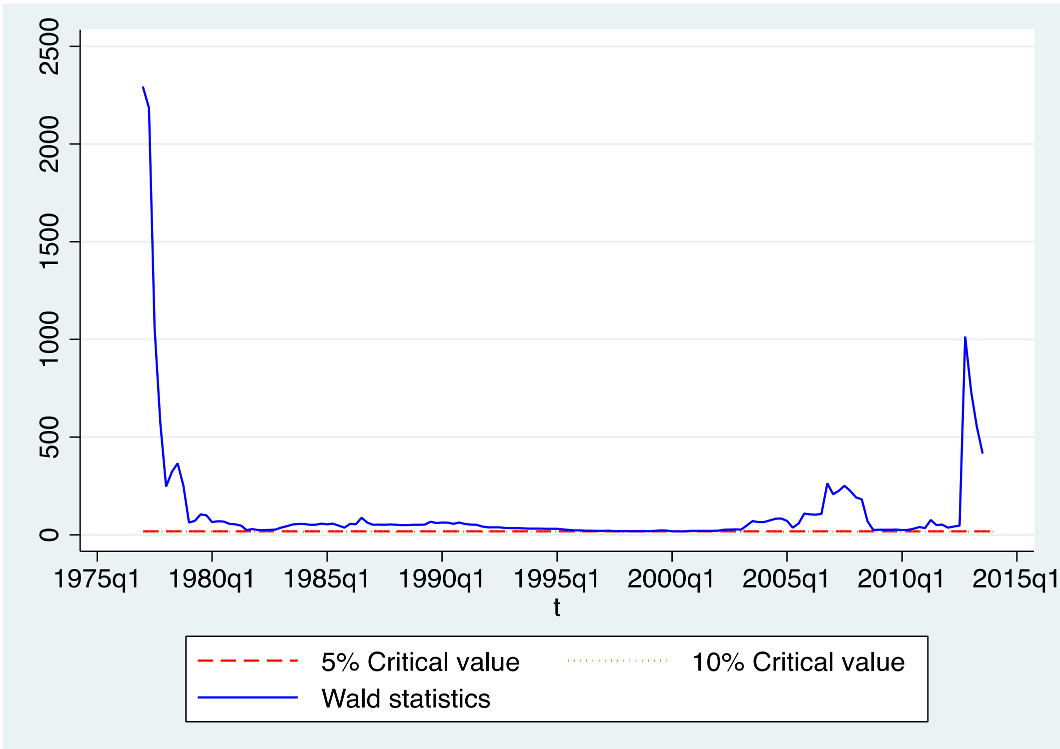
Note: See Notes to Figure A1; t: corresponds to quarterly data; and the vertical axis measure the test statistic.

Figure A3. Time-varying Wald statistics with VAR(2) under SIC, testing whether GLP Granger-causes GI2



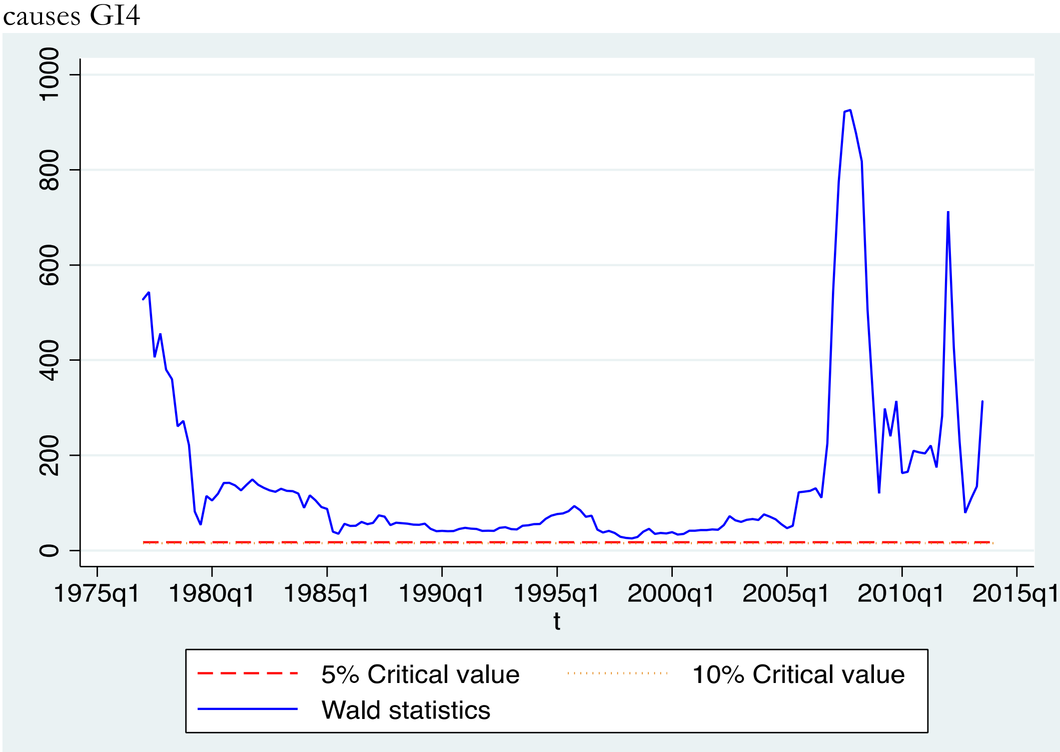
Note: See Notes to Figure A1 and Figure A2.

Figure A4. Time-varying Wald statistics with VAR(2) under SIC, testing whether GLP Granger-causes GI3



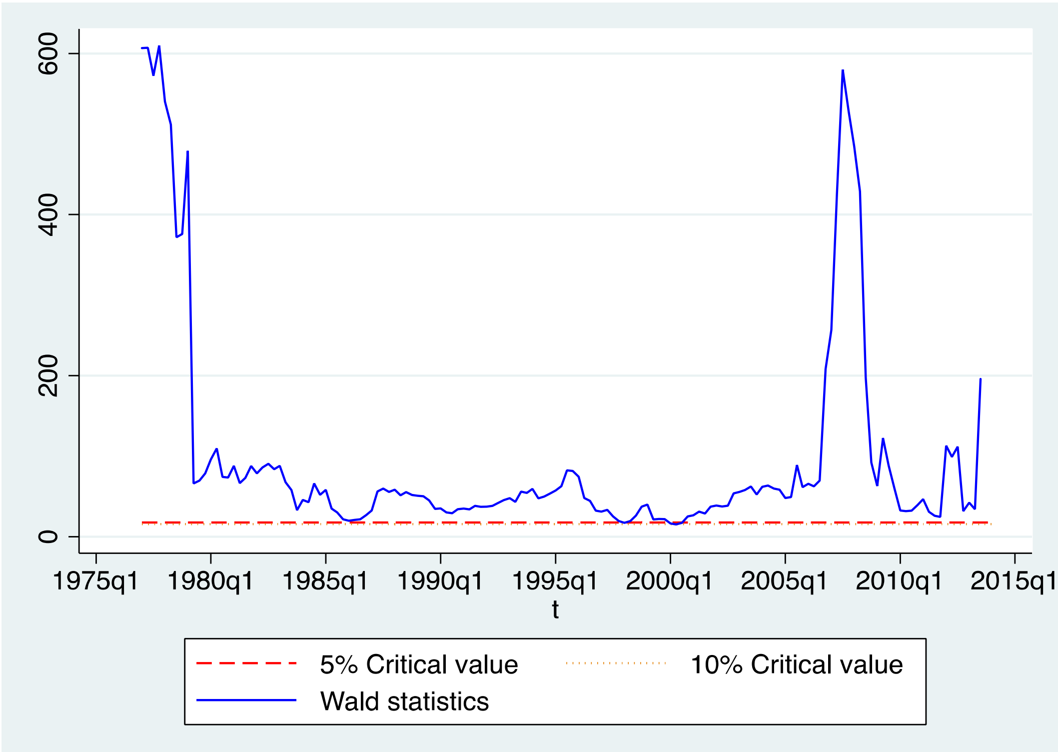
Note: See Notes to Figure A1 and Figure A2.

Figure A5. Time-varying Wald statistics with VAR(2) under SIC, testing whether GLP Granger-causes GI4



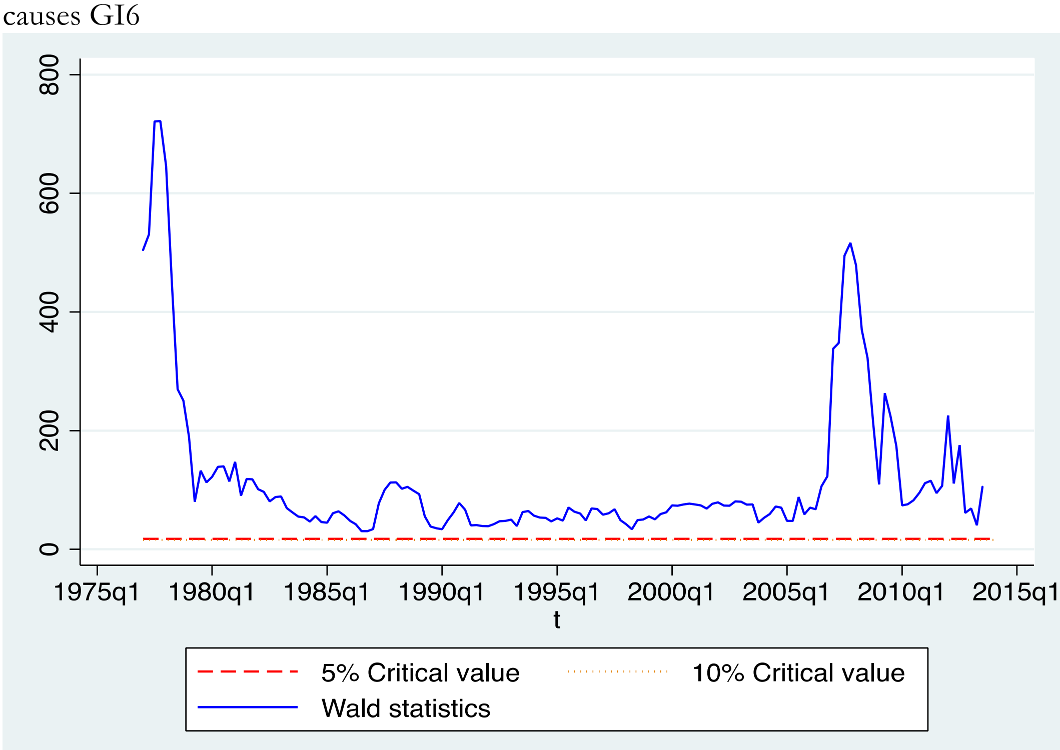
Note: See Notes to Figure A1 and Figure A2.

Figure A6. Time-varying Wald statistics with VAR(2) under SIC, testing whether GLP Granger-causes GI5



Note: See Notes to Figure A1 and Figure A2.

Figure A7. Time-varying Wald statistics with VAR(2) under SIC, testing whether GLP Granger-causes GI6



Note: See Notes to Figure A1 and Figure A2.