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DO RISING TOP INCOMES SPUR ECONOMIC GROWTH? EVIDENCE FROM OECD COUNTRIES BASED ON A NOVEL IDENTIFICATION STRATEGY

BY HELMUT HERWARTZ and YABIBAL M. WALLE*

Georg-August-University of Goettingen, Germany

We investigate the causal relationship between the growth rate of top income shares and economic growth in 12 OECD economies for the period 1950–2010. To analyze patterns of short- and long-run causality, we build upon recent advances in structural-vector autoregressive modeling of non-Gaussian systems. This framework allows us to discriminate between rival transmission channels by means of dependence tests, since independent shocks are unique for a particular causation pattern. We consider the share of income accruing to the top 1 percent ($\mathcal{T}1$), to the next 9 percent ($\mathcal{T}9$), and to the top decile ($\mathcal{T}10$). While structural models display considerable heterogeneity across countries, mean group and pooled results strongly favor a specific transmission pattern. In particular, $\mathcal{T}1$ has a long-run positive impact on economic development. This result, which is also confirmed by identified impulse-response functions, is particularly evident for the post-1980 period.

JEL Codes: C32, D31, O47

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1. Introduction

A growing empirical literature has recently constructed long time series data on top income shares for several OECD and a few non-OECD countries. Top income shares are often found to be highly correlated with broader inequality measures such as the Gini coefficient (see, e.g., Atkinson *et al.*, 2011; Burkhauser *et al.*, 2012; Leigh, 2007). Taking advantage of this high correlation, researchers have used top income shares data to study the inequality–growth nexus in cases in which data for broader inequality measures are missing or not of sufficient quality. However, the top income shares–growth relationship is not just a proxy for the inequality–growth nexus; it is also an interesting policy issue in its own right. For instance, while top income earners represent a very small share of the population, they, however, receive a substantial share of national income (Atkinson *et al.*,

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*Correspondence to: Yabibal M. Walle, Chair of Econometrics, Georg-August-University of Goettingen, Humboldtallee 3, D-37073 Goettingen, Germany (ywalle@uni-goettingen.de).

2011).[1] Changes in top income shares could thus exert a sizeable impact on several macroeconomic aggregates; in particular, national income, welfare, and inequality. Furthermore, top income shares represent (a specific kind of) inequality at the top quantiles of income distributions. Consequently, distinct transmission channels in the inequality–growth relationship might be at work when considering the top income–growth link *vis-à-vis*, say, the Gini coefficient–growth link.[2]

Similar to the highly debated role of income inequality in economic growth, theoretical predictions on the impact of rising top incomes on aggregate economic growth are not clear *a priori*. The conventional textbook approach views inequality (including top income inequality) as good for incentives and, hence, as growth promoting (Aghion *et al.*, 1999; Mankiw, 2013). However, inequality may hamper economic growth by diminishing national savings, reducing the number of individuals who have access to credit, undermining social and political stability, and exacerbating rent-seeking activities (Galor and Zeira, 1993; Perotti, 1996; Solow *et al.*; 2014; Todaro and Smith, 2011). In line with the conflicting theoretical predictions, existing empirical studies on the relationship between top income shares and economic growth have documented inconclusive results (see, e.g., Andrews *et al.*, 2011; Herzer and Vollmer, 2013; Roine *et al.*, 2009).

In this paper, we take advantage of recent contributions to identification in structural-vector autoregressive (SVAR) models. As shown by Lanne *et al.*, (2017), Moneta *et al.*, (2013), and Gouriéroux and Monfort (2014), the traditional identification problem of distinguishing between rival causation patterns—for example, Cholesky factors (Sims, 1980) or long-run relations (Blanchard and Quah, 1989)—can be resolved in a data-driven manner in non-Gaussian systems. Specifically, the detection of independent orthogonalized shocks in non-Gaussian systems provides external information which allows the testing of otherwise just-identifying structural assumptions. Taking advantage of non-Gaussianity of growth rates of income shares and per capita income, we assess the level of dependence between orthogonalized shocks that are determined under the presumptions of distinct causation patterns. While alternative profiles of short-run causality refer to potential links among growth rates, long-run causality profiles represent relationships among variables in levels. Assuming that the "true" structural shocks are independent and non-Gaussian, independence diagnostics allow us to rank overall four alternative structural hypotheses in their scope to filter out independent shocks from the data. To diagnose the actual level of dependence of alternatively composed samples of structural shocks, we rely on a recent test of the null hypothesis of independence of random variables (Bakirov *et al.*, 2006). This test has been shown to be consistent against any form of dependence. Noting that our identification strategy rests on the maximum p-value out of four alternatives, the structural model selection builds upon the principles of Hodges–Lehmann estimation.

Dictated by data availability, we study the link between top income shares and economic growth in 12 OECD economies for the post-1950 period. Noting that

[1]For an empirical support to this view, see, among others, Voitchovsky (2005), who reports that inequality at the top end of the income distribution is growth promoting, while inequality among the poor has a negative relationship with economic growth.

[2]For instance, the top 1 and 10 percent of the U.S. population received about 17.45 and 46.35 percent of the aggregate national income, respectively, in 2010 (Alvaredo *et al.*, 2016).

the top decile group is highly heterogeneous (Atkinson *et al.*, 2011; Roine *et al.*, 2009), we consider three top income inequality measures: the share of income accruing to the top 1 percent (henceforth, $\mathcal{T}1$), to the next 9 percent ($\mathcal{T}9$), and to the top decile ($\mathcal{T}10 = \mathcal{T}1 + \mathcal{T}9$). We find that causality directions linking growth of per capita income and top income shares display considerable heterogeneity across economies. However, both mean group averages of identified impulse-response functions and inferential results from pooled samples strongly favor a long-run positive impact of $\mathcal{T}1$ on economic activity against other postulated causal relationships. Conditional pooling reveals that the positive role of $\mathcal{T}1$ in spurring macroeconomic performance is particularly strong during the post-1980 period—a period in which $\mathcal{T}1$ has been on the rise in most of the economies considered. Unlike the link between $\mathcal{T}1$ and per capita income, however, the structural relations between $\mathcal{T}9$ ($\mathcal{T}10$) and per capita income are heterogeneous in direction and generally more in line with an *a priori* view that economic growth impacts on the growth of top income shares in the short run. In fact, long-run causality from top income inequality to economic activity is significantly rejected in pooled samples of residuals from $\mathcal{T}10$ or $\mathcal{T}9$ growth rates.

Our result that $\mathcal{T}1$—but not $\mathcal{T}9$—exerts a long-run impact on per capita income is consistent with both the "superstar" and financial deregulation theories on the rise of top incomes in recent decades. First, according to the "superstar" hypothesis, the recent increase in top income shares could be attributed to globalization and advances in information and communications technology that have increased the relative productivity of highly talented individuals (Kaplan and Rauh, 2013; Rosen, 1981). These "superstars" more likely belong to the top percentile than the next top nine percentiles. Moreover, the positive and significant role of $\mathcal{T}1$ on economic performance is not obtained in the pre-1980 period but, rather, in the post-1980 period, where the "superstar" hypothesis is more likely to hold. Therefore, the "superstars" might have been an important driving force behind our result that $\mathcal{T}1$—but not $\mathcal{T}9$—has a long-run impact on economic activity. Second, our result is also in line with the hypothesis that the financial deregulation of the past four decades, through its role in driving up wages in the financial sector, is partly responsible for the recent rise in top income inequality (Boustanifar *et al.*, 2018; Tanndal and Waldenström, 2018). Given that these high-wage earners likely belong to the top percentile earners, the result that $\mathcal{T}1$—but not $\mathcal{T}9$—has a long-run impact on economic activity could also be reflecting the positive role of financial deregulation in economic development (see, e.g., Levine, 2005).

If we investigate whether $\mathcal{T}1$ benefits income groups other than the top 1 percent, we find that it indeed drives up the per capita income of the next 9 percent. However, $\mathcal{T}1$ does not exert a statistically significant impact on the per capita income of the bottom 90 percent. Hence, according to our results, the bottom 90 percent have, on average, neither benefited from "trickle-down" effects nor experienced decreasing group-wise per capita income despite the decline in their share of aggregate income.

Section 2 provides a brief literature review. Section 3 describes the data, while Section 4 sketches our methodological approach. The empirical results are presented and analyzed in Section 5. Section 6 concludes. The first four appendices (in the online Supporting Information) provide an explicit representation of the employed independence diagnostic (Appendix A), a simulation study which highlights that independence testing provides a consistent means to detect contemporaneous causation patterns in non-Gaussian SVARs (Appendix B), panel unit root and cointegration test results (Appendix C), and a table and discussions on country-specific SVAR results (Appendix D). Two further appendices contain a discussion of Granger-causal relations among top income shares and macroeconomic performance (Appendix E) and further tables on country-specific SVAR results (Appendix F), using $\mathcal{T}9$ and $\mathcal{T}10$ as well as pooled sample evidence employing $\mathcal{T}0.5$ and $\mathcal{T}0.1$ data.

2. The Link Between Top Income Shares and Growth

In this section, we briefly review the theoretical and empirical literature on the relationship between top income shares and economic growth. Moreover, we outline theoretical possibilities as to why $\mathcal{T}1$ and $\mathcal{T}9$ could have different impacts on economic growth.

To begin with, it is noteworthy that, other things being constant, a rise in top incomes raises national income per capita by construction. However, other things will not remain constant in reality, and forces at work behind this rise in top incomes may reduce the incomes of a certain section of the population. As a result, some or all of the gains in national income per capita arising from rising top incomes may be counterbalanced by the decline in the income of the bottom 90 percent. Hence the overall impact of rising top incomes on the national income per capita is not clear *a priori*.

There are several reasons why changes in top income shares might affect economic growth. On the one hand, the conventional textbook approach views inequality as good for incentives and, hence, as growth promoting (Aghion *et al.*, 1999; Mankiw, 2013). In accordance with this view, rising top incomes—as one aspect of income inequality—could spur economic growth. In particular, rising top incomes could imply the absence or minimal presence of distortionary policies, such as high and progressive taxes, which distribute a portion of the fruits of the investments of the rich to the rest of society. Lower tax rates could provide a strong incentive for the rich to invest and generate further economic growth. The so-called "trickle-down" theory of development postulates that overall economic growth generated by the rich will eventually benefit the poor through job creation and other opportunities.[3]

On the other hand, higher top incomes might also hamper economic growth. First, concentration of wealth and income at the top end of the distribution could reduce the number of individuals that have access to credit in the presence of capital market imperfections. This in turn reduces the level of human capital investments, finally leading to a decline in the long-term growth rate (Galor and Zeira, 1993). Second, as the highest average saving rates are found among the middle-income individuals, and not the rich, rising top income shares can also reduce national savings (Todaro and Smith, 2011). Third, rising top incomes (or

[3]See, among others, Arndt (1983) for the origin of the "trickle-down" theory of development, and Böhm *et al.* (2015) for a recent survey of the related literature.

inequality in general) could reduce long-run growth by undermining social and political stability (Perotti, 1996; Todaro and Smith, 2011). Fourth, growing top income inequality may exacerbate rent seeking, including actions such as excessive lobbying, large political donations, and corruption (Todaro and Smith, 2011; Solow *et al.*, 2014).[4] Hence the overall effect of rising top income shares on economic growth is not clear *a priori*.

The impact of top income shares on economic growth may depend crucially on whether we measure top income shares by means of the top percentile, the next nine percentiles, or the top decile income shares ($\mathcal{T}1$, $\mathcal{T}9$, or $\mathcal{T}10$). In turn, this dependence stems from the particular behavior of the individuals in these income groups and the factors behind changes in $\mathcal{T}1$ and $\mathcal{T}9$. Hence it is important to review potential explanations for the recent rises in top income shares.

One proposed explanation for the growth of top income shares in many OECD countries in the past three decades is the so-called "superstar" hypothesis. Rosen (1981) predicted that technological advances, particularly in information and communications, can boost the relative productivity of highly talented individuals, or "superstars." These changes allow the highly talented to apply their talent to a wider pool of resources, and to reach a larger number of customers, and hence, to receive a higher compensation. Using empirical data on earnings of public company executives, private company executives, financial executives, corporate lawyers, and professional athletes in the U.S. from 1993 to 2011, Kaplan and Rauh (2013) find that the top 1 percent is spread broadly across a variety of occupations, which supports the "superstar" hypothesis promoted by Rosen (1981). If this is the main reason for the rising top incomes in recent decades, it is thus plausible to expect that top incomes have been growing together with the overall economic activity.

Alvaredo *et al.* (2013) consider the technology-based explanation for rising top incomes as too narrow, as it fails to explain the fact that top income shares in high-income countries have often gone through distinct paths even when the countries have experienced similar technological and productivity developments. Instead, they argue in favor of institutional and policy differences, in particular tax rate changes, as key determinants of top income shares. On the one hand, low tax rates might stimulate increased economic activities of the top earners, involving more effort, risk-taking, and innovation. In this case, tax-policy-induced top income inequality can be growth promoting. On the other hand, low tax rates might lead top earners to aggressively bargain for their compensation. However, even without aggressive bargaining, tax reductions might have coincided with increased deregulations and globalization that not only increased the demand for high-skilled labor, but also changed the way in which remunerations are calculated in top earner's favor. In either case, rising top incomes could come at the expense of the remaining 99 (or 90) percent, and hence might not generate overall economic

[4]In Solow *et al.* (2014), Robert Solow asserts that the political influence of the rich "may be the most dangerous adverse consequence of extreme inequality at the top," while Gregory Mankiw (in the same article as Solow) states that he is "less worried" about this effect. Mankiw supports his argument by noting that the rich are supporters of both the left and the right, and that the United States (U.S.) elected a left-leaning president in 2008 and 2012 despite rising top incomes and the president's promise to increase taxes on the rich.

growth. Noting that effective tax rates are more or less the same for the top 1 percent and for the next 9 percent, and that there is no strong reason to believe that lower taxes could have differing impacts on the incentives of the top 1 percent and the next 9 percent, we do not expect tax-policy-induced changes to alter the relative importance of $\mathcal{T}1$ versus $\mathcal{T}9$ in economic growth.

Another important factor that is thought to have contributed significantly to the recent increase in the share of income of the top income earners is financial deregulation, which has become prevalent after the 1980s. For instance, Tanndal and Waldenström (2018) show that top income shares increased after the two "Big Bangs" of financial deregulation: the deregulation episodes in the United Kingdom (U.K.) in 1986 and Japan in 1997–9. Similarly, using data from a set of developed economies for the period 1970–2011, Boustanifar *et al.* (2018) find that financial deregulation is the single most important force behind the fast-growing wages in the financial sector, and high wages in finance exacerbate overall income inequality. It is worth noting here that these high-wage earners in the financial sector likely belong to the top percentile, and not so much to the next nine percentiles. Hence the positive role of financial development on economic growth (see, e.g., Levine, 2005) could render a positive relationship between growth in $\mathcal{T}1$—but not $\mathcal{T}9$—and economic growth.

Existing empirical studies on the relationship between top income shares and economic growth have documented inconclusive results. For instance, Andrews *et al.* (2011) find no systematic relationship between the top decile's income share and economic growth in a panel of 12 developed countries, observed between 22 and 85 years. Restricting the time coverage to post-1960 data, however, they document a positive impact of a rise in $\mathcal{T}10$ on per capita income growth in the following year. Splitting the top decile share into the top percentile share ($\mathcal{T}1$) and the share of the remaining 9 percent ($\mathcal{T}9$), they document that the positive impact of $\mathcal{T}10$ on economic growth could not be attributed to $\mathcal{T}1$, rather to $\mathcal{T}9$. Using panel cointegration techniques, Herzer and Vollmer (2013) document evidence in favor of bidirectional causality between $\mathcal{T}10$ and economic growth. Specifically, they report that economic growth boosts $\mathcal{T}10$, whereas—in contrast to the evidence in Andrews *et al.* (2011)—an increase in $\mathcal{T}10$ retards economic growth. Roine *et al.* (2009) use data from 16 countries over the entire twentieth century to study the growth–inequality nexus by means of top income shares. Their results show that economic growth disproportionately increases $\mathcal{T}1$ at the expense of $\mathcal{T}9$.

In sum, neither the theoretical predictions nor the existing empirical studies are conclusive on the relationship between top income shares and economic growth. Moreover, due to the substantial heterogeneity in the top decile group, the link between top income shares and economic growth might be specific for alternative choices of the top income measures ($\mathcal{T}1$, $\mathcal{T}9$, or $\mathcal{T}10$).

3. The Data

Our dataset covers 12 OECD economies: Australia, Canada, France, Germany, Japan, the Netherlands, New Zealand, Norway, Sweden, Switzerland, the U.K., and the U.S. The choice of economies is dictated by the availability of

TABLE 1
Summary Statistics

Variable	Period	Mean	SD	Min.	Max.	Period	Mean	SD	Min.	Max.
Australia						New Zealand				
PCI	1951–2010	21,572	8,313	10,199	37,584	1951–2002	16,015	4,168	9,424	25,206
Growth	1951–2010	1.95	3.02	−10.14	7.93	1951–2002	1.62	4.11	−8.87	9.21
$\mathcal{T}1$	1951–2010	7.02	1.52	4.61	10.06	1951–2002	7.56	1.62	5.04	12.88
$\mathcal{T}9$	1951–2010	21.21	1.55	*16.95*	22.99	1951–2002	23.94	1.18	20.97	26.03
Canada						Norway				
PCI	1951–2000	19,646	6,803	9,849	33,487	1951–2010	22,802	12,331	8,302	**53,100**
Growth	1951–2000	2.48	2.66	−4.84	7.03	1951–2010	3.10	3.51	*−10.49*	13.97
$\mathcal{T}1$	1951–2000	9.37	1.20	7.60	13.56	1951–2010	6.69	2.12	4.13	16.49
$\mathcal{T}9$	1951–2000	27.94	0.77	26.19	29.42	1951–2010	21.97	2.80	17.70	26.96
France						Sweden				
PCI	1951–2010	18,662	7,596	6,539	31,300	1951–2010	20,205	7,858	8,902	35,234
Growth	1951–2010	2.67	2.59	−5.46	6.88	1951–2010	2.36	2.92	−6.69	6.83
$\mathcal{T}1$	1951–2010	8.44	0.75	6.99	9.88	1951–2010	*5.74*	1.02	*3.97*	7.33
$\mathcal{T}9$	1951–2010	24.73	1.09	22.86	27.57	1951–2010	*20.95*	1.82	18.07	23.82
Germany						Switzerland				
PCI	1962–2008	20,226	7,274	9,494	33,467	1951–2010	**27,031**	8,496	12,678	44,403
Growth	1962–2008	2.75	2.38	−3.15	7.10	1951–2010	2.17	2.78	−7.75	8.16
$\mathcal{T}1$	1962–2008	10.70	1.06	8.84	13.89	1951–2010	9.68	0.92	8.39	11.00
$\mathcal{T}9$	1962–2008	22.04	2.03	19.10	25.73	1951–2010	21.43	0.55	19.94	22.85
Japan						U.K.				
PCI	1951–2010	16,904	10,435	*2,165*	31,683	1951–2000	*15,670*	5,660	8,129	30,120
Growth	1951–2010	4.60	4.93	−4.17	**26.12**	1951–2000	2.65	2.37	−5.64	8.68
$\mathcal{T}1$	1951–2010	7.85	0.81	6.77	9.71	1951–2000	9.35	1.68	6.52	12.63
$\mathcal{T}9$	1951–2010	**25.36**	3.06	21.56	**31.48**	1951–2000	24.48	2.16	21.84	27.93
Netherlands						U.S.				
PCI	1951–2010	19,986	9,310	6,543	38,333	1951–2010	27,017	9,902	13,387	44,372
Growth	1951–2010	2.94	2.88	−5.18	8.63	1951–2010	1.99	2.45	−3.55	6.78
$\mathcal{T}1$	1951–2010	7.56	2.24	5.24	12.61	1951–2010	**11.07**	3.50	7.74	**18.33**
$\mathcal{T}9$	1951–2010	23.10	0.81	21.35	24.77	1951–2010	25.08	1.77	22.30	28.90

Notes: "PCI" denotes real GDP per capita, while "Growth" refers to the growth rate of PCI. $\mathcal{T}1$ and $\mathcal{T}9$ denote the share of national income earned by the top 1 percent and the next 9 percent of the population. "Max.," "Min.," and "SD" represent "maximum," "minimum," and "standard deviation," respectively. Comparing across countries, the smallest mean and minimum values are put in italics, while the largest mean and maximum values are highlighted in bold.

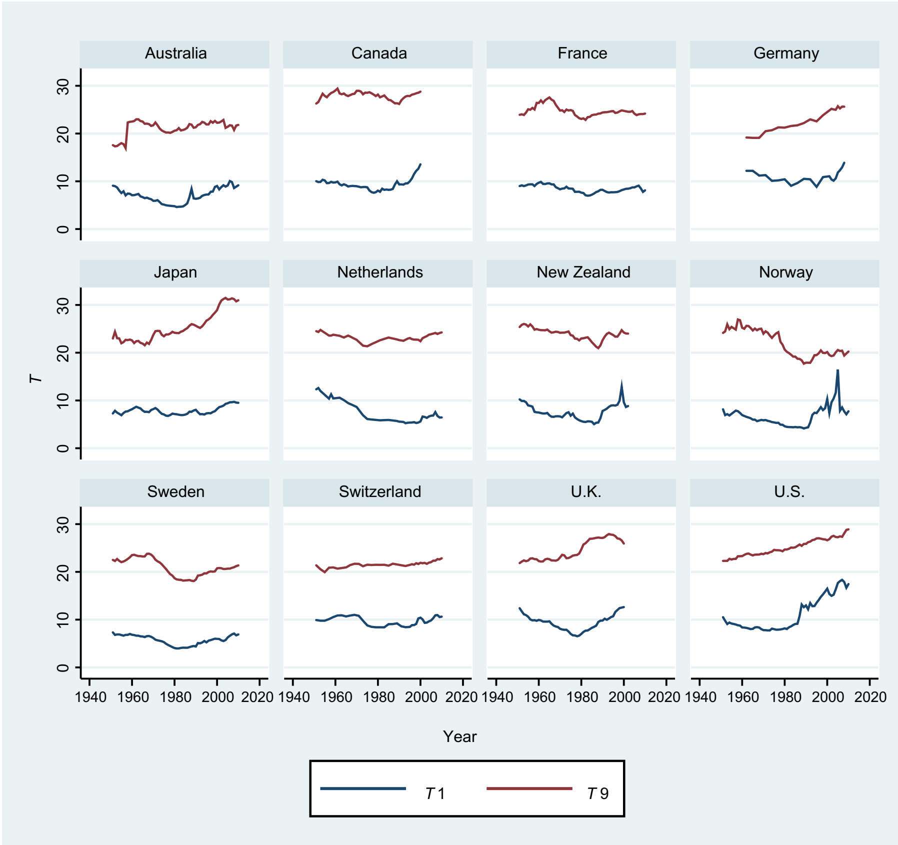

Figure 1. Top Income Shares

Notes: $\mathcal{T}1$ and $\mathcal{T}9$ denote the share of national income earned by the top 1 percent and the next 9 percent of the population. [Colour figure can be viewed at wileyonlinelibrary.com]

sufficiently long time series data for the inequality measures. Whereas the dataset spans the period from 1951 to 2010 for most economies, it begins as late as 1962 for Germany and ends as early as 2000 for Canada and the U.K. GDP per capita (per capita income, PCI) is measured using the expenditure-side per capita real GDP at chained PPPs (in 2005 U.S. dollars (US$)) series from the Penn World Tables version 8.1 (Feenstra *et al*., 2015).

We measure top incomes by means of the share of national income accruing to the top 1 or top 10 percent income earners ($\mathcal{T}1$ and $\mathcal{T}10$). To investigate potential differences between the roles of growth rates of $\mathcal{T}1$ and $\mathcal{T}10$ in spurring economic growth, we also consider the share of income of top decile income earners except for the top percentile ($\mathcal{T}9 = \mathcal{T}10 - \mathcal{T}1$). Top income shares data for most countries are drawn from the World Wealth and Income Database (WID) provided by Alvaredo *et al*. (2016), while respective data for the U.K. and New Zealand are taken from Leigh (2007). The top income shares series represent pre-tax national income shares held by the top income earners. Pre-tax national income is, in turn, defined as the sum of all pre-tax/transfer personal income flows accruing to the owners of labor and capital, but after taking into account the operation of pension systems. Thus, despite efforts by the respective authors to make the data comparable, there are still unavoidable differences in the definition of taxable income, both over time and across countries. In particular, there are differences among income tax systems in the degree to which items such as interest paid, depreciation, pension contributions, and charitable contributions are deducted. Moreover, differences in the definition of the tax unit across countries are another source of variation in measuring top income shares across countries. Alvaredo *et al.* (2016) attempt to address this issue by taking the adult individual (aged 20 years and above) as the observational unit. Our analysis is to some extent guarded against adverse effects from distinct definitions, as we will analyze vector autoregressive (VAR) models comprising growth rates of income shares.

Summary statistics are provided in Table 1. The smallest and largest per capita incomes are registered in Japan in 1951 (US$2,165) and in Norway in 2008 (US$53,100), respectively. For the entire period, the U.K. has the lowest mean PCI (US$15,670), which is likely because the data for the U.K. cover only the period up to 2000. Switzerland has the largest mean PCI (US$27,031). Regarding annual growth rates in PCI, the table reports small growth rates as low as −10.49 percent (Norway, 2009) and large growth rates as high as 26.12 percent (Japan, 1970). The means of the growth rates for the entire period vary between 1.62 percent (New Zealand) and 4.60 percent (Japan). The income share of the top 1 percent population ($\mathcal{T}1$) ranges between 3.97 percent (Sweden, 1981) and 18.33 percent (U.S., 2007), with mean $\mathcal{T}1$ varying between 5.74 percent (Sweden) and 11.07 percent (U.S.). The top decile share excluding the top percentile share of national income ($\mathcal{T}9$) has its smallest entire-period mean in Sweden (20.95) and its largest mean in Japan (25.36), with individual-year records ranging between 16.95 percent (Australia, 1957) and 31.48 percent (Japan, 2004).

Economy-specific $\mathcal{T}1$ and $\mathcal{T}9$ time series are displayed in Figure 1. Both time series display trending behavior over time. In general, $\mathcal{T}1$ was declining until the beginning of the 1980s and has been on the rise since then. While this pattern is observable in all economies, there are substantial variations in the magnitude of the rise in $\mathcal{T}1$ during more recent decades. The strongest increases in $\mathcal{T}1$ are recorded for Norway and the U.S. The increases observed for Austria, Canada, Germany, New Zealand, and the U.K. are relatively moderate. The least noticeable rises in $\mathcal{T}1$ are observed in France, Japan, the Netherlands, Sweden, and Switzerland. Moreover, it appears that the recent global financial crisis has contributed to a marked reduction in $\mathcal{T}1$ in several economies, especially in Norway. It is also worth noting that the $\mathcal{T}9$ series often follows a trend that is distinct from $\mathcal{T}1$. In particular, $\mathcal{T}9$ shows relatively small changes during the entire period in countries such as Australia, Canada, France, the Netherlands, New Zealand, Sweden, and Switzerland. A steady increase in $\mathcal{T}9$, starting at least from the early 1970s, is observed in Germany, Japan, the U.K., and the U.S. On the contrary, $\mathcal{T}9$ in Norway has generally been falling for most of the period under study.

While discussing trends in top income shares, it is worthwhile noting that some of the abrupt changes in the series emanate from policy changes in terms of items to be exempted from taxation. The shifts could also arise from changes in the decisions of tax authorities to publish "taxable income" (where all deductions are subtracted) or actual income (before deductions). For instance, in 1958 the Australian authorities decided to publish "taxable income," and no more "actual income." Despite adjustments to make the pre- and post-1958 series comparable, the adjusted $\mathcal{T}9$ still jumps sharply between 1957 and 1958 Atkinson and Leigh (2007) This does not mean, however, that most of the sharp jumps are due to measurement issues. For instance, Atkinson and Leigh (2008) argue that the sharp rise and fall in $\mathcal{T}1$ in New Zealand in the period from 1998 to 2000 reflects the fact that many taxpayers realized their business earnings in 1998 and 1999, following the Labour Party's election promise to raise the top marginal tax rate from 33 percent to 39 percent in the 2000 tax year. Hence these top income data, despite their limitations, are considered to be good enough to be used for distributional analysis, and they are often the only inequality measures covering such a long period of about six decades (Atkinson *et al.*, 2011).

To ensure that our analysis will not be affected by distortions emanating from non-stationary behavior of the data, we test for panel unit roots of the GDP per capita growth as well as the logs and growth rates of top income shares. We use a set of panel unit root tests, ranging from the widely used tests in Levin *et al.* (2002) and Breitung (2000) to the recently suggested heteroskedasticity-robust tests in Herwartz *et al.* (2016) and Demetrescu and Hanck (2012). As shown in Table C.1, all the tests indicate that GDP per capita growth and the growth rates of the three top income shares are stationary, while the logs of the top income shares are diagnosed as non-stationary processes. Moreover, results documented in Table C.2 show that the null hypothesis of no cointegration between the logs of per capita income and top income shares cannot be rejected using the panel cointegration tests of Pedroni (2004) and Westerlund (2007). Hence our analysis in the next section concentrates on the structural relations between the stationary growth rates of GDP per capita and top income shares.

4. Modeling Contemporaneous Relations

4.1. *The Structural VAR*

To analyze the contemporaneous relations between the growth rates of per capita income (PCI) and top income shares ($\mathcal{T}$), consider country-specific bivariate reduced-form and structural VAR models of the following type:[5]

$$y_t = \nu + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \tag{1}$$

$$= \nu + A_1 y_{t-1} + \ldots + A_p y_{t-p} + D\xi_t, \tag{2}$$

$$\Leftrightarrow D^{-1} y_t = D^{-1}\nu + D^{-1} A_1 y_{t-1} + \ldots + D^{-1} A_p y_{t-p} + \xi_t, t = 1,2,\ldots,T, \tag{3}$$

[5]Taking full account of cross-sectional parameter heterogeneity and simplifying the notation, we refrain at this stage from indicating the cross-section dimension by means of an additional index. By construction, vector disturbances u_t extracted from estimated VARs are not contaminated by country fixed effects.

where $y_t = (y_{1t}, y_{2t})'$, ν is a vector of intercept terms, $\mathrm{Cov}[\xi_t] = I_2$ (i.e. the bivariate identity matrix), and, hence, $\mathrm{Cov}[u_t] = \Sigma_0 = DD'$. Pre-sample values $y_0, y_1, \ldots, y_{1-p}$ are assumed to be available. The autoregressive representation in equation 1 characterizes the jointly endogenous variables y_{1t} and y_{2t} conditional on their history. As a consequence, contemporaneous relations are only implicit in this model representation, since the matrix $\mathrm{Cov}[u_t] = \Sigma_0$ is allowed to comprise non-zero covariances. By including covariance estimation, the reduced-form model in equation 1 can be quantified, for example, by means of OLS estimation up to approximation errors that vanish asymptotically. The structural model in equation 2 provides an explicit view at the transmission of cross-equation uncorrelated (i.e. isolated) innovations ξ_t to reduced-form disturbances u_t. By assumption, the latent shocks ξ_t and the (asymptotically) observable reduced-form disturbances u_t obey a linear relation that is formalized by means of the non-singular matrix D; that is, $u_t = D\xi_t$. Although the model in equation 3 is a one-to-one reformulation of the structural representation in equation 2, it has its own merit, and we note that its left-hand side is explicit on the contemporaneous link between the variables in y_t—that is, $D^{-1}(y_{1t}, y_{2t})'$—conditional on $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$.

The typical problem in SVAR analysis is to determine the matrix D. In the (joint) Gaussian case—that is, $u_t \sim N(0, \Sigma_0) \Leftrightarrow \xi_t \sim N(0, I_2)$—the model in equation 2 cannot be identified without further external information. The normal distribution is fully specified in terms of its first- and second-order moments and rotations of Gaussian shocks ξ_t remain Gaussian. Lanne *et al.* (2017) prove uniqueness of D for non-Gaussian causal VAR models. To ensure identification of D, we follow Lanne *et al.* (2017) and make the following assumptions: (i) The VAR model in equation 1 is causal; that is, $\det(A(z)) \neq 0 \ \forall |z| \leq 1$, where $A(z) = I_2 - A_1 z - \ldots - A_p z^p$. Focusing on the causal VAR implies that the reduced-form disturbances u_t can be represented in terms of historical shocks ξ_{t-i}, $i \geq 0$. (ii) The elementary shocks $\xi_{jt} \sim (0, 1), j = 1, 2$, are independent, with at most one element being Gaussian.

4.2. *Modeling Contemporaneous Relations*

The assumption of independent non-Gaussian innovations allows us to test restrictions on D which are just identifying in the Gaussian model. In the early literature on Gaussian SVARs, two particular assumptions have been suggested for model identification. On the one hand, authors have suggested the imposition of zero restrictions (Bernanke, 1986; Sims, 1980, 1986) to apply for particular elements of D. The use of Cholesky factors of Σ_0 to replace D in equation 2 *a priori* excludes specific channels of short-run transmission linking elements in ξ_t and u_t. Distinguishing alternative variable orderings, $(y_{1t}, y_{2t})'$ and $(y_{2t}, y_{1t})'$, and opting for a lower-triangular structure of $D_0 = C_0, \Sigma_0 = C_0 C_0'$, implies the following patterns of contemporaneous causality:[6]

[6]For the distinction of causal versus non-causal relations, we apply the standard symbols → and \nrightarrow, respectively. Since we are going to further distinguish patterns of short- and long-run (non)causality, we use the subindices "0" and later "∞" to indicate distinct time horizons.

- Original ordering:

$$D_0^{-1}(y_{1t},y_{2t})' \Rightarrow y_{1t} \rightarrow_0 y_{2t} \wedge y_{2t} \nrightarrow_0 y_{1t}.$$

- Reversed ordering:[7]

$$D_0^{-1}(y_{2t},y_{1t})' \Rightarrow y_{1t} \nrightarrow_0 y_{2t} \wedge y_{2t} \rightarrow_0 y_{1t}.$$

Restriction of the long-run effects of orthogonalized shocks has been suggested by Blanchard and Quah (1989). Using $\Sigma_0 = DD'$, the long-run covariance matrix implied by the reduced-form model in equation 1 is as follows:

(4) $$\Sigma_\infty = (I_K - A_1 - \ldots A_p)^{-1} DD'(I_K - A_1' - \ldots A_p')^{-1} = C_\infty C_\infty'.$$

Given that Σ_∞ can be estimated from the data (through estimates of $A_i, i = 1,\ldots,p$, and Σ_0), estimates of structural parameters could be retrieved from the relation

(5) $$D_\infty = (I_K - A_1 - \ldots - A_p) C_\infty.$$

Opting for lower-triangular Cholesky factors C_∞ in equation 4 excludes specific channels of transmission of structural shocks to long-run process variation. In practice, the notion of long-run (non-)causality is of particular relevance if y_t consists of *stationary growth rates*. Then, the long-run covariance in equation 5 refers to the respective *trending levels* which motivate the notion of long-run (non-)causality. Formally, one may distinguish two respective effect directions, as follows:

- Original ordering:

$$D_\infty^{-1}(y_{1t},y_{2t})' \Rightarrow y_{1t} \rightarrow_\infty y_{2t} \wedge y_{2t} \nrightarrow_\infty y_{1t}.$$

- Reversed ordering:

$$D_\infty^{-1}(y_{2t},y_{1t})' \Rightarrow y_{1t} \nrightarrow_\infty y_{2t} \wedge y_{2t} \rightarrow_\infty y_{1t}.$$

By the definition in equation 7, the implied contemporaneous transmission linking ξ_t and u_t is generally not of a triangular structure. Rather, the off-diagonal elements of D_∞ are likely to quantify a short-term feedback relation:

$$D_\infty^{-1}(y_t) \Rightarrow y_{1t} \leftrightarrow_0 y_{2t}.$$

In light of cross-sectional heterogeneity, country-specific off-diagonal elements of D_∞ might lack comparability owing to scale dependence. To provide

[7]The model with reversed variable ordering might be formally represented as a permutation of the original model. For the sake of an explicit exposition of the economic arguments/hypotheses, however, we prefer to distinguish alternative variable orderings in the notation.

scale-free estimates of the short-term transmissions implied by D_∞, let Γ denote a diagonal matrix with the variances of reduced-form disturbances on its diagonal. We consider the following:

$$\widetilde{D}_\infty = \Gamma^{-1/2} D_\infty. \quad (6)$$

For instance, with the initial ordering of the variables in the VAR, the off-diagonal elements $\tilde{d}_{21}$ and $\tilde{d}_{12}$ of $\widetilde{D}_\infty$ quantify contemporaneous relations $y_{1t} \rightarrow_0 y_{2t}$ and $y_{2t} \rightarrow_0 y_{1t}$, respectively. Since these statistics are scale free, they are later subjected to mean group inference.[8]

4.3. *Identification by Means of Independence Diagnosis*

Next, we illustrate how the uniqueness of non-Gaussian independent shocks can be exploited for structural analysis.[9] For this purpose, consider VARs with y_{1t} and y_{2t} denoting the growth rate of top income shares ($\Delta\tau$) and economic growth (Δpci), respectively. Throughout, decompositions of $\Sigma_0 = C_0 C_0'$ or $\Sigma_\infty = C_\infty C_\infty'$ are presumed to be lower triangular. This formalizes the fact that, in the short run, top income share growth might affect economic growth, while the reverse transmission channel is ruled out. Similarly, structural shocks imply that long-run variations of top income shares might affect per capita income, while the reverse transmission channel is ruled out. Formally, these considerations read as follows:

$$H_{01}: \Delta\tau \rightarrow_0 \Delta pci \wedge \Delta pci \nrightarrow_0 \Delta\tau \quad \text{(in short,} H_{01}^{(s)}: \Delta\tau \rightarrow_0 \Delta pci)$$

or

$$H_{02}: \tau \rightarrow_\infty pci \wedge pci \nrightarrow_\infty \tau \quad \text{(in short, } H_{02}^{(s)}: \tau \rightarrow_\infty pci).$$

Setting $D = D_0 = C_0$ and $D = D_\infty = (I_K - A_1 - \ldots A_p)C_\infty$, samples of orthogonalized shocks associated with the presumptions in H_{01} and H_{02} are, respectively,

$$\{\xi_t^{(1)}\}_{t=1}^T = \{D_0^{-1} u_t\}_{t=1}^T \quad \text{and} \quad \{\xi_t^{(2)}\}_{t=1}^T = \{D_\infty^{-1} u_t\}_{t=1}^T,$$

where orthogonalized shocks $\xi_t^{(h)}, h = 1, 2$, correspond to a specific hypothesis of interest. In the case that one of the presumed transmission patterns holds, the respective elements in $\xi_t^{(1)}$ or $\xi_t^{(2)}$ are assumed to be independent. In the non-Gaussian case, independence of the elements in $\xi_t^{(1)}$ implies that elements in $\xi_t^{(2)}$ are dependent (and vice versa). As an illustration, assume that D_0 describes the "true" structural model (i.e. $u_t = D_0 \xi_t, \xi_t^{(1)} = \xi_t$), but the analyst falsely presumes a structural model implied by setting $D = D_\infty$. Then, estimates of the model-implied shocks read as follows:

$$\tilde{\xi}_t^{(\infty)} = D_\infty^{-1} u_t = D_\infty^{-1} D_0 \xi_t. \quad (7)$$

[8]While the estimates $\tilde{d}_{ij}$ are more "homogeneous," mean group results for scaled and unscaled estimates are qualitatively identical.

[9]Simulation-based evidence on the identification of correct variable orderings by means of (in)dependence statistics is provided in Appendix B.

Given that the elements in ξ_t are independent (by assumption), and considering $D_\infty^{-1}D_0$ to be a non-diagonal matrix, the elements in $\tilde{\xi}_t^{(\infty)}$ process information from both (independent) elements of ξ_t; that is, ξ_{1t} and ξ_{2t}. Hence, in the non-Gaussian case, the elements in $\tilde{\xi}_t^{(\infty)}$ (i.e. $\tilde{\xi}_{1t}^{(\infty)}$ and $\tilde{\xi}_{2t}^{(\infty)}$) are dependent. Put differently, if one of the hypotheses H_{01} or H_{02} holds true, the corresponding shocks are independent. Then, under the remaining null hypothesis and within the space of the causal alternatives

$$H_{11}: \Delta\tau \leftrightarrow_0 \Delta pci \quad \text{and} \quad H_{12}: \tau \leftrightarrow_\infty pci \tag{8}$$

implied orthogonalized shocks lack independence.

Apart from testing the hypotheses H_{01} and H_{02} that exclude channels of causality from economic activity to income shares, we test null hypotheses H_{03} and H_{04} that exclude channels of causality from top income shares to economic activity. Formally, these hypotheses are as follows:

$$H_{03}:\Delta pci \rightarrow_0 \Delta\tau \wedge \Delta\tau \nrightarrow_0 \Delta pci \quad (\text{in short, } H_{03}^{(s)}:\Delta pci \rightarrow_0 \Delta\tau),$$

or

$$H_{04}:pci \rightarrow_\infty \tau \wedge \tau \nrightarrow_\infty pci \quad (\text{in short, } H_{04}^{(s)}:pci \rightarrow_\infty \tau).$$

4.4. *Testing Contemporaneous Relations*

Now that we have four rival structural hypotheses, we use the overidentifying information inherent in non-Gaussian systems of independent shocks to provide a ranking of implied structural shocks in terms of their inherent dependence. Specifically, we use a set of (in)dependence diagnostics to detect the causal transmission pattern obtaining implied least-dependent orthogonalized shocks. It is worth pointing out that opting for the one (out of four) alternative structural assumptions according to the maximum p-value of testing the null hypothesis of independence could be considered as structural model selection in the sense of Hodges–Lehmann estimation.[10] As an implication of multiple testing and opting for a supremum p-value, however, the selected maximum p-value no longer bears its common informational value for testing the null hypothesis of independence. However, small (i.e. significant) p-values obtained for a single structural hypothesis still might indicate a rejection of the null hypothesis of independence and, hence, provide evidence against the respective structural transmission channels.

To test for independence in samples of hypothesis-implied orthogonalized shocks $\{\xi_t^{(h)}\}_{t=1}^T, h = 1, 2, 3, 4$, we employ the dependence coefficient introduced by Bakirov *et al.* (2006).[11] This statistic, denoted $\mathcal{C}$, is suitably bounded between zero (independence) and unity (complete dependence), and is consistent against any form of dependence. Moreover, $T\mathcal{C}^2$ exhibits a bounded non-degenerate

[10]An explicit representation of the test statistic is given in Appendix A.

[11]So-called Hodges–Lehmann estimators have recently attracted interest (Dufour, 1990 Hodges and Lehmann, 2006). Given a nuisance-free test of a null hypothesis, $H_0:\theta = \theta_0$, the Hodges–Lehmann estimator of θ is the particular choice of θ_0 that maximizes the p-value of the test.

distribution under the null hypothesis of independence, and bootstrap methods allow the determination of respective p-values, $p(C)$.[12]

5. Empirical Results

Given internationally heterogeneous policies and shocks to both per capita income and top income shares (e.g. distinct tax policies), one may hardly expect unique outcomes of structural models for a cross-section of developed economies evaluated over a period of six decades. In Appendix D, we are explicit on country-specific evidence with regard to structural model selection among the alternative hypotheses H_{01} to H_{04}. In light of cross-sectional heterogeneity and aiming to unravel some overall evidence, we first discuss mean group (Pesaran and Smith, 1995) diagnostic and estimation results in this section. As a further means to yield overall conclusions, we provide independence diagnostics for samples of pooled country-specific orthogonalized shocks in the second place. Complementary to unconditional pooling, we examine results for conditional subsamples distinguished according to time and the levels of top income shares and GDP per capita.[13] Third, to provide a joint perspective on country-specific reduced-form and structural estimation, we discuss impulse-response functions implied by the most favorable model specification per country (i.e. the maximum p-value from testing H_{01} to H_{04}).[14]

We first analyze the structural relations between the top percentile income shares ($\mathcal{T}1$) and per capita income (PCI). Subsequently, the nexus between top income shares and per capita income is reconsidered for the top decile ($\mathcal{T}10$) and the top decile minus the top percentile income share ($\mathcal{T}9$). To give some core implications of identified SVARs, this section also provides mean group cumulated impulse-response functions for all income shares. As it will turn out that a rising $\mathcal{T}1$ raises PCI, it is important in terms of policy relevance to examine who benefits from this economic growth driven by top percentile inequality. In particular, it is important to investigate if there is a "trickle-down" effect so that rising $\mathcal{T}1$ benefits not only the top 1 percent but also the rest of the income groups, which could be witnessed by increases in respective group-specific PCIs. Moreover, it is also worthwhile to examine if there are income groups whose group-specific PCI may decline

[12]The dependence coefficient and bootstrap p-values for $\mathcal{TC}^2$ are provided in the R package "energy": E-Statistics: Multivariate Inference via the Energy of Data, Version 1.7-0, command: "indep. test," available at https://cran.r-project.org/web/packages/energy.

[13]We have also investigated if our bivariate models are too restrictive in terms of processed information. Accordingly, we have estimated a trivariate VAR comprising Δpci, $\Delta\tau 1$, and $\Delta\tau 10$. The results show that residual correlations of single elements of trivariate residual vectors ($\hat{u}_t$) with corresponding residuals obtained from bivariate VARs are quite substantial and generally above 0.9. From these correlation levels, we conclude that biases possibly due to omitted information are likely negligible in our framework. Moreover, bivariate tuples of reduced-form residuals composed from trivariate VARs obtain outcomes of independence tests that are very similar to those of the original bivariate VARs. These results are available upon request.

[14]As a common approach to causality detection, results on Granger-causal relations between top income shares and PCI growth are shown in Table E.1. Analysing annual growth rates, the empirical evidence for Granger-causal relations is generally restricted to a few economies and is heterogeneous in direction. Moreover, patterns of Granger causality lack uniformity when analysing the relation between PCI growth and the growth of alternative top income shares.

TABLE 2
Mean Group SVAR Results

	JB Test		H_{01}		H_{02}			H_{03}	H_{04}		
	p(JB)	ρ_0	$p(C_0)$	ρ_∞	$p(C_\infty)$	$\tilde{d}_{12}$	$\tilde{d}_{21}$	$p(C_0)$	$p(C_\infty)$	$\tilde{d}_{12}$	$\tilde{d}_{21}$
Top income measure: $\Delta\tau 1$											
Mean	0.054	0.12	0.439	0.262	**0.453**	0.026	0.089	0.392	0.367	−0.177	0.284
SD/$\sqrt{12}$		0.041		0.065		0.055	0.051			0.058	0.066
t-ratio		2.79		4.03		0.47	1.74			−3.06	4.32
Fisher			57.1		26.8			34.5	45.8		
p-value <0.1	11		5		2			3	5		
Top income measure: $\Delta\tau 9$											
Mean	0.198	−0.11	0.491	−0.149	*0.370*	0.063	−0.163	**0.533**	0.480	−0.014	−0.097
SD/$\sqrt{12}$		0.075		0.117		0.055	0.106			0.050	0.089
t-ratio		−1.48		−1.28		1.15	−1.54			−0.29	−1.08
Fisher			25.5		41.1			23.3	43.3		
p-value <0.1	8		1		4			2	2		
Top income measure: $\Delta\tau 10$											
Mean	0.039	0.02	0.432	0.096	*0.301*	0.046	−0.023	**0.452**	0.427	−0.121	0.139
SD/$\sqrt{12}$		0.060		0.087		0.051	0.064			0.040	0.082
t-ratio		0.37		1.10		0.90	−0.36			−3.00	1.69
Fisher			31.9		39.9			28.2	43.9		
p-value <0.1	10		3		3			1	1		

Notes: The reported numbers are mean group values of the country-specific SVAR results reported in Table D.1. SD/$\sqrt{12}$ (t-ratio) refers to the standard deviation (t-ratio) of the group mean. "Fisher" refers to the Fisher's combined test, which follows a χ^2_{2k} distribution, where k denotes the number of p-values to be combined. The 10 percent critical value for the Fisher test with 24 degrees of freedom is 33.2. For further notes, see Table D.1.

in the process of top income led economic growth. Accordingly, this section ends by examining the impacts of a rising $\mathcal{T}1$ on the PCIs of the top 1 percent, the next 9 percent, and the bottom 90 percent.

Throughout, the discussion of empirical results refers to the 10 percent nominal significance level. All country-specific VAR models share an autoregressive order of one, which is not implausible as we are analysing low-frequency growth data.[15]

5.1. *Structural Analysis for Top Percentile Share and Per Capita Income Growth*

5.1.1. Diagnostic Evidence and Mean Group Results

Country-Specific Correlations and Normality Tests. Estimation and diagnostic results from country-specific SVARs are documented in Table D.1. The upper panel of the table documents normality and independence test results as well as short-run and long-run correlation estimates for VAR(1) regressions involving top percentile and per capita income growth. Mean correlation statistics retrieved from short- (Σ_0) and long-term covariance matrices (Σ_∞) are 0.12 (the cross-sectional average of ρ_0 estimates) and 0.262 (ρ_∞), respectively. Hence, on average, short-run contemporaneous transmission invokes minor reduced-form correlation, while the long-run mean correlation is sizeable. In addition, correlation statistics retrieved from short- and long-term covariance matrices are mostly positive. Negative correlations are only detected for Canada (ρ_0), the Netherlands (ρ_∞), and Norway (ρ_∞). Consequently, except for these three cases, triangular decompositions of short- and long-term covariances are specified with positive lower left elements of the matrices C_0 (and, hence, D) and C_∞.

A unique discrimination among independent orthogonalized shocks can only be achieved in non-Gaussian models. As documented in Table D.1, the residuals of the country-specific VARs are clearly at odds with the jointly Gaussian model. With the exception of Canada, Jarque Bera statistics are highly significant and, hence, justify the use of independence diagnostics to discriminate among rival identification schemes. Further discussions on country-specific SVAR results are provided in Appendix D.[16]

Mean Group Diagnostics. Conditioning on small sample dimensions for a given economy is at the risk of ending up with biased and/or inconclusive results due to a lack of power. Against this background, panel approaches have been frequently motivated to enhance the power of econometric analysis. While taking a panel

[15]For a given dataset, bootstrap-based p-values might vary and depend on a particular collection of bootstrap samples. From this, we carefully checked the p-values documented in Table D.1 with alternative statistics that we obtained from averaging 49 independent p-values determined for each sample. The results (which are available upon request) show, however, that core conclusions on the structural models remain unaffected if we base our analysis on p-values from single-bootstrap samples or on averages from a set of 49 repetitions of the bootstrap procedure, each using 1,000 replications.

[16]From country-specific VAR order selection by means of the BIC criterion, VAR(1) is mostly preferred over both the more restricted VAR(0) and the more flexible VAR(2). In the use of AIC for model selection, VAR(1) is also mostly favored, but one obtains higher VAR orders for a sizeable fraction of all 36 samples (three top income shares, 12 countries). To summarize the outcome of country-specific VAR order selection, therefore, using uniquely first-order VARs is well in line with likelihood-based diagnostics.

TABLE 3
Empirical Results from Pooled Data

Subsample ($\mathcal{A}$)	Obs.	H_{01} C_0	H_{01} $p(C_0)$	H_{02} C_∞	H_{02} $p(C_\infty)$	H_{03} C_0	H_{03} $p(C_0)$	H_{04} C_∞	H_{04} $p(C_\infty)$
$\mathcal{T}1$									
Full sample	667	0.046	*0.025*	0.044	**0.273**	0.046	0.085	0.048	0.026
PCI < med.	334	0.050	0.392	0.057	0.251	0.060	**0.503**	0.088	*0.224*
PCI > med.	333	0.068	0.025	0.057	**0.407**	0.068	0.050	0.072	*0.018*
$\mathcal{T}1$ < med.	334	0.057	*0.065*	0.058	**0.355**	0.057	0.121	0.062	0.086
$\mathcal{T}1$ > med.	334	0.054	0.126	0.051	**0.305**	0.054	0.166	0.054	*0.094*
Pre-1980	337	0.051	0.352	0.053	0.242	0.058	**0.357**	0.083	*0.034*
Post-1980	330	0.071	0.025	0.056	**0.557**	0.070	0.050	0.072	*0.012*
Pre-2008	642	0.042	0.015	0.043	**0.342**	0.044	0.075	0.049	*0.010*
1981-2007	305	0.066	0.030	0.051	**0.633**	0.061	0.085	0.068	*0.010*
PCI < med., pre-1980	290	0.052	0.503	0.055	0.329	0.056	**0.553**	0.080	*0.174*
PCI < med., post-1980	44	0.145	0.216	0.136	0.317	0.129	**0.337**	0.140	*0.210*
PCI > med., pre-1980	47	0.156	0.116	0.153	**0.160**	0.158	0.131	0.199	*0.002*
PCI > med., post-1980	286	0.076	0.015	0.063	**0.573**	0.079	0.060	0.084	*0.014*
$\mathcal{T}1$ < med., pre-1980	166	0.081	*0.101*	0.071	**0.703**	0.076	0.166	0.111	0.112
$\mathcal{T}1$ < med., post-1980	168	0.081	0.116	0.078	**0.451**	0.072	0.372	0.080	0.114
$\mathcal{T}1$ > med., pre-1980	171	0.073	**0.764**	0.076	*0.068*	0.072	0.698	0.082	0.096
$\mathcal{T}1$ > med., post-1980	162	0.092	0.040	0.080	**0.695**	0.101	0.015	0.099	*0.038*
PCI < med., $\mathcal{T}1$ < med.	165	0.072	*0.101*	0.073	**0.754**	0.083	0.231	0.134	0.495
PCI < med., $\mathcal{T}1$ > med.	169	0.074	**0.844**	0.081	*0.090*	0.068	0.784	0.077	0.134
PCI > med., $\mathcal{T}1$ < med.	169	0.085	0.171	0.085	0.234	0.079	**0.246**	0.091	*0.032*
PCI > med., $\mathcal{T}1$ > med.	164	0.084	*0.010*	0.080	**0.721**	0.089	0.040	0.092	0.080

Table 3 *Continued*

Subsample ($\mathcal{A}$)	Obs.	H_{01}: C_0	H_{01}: $p(C_0)$	H_{02}: C_∞	H_{02}: $p(C_\infty)$	H_{03}: C_0	H_{03}: $p(C_0)$	H_{04}: C_∞	H_{04}: $p(C_\infty)$
$\bar{p}$			0.193		**0.403**		0.244		*0.096*
$\#p$<0.1			9		2		8		14
$\mathcal{T}9$									
Full sample	667	0.048	0.492	0.048	*0.034*	0.043	**0.648**	0.046	0.228
PCI < med.	334	0.063	0.377	0.064	*0.040*	0.065	**0.709**	0.062	0.371
PCI > med.	333	0.064	**0.598**	0.062	0.216	0.059	0.387	0.059	0.164
$\mathcal{T}9$ < med.	334	0.065	**0.859**	0.061	0.425	0.060	0.678	0.064	*0.096*
$\mathcal{T}9$ > med.	334	0.066	0.131	0.074	*0.004*	0.055	0.538	0.058	**0.555**
Pre-1980	337	0.065	0.296	0.065	*0.078*	0.061	**0.648**	0.058	0.339
Post-1980	330	0.063	**0.719**	0.061	*0.202*	0.056	0.648	0.060	0.214
$\bar{p}$			0.496		*0.143*		**0.601**		0.281
$\mathcal{T}10$									
Full sample		0.043	0.126	0.052	*0.006*	0.042	**0.256**	0.046	0.068
PCI < med.	334	0.066	**0.322**	0.075	0.064	0.076	0.161	0.086	*0.026*
PCI > med.	333	0.063	0.075	0.062	*0.054*	0.060	**0.407**	0.064	0.395
$\mathcal{T}10$ < med.	334	0.051	**0.538**	0.062	0.208	0.062	0.216	0.065	*0.092*
$\mathcal{T}10$ > med.	334	0.061	0.035	0.065	*0.014*	0.054	0.417	0.054	**0.323**
Pre-1981	337	0.066	**0.347**	0.073	0.132	0.072	0.126	0.083	*0.006*
Post-1980	330	0.066	0.080	0.064	*0.048*	0.060	0.422	0.060	**0.507**
$\bar{p}$			0.218		*0.075*		**0.286**		0.202

Notes: We pool the empirical counterparts of $\xi_t^{(h)}$. "Med." stands for the median value of the respective variable from the pooled data. For example, "PCI < med." means that we pool the $\xi_t^{(h)}$ that correspond to the country and year where income was less than the median income for the full pooled data (US$19,142). For further notes, see Table 2.

perspective, we are not saying that our analysis is "equivalent" to an analysis of large samples drawn from a homogeneous distribution. However, mean group analysis guards to some extent against spurious single-country evidence, since the likelihood of unidirectional finite sample biases is small (if not negligible) under the null hypothesis. With regard to pooling, a similar argument applies. While single-country estimates of structural innovations suffer from approximation errors under both the null and alternative hypotheses, pooled evidence supporting

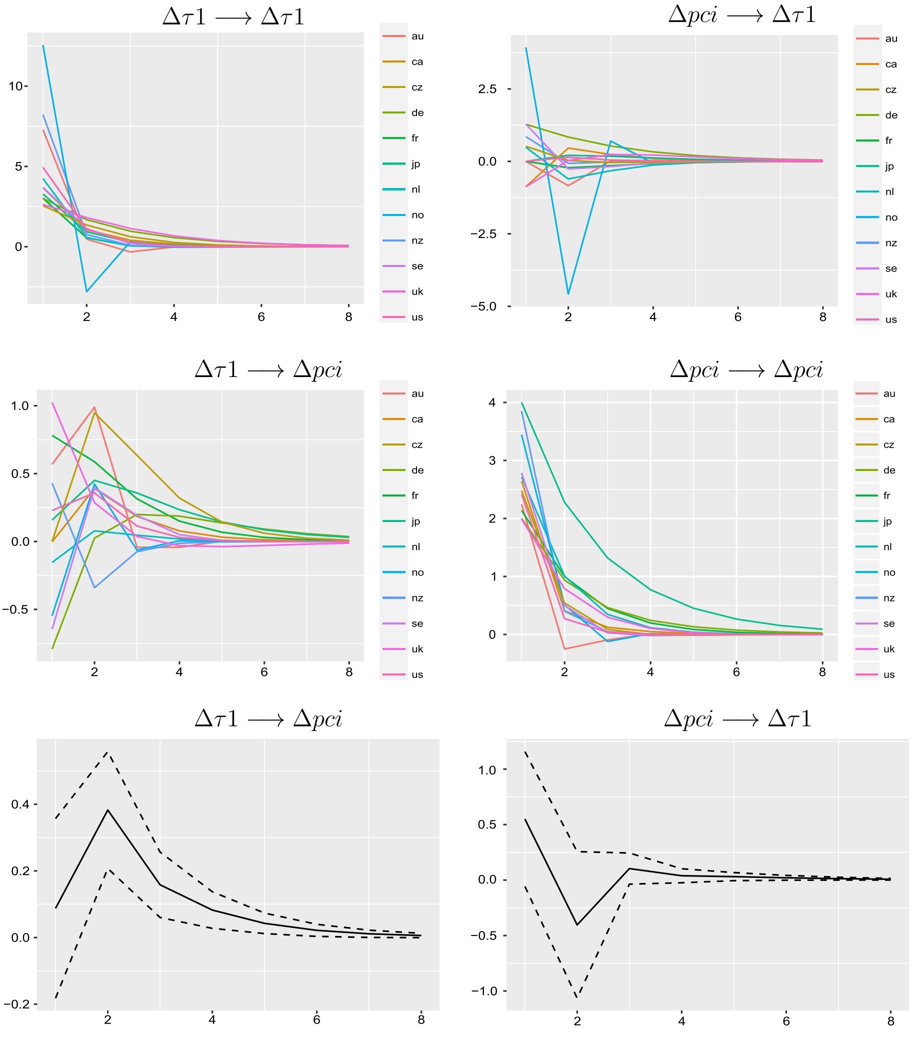

Figure 2. Impulse-Response Functions Between Economic Growth and Δτ1

Notes: The D matrices are taken from the most favored hypothesis out of testing H_{01} to H_{04} per country. The bottom panels depict mean group estimates, with upper and lower 1.65SD bounds (approximating 90 percent confidence intervals). [Colour figure can be viewed at wileyonlinelibrary.com] the alternative hypothesis is unlikely to be driven by finite sample and single-country approximation errors occurring under the null hypothesis.

Table 2 documents the panel means of the correlation estimates and the summary statistics for the p-values of the independence tests. The (undocumented) panel means of the dependence coefficient are very similar for orthogonalized residuals corresponding to the alternative hypotheses ($.135 \leq \bar{\mathcal{C}}_{(h)} \leq .143, h = 1, \dots, 4$). The largest average p-value is reported for H_{02} and, hence, favors a panel-based diagnosis of a (mostly positive) long-run impact of $\mathcal{T}1$ inequality on economic activity. The smallest average p-value is documented for H_{04} pointing at the opposite long-run causation pattern.[17] In addition, with 10 percent significance, 5 out of 12 single-economy diagnostics are significantly at odds with H_{01} and H_{04}, while H_{02} is rejected for only two economies (Sweden and Switzerland). Similarly, the results from the Fisher's combined test, which are also reported in Table 2, reveal that all the hypotheses, except for H_{02}, are rejected at the panel level.

Not surprisingly, in averaging the off-diagonal elements of $\widetilde{D}_{\infty}$ implied by the two rival assumptions on long-run (non-)causality, we obtain distinct mean group directions and magnitudes of contemporaneous transmission. Taking mean group results $\widetilde{D}_{\infty}(H_{02})$, for instance, short-run effects going from PCI growth to $\mathcal{T}1$ growth are insignificant, while we detect a significantly positive link in the opposite direction. Next, we turn to inferential results offered from samples of pooled orthogonalized innovations.

5.1.2. *Results from Pooled Data*

Unconditional and State-Dependent Pooling

Covering a period of six decades (with annual data), the structural analysis for the cross-section of developed economies offers heterogeneous insights into the relation between $\mathcal{T}1$ growth and PCI growth. In light of sample-specific conclusions, it is useful to trace back heterogeneous diagnostic outcomes to underlying economic characteristics shared by economies and/or episodes of time.

As potential determinants of the link between $\mathcal{T}1$ growth and PCI growth, we consider the level of $\mathcal{T}1$ and PCI. There are studies which postulate varying impacts of inequality on growth depending on the level of economic development. For instance, the results in Barro (2000) indicate that higher inequality is bad for growth in low-income economies and promotes growth in richer areas. Contradicting these results, Ezcurra (2007) finds, from a European-level household panel (1993–2002), that the correlation between income inequality and economic growth in these mostly high-income economies is significantly and robustly negative. The potentially significant role of the level of income inequality on the inequality–growth relationship is also suggested in Banerjee and Duflo (2003). Specifically, these authors document that economic growth is an inverted U-shaped function of the net changes in inequality, implying that a change in inequality in

[17]The detection of critical values for $\mathcal{C}$ by means of bootstrap methods accounts for nuisance parameters that affect the distribution of the dependence coefficients. As a consequence, dependence statistics of similar magnitude might exhibit distinct levels of significance.

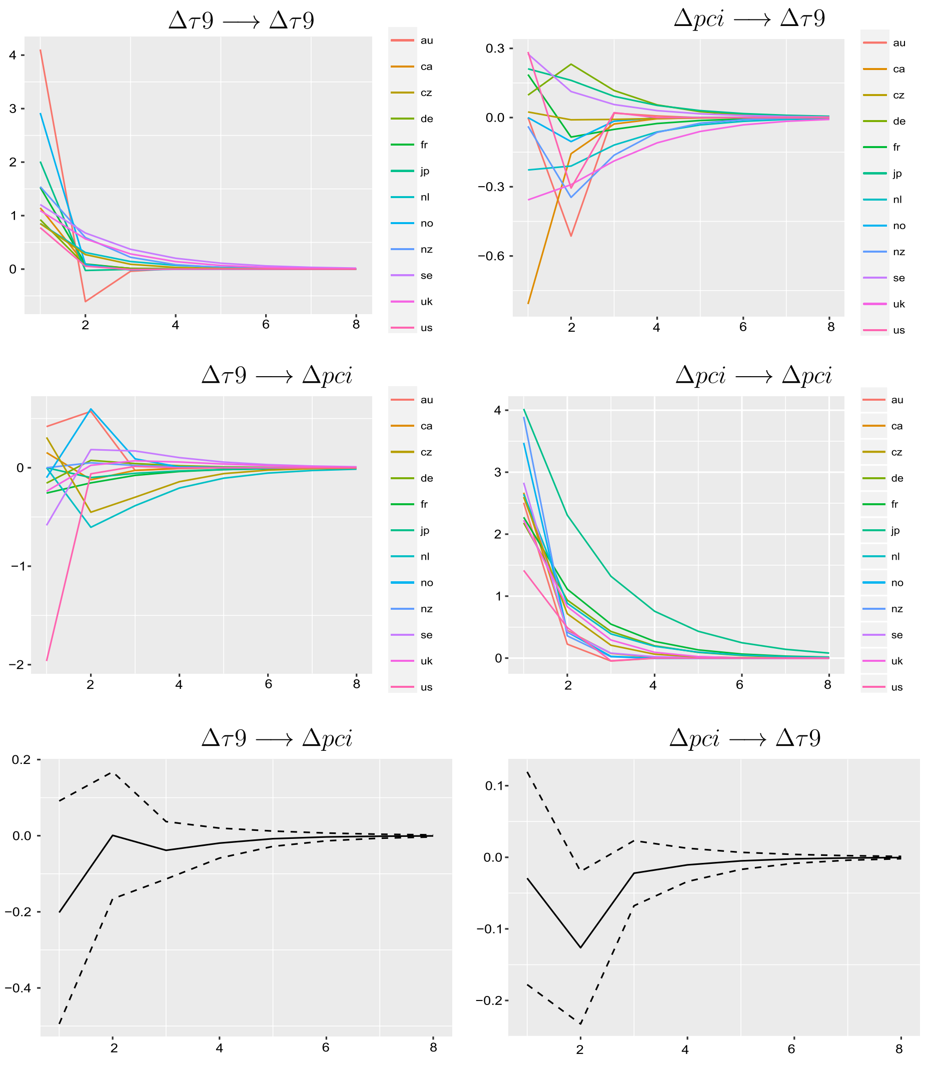

Figure 3. Impulse-Response Functions Between Economic Growth and $\Delta\tau 9$

Notes: See the notes to Figure 2. [Colour figure can be viewed at wileyonlinelibrary.com]

any direction could affect economic growth negatively. Similarly, Voitchovsky (2005) reports that inequality at the top end of the income distribution positively encourages growth, while inequality at the lower end retards it. In view of the fact that many countries have experienced marked variations in levels of top income shares during the past six decades, and several global shocks have occurred in the same period, it is also interesting to see differences in the relationship between $\mathcal{T}1$ growth and PCI growth across time periods.

To be explicit on data pooling, let $i = 1, 2, \ldots, N = 12$, denote a cross-sectional index. Independence diagnostics for (un)conditionally pooled data are retrieved from samples $\{\{\xi_{it}^{(h)} | (PCI_{it}, \mathcal{T}_{it}, t) \in \mathcal{A},\}_{i=1}^{N}\}_{t=1}^{T}$, where $h = 1, 2, 3, 4$ refers to the null

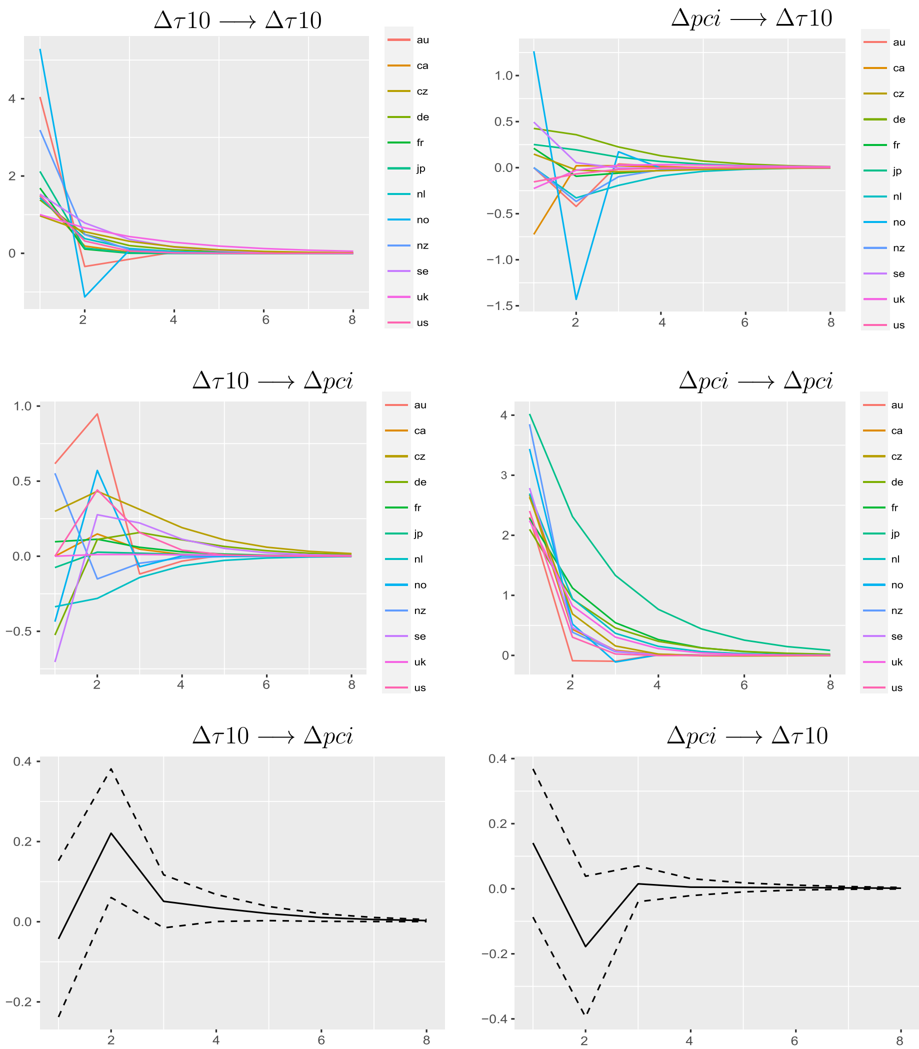

Figure 4. Impulse-Response Functions Between Economic Growth and Δτ10

Notes: See the notes to Figure 2. [Colour figure can be viewed at wileyonlinelibrary.com]

hypotheses H_{01} to H_{04} and vectors $(PCI_{it}, \mathcal{T}_{it}, t)$ collect economic indicators; that is, measures of per capita income, top income shares, and time. It is noteworthy that the pooling step involves orthogonalized shocks that are retrieved from country-specific VARs, implicitly accounting for fixed effects. As a criterion for the composition of pooled samples, the economic indicators have to be in excess of or below particular thresholds. In distinguishing the levels of the economic indicators, we consider full-sample median values of PCI (US$19,142) and $\mathcal{T}1$ (8.21).[18]

[18]As an alternative to using "global" thresholds, one may also use country-specific median values of the economic indicators for the composition of pooled samples. The results from pooling with country-specific thresholds are very similar to those obtained from full-sample thresholds, and can be obtained from the authors upon request.

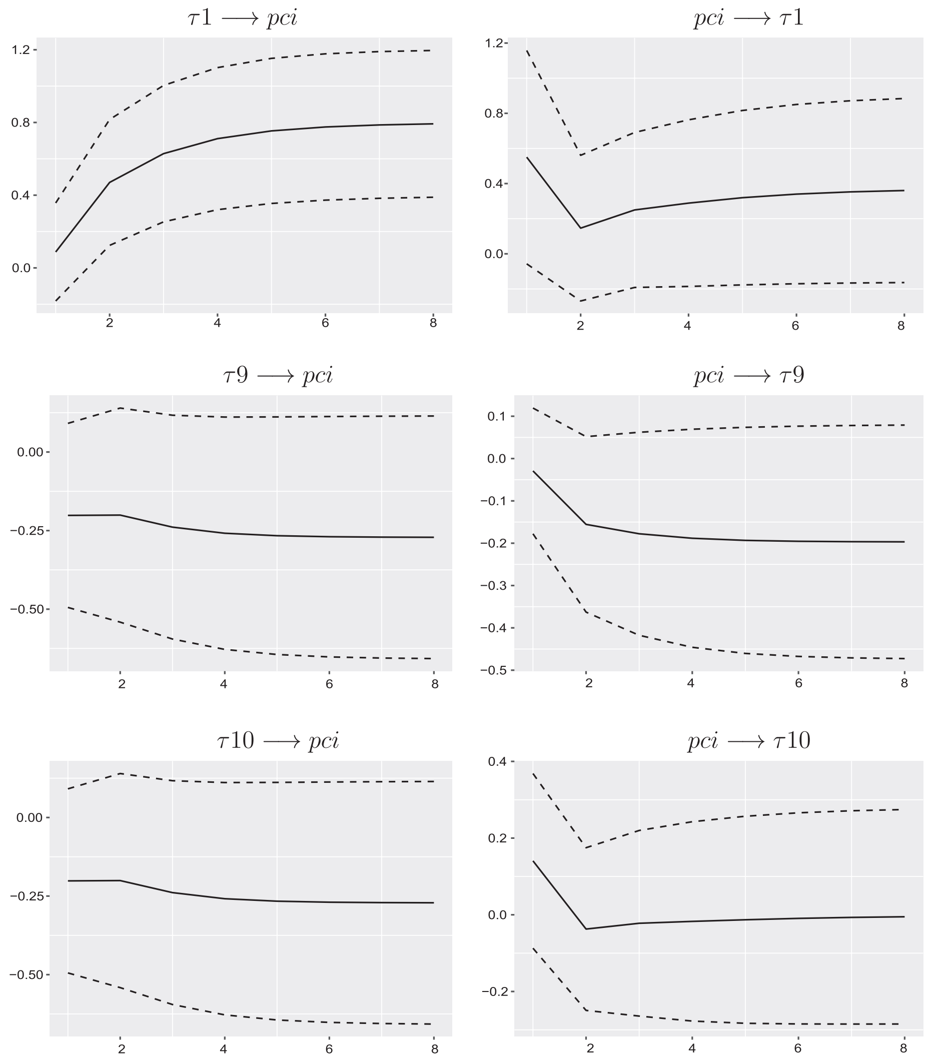

Figure 5. Mean Group Cumulative Impulse Responses

Notes: See the notes to Figure 2.

Explicit choices for the sets $\mathcal{A}$ are documented along with inferential results in Table 3.

Independence Tests in Pooled Samples

Results from pooled data are documented in Table 3. The first row displays test results obtained after pooling the orthogonalized innovations $\xi_t^{(h)}$ across all countries and years. These results show that the hypotheses H_{01}, H_{03} and H_{04} are rejected, while H_{02} is not. Hence the full-sample pooled results are in line with the hypothesis that $\mathcal{T}1$ income shares have a long-run (most likely positive) impact on PCI. Without putting too much emphasis on the collection of dependent

Table 4
$\Delta\tau 1$ and Growth Rates of Group-Wise PCIs: Results from Pooled Data

		H_{01}		H_{02}		H_{03}		H_{04}	
Group-Wise PCI	Obs.	C_0	$p(C_0)$	C_∞	$p(C_\infty)$	C_0	$p(C_0)$	C_∞	$p(C_\infty)$
$\Delta pci1$	667	0.046	0.020	0.044	**0.261**	0.074	0.000	0.072	0.000
$\Delta pci9$	667	0.044	0.010	0.044	**0.046**	0.051	0.010	0.063	0.002
$\Delta pci90$	667	0.047	0.030	0.043	**0.246**	0.065	0.000	0.049	0.006

Notes:. [a] We pool the empirical counterparts of $\xi_t^{(h)}$. In H_{01} and H_{02}, $\Delta\tau 1$ is the first variable in the VAR, while in H_{03} and H_{04} one of the growth rates of group-wise PCIs is the first variable. The results are for full sample data. For further notes, see Table 2.

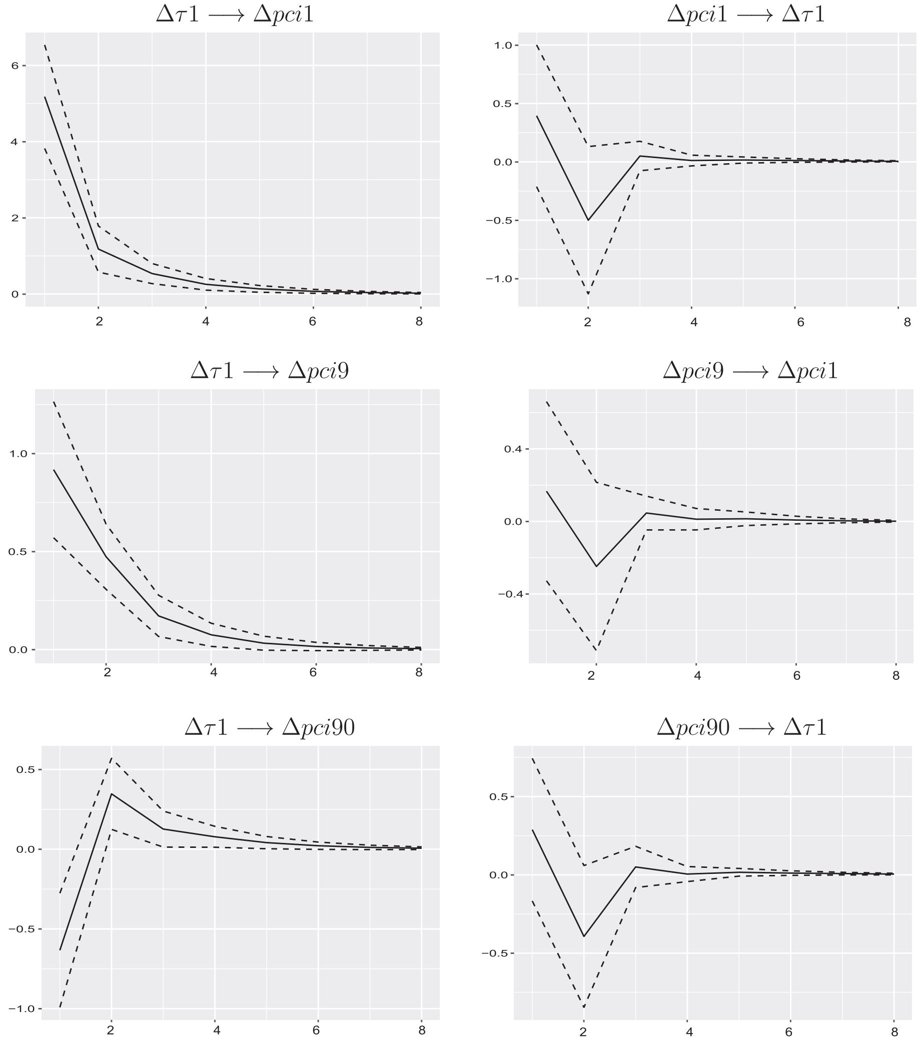

Figure 6. Mean Group Impulse-Response Functions Between $\Delta\tau 1$ and Growth Rates of Group-Wise PCIs

Notes: The D matrices are obtained by assuming H_{02}. Dashed lines represent upper and lower 1.65SD bounds (approximating 90 percent confidence intervals).

diagnostics obtained from different directions of data pooling, it is striking to see that from 20 p-values documented in Table 3 for testing H_{02} in conditionally pooled data, only two are below the 10 percent threshold. Moreover, the average of all p-values obtained from testing H_{02} is 0.407, which is much larger than the corresponding values for the other three hypotheses. Stating the opposite direction of long-run (non)causality, $H_{04}^{(s)}: pci \rightarrow_{\infty} \tau 1$ is the least preferred one, receiving an average p-value of 0.105 and being rejected for ten pooled samples.[19]

[19]Two of the subsamples consist of less than 50 observations, such that the results should be viewed with some caution. However, the remaining subsamples comprise more than 160 observations, and the fact that H_{02} is the most preferred hypothesis despite the use of distinct subsamples shows that the documented results are unlikely to be driven by (systematic) small sample biases.

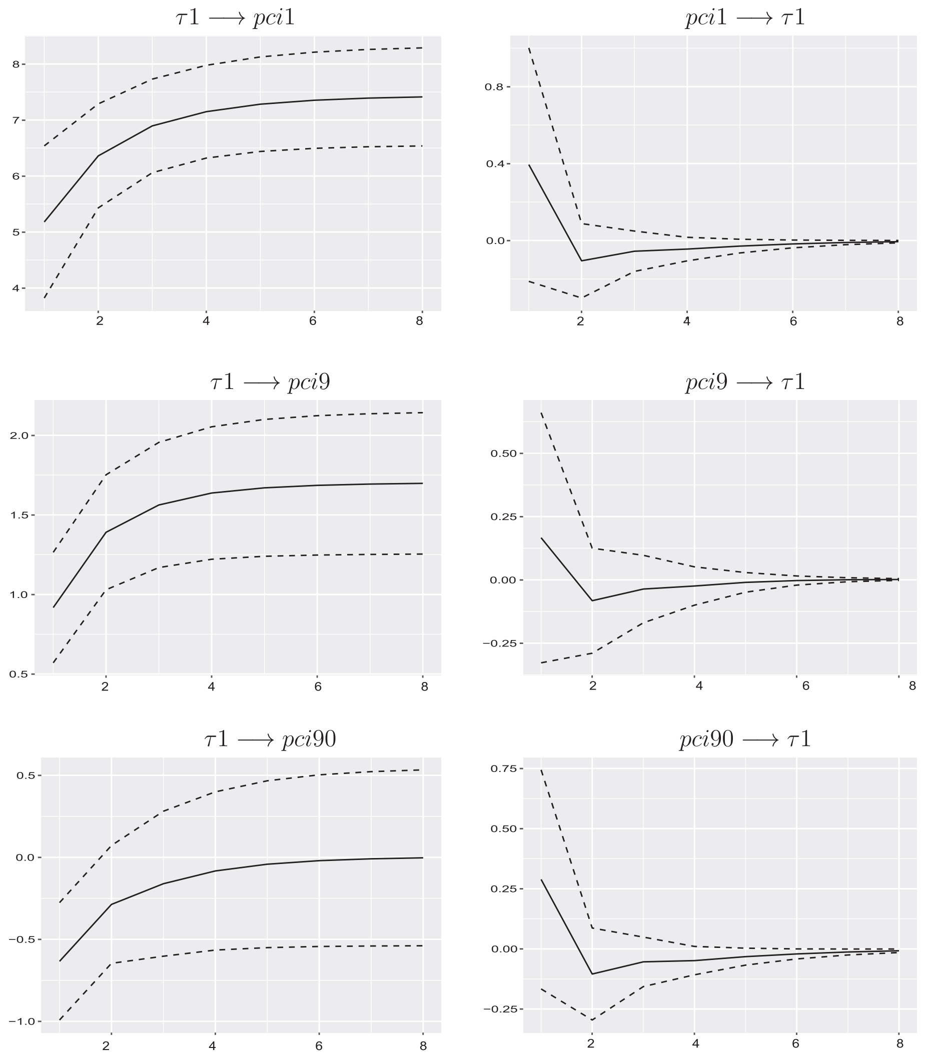

Figure 7. Mean Group Cumulative Impulse Responses Between $\mathcal{T}1$ and Group-Wise PCIs
Notes: See the notes to Figure 6.

From the upper panel of Table 3, we see that full-sample results supporting $H_{02}^{(s)}\!:\tau 1 \rightarrow_{\infty} pci$ (and rejecting the remaining three hypotheses) are confirmed when we consider observations for which income is above the full-sample median income (US\$19,142) or conditional on post-1980 data. Focusing on maximum p-values, we see that patterns of contemporaneous transmission might have been subjected to a structural variation. Conditional on data up to 1980, $H_{03}^{(s)}\!:\Delta pci \rightarrow_0 \Delta\tau 1$ refers to the most favorable model, while evidence in favor of $H_{02}^{(s)}\!:\tau \rightarrow_{\infty} pci$ reflects sample information from more recent decades and/or for both higher PCIs and $\mathcal{T}1$. The fact that the empirical support for H_{02} relates, in particular, to the second half of the sample is further sharpened by the results from decomposing the data along two factors. Specifically, the smallest p-values for testing H_{02} are documented for quadrants where $\mathcal{T}1$ is above its median and the observations date to before 1980, or PCI is below its median. Interestingly, for these subsamples, innovations drawn under $H_{01}^{(s)}\!:\Delta\tau 1 \rightarrow_0 \Delta pci$ obtain the largest p-values. This evidence likely reflects the fact that above-median $\mathcal{T}1$ scenarios have an incentive effect in generating economic growth, but the impact lacks persistence under a lower level of economic development. The bottom two rows in the upper panel of Table 33 provide results obtained by excluding the post-2007 data and show that the main results are not driven by the recent global financial crisis.

In summary, the full-sample pooled results suggest that $\mathcal{T}1$ exerts a long-run (mostly) positive impact on economic activity. Moreover, this transmission channel is particularly typical for the post-1980 period, when economies exhibited substantial increases in the level of the top percentile income shares together with sustained small but positive economic growth rates. This result is consistent with both the "superstar" and financial deregulation explanations for the significant increase in top income shares in recent decades. According to the "superstar" hypothesis, globalization and advances in information technology since the 1980s have increased the relative productivity of highly talented individuals (Kaplan and Rauh, 2013 Rosen, 1981). Hence the "superstars" may have generated economic growth while increasing their own share of national income. A long-run positive impact of growth in $\mathcal{T}1$ on economic growth is also consistent with the theory, which ascribes the recent rise in $\mathcal{T}1$ to the financial deregulation measures that commenced in the 1980s (Boustanifar *et al.*, 2018 Tanndal and Waldenström, 2018). Given the generally positive impact of financial development on economic growth (Levine, 2005), top income earners in the financial sector may have promoted economic growth through financial development while increasing their own share of total income.[20]

5.1.3. *Identified Impulse Responses*

From the VAR literature, impulse-response functions are known to process information on both the identified structural covariance decomposition $\Sigma_0 = DD'$ and the reduced-form autoregressive parameter matrices A_i, $i = 1, 2, \ldots, p$ (see, e.g., equation 2).[21] In this section, we extract impulse responses from the particular model structure obtaining least dependent orthogonalized shocks for each economy. Country-specific impulse-response functions are displayed in Figure 2.

While the "diagonal" panels of Figure 2 highlight the fact that the effects of "own" shocks on growth rates of $\mathcal{T}1$ and PCI die out exponentially, not surprisingly, cross-equation ("off-diagonal") impacts show more cross-sectional

[20]We have tried to reproduce Table 3 using the top 0.5 percent and top 0.1 percent data, although data are missing for the Netherlands and New Zealand, respectively. In view of space considerations, we have provided these results in Tables F.2 and F.3. In particular, the post-1980 pooled results are qualitatively similar to the $\mathcal{T}1$ results in that they support H_{02} and, hence, are in line with the hypothesis that $\mathcal{T}0.5$ and $\mathcal{T}0.1$ income shares have a long-run impact on PCI. Therefore, the $\mathcal{T}0.5$ and $\mathcal{T}0.1$ results strengthen our narrative that the "superstars" and top-paid employees in the financial sector have driven up the overall per capita income, especially after the 1980s, when globalization and financial deregulation have become prevalent.

[21]For details about impulse-response functions, see, for example, Lütkepohl (2007).

heterogeneity. The responses of Δpci to orthogonalized shocks originating from the $\Delta\tau 1$ equation are, on impact, heterogeneous in direction and magnitude. After 1 or 2 years, however, these impulse-response patterns are almost uniformly positive. As a result, shocks in top 1 percent shares spur economic growth for up to 4 years, say. The evidence from country-specific impulse responses is underpinned by mean group response patterns showing that the average response of income growth to shocks originating in the growth of top percentile income shares is significant at conventional levels.

5.2. *Top Decile Income Shares and Per Capita Income*

5.2.1. Mean Group Diagnostics Using $\Delta\tau 9$ and $\Delta\tau 10$

In light of the heterogeneity of the top decile income group (see Figure 1 and Roine et al., 20029), we examine if the results we have obtained for the top percentile also hold for the top decile income earners. In addition, we provide an even more distinguished perspective for the second to the tenth percentile income shares (i.e. using $\Delta\tau 9$).

The mean group results are documented in the middle and lower panels of Table 2, while detailed country-specific results are shown as online Supporting Information (Table F.1).[22] Apparently, the structural results for the relation between per capita income growth and top decile share growth are quite different from the conclusions obtained from the corresponding relation using top percentile income. First, panel means of short- and long-run correlation coefficients are no longer significantly positive when extracted from VARs using $\Delta\tau 10$. Hence, for this group of top income earners, the directions of both short- and long-run causality show cross-sectional heterogeneity. Second, and most striking, $H_{02}^{(s)}\colon \tau 10 \rightarrow_{\infty} pci$ finds the weakest support among all tested hypotheses. At the same time, the Fisher statistics indicate that both hypotheses formalizing short-run causal relations are found in line with the data at the panel level. While this result could reflect power weakness of the independence test in small samples, the (panel-level) rejection of H_{02} hints markedly at the heterogeneity of the roles of $\mathcal{T}1$ and $\mathcal{T}10$ for overall macroeconomic performance. Hence it is instructive to concentrate the comparative discussion on the top percentile on the one hand, and the next nine percentiles of income earners on the other. Rather intuitively, the summary results documented in Table 2 underline that the statistical evidence provided for $\mathcal{T}10$ is somehow mixed up from the respective diagnostics attached to $\mathcal{T}1$ and $\mathcal{T}9$. For instance, the Fisher criteria and mean correlations (ρ_0 and ρ_∞) shown for VAR models comprising $\Delta\tau 10$ are between those of VARs comprising $\Delta\tau 1$ or $\Delta\tau 9$.

[22]If we subject the reduced-form VAR residuals u_t from regressions with $\Delta\tau 9$ or $\Delta\tau 10$ to normality testing, the country-specific evidence against the Gaussian model is weaker in comparison with the results discussed for VARs comprising $\Delta\tau 1$. For instance, if we model with $\Delta\tau 9$, we obtain insignificant statistics for four economies. In consequence, at the country level, the outcomes of independence tests should be interpreted with caution. Pooled samples of orthogonalized shocks, however, are markedly at odds with the Gaussian distribution, pointing to the informational content of independence diagnostics to distinguish among hypotheses H_{01} to H_{04}.

5.2.2. Independence Tests in Pooled Samples

The bottom and medium panels of Table 3 document pooled results for the top decile and top decile excluding the top percentile groups, respectively. After unconditional pooling, $H_{02}^{(s)}$:$\tau \rightarrow_{\infty} pci$ is the most strongly rejected hypothesis for innovation tuples gathered from $\mathcal{T}10$ or $\mathcal{T}9$. Instead, for pooled samples, $H_{03}^{(s)}$:$\Delta pci \rightarrow_{0} \Delta\tau$ obtains the largest p-value. Hence, for top decile income shares, the empirical evidence supports the view that macroeconomic performance impacts on top income shares, while the reverse impact channel is excluded. Given heterogeneous, and at the panel level insignificant, residual correlations (ρ_0), the direction of this impact is country specific. Focusing on $\mathcal{T}9$, it is worth noting that conditional pooling does not reveal any stronger evidence against H_{03}. Among the seven documented p-values from independence testing, the smallest statistic is 38.7 percent.[23] Hence, while we have diagnosed above some indication of structural change of transmission between PCI and $\mathcal{T}1$, the link between PCI and $\mathcal{T}9$ appears more stable over time. This is also in line with the fact that $\mathcal{T}1$ has been rising since the early 1980s in most countries, while such a general pattern is not observed for $\mathcal{T}9$.

5.2.3. Identified Impulse Responses

Similar to Figure 2, Figures 3 and 4 display the country-specific impulse-response functions implied by those models providing the least significant dependence diagnostics attached to the null hypotheses H_{01} to H_{04}. Pointing to internal consistency of structural inference and model selection, the cross-equation results documented at the mean group level for $\mathcal{T}10$ resemble some mean evidence displayed for $\mathcal{T}1$ and $\mathcal{T}9$. Identified IRFs for the latter show that orthogonalized shocks originating in $\mathcal{T}9$ affect PCI in early periods (i) more heterogeneously and (ii) such that the eventual positive effects on PCI are smaller in magnitude. At the mean group level, orthogonalized shocks originating in $\mathcal{T}9$ lack any significant impact on PCI, while one might diagnose a significant reduction of $\mathcal{T}9$ incomes 2 years after an orthogonalized shock originating in PCI.

Both variables entering the country-specific SVARs have been obtained after taking first differences of log levels of PCI and top income shares. Therefore, and noting that patterns of long-run (non-)causality materialize in the trending level data, it is of interest to examine cumulated identified impulse responses. Complementing the discussion of mean group identified impulse responses for $\Delta\tau 1$, $\Delta\tau 9$ and $\Delta\tau 10$, Figure 5 displays mean group cumulated cross-equation impulse-response patterns. Apparently, the only significant and sizeable mean group long-run effect is found for orthogonalized shocks originating in $\tau 1$ and impacting on log PCI. The cumulated effects of such unit shocks converge after 6 years. The remaining cumulated IRFs as displayed in Figure 5 fail to reveal any non-zero long-run effect. Innovations originating in $\tau 9$ or $\tau 10$ do not spur long-run macroeconomic performance; nor do shocks originating in *pci* exert a persistent impact on top income shares.

[23]For conditional pooling, the relevant global medians of $\mathcal{T}9$ and $\mathcal{T}10$ are, respectively, 23.23 and 31.51.

5.3. *Which Income Groups Benefit from Rising Top Incomes?*

The foregoing subsections have consistently documented that a rising $\mathcal{T}1$ drives up overall PCI. As the top 1 percent are the leading forces behind this inequality-led economic growth, it is straightforward that they reap large gains from it. What needs to be investigated further is the extent to which the remaining income groups benefit from this economic growth in terms of increases in their respective per capita incomes; that is, if there is evidence for the "trickle-down" effect from the top 1 percent to the rest of the society.

This subsection breaks down the PCI into the PCIs of the top 1 percent (PCI1), the next 9 percent (PCI9), and the bottom 90 percent (PCI90), and examines how a rising $\mathcal{T}1$ benefits each of the three PCIs. We construct group-wise PCIs as follows:

$$\begin{aligned} \mathrm{PCI1} &= (\mathcal{T}1)\times(\mathrm{PCI}/0.01), \\ \mathrm{PCI9} &= (\mathcal{T}9)\times(\mathrm{PCI}/0.09), \\ \mathrm{PCI90} &= (100-\mathcal{T}10)\times(\mathrm{PCI}/0.90). \end{aligned}$$

Results on the contemporaneous causality between $\Delta\tau 1$ and growth rates of group-wise PCIs ($\Delta pci1$, $\Delta pci9$, and $\Delta pci90$) based on pooling the empirical counterparts of $\xi_t^{(h)}$, where h refers to the null hypotheses H_{01} to H_{04}, are reported in Table 4. The results show that $H_{02}(s){:}\tau 1 \rightarrow_{\infty} pci$ is the most favorable hypothesis, irrespective of using $\Delta pci1$, $\Delta pci9$, or $\Delta pci90$.[24]

Looking at the mean group non-cumulative and cumulative impulse responses depicted in Figures 6 and 7, it is evident that growth in $\mathcal{T}1$ raises the PCI of the top 1 and the next 9 percent income earners, although the impact on the former is, as expected, stronger. However, the impact on PCI is negative and significant only for the first period and becomes insignificant thereafter. The results imply that the increase in the top 1 percent income share not only increases their own per capita income, but it also drives up the per capita income of the next 9 percent. This result is apparent evidence of a "trickle-down" effect, which might be caused by increased employment and business opportunities that are made available to the next 9 percent income earners because of the innovative activities of the top 1 percent. The generally statistically insignificant impact on the PCI of the bottom 90 percent reveals that they have, on average, neither benefited from "trickle-down" effects nor experienced a decreasing group-wise PCI, despite the decline in their share of aggregate income.

6. Conclusions

The relationship between top income shares and economic activity is highly debated. Theoretical predictions as well as existing empirical evidence are inconclusive on the direction of causality between top income shares and economic activity. In this paper, we have revisited the top income – growth relationship using novel causality tests that build upon recent advances in structural-vector

[24]Corresponding country-specific SVAR results, which also generally support H_{02}, are available from the authors upon request.

autoregressive modeling of non-Gaussian systems. This framework allows us to distinguish among rival contemporaneous causality directions by means of formal dependence tests, which make use of the fact that independent shocks are unique for a particular causation pattern.

For the empirical analysis, we have employed annual data on growth rates of GDP per capita and the share of income of the top 1 percent ($\mathcal{T}1$), the next 9 percent ($\mathcal{T}9$), and the top decile ($\mathcal{T}10$) from 12 OECD economies for the post-1950 period. Our results show that the structural models might differ from country to country. Taking the mean of country-specific results as well as pooling the data, however, obtains results that strongly favor a long-run (mostly) positive impact of $\mathcal{T}1$ on economic activity against other causal relationship possibilities. This result is particularly strong for the post-1980 period. Use of the top decile minus the top percentile share of income ($\mathcal{T}9$), however, reveals a different picture, where the hypothesis of a long-run impact of $\mathcal{T}9$ on economic activity is, especially at the pooled level, the most strongly rejected hypothesis of all the four causal relationship possibilities.

Our result that $\mathcal{T}1$—but not $\mathcal{T}9$—has a long-run impact on economic activity may be explained by resorting to the "superstar" and financial deregulation theories for the rise of top percentile incomes in recent decades. According to the "superstar" theory (Kaplan and Rauh, 2013; Rosen, 1981), globalization and advances in information and communications technology have increased the relative productivity of highly talented individuals and, hence, increased the top 1 percent's share of aggregate national income. The "superstars" may be behind our result for two reasons. First, these highly talented individuals are more likely to be in the top percentile than in the next top nine percentiles. Second, the positive and significant role of $\mathcal{T}1$ is not obtained in the pre-1980 period but, rather, in the post-1980 period where the "superstar" hypothesis is supposed to hold. The other important factor that is likely to be behind the top income-inequality relationship documented in this study is the financial deregulation of the past four decades. Several studies have shown that financial deregulation has contributed to the recent rise in $\mathcal{T}1$ by driving up wages in the financial sector (Boustanifar *et al.*, 2018; Tanndal and Waldenström, 2018). Given the generally positive impact of financial development on economic growth (Levine, 2005), top income earners could have promoted economic growth through financial development while increasing their own share of total income.

As partial support for the so-called "trickle-down" hypothesis, we find that growth in $\mathcal{T}1$ not only increases the per capita income of the top 1 percent, but it also drives up the per capita income of the next 9 percent. However, the bottom 90 percent have, on average, neither benefited from "trickle-down" effects nor experienced decreasing PCIs, despite the decline in their share of aggregate income. In this regard, it would be interesting to uncover the threshold level of income shares (say, deciles) below which the "trickle-down effect" could not be felt. In fact, rising top income inequality could even have a negative impact on the poor, as documented in van der Weide Milanovic (2014). With the availability of data on income shares for more quantiles, in future research one could examine the "trickle-down" effects at a finer resolution.

A particular limitation of our study is related to the fact that we ascribe our result that $\mathcal{T}1$—but not $\mathcal{T}9$—has a long-run impact on economic activity to the rise of the "superstars" and to financial deregulation. While these two factors are likely to be complementary in their effects on the top income – growth relationship, it remains unclear which of the two is the most important driver of this relationship. An explicit weighting of the impacts of these two factors is left for future research.

As the top income share data continues to be constructed for more and more countries, future research could extend this study by broadening the sample to include both developing and emerging economies. Another way of extending this study could be to investigate the institutional and economic factors (other than the income and inequality levels considered in this paper) that affect the link between top income shares and economic growth. A reexamination of the inequality–growth nexus by employing the new tools of causality testing that are used in this paper, together with broader inequality measures such as the Gini index, is also an interesting avenue for future research.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Appendix

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