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Trade, global value chains and wage-income inequality

Javier Lopez Gonzalez,
Przemyslaw Kowalski, Pascal Achard

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Abstract

TRADE, GLOBAL VALUE CHAINS AND WAGE-INCOME INEQUALITY

Javier Lopez-Gonzalez, Przemyslaw Kowalski and Pascal Achard

The rise in global value chain (GVC) participation has coincided with significant changes in the distribution of wage income both within and across countries. This paper sets out to identify the linkages between these phenomena. It shows that GVC participation has a small effect on the distribution of wages and, when it has, it can reduce wage inequality when it concerns participation related to low-skilled segments of the labour force. This suggests that the potential tensions between equity and aggregate economic outcomes of GVC participation hold only in particular cases, namely when participation relates to high-skilled segments of the labour force. For policy-makers seeking to maximise the benefits of GVC participation, questions of a more equitable distribution of returns to workers might focus on skill-upgrading of low-skilled labour by promoting further tertiary education and development of skills

Key words: Global value chains; GVCs; trade in value added; offshoring; trade in tasks; wage inequality; global wage inequality; income inequality; globalisation; equity-efficiency trade off.

JEL: F14, F16, F6, J31

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Abbreviations of names of countries and territories

AUS	Australia
AUT	Austria
BEL	Belgium
BGR	Bulgaria
BRA	Brazil
CAN	Canada
CHN	China (People's Republic of)
CYP	Cyprus
CZE	Czech Republic
DEU	Germany
DNK	Denmark
ESP	Spain
EST	Estonia
FIN	Finland
FRA	France
GBR	United Kingdom
GRC	Greece
HUN	Hungary
IDN	Indonesia
IND	India
IRL	Ireland
ITA	Italy
JPN	Japan
KOR	Korea
LTU	Lithuania
LUX	Luxembourg
LVA	Latvia
MEX	Mexico
MLT	Malta
NLD	Netherlands
POL	Poland
PRT	Portugal
ROM	Romania
RUS	Russian Federation
SVK	Slovak Republic
SVN	Slovenia
SWE	Sweden
TUR	Turkey
TWN	Chinese Taipei
USA	United States

Executive Summary

Income inequality has been on the rise in several countries since the beginning of the 1990s (OECD, 2014 and 2015b) even at a time when global inequality appears to have fallen (Milanovic, 2012). Changes in the distribution of income are not only an important economic phenomenon but can also be a formidable social and political challenge, and globalisation and trade are often seen as potentially implicated. Economic research on its own cannot substitute for the political process in deciding whether and if so how, income inequality should be reduced, but it can help by disentangling the different determinants as well as shedding light on the underlying mechanisms that result in income inequality.

Factors that contribute to income inequality are multifaceted; they include, for example, unequal returns to factors of production (e.g. factor scarcity), exposure to competition, taxation, access to education, skill-biased technological change and employment or welfare policies (i.e. public transfers, income tax policies and the like, see OECD, 2011, 2014 and 2015b). But with the concurrent wave of globalisation, evidenced through the growing participation in global value chains (GVCs) as shown in OECD (2013 and 2015a), questions related to how these processes are linked are increasingly coming to the fore.

The objective of this paper is to contribute to a better understanding of the relationship between inequality and trade by revisiting the links between one important component of income inequality—wage inequality—and the proliferation of global value chains. This is, to our knowledge, the first empirical attempt at linking these two phenomena since the emergence of measures of GVC activity based on inter-country input-output tables and trade in value added data.

The data suggests that whilst some emerging countries have experienced reductions in wage inequality, most developed countries have seen their wage inequality rise. Where the links between GVC participation and wage inequality are concerned, the empirical findings show that:

- Participation in GVCs is not the main driver of wage inequality: it plays a relatively small role.
- There is little evidence to support the negative publicity often associated with offshoring. On aggregate and controlling for other factors, countries which engage more widely in GVCs through offshoring—i.e. using foreign value added to produce exports—tend to have lower levels of wage inequality.
- The nature of GVC participation matters; a greater degree of low-skill task offshoring is associated with lower levels of wage inequality. That is to say that the gap between the wages of low and high skilled workers is reduced as the wages of low skilled workers rise faster than those of high skilled workers. The intuition is that positive productivity and labour demand effects of offshoring dominate the negative labour supply effects. First, offshoring boosts the productivity of remaining low-skilled workers which can focus on tasks they are most efficient at. Second, it increases the productivity of firms relying more on low-skilled labour, thereby further boosting the demand for—and thus wages of—this type of labour. These two effects outweigh the more traditional labour supply effect which exerts downwards pressure on the wages of workers.
- However, engaging in high-skill task offshoring is likely to boost high-skill labour productivity relative to low-skilled workers and in so doing contribute to increasing the gap between the wages of low and high skilled workers through similar mechanisms as explained above.

- Importantly, the results show that low-skilled labour value added is traded within value chains more intensely than high-skilled labour value added, hence the observation of the recent positive net effect of GVC participation on wage inequality.

Since the focus of this paper is on wages, the principal empirical analysis captures only relative changes in returns for those in employment. However, the general results hold when using alternative measures of inequality that account for the incomes of the unemployed. This suggests that while separate research may be needed to understand how GVCs shape jobs (and the distribution of capital returns or wealth), the reported links between GVCs and inequality appear to be robust.

From a policy stand-point, and in the context of the emerging empirical results showing the aggregate benefits of GVC participation in terms of productivity, product sophistication and diversification (OECD, 2015a), the results of this study suggest that the equity-efficiency trade-off—or the potential tension between equity and the aggregate economic outcomes of GVC participation—holds only in certain particular cases. GVC participation has a small effect on the distribution of wages and, when it has, it can reduce wage inequality when it concerns GVC participation of low-skilled segments of the labour force.

For policy-makers seeking to maximise the benefits of GVC participation, questions of a more equitable distribution of returns to workers might focus in particular on skill-upgrading of low-skilled labour by promoting further tertiary education and development of skills since this is found to reduce inequality both in developed and emerging economies. This latter result is consistent with the more general finding from the literature on inequality which suggests that diffusion of knowledge and investment in training and skills are the main forces that can reduce income inequality (e.g. Piketty, 2014).

1. Introduction

The proliferation of global value chains (GVCs) has not only fundamentally altered the geography of production but also its complexity.[1] International production now involves a mix of cross-border flows of information, intermediate inputs, know-how, investment, services and people (Baldwin, 2012; OECD, 2013). Driven by ambitious trade reforms in emerging economies and a revolution in information and communication technology (OECD, 2009; 2013), this new wave of globalisation has coincided with a faster—and broader in terms of country coverage—catching up of developing countries' per capita incomes with those of high-income countries (e.g. Subramanian and Kessler, 2013).[2] This growth has also lifted many people out of poverty (Dollar et al., 2013).

Concurrently, income inequality has purportedly risen in a large number of OECD countries and some emerging economies (OECD, 2011, 2014 and 2015b) and has become a major policy challenge (OECD, 2008; 2011, 2013). The rise in country-level inequality has many non-trade related determinants; for example access to education, skill-biased technological change and employment or welfare policies (OECD, 2011), but trade remains another potential factor. While the empirical consensus of the 1980s and 1990s was that the effect of trade on inequality was probably modest (WTO, 2008), some prominent thinkers have been arguing more recently that this new wave of globalisation may require us to revisit these links (Krugman, 2007).[3] Changes in income distribution are not only an important economic phenomenon but also a formidable political challenge, and globalisation and trade are at the heart of these concerns.

The bulk of the existing empirical literature on trade and inequality focuses on the question of the extent to which trade has contributed to the observed increase in inequality of incomes or wages, compared to other factors. As noted in recent reviews (e.g. WTO, 2008; and OECD, 2012) there is no firm answer to this question. Some studies find that trade has not had an impact while others find that it has. Moreover, even if trade were to contribute, it is not clear whether and how this should be remedied since the trade-inequality link can reflect differences in productivities and preferences and thus, as argued recently by Mankiw (2013), can be seen as economically—and from certain viewpoints also socially—acceptable.

In parallel, our understanding of GVCs is at an early stage (e.g. OECD, 2013 and 2015a) and thus the role that these play in the inequality debate remain largely unexplored. This seems a particularly important gap to fill since understanding GVCs is central to analysing the causes and consequences of the global division of labour and therefore distribution of income (Brewer, 2011).[4]

The primary objective of this paper is therefore to extend previous OECD analysis on the trade determinants of inequality OECD (2011) by looking at how the proliferation of global value chains has affected the distribution of wage income within the working population. The aim is to capture first the direction of the changes and thereafter to identify the channels that bring these about. Two key dimensions of wage inequality are considered; i) global and ii) country-specific although the empirical

1. See Feenstra and Hanson 1996; Yeats, 1998; Hummels et al., 2001; Amador and Cabral, 2009; Koopman et al., 2010; Daudin et al., 2011; Johnson and Noguera, 2012; Lopez-Gonzalez, 2012 and Baldwin and Lopez-Gonzalez, 2013 for a discussion on the proliferation of GVCs.

2. Developing and emerging economies shares of global value added have been on the rise since the beginning of 2000s while those of the OECD countries have shrunk.

3. The question of winners and losers from trade continues to be an important feature of the debate on merits of free trade (e.g. WTO, 2008; OECD, 2012). Some go as far as arguing that inequality is one of the major threats to the future of globalisation process (Wolf, 2013).

4. For example, Brewer (2011) points out that "the commodity chain analysis is an intellectual offspring of a larger theoretical perspective—world-systems analysis—that has hypothesised a persistent, unequal global distribution of wealth as a structural "fact" of a capitalist economy."

analysis focuses on the latter. This distinction is made because globally, the opening up of many emerging economies to trade and investment and the evolving fragmentation of production appear to have resulted in an important redistribution of economic activity, and therefore world income, towards emerging economies (as suggested by Baldwin and Lopez-Gonzalez, 2013). However, country experience has been mixed (OECD, 2011).

The results suggest that global wage inequality has indeed been falling. Interestingly the results show that this reduction appears to be driven by changes at the top end of the distribution (i.e. in the data the gap between high and middle earners is becoming smaller but that between the middle and the bottom earners is widening albeit at a slower pace). Where country-specific inequality is concerned, the results are more mixed.[5] However, certain empirical regularities can be observed; wage inequality in emerging countries appears to be, on average, higher than that of developed economies but is falling, while in developed countries inequality has generally been rising.

There is also consistency in the correlation between GVC participation and wage inequality; countries with a higher degree of backward participation in GVCs, as measured by the foreign value added content of exports, tend to have lower levels of wage inequality among their working population. However, the type of offshoring appears to matter. A higher degree of low-skilled task offshoring is associated with lower wage inequality. This happens because offshoring low skilled tasks leads to a productivity boost to remaining low-skilled workers and therefore an increase in their wage thereby reducing the gap between high and low skilled wages. Similarly, offshoring high-skilled tasks also leads to a productivity boost to this type of labour and therefore higher high-skilled wages with a consequent increase in the gap between high and low skilled wages.[6] Since low-skill offshoring is more prominent than high-skill offshoring, on aggregate, engaging in a wider backward participation is associated with lower wage inequality.

Where being the recipient of the offshoring activity is concerned (the forward linkage), there is also evidence that the nature of the linkage matters. When it is a low-skill (high-skill) task that is received, then the labour-augmenting productivity effect pushes the wages of low-skilled (high-skilled) workers up thereby reducing (increasing) wage inequality. However, in this instance it is the high-skill effect which dominates and therefore being the recipient of an offshored task tends to increase wage inequality.

Although these effects are robust to different empirical model specifications and sources of inequality measures it is important to contextualise the results. First, GVC participation helps explain only a small part of the variation in wage inequality across the sample, implying that there are other more important determinants of wage inequality. Second, the employment reallocation effects arising from enhanced participation in GVCs are not directly captured (since the dependent variable is wage inequality).[7] Nevertheless, the results hold when using the more holistic OECD inequality measures which do account for incomes of the unemployed.

5. And relatively sensitive to the source of the underlying data used to compute the inequality measures. For example, somewhat different evolutions can be perceived depending on whether the analysis uses measures of inequality derived from; WIOD; the University of Texas Inequality Project; the World Development Indicators; or the OECD inequality indicators.

6. These findings are in line with the predictions of the new theoretical literature on GVCs; notably Grossman and Rossi-Hansberg’s (2008) *trade in tasks* model. They suggest that offshoring can give rise to a positive productivity shock which ultimately benefits the type of workers whose tasks have been offshored. The intuition is that offshoring is tantamount to “*labour-augmenting technological change”* or in other words it acts like technical progress which increases the productivity of the labour whose task has been offshored.

7. The indirect effect that is captured is the influence of unemployment rate on wage developments.

From a policy stand-point, and in the context of the emerging empirical results showing the aggregate benefits of GVC participation in terms of productivity, product sophistication and diversification (OECD, 2015a), the results of this study suggest that the equity-efficiency trade off—or the potential tension between equity and the aggregate economic outcomes of GVC participation—holds only in certain cases. GVC participation has a small effect on the distribution of wages and, when it has, it can actually reduce wage inequality, especially when it concerns GVC participation of low-skilled segments of the labour force.

For policy-makers seeking to maximise the benefits of GVC participation, questions of a more equitable distribution of returns to workers might focus in particular on skill-upgrading of low-skilled labour by promoting further tertiary education and development of skills since this is found to reduce inequality both in developed and emerging economies. This latter result is consistent with the more general finding from the literature on inequality which finds that diffusion of knowledge and investment in training and skills are the main forces that can reduce income inequality (e.g. Piketty, 2014).

The paper is organised as follows. The next section provides an overview of the related theoretical and empirical literature on the links between GVCs and inequality. The aim here is to give context and identify testable hypotheses on the direction of the effects so as to set the stage for the subsequent empirical investigation. Section 3 begins with a description of the data and discusses the calculations needed to identify both GVC participation and wage inequality. Sections 4 and 5 are concerned with the evolution of wage inequality and GVC participation respectively. Section 6 then shows the results obtained from the econometric work and Section 7 concludes by providing a brief discussion of the key policy implications of the findings.

2. Trade, GVCs and inequality: Why it might matter

The significant increase in international trade and foreign direct investment and the proliferation of GVCs observed since the beginning of the 1990s have coincided with rising developing countries' per capita incomes and reductions in poverty (e.g. Subramanian and Kessler, 2013; Dollar et al., 2013). In parallel, income inequality has risen in a large number of OECD countries and some emerging economies (OECD, 2011a, OECD, 2014) and become, once again, a hotly debated policy concern (OECD, 2008; OECD, 2011a; OECD 2013b).

Income inequality has always been a central issue in economics and globalisation and trade are seen as potentially implicated but it is primarily an important political and social issue. Economic analysis can help identify some of the potential sources of inequality—including international trade—as well as establish links between inequality and other measures of economic performance such as, for example, economic growth. However, in most cases economics cannot help in deciding whether inequality should be actively countered and, indeed, what levels—or what types—of inequality are acceptable. Answering these questions requires inputs from sociology, history, philosophy and, indeed, politics (see Box 1).

Factors that have been shown in the economic literature to contribute to income inequality include unequal returns to factors of production arising from natural economic conditions (e.g. factor scarcity), unequal exposure to market competition, taxation, access to education, skill-biased technological change and employment or social and welfare policies (i.e. public transfers, income tax policies and the like; see e.g. OECD, 2011). However, changing specialisation patterns arising from a wider engagement in trade are theoretically consistent with changing inequality and are often perceived by the public to be a burden to the economy (Pew, 2014) and also drivers of rising inequality.

While the empirical consensus of the 1980s and 1990s was that the effect of trade on inequality was probably modest (WTO, 2008), more recently several economists have been arguing that it is no longer correct to assert so because of the rise of emerging economies and the growing fragmentation of production (e.g. Krugman, 2007). The question of income inequality thus continues to be an important feature of the debate on merits of free trade (e.g. WTO, 2008; OECD, 2012). Some even argue that inequality is one of the major threats to the future of the globalisation process (Wolf, 2013).

Box 1. Why is inequality important and what is the role of economics in addressing it?

Inequality has always been a great political challenge. It can have many dimensions (e.g. inequality of opportunities, access to health or clean environment, income, wealth) and its perceptions can be subjective but its importance boils down to the fact that to some extent it concerns everyone: “Each has his or her own unique vantage point and sees important aspects of how other people live and what relations of power and domination exist between social groups, and these observations shape each person’s judgment of what is and is not just.” (Piketty, 2014). Inequality is thus a key determinant of social cohesion and political stability.

Causes and consequences of inequality have thus always been in the core interest of social sciences and economics has made important contributions to this debate from its very beginning. Political tensions associated with income inequality were in fact one of the key motivations for the early economic research by Thomas Malthus, David Ricardo and Karl Marx which focused on the organisation of economic activity and generation and distribution of income. Moreover, the equity-efficiency trade-off—or the potential tension between equity and the aggregate economic outcomes—has remained a central issue in economics ever since (e.g. Offer, 2014). But, ultimately, economic analysis cannot, on its own, resolve the question of what may or may not be just or what is socially acceptable. Such investigation requires insights from sociology, history, philosophy and, ultimately, inputs from citizens through political process.

One of the key insights from the economic literature on the equity-efficiency trade-off is that income inequality can be a natural feature of a market-based economic system in the sense that it can reflect differences in productivity or preferences (e.g. Mankiw, 2013). For example, some individuals may choose to work more or devote more effort to work and thus be more productive and earn more. Also, the forces of supply and demand may privilege owners of scarce factors of production or those possessing unusual talents. Such income inequality can then be related positively to aggregate economic efficiency. When it comes to advising policy makers on what action should be taken with respect to such inequality, economics in itself cannot offer more than help determining the least economically inefficient ways of reducing it.

However, economics suggests also that in some cases income inequality can arise from market imperfections, rent-seeking and policy-related barriers and distortions, which create inefficiency or, in other words, decrease the overall size of income generated by a society. Inequality can also itself be a source of economic inefficiency. For example, it can reduce upward social mobility between generations and, in turn, adversely affect the equality of opportunities and influence the allocation of resources, such as talent or human capital, to the detriment of the economic performance of a country as a whole (e.g. OECD, 2008; Stiglitz, 2012). Recent OECD research suggests that efficiency costs of inequality can indeed be quite high (OECD, 2015b). It is relatively uncontroversial that such efficiency-decreasing inequality should be countered since this can improve income distribution, contribute to social cohesion and increase the overall size of the economic pie at the same time.

The equity-efficiency trade-off is also relevant for the analysis of distributional effects of international trade. On the one hand, productivity and preference differences—and thus the income inequality that may be associated with them—are at the heart of international exchange which brings about higher aggregate incomes. On the other hand, trade barriers and distortions can be a source of not only economic inefficiency but also income inequality.

The bulk of the existing empirical literature on trade and inequality focuses on the extent to which trade has contributed to the observed increase in inequality of incomes or wages compared to other factors (e.g. WTO, 2008; and OECD, 2012). Some studies find that trade has not had an impact while others find that it has. Moreover, even if trade were to contribute, it is not clear whether and how this should be remedied since the trade-inequality link can reflect differences in productivities and preferences and thus can be seen as economically—and from certain viewpoints also socially—acceptable see also Box 1).

In contrast, empirical work on the implications of GVC trade is nascent (e.g. OECD, 2013; OECD, 2015a) and the impact of GVCs on income inequality is even less researched. The latter seems a particularly important gap to fill not only because GVCs seem to be increasing in importance but also because some of their features challenge our thinking about the effects of trade and investment. GVC trade is characterised by trade in intermediate inputs and specialisation not at the level of whole products as in traditional trade analysis but at the level of tasks which are discrete pieces of work that can be performed in different geographical locations. With specialisation at the task level, producers can increasingly draw on international resources and production factor base and this might in turn have implications for the trade-inequality link. Moreover, value chains are thought of in the context of power and governance structures where certain actors can dictate conditions for other participants or organise production with possible implications for income distribution.[8]

In this context, the objective of this paper is to contribute to a better understanding of the relationship between inequality and trade by revisiting the links between one important component of income inequality—wage inequality—and the proliferation of global value chains. This is, to our knowledge, the first empirical attempt at linking these two phenomena since the emergence of measures of GVC activity based on inter-country input-output tables and trade in value added data in recent years (OECD, 2013).

2.1. What the theory suggests

The hypotheses regarding links between *trade* and inequality are, in essence, extensions of the different views that have been put forward by the evolving theories of trade. Reviewing these helps to identify what might be new about value chains and inequality. Some believe that there is nothing new with the emergence of GVCs, just more trade at a finer level of specialisation, in which case the old axioms are likely to continue driving the links between GVC trade and inequality. However, there is an emerging literature which points to specific features of GVC trade (e.g. trade in tasks) and suggests the need for a new paradigm through which new channels linking participation and inequality emerge.

The traditional framework for the analysis of international trade and inequality is the Heckscher-Ohlin-Samuelson (HOS) model where trade is driven by differences in relative factor endowments across countries. Specialisation follows factor abundance and therefore when a high-skill labour abundant country opens up to trade, the ensuing specialisation favours the product that uses this factor more intensely. This happens at the expense of the product that uses the relatively less abundant factor. The general implication of this model is that trade creates winners and losers and adjustments happen through changes in wages. As a consequence of trade, and following changes in prices, the relatively abundant factor sees an increase in its returns while the relatively scarce factor experiences falls in its returns. Therefore, engaging in international trade, drives changes in inequality within countries. However, the direction of these depends on the relative factor abundances across countries.

In developed economies, which tend to be relatively endowed with high-skilled workers, wages would be predicted to increase for high-skill workers but decrease for low-skill workers therefore leading to increasing inequality. In contrast, in developing economies, where factor abundance tends to be in low-skilled labour, it is the returns to this factor that would increase with those of high-skilled labour falling hence causing reductions in inequality. The prediction of the simple version of this model is relatively straightforward; *trade drives increases in inequality in developed countries but reduces inequality in developing economies*.[9] Many have tried to test some of these HOS predictions empirically and the results have been mixed (see Baldwin, 2008 for a historical appraisal).[10]

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8. Kaplinsky (2001), for example, lists several important characteristics of GVCs which make them a useful analytical framework for analysing the link between trade and inequality. These include: rents, governance and systemic effectiveness of value chains. Brewer (2011) argues that the traditional application of the GVC approach was to investigate the geographical dispersion, governance and institutional context of a given chain to illuminate the ways in which the most powerful actors and agencies drive the organisation of the chain, to above all else, their own benefit.

9. However, Meschi and Vivarelli (2007) note that what matters is relative factor endowments with respect to other countries. For example, some developing countries may be globally low-skilled labour abundant, but less so than other developing countries. This may have important implications for the prediction of the HOS model.

10. One of the recently-emerged interpretations of this is that it is important to consider how wages depend on the characteristics of exporting firms, a feature that the neoclassical HOS model does not offer (e.g. Helpman et al., 2011). The firm-level literature that emerged posits that a sector, task, skill level or occupations may not be the right unit of analysis of wage inequality as there is growing evidence that

Another recent strand of literature points to intermediate trade in tasks and offshoring as a new optic relevant for studying trade and inequality.[11] The existence of this type of trade undermines the traditional assumption of different kinds of labour (and other factors of production) being confined to a particular economy. If an intermediate input or a machine can be imported, or a task offshored, this allows producers to draw on international resources and production factor base (see Baldwin and Robert-Nicoud, 2010).

In Grossman and Rossi-Hansberg's (2008) trade in tasks model the impact of offshoring is decomposed into three effects: i) a productivity effect—where firms benefit from cost savings relative to the task that is more easily offshored; ii) a relative price effect—arising from changes in terms of trade; and iii) a labour supply effect—reabsorption of workers whose work has been offshored. Offshoring is modelled as a positive technological change introduced as a cost of coordination.[12] As these costs fall, firms adapt their production strategies. Lower costs of offshoring of low-skilled tasks do not necessarily lead to a reduction in the wages of low-skilled labour, like in the traditional HOS model, but rather can lead to their increase if the productivity effect outweighs the combined labour supply and the terms of trade effects.[13]

Falling costs of offshoring can have a positive effect on low-skilled wages because they can lead to cost savings that are akin to increasing the productivity of the labour whose task is more easily offshored and can therefore result in an increase in the returns to this factor.[14] For example, if the costs of offshoring a low-skilled task fall, a firm will choose to initiate or increase offshoring which will create two opposing effects. On the one hand, offshoring will make some of the low-skilled workers redundant thereby exercising downward pressure on low-skilled wages. This is the more commonly expected negative effect on low-skilled wages—the labour supply effect. On the other hand, cheaper offshoring will make firms more productive, liberate workers from unproductive tasks and lead to further specialisation and this effect will be disproportionate for firms specialising in low-skill intensive tasks triggering an increase in relative demand for unskilled labour and thus low-skilled wages—the productivity effect.[15]

The prediction of decreasing wage inequality of Grossman and Rossi-Hansberg (2008) can materialise when it is the low-skill intensive task that is offshored but if it is the high-skill intensive task which is offshored, then increases in inequality, due to the productivity effect augmenting high-skill labour returns through similar specialisation channels, are possible. The predictions of this model are therefore ambiguous relative to those in the HOS framework and depend on the type of task which is offshored as well as whether the productivity effect dominates the other effects.

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wages vary less between than within these categories and that this "within" variation is closely linked to the characteristics of trading firms.

11. Tasks are typically defined as identifiable and discrete pieces of work (see Lanz et al., 2011).

12. See Jones and Kierzkowski (1990) and Deardorff (2001) who first introduced the idea of technological change acting as an enabler for offshoring.

13. Jones and Kierzkowski (1990), in a non-theoretical paper, allude to a similar effect. They argue that offshoring, which is also akin to technological progress, can lead to instances where workers whose jobs have relocated offshore rise as is predicted in Grossman and Rossi-Hansberg (2008).

14. Note that this is partly due to the general equilibrium conditions in the model which assume that markets clear.

15. The productivity effect occurs not so much because of the additional units of unskilled labour that can be offshored in reaction to falling offshoring costs (second order effect) but because of the costs savings associated with the part of the low-skilled tasks that had already been offshored before (first order effect). The productivity effect would then be large when the extent of offshoring is already large. The labour supply effect would be large when the share of skilled labour in total costs is large and when high-skill tasks substitute poorly for low-skill tasks in the production process.

In contrast to Grossman and Rossi-Hansberg (2008), Zhu and Trefler (2005) develop a model where offshoring leads to greater inequality both in developed and developing countries. The relocation of lower-skill-intensive tasks from developed to developing countries has the effect of raising the skill premium in both since the lower-skill-intensive task that was outsourced becomes a relatively high-skill intensive task in the developing country.[16]

Although some of these nascent modelling approaches yield conflicting results, there are two unifying elements. The first is that offshoring is analogous to technological progress and therefore has a direct productivity effect. The second is that the traditional idea that it is the low-skilled task which is always offshored might need an overhaul. Autor, Levy and Murnane (2003) suggest that it is routine versus non-routine tasks that should drive this type of analysis while Blinder (2006) proposes a distinction between personal and impersonal services. What this literature suggests is that it is *offshorability*, which is indirectly associated with wages across different skills, that is important in determining changes in inequality (see also Blinder, 2009) even though the direction of these changes remains contested.

This poses a number of empirical challenges. First, the concept of offshorability is abstract and hard to quantify. Second, tasks that are offshored are likely to contain a heterogeneous mix of high and low-skilled labour with theoretically unpredictable impacts on the returns to these and, by extension, wage inequality. Accountancy services, for example, driven by better internet connectivity and their easily codifiable nature (see Leamer and Storper, 2001), may have now become more offshorable. Since these services are high-skill labour intensive, theory would suggest that these being offshored to India would lead to increases in inequality in India as wages of high-skilled workers rise relative to low-skilled workers. This stands against the traditional assumption that it is only low-skilled labour tasks that are going to be offshored to India (and in line with the assumptions of Zhu and Trefler, 2005). But at the same time, firms may also outsource their telephone services to India which involves a relatively less skilled labour force. It is therefore the mix of what is offshored and the composition of high and low-skilled labour in these activities which is likely to have implications for wage inequality.[17]

Ultimately, the impact of increased participation in GVCs on wage inequality is likely to be multifaceted. The HOS model, the old standard for this type of analysis, still delivers some important insights but in a setting where fragmentation is pervasive it is the mix of high and low-skilled labour in offshorable tasks which is likely to be important. The nuances introduced in the various theoretical papers reviewed here suggest very different impacts and channels of transmission. Since these are not unequivocal, the issue ultimately becomes an empirical one.

2.2. What the empirical literature finds

A number of studies have attempted to investigate empirically the links between trade and inequality but the topic is generally approached in the context of a single country and this entails a greater focus on the country-specific mechanisms that drive change. Furthermore, much of the literature is concerned with impacts on income inequality rather than wage inequality which is where the theoretical predictions of the GVC literature would lie. Work on cross-country analysis of trade and inequality is less common and this is due to data limitations related to constructing comparable measures of inequality across and within countries—an issue which is discussed in more detail in the next section.

16. In an attempt to reconcile some of the different predictions made in this nascent literature, Baldwin and Robert-Nicoud (2010) propose a unifying theory of trade in tasks. They suggest that the predictions of traditional HOS models continue to stand when one incorporates 'shadow migration' which is akin to using foreign factors of production but where these are paid foreign rather than local wages.

17. The idea of offshoring costs driving GVC activity and inequality is also explored in the so-called Ricardian framework. See the Annex for a discussion of this literature.

The general consensus of the empirical literature is that the role of trade on inequality is small, and often insignificant, (see WTO, 2008 and OECD, 2011). For example, the OECD report *Divided we stand* (OECD, 2011) identified the main determinants of inequality as technological change—often referred to as skill-biased technical change—financial flows, captured through growing outward FDI, and internal policies related to access to education and employment legislation.[18] These, in conjunction with changes in hours worked, gender, race, changes in household structure, and welfare policies (public cash transfers, income tax policies and the like) are the key drivers of inequality in OECD countries.[19]

One interesting question however is whether the insignificant role of trade is due to the small role that trade has played in the past relative to the overall economic activity of countries. Many OECD countries had lower openness ratios and therefore lower exposure to international trade than they do now since a corollary of the proliferation of GVCs is a rising reliance on foreign sourced intermediate products. As tasks are offshored, the share of GDP that depends on trade is likely to increase and therefore the role of trade on inequality could rise.

A notable early attempt at capturing the impact of offshoring on inequality comes from the work of Feenstra and Hanson (1996) who use industry estimates of outsourcing based on intermediate imports to identify whether offshoring contributed to a relative increase in the demand for skilled labour in the US between 1972 and 1990. Their results suggest that offshoring can help explain 30%-50% of the rise in demand for skilled labour and therefore that offshoring can lead to increases in wage inequality.

Meschi and Vivarelli (2009) find that trade with high-income countries worsens the income distribution in developing countries and attribute this effect to skill-biased technological change (where technology is complementary to skilled labour) arising from more integration in world markets.[20] This goes against the predictions of the HOS models but lends support to the arguments put forward by Zhu and Trefler (2005) who identify a similar effect for developing countries.

Kuznets (1955) suggested that as countries move from agriculture-based production to industrial activities they would experience rising inequality as wage disparities between these sectors are important. As countries continue to industrialise, the importance of the agricultural sector wanes and wages begin to equilibrate and therefore inequality falls (giving rise to the famous inverted U-shaped relationship between inequality and development). Frazer (2006) explores this relationship and finds mixed results; while there does appear to be an important relationship between inequality and development it does not necessarily follow Kuznets' predictions.

Michaels et al. (2010) look at whether the ICT revolution has had an impact on the polarisation of skill demand, essentially testing whether there is evidence of skill-biased technological change. Their results suggest that industries which have witnessed greater growth in ICT technologies have seen higher relative demand for educated workers, suggesting that ICT can be a cause of greater inequality.

The role of technology as a determinant of wage inequality is a hotly debated issue. While the consensus view is that it largely benefits high-skilled workers (skilled-biased technological change), Figini and Gorg (2007) suggest that technology transfers, through FDI, may have different effects

18. Although it did find evidence that increased imports from low-income countries did tend to cause greater wage dispersion in countries with weaker employment protection law.

19. The report also highlights inter-generational inequality, upward social mobility, inequality of opportunities and access to education as important drivers of future changes in inequality.

20. Meschi and Vivarelli (2009) undertake a cross-country analysis where they attempt to identify the role of trade on inequality in developing countries. They decompose the impact according to both the source and destination of trade flows (whether these involve other developing countries or industrialised economies).

across developed and developing countries. Indeed, FDI can bring ubiquitous technologies to a country which can also benefit lower skilled labour thereby raising their wages (think of mechanisation in assembly plants).

Overall, the empirical literature suggests that the determinants of wage inequality are likely to be multifaceted and fall within five key categories:

- GVC participation or offshoring
- Levels of development
- Financial flows
- Technology
- Domestic policies such as employment legislation or education.

3. Measurement issues

Measurement issues related to capturing both GVC activity and inequality are likely to be contentious and there are important limitations in the proposed dependent and independent variables worth highlighting.

A conditioning factor in this analysis is the need to have consistent measures of both GVC engagement and inequality across time and countries. The emergence of harmonised inter-country input-output (ICIO) tables has enabled better characterisation of countries' GVC engagement.[21] In contrast, inequality measures, which are often based on micro-surveys, are not easily comparable along these dimensions. To maximise comparability and the number of observations, the WIOD database is used to calculate both indicators of GVC activity as well as measures of inequality. The use of this database is uncontroversial for the former but calculating measures of inequality using aggregate industry data from WIOD is being done for the first time to the best of our knowledge.

The WIOD database has two components: i) an annual inter-country input output table; and ii) an accompanying set of Socio Economic Accounts (SEAs).[22] Information is available for 40 countries and a rest of world (RoW) grouping annually from the period 1995 to 2009.[23] It covers a mix of developed and emerging economies. Twenty-seven EU member states are represented and therefore the sample is EU-biased. The other economies that are covered are Turkey, Canada, Mexico, United States, Japan, Korea, Chinese Taipei, Australia, Brazil, Russian Federation, India, Indonesia and the People's Republic of China (hereafter "China"). Importantly, there are few developing countries and no individual least developed countries.[24] The harmonised sectoral aggregation includes 20 service, 11 manufacturing, and 4 primary sectors.

The WIOD ICIO tables are used to calculate measures of GVC participation whilst the SEAs, which decompose the wage bill associated with labour across high, medium and low-skill labour by shares of total wage labour value added, serve as the basis for the calculation of measures of wage inequality. These calculations are discussed in more detail below. The remaining variables used in the empirical specification are detailed in Table 1. They are classified according to the different sets of determinants of inequality identified from the literature.

21. ICIO tables are interlinked input-output tables that capture country and industry linkages across the globe (see Timmer et al. 2011 and OECD, 2013).

22. See Annex Tables 15 and 16 for a description of the country coverage as well as the variables in the SEAs.

23. The ICIO has recently been extended to incorporate data till 2011 but the SEAs only go as far as 2009.

24. Different measures of inequality are used for the robustness checks in order to identify the extent to which the results are driven by the sample.

Table 1. Determinants of inequality and data sources

Determinant	Variable	Description	Source
Offshorability	Backward participation (later decomposed into high and low skill components)	Foreign value added content of exports	World Input-Output Database (WIOD)
Levels of development	Log of per capita GDP (and its square)	At constant PPP 2005 prices. Serves capture Kuznets type effects, see also Frazer (2009) and Barro (2000)	World Development Indicators (WDI)
Financial flows	FDI	Inward and outward stocks (OECD, 2011)	World Development Indicators (WDI)
Technology	R&D expenditure	As a share of GDP	World Development Indicators (WDI)
Domestic policies	School enrolment in tertiary education share Unemployment, total share	To proxy for education policy As proxy for wage rigidities	World Development Indicators (WDI)

Note: See the Table A.3 for descriptive statistics on these variables.

3.1. Capturing GVC activity

The emergence of databases such as the OECD-WTO TiVA and the WIOD have enabled researchers to better measure GVC activity and therefore gauge its nature and evolution. Two key indicators of are proposed in OECD (2013); i) backward participation; and ii) forward participation. Backward participation captures the share of foreign value added that is embodied in exports. Forward participation, in contrast, is the share of domestic value added in exports that a country sells to other countries in order for these to produce exports.

This distinction is important because it allows one to capture different forms of engagement. For example, a country that is predominantly assembling products into final goods and subsequently exporting these will have a strong backward participation index but a very weak forward participation. Conversely, a country which predominantly supplies intermediates to an assembler will have a highly developed forward participation indicator but a small backward participation measure. These participation measures can therefore give a metric of engagement in the form of *buying* from (backwards) and *selling* to (forward) GVCs (e.g. OECD, 2015a).

Backward participation is a measure of offshoring that should be increasing with the falling costs of coordination as in Grossman and Rossi-Hansberg (2008) or Costinot et al. (2011). It is therefore a measure of 'revealed offshorability'.[25] Forward participation captures the extent to which a country might be receiving offshored activities (the selling side of value chain or technically the extent to which a country's exports are used by other countries to produce their own exports). The link between this indicator and inequality could in principle be thought of the mirror image of the link between the backward linkage and inequality although this is harder to trace from the theoretical literature which tends to consider impacts on the offshoring country rather than that receiving the offshored task.

The skill content of the linkage that countries engage in is likely to matter according to Grossman and Rossi-Hansberg (2008) and Zhu and Trefler (2005). Since information on how value added distributes across skill groups is available (from the SEAs) the backward and forward participation indicators can be broken down into foreign value added originating from high, medium and low

25. 'Revealed' distinguishes it from 'actual' in that it combines the extent to which certain activities are naturally offshorable (e.g. with the currently available technology) but also the impact of policy measures such as trade barriers (e.g. with respect to certain intermediate inputs which embody the offshored tasks) as well as regulations (e.g. with respect to trade of services which also embody the offshored tasks).

skilled value added as well as that associated to capital.[26] This then allows further investigation of how the skill content of the offshored activity, both in terms of the country doing the offshoring or receiving it, impacts wage inequality.

3.2. Measuring inequality

Many measures can be used to capture economic inequality (see Box 2). Each is suited to capturing different facets of this broad concept. The more established methods for calculating inequality rely on micro data such as that obtained from labour force or household surveys (see OECD, 2011). However, this can be problematic in cross-country comparisons as noted by Galbraith and Kum (2004).[27] To make such comparisons feasible, Galbraith and Kum (2004) used the Deininger and Squire (1996) dataset in conjunction with more aggregate data on industrial value added and wages to construct inter-temporal and cross-country comparable measures of inequality. This set an important precedent in the use of industry-level measures of inequality.[28]

This paper uses measures of inequality based on industry data from the Socio Economic Accounts of the WIOD.[29] The main advantage of using this source of data to calculate measures of inequality is consistency with metrics of GVC integration which, as described above, are derived from the same database. This also provides a larger sample of developed and emerging economies over which wage inequality and GVC activity can be measured relative to the more established OECD inequality measures which are mostly available for OECD countries. Another advantage is the flexibility of breaking the working population of a country into different skill levels within sectors which allows capturing different facets of wage inequality such as within-country and within sector inequality as well as global inequality.

This approach is not, however, without limitations. Only wage-income inequality can be captured therefore missing important effects related to unemployment, informality, unincorporated businesses, and wealth transfers, amongst other things. Omitting wealth transfers in the calculation of measures of inequality can have consequences and these are particularly important at the top end of the income distribution (see Piketty, 2014). For example, Bill Gates earns a substantial amount in profits from Microsoft and hence removing him from a sample is likely to understate the level of inequality in the US. Similarly, working with wage bill data may also lead to an underestimation of inequality at the bottom end of the distribution since those workers who are unemployed are not captured.[30] Finally, the reliance on wage-based measures of inequality implies that it is only possible to partially capture how labour markets adjust via changes in employment and how this reflects into changes in inequality.[31] These are arguably important drivers of inequality in OECD countries (OECD, 2011 and 2014) and

26. So that the following will hold: backward participation (FVAE) = high-skillFVAE+ med-skillFVAE + low-skillFVAE + capitalFVAE where FVAE is foreign value added in exports.

27. Galbraith and Kum (2004) , suggest, for example, that the Deininger and Squire (1996) database, which was a laudable first effort to harmonise the use of inequality measures for cross-country analysis, suffered from methodological drawbacks related to the comparability of the underlying data. Often, income based household data was used in one year but in the next, household net expenditure would be used to calculate measures of inequality resulting in important fluctuations in within country inequality measures across time. show how measures based on household gross income tend to be systematically larger than those measured on household net expenditure.

28. This approach has been followed by Meschi and Vivarelli (2007) and Michaels et al. (2010).

29. Galbraith and Kum (2004) used UNIDO data.

30. People who participate in the labour force informally will also not be captured.

31. For example, workers leaving employment would not be captured but pressures on wages resulting from higher unemployment would.

this is why a significant robustness exercise is undertaken using measures of inequality which account for incomes of the unemployed derived from other sources.[32]

What is therefore captured is not the actual degree of household inequality within a country but rather a measure of wage-income inequality amongst the working population. It is in this context that the results are to be interpreted. Nevertheless, recent work by the OECD (2011; p22) suggests that wages and salaries account for 75% of household incomes among working-age adults and, therefore, that increases in household income inequality may have largely been driven by changes in the distribution of salaries.[33] Additionally, working with wage data also provides a better link with the theoretical literature on the impact of value chain trade and inequality which makes predictions related to changes in wages. It could therefore be expected that these predictions will be better reflected in measures of wage-income inequality than in others which take into consideration more holistic measures of inequality.[34]

The first step in calculating measures of inequality is calculating wages. The number of workers across skill-groups and within a sector is identified under the assumption that within sectors, workers engage in the same amount of hours across the different labour categories (high-skilled, medium-skilled and low-skilled).[35] In the second step, to calculate a wage for each of these worker categories, the value added of a given worker category (the wage bill) is divided by the number of workers in that category and sector. The resulting output is an average wage rate for each of the three categories of workers within a sector giving rise to a maximum of 105 country-sector-skill category-year wage observations.[36] This information is then used to calculate aggregate measures of wage inequality[37] – a Gini coefficient—using weights capturing the number of workers across skill categories and sectors within a country (Box 2).[38]

32. Great care has been taken to harmonise cross-country measures of inequality by the OECD in the Income Distribution database (which does not suffer from the problem of using income and expenditures in different years). It includes these very important facets of inequality but has the draw-back of having very few developing countries. This is an important shortcoming when looking at the role of GVCs on inequality since much of the GVC revolution revolves around emerging countries (Baldwin and Lopez-Gonzalez, 2013).

33. Although it is important to note that this 75% figure is an average and therefore hides differences in the reliance on wage income across poorer and richer households.

34. Milanovic and Squire (2007) also argue that wage inequality is likely to better reflect the theoretical predictions.

35. Thus, to compute the number of workers by category the amount of workers in a given sector is multiplied by the share of hours that each occupies across the different skill categories. For example, for Country A if there are 1 000 people working in sector 1, and 50% of the hours put in are from low skilled workers it is assumed that there are 500 low skilled workers in this sector.

36. i.e. 35 sectors multiplied by three categories of labour. By using average wages across skill groups within sectors there is a smoothening of the possible variance arising from differences in wages within particular sectors and skill groups.

37. In addition to country-wide rather than sector specific inequality being of policy importance, the use of an aggregate measure of wage inequality should capture both inter and intra sectoral reallocations of wages and workers.

38. It is important to bear in mind that much of the data used to calculate these Gini coefficients originates from the EUKLEMS dataset and other national sources. Worker skill is defined by educational attainment and therefore not the actual skill level of workers. Whilst this is not hugely problematic at the country level since the definition of skill levels does not vary within country, it can be cumbersome when calculating inequality at the global level. It also presupposes that educational attainment is directly linked to skill levels.

To calculate global inequality a similar technique is used but the 105 wage data points for each country-year are pooled across the entire sample giving 4 200 yearly observations of wages across different countries, sectors and skill-levels. These observations are then weighed by the number of individuals employed in each country-sector-category.[39]

Other sources of comparable inequality data are also used to undertake robustness checks. Three other sources are identified. The first is the Gini coefficient from the Word Development Indicators (WDI) database—WDI Gini. The second is the OECD's Gini coefficient—OECD Gini—where measures before tax are used to ensure comparability with the WIOD measures. Also used is the Estimated Household Income Inequality (EHII) measure from the University of Texas Inequality Project (UTIP) – EHII Gini—which was discussed earlier (see Galbraith and Kum, 2004).

Box 2. Measures of inequality

Percentiles

A relatively straightforward measure of inequality is the ratio between top and bottom percentiles within a population (i.e. income/wages held by the 90^{th} percentile divided by that of the 10th percentile). Since it identifies how much more top earners are earning relative to bottom earners it is an intuitive and readily interpretable measure.

Coefficient of Variation

The coefficient of variation is the ratio of the distribution's standard deviation against its mean. The higher the ratio, the larger the inequality.

Wage bill share

In a cross-country analysis investigating the impact of ICT on polarization of demand for different skilled workers Michaels et al. (2010) use the following wage bill share as their dependent variable:

Share S = (WSNS / (WHNH + WMNM + WLNL)

Where W = hourly wages, S = skill category, N = number of hours worked by skill group.

They test the hypothesis of Autor, Levy and Murnane (2003) positing that ICT substitutes for routine tasks but complements non-routine tasks or, in other words, whether there is evidence of skilled-biased technological change.

Gini Coefficient

The Gini coefficient is a measure of inequality that is based on the joint distribution of cumulative population shares and cumulative income or wage shares. It is computed by ranking individuals from poorest to richest and comparing the cumulative share of the population these represent against their cumulative share of income. If each individual earned the same share of total income, then we would have complete equality. The Gini is calculated by comparing the actual distribution of income to the complete equality benchmark. Values close to 0 identify more equality whereas values near 1 show higher degrees of inequality.

Although a well-established measure of inequality, the Gini coefficient is not without problems. It has often been criticised for not having an intuitive interpretation such as indicators based on percentiles. Moreover, the same Gini coefficient can identify quite different income distributions. For example, countries with relatively large shares of workers earning low salaries are indistinguishable from countries with a relatively large share of workers earning high salaries. That is to say that the Gini does not allow one to capture whether the inequality is driven at the top or the bottom of the distribution which may be relevant for policy.

Theil index

The Theil index is a measure of inequality based on the deviations of each observation from the mean of the distribution. The more disperse the distribution, the higher the sum of the differences from the mean, therefore the higher the index. More precisely the Theil index is a weighted sum of the log ratios of each observation. For example, if an individual's income is exactly at the mean, the ratio is equal to one and therefore its log equal to zero implying that this individual does not contribute to inequality. The sum of the log ratios is weighted by each observation's share of total income.

The Theil index has the convenient property of being decomposable. For instance if one calculates a Theil measure of inequality for the world and then one for each continent, there will be a remaining part of inequality that is not explained by the differences in continents (betweenness) and thus attributed to the variation within continents. This property allows studying how the share of world inequality explained by differences between/within countries, skill groups, sectors has evolved through time.

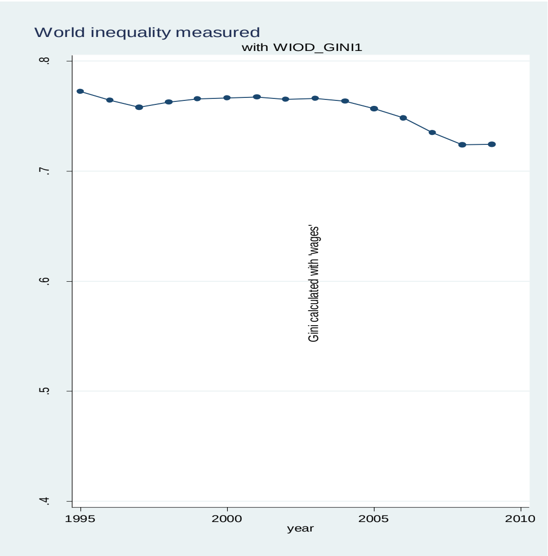
39 This is close to Milanovic's (2012) global inequality (concept 3) although here PPP adjustments are not made implying that the calculated measure is likely to overestimate the degree of global inequality.

4. How has global and country-specific inequality evolved?

4.1. Global wage inequality is falling…

A number of recent contributions, including OECD (2009), OECD (2011) and Baldwin and Lopez-Gonzalez (2013), suggest that what is new about the current wave of globalisation is its North-South dimension (since the fragmentation of production between developed countries has existed for some time). For example, the share of world GDP held by the G7 countries has steadily declined in favour of seven emerging economies, in particular China and India. This redistribution of GDP should translate into a reduction in global inequality and indeed the global measure of wage inequality shown in Figure 1 confirms this.[40]

Figure 1. Evolution of global wage inequality 1995-2009



Note: Global wage inequality is calculated using a population weighted Gini index calculated from pooled country-sector-year wage data from the WIOD database (4 200 observations per year; 40 countries, 35 sectors and three skill categories).

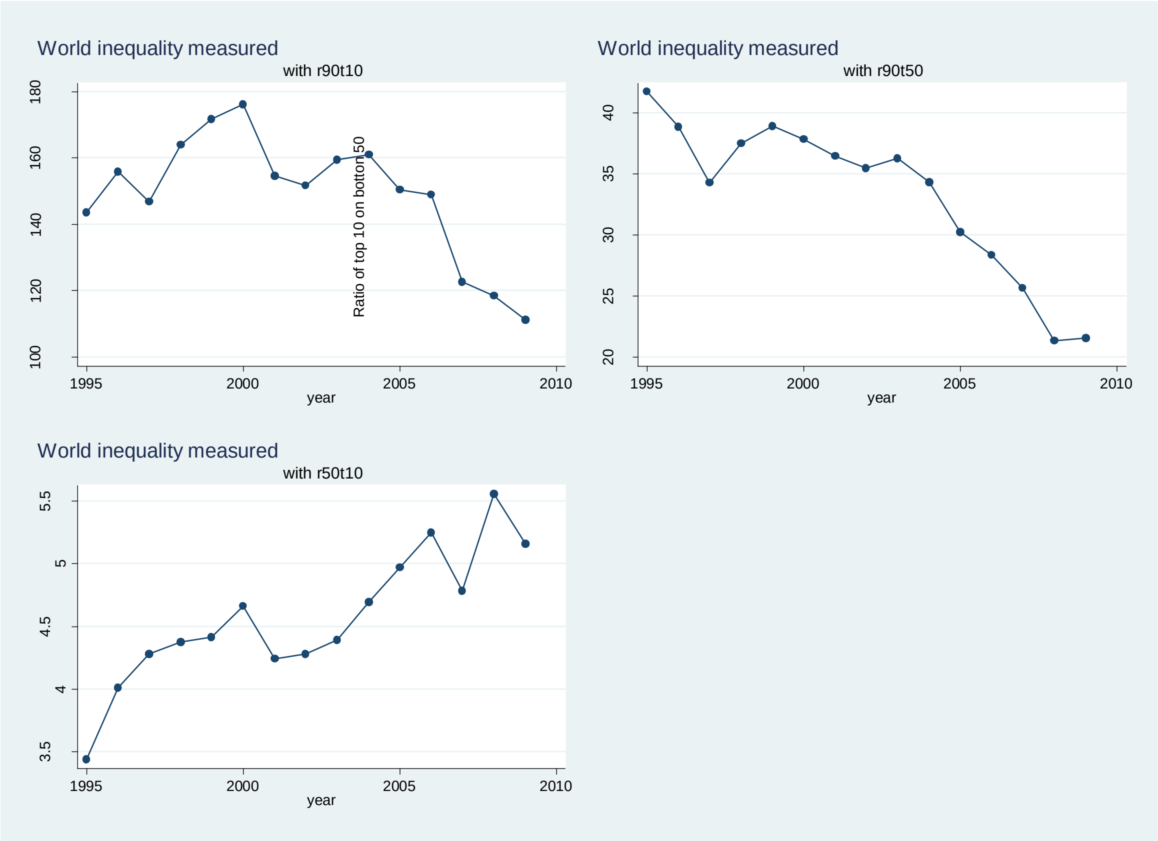
Source: Authors' calculation based on WIOD SEA data.

The percentile based measures of global wage inequality (Figure 2) show an initial increase and then a decline in global inequality across the whole distribution. Interestingly, the perceived reduction in global wage inequality (*with r90t10*) appears to have been driven predominantly by reductions in inequality at the top end (*with r90t50*) of the distribution since inequality worsened at the bottom end (*with r50t10*).[41] These are mainly driven by differences across countries rather than within countries (i.e. differences between, for example, the US and Brazil rather than differences in wages within the United States)—a finding similar to that of Bourguignon and Morrison (2002). See the Annex for a discussion.

40. Global inequality is calculated by pooling the 105 country-sector-year wage observations across the entire sample (giving = 4 200 yearly data-points) and then using this information to calculate a weighted Gini coefficient. Note that the figure is close to the 0.7 Gini reported in Milanovic (2012).

41. Using a Theil index to investigate what is driving changes in global wage inequality it is found that these are mainly driven by differences across countries rather than within countries (i.e. differences between, for example, the US and Brazil rather than differences in wages within the US)—a finding similar to that of Bourguignon and Morrison (2002). See the Annex section on global inequality for a discussion.

Figure 2. Evolution of percentile measures of global wage inequality 1995-2009



Note: Global inequality is calculated using a percentile based measure using pooled country-sector-year wage data from the WIOD database (4 200 observations per year; 40 countries, 35 sectors and three skill categories).
Source: Authors' calculation based on WIOD SEA data.

4.2. … But the evolution of country-specific inequality is mixed

There is evidence of a HOS pattern emerging when looking at the levels and evolution of inequality across different indicators (Table 2).[42] For example, the *WIODGin*i measure identifies 17 countries with falling inequality, nine of which are emerging economies (out of a possible 14 in the sample) while the remaining eight are developed economies (see Table A.1). Nevertheless, on aggregate and across different measures of inequality it is found that:

42. Table 2 presents simple growth regressions showing the evolution of the Gini coefficient for individual countries clustered into emerging and developing countries for the period 1995-2009 so as to identify the direction and magnitude of changes in inequality across broad groups (for the full country breakdown see Table A.1). The intercept gives an indication of the starting average level of inequality whilst the coefficient shows the gradient of the regression line (the growth rate). The 'coverage' of the indicators varies significantly across the different sources. While the *WDIGini* coefficient covers 15 of the countries with a mix of developing and developed economies, the *OECDGini* sample is heavily biased towards developed economies. Biases associated with different country coverage can be problematic, particularly if there are key differences between developed and emerging economies, which are found to be important.

- emerging economies tend to have higher initial levels of inequality relative to developed economies (and this seems to be quite robust across the different indicators and in line with the findings of OECD (2014).[43]
- On average, emerging economies appear to have been able to reduce inequality but developed countries have generally seen inequality rise.

Table 2. Levels and growth rates of Gini coefficients between the period 1995-2009

	WIOD GINI		WDI GINI		OECD GINI		EHII Gini	
	Cons	β	Cons	B	Cons	β	Cons	β
Average								
TOTAL	0.27	0.00%	0.35	0.16%	0.41	0.03%	0.38	0.06%
Emerging	0.36	-0.09%	0.37	0.11%	0.59	-1.26%	0.43	-0.05%
Developed	0.21	0.05%	0.30	0.33%	0.39	0.14%	0.35	0.12%
Average (only for significant changes in time calculated using growth regressions)								
TOTAL	0.27	-0.02%	0.35	0.18%	0.41	0.18%	0.38	0.08%
Emerging	0.36	-0.13%	0.37	0.09%	0.59	-1.64%	0.43	-0.13%
Developed	0.21	0.05%	0.30	0.46%	0.39	0.35%	0.35	0.15%

Note: β identifies the gradient of the time trend and therefore the growth in inequality, the constant gives an indication of the starting levels of inequality in a country. Number of observations across the different indicators varies and data has not been deflated. *WIOD GINI* is a measure of wage inequality whereas the other measures capture different facets of income inequality. See Table A.1 for the scores of different countries covered across the different measures.

5. How has GVC participation evolved?

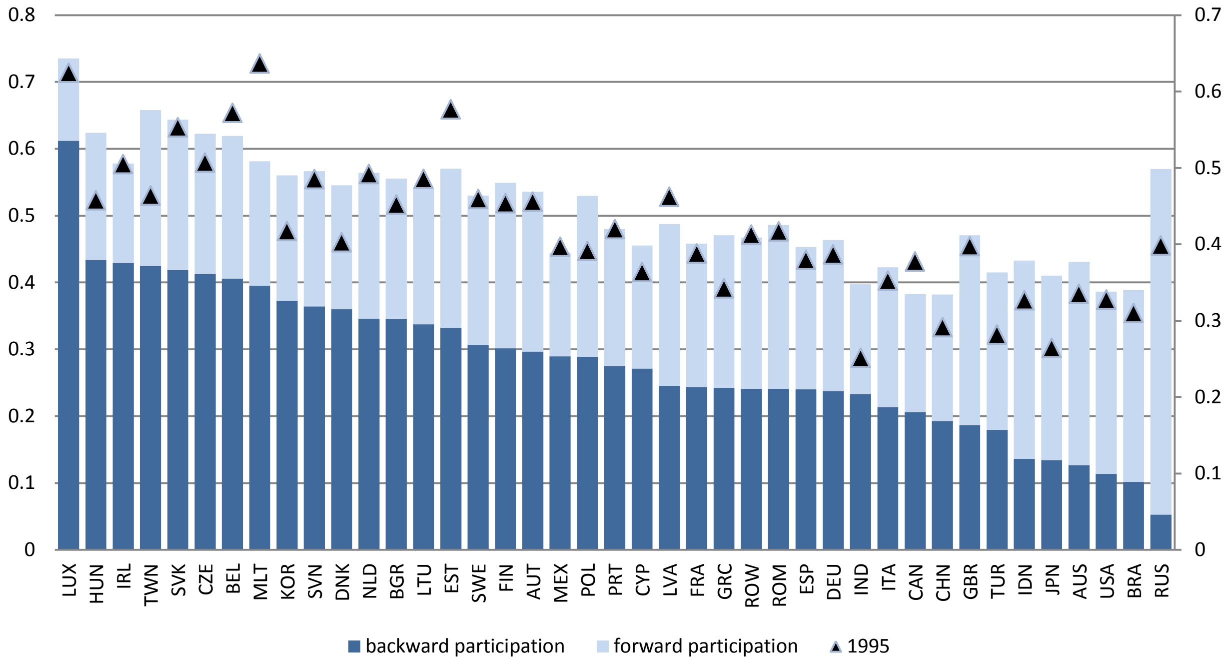
Concurrent with the changes in wage inequality described above is a growing participation in GVCs (Figure 3) although the patterns of engagement vary between countries.[44] On the one hand countries such as Luxembourg, Hungary and Ireland have very prominent buying elements (backward linkage) whilst on the other hand natural resource rich countries such as Russia and Brazil mainly engage through selling inputs into value chains (forward linkage).

Participation in GVCs is associated with desirable outcomes such as growing productivity, increased sophistication of exporting bundles and greater diversification of trade (OECD, 2015a). This implies that the benefits of engaging in international production networks may need to be weighed against the possible distributional consequences that may arise from further participation. Governments may therefore want to promote further engagement but they may wish also to consider mitigation of possible distributional pressures through accompanying policies.

43. At the individual country level it is important to note that the consistency of the sign of these changes is not overwhelming and this suggests that the choice of indicator may be important (it also motivates the use of different measures of inequality as robustness checks). This arises from i) having different years in the samples within a country; ii) using measures that are calculated using different methods (i.e. post- or pre-tax measure; and/or iii) using different types of calculations for the gini coefficients (i.e. weighted versus unweighted). Only in Canada, where data is available for all four measures, the same direction of changes across all indicators is observed. Imposing lower order consistency conditions (i.e. where inequality is going in the same directions across less than four measures of inequality) rising inequality is consistent in three measures for Austria, the Czech Republic, United Kingdom, Hungary, Japan, Korea, Luxembourg, and the United States. Consistent falling inequality arises in Brazil, Russian Federation and Turkey.

44. For all countries except Belgium, Malta, Estonia, Latvia and Canada.

Figure 3. GVC participation (2009)



Source: Authors' calculations from WIOD. 1995 values represent GVC participation (i.e. Backward and forward participation).

Determinants of participation, and therefore the role that governments can play in promoting more engagement, can be divided into two broad elements according to OECD (2015a): i) structural factors which are hard to influence in the short to medium run; and ii) policy factors which governments can use to shape participation. While the structural factors—which include levels of development, geographical location, size of the market—are the main determinants, governments can shape participation through measures that promote trade and investment openness.

One key prediction of Grossman and Rossi-Hansberg's (2008) and Zhu and Trefler (2005) is that the type of linkage that countries engage in is likely to matter for wage inequality and in particular whether this involves high or low skilled labour. When looking at the evolving patterns of production decomposed according to three types of value added; two by skill (high or low-medium skill) and one by returns to capital, which includes profits, several observations emerge (see Figure 4 and Figure A.4)[45]:

- 75% of globally traded value added comes from developed countries (29 percentage points from capital returns, 28 from the value added of low and medium skilled workers, and 18 from high-skilled worker value added).
- Emerging economies represent 25% of globally traded value added with capital returns being the main source (15 percentage points – see Figure A.4).
- Most of the value added embodied in exports remains domestic. In developed countries this is mainly from capital and low-skill labour whilst in emerging economies it is overwhelmingly

45. The left panel shows the share that each of these elements occupy in the production of a unit of exports across developed and emerging countries (each column therefore adds up to 100%) in 1995 and in 2009. The origin of this value added; whether domestic, or imported from developed or emerging countries is also shown. For example, the left hand panel (bottom right) shows that 49% of the domestic value added embodied in emerging country exports is accounted for by returns to capital.

from capital. However, where changes in time are concerned, developed countries are increasingly providing high-skilled labour value added whilst emerging economies have seen increases in capital and low-skilled value added.

- Returns to capital are the largest category of imported value added used for exports.[46]
- Offshoring of low-skilled value added tends to be higher than offshoring of high-skilled value added for both developing and emerging economies (see also Figure A.3).

Figure 4. Origin of value added embodied in exports by type across developed and emerging countries

		1995		2009	
		Developed	Emerging	Developed	Emerging
Developed	High skill	3%	2%	5%	3%
	Low-medium skill	8%	5%	7%	5%
	Capital	6%	4%	7%	5%
Emerging	High skill	0%	0%	1%	0%
	Low medium skill	1%	1%	2%	1%
	Capital	1%	1%	4%	2%
Domestic	High skill	13%	5%	18%	7%
	Low-medium skill	38%	37%	29%	28%
	Capital	29%	44%	27%	49%

		1995		2009	
		Developed	Emerging	Developed	Emerging
Developed	High skill	15%	16%	18%	19%
	Low-medium skill	42%	40%	28%	30%
	Capital	33%	32%	28%	30%
Emerging	High skill	1%	1%	2%	2%
	Low-medium skill	4%	5%	8%	7%
	Capital	6%	6%	16%	13%

Note: Left panel shows the share that each column country type represents in the exports of the row country-skill type. For example, in 1995 38% of the value added of developed country exports came from domestically employed low-medium skilled labour. The right panel shows how foreign value added is being used according to its origin and destination so that in 1995 15% of the foreign value added that developed countries use to produce exports comes from high-skilled workers from other developed countries.

Source: Authors' calculations from WIOD.

6. What is the impact of GVC participation on wage inequality?

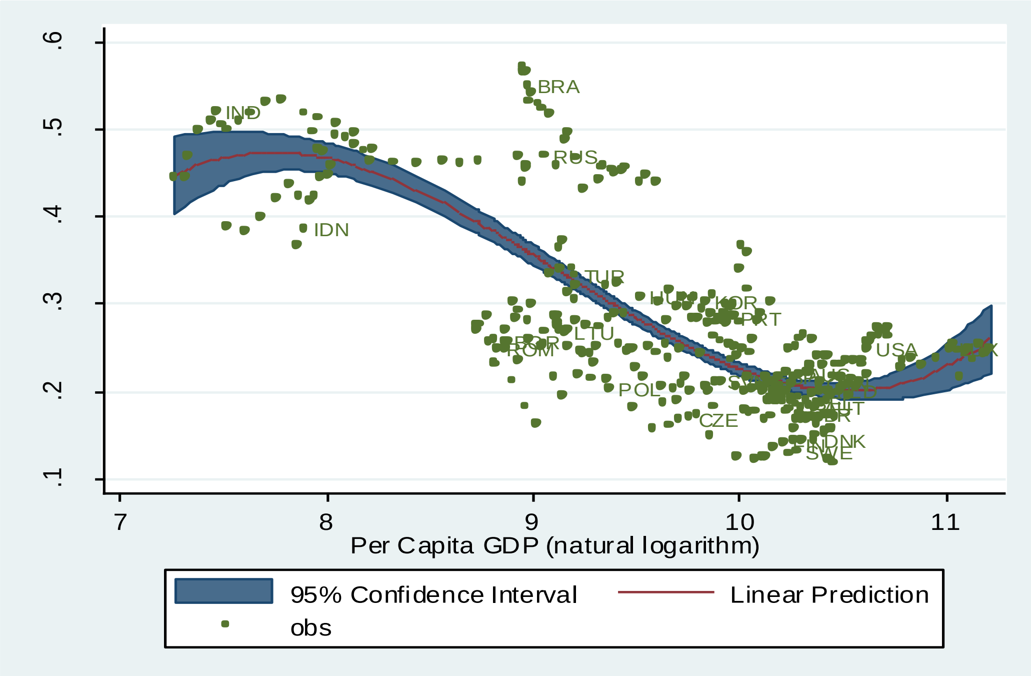
6.1. Cross-country correlations

The correlation between the WIOD Gini measure of wage inequality and the level of economic development as proxied by GDP per capita (Figure 5) shows that developing countries tend to be more unequal than developed countries.[47] Importantly, the explanatory variables used, the per capita GDP and its non-linear transformations, explain a large part of the variance in the Gini indicators; 55%, and this suggests that the development dimensions is a key feature of differences in levels of wage inequality.

46. A more detailed analysis of the role of capital offshoring in determining wage inequality was undertaken. The results are not discussed herein but some be seen in Figure A.14.

47. They also lend support to the earlier finding that it is the between country variation which might be driving differences in inequality (note that individual countries tend to cluster at particular intervals of the development spectrum).

Figure 5. Levels of development and wage inequality



Note: correlation remains negative when other measures of inequality such as the WDI, and the EHII Gini are used.

Source: Authors' calculations from WIOD, GDP from WDI indicators at constant 2005 PPP prices.

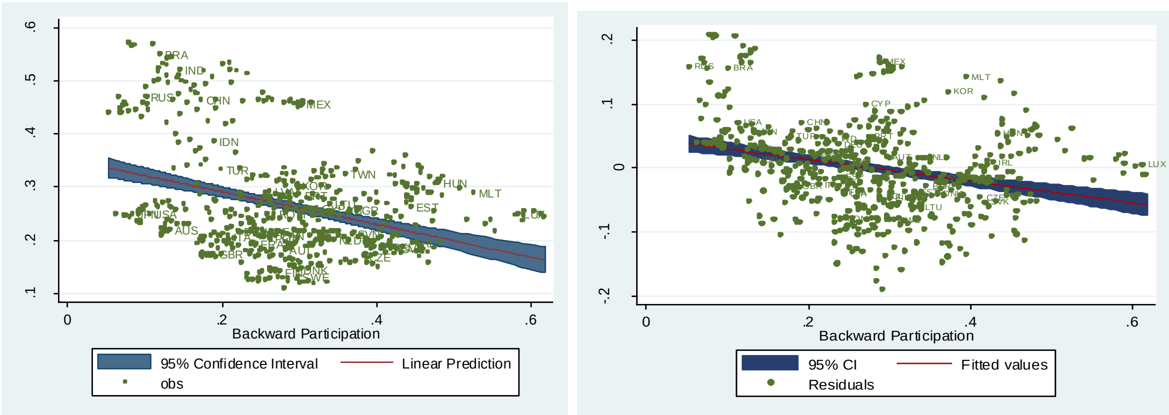
When looking at the correlation between the WIOD Gini coefficient and the measure of offshoring—the backward GVC participation index (Figure 6), the data suggest that countries which have a higher backward participation also tend to have lower levels of wage inequality.[48] The observed correlation continues to hold when controls for other confounding factors, such as the role of levels of development affecting both wage inequality and backward participation, have been factored out (right panel of Figure 6).

Finally, when looking at the correlations between wage inequality and the nature of the linkage that countries engage in (Figure 7) it is observed that countries which engage in a higher degree of low and middle-skill offshoring (the low skill backward linkage) have lower levels of wage inequality. However, countries with a higher high-skill share of offshoring are seen to have higher wage inequality. Similarly, it is found that being the recipient of a low skilled (high) task is also associated with lower (higher) wage inequality.

This provides some evidence supporting Grossman and Rossi-Hansberg's (2008) conjectures that offshoring is complementary to the wages of the skill type that is being offshored. However, since the low to medium skill backward participation rate dominates over the high-skill backward participation rate (Figure A.1), the inequality reducing element of backward participation appears to dominate as was shown in Figure 6.

48. The explanatory power (R-sq) of the regression involving the WIOD measures of wage inequality and the backward participation indicator is 12% with statistically significant estimated negative coefficients.

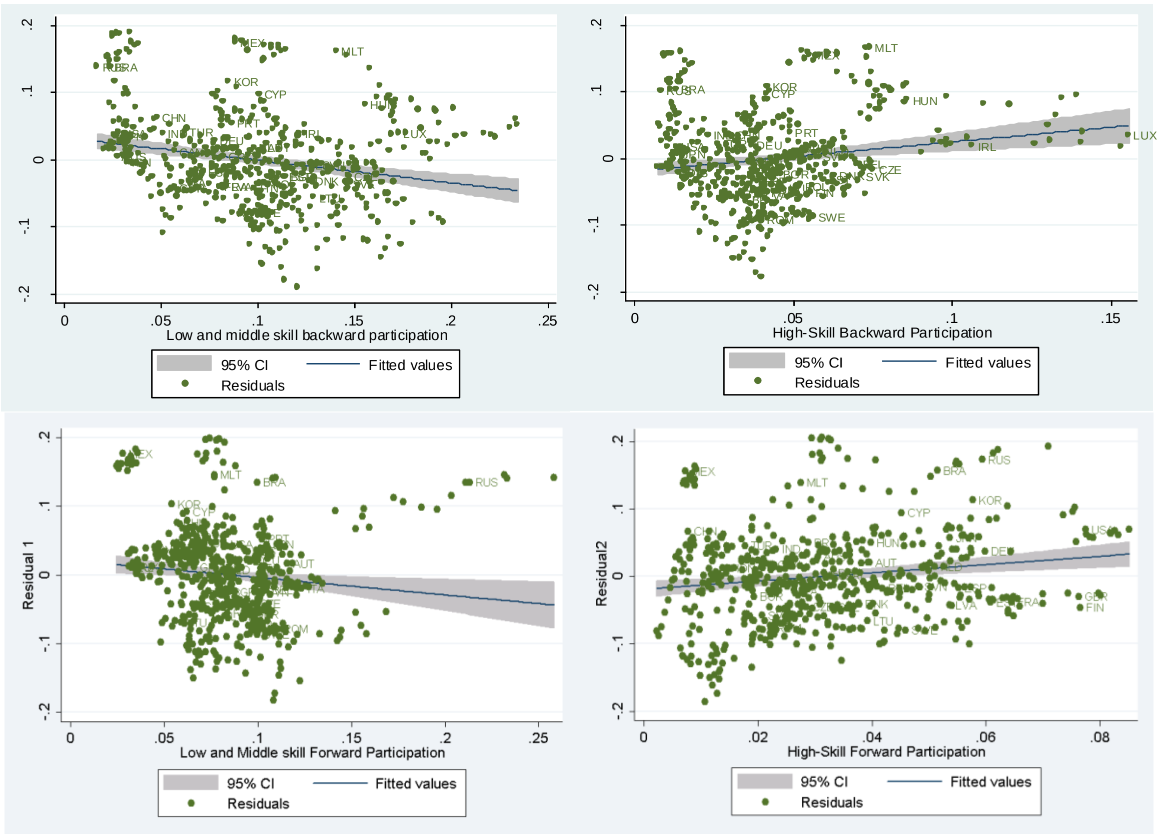
Figure 6. Backward participation in GVCs and wage inequality



Note: The correlation remains negative across different measures of inequality such as the WDI, and the EHII Gini. The right panel shows the correlation between the residuals obtained from regressing the Gini measure against the per capita GDP and its square (residual) and the backward GVC participation index.

Source: Authors' calculations based on WIOD.

Figure 7. Nature of participation and residual wage inequality



Note: Left panels obtain residuals from regressing the Gini coefficient against GDP per capital and its square as well as the high-skill backward (forward) linkage (residual 1). Right panels obtain residuals from regressing the Gini coefficient against GDP per capital and its square as well as the low-and-medium-skill backward (forward) linkage (residual 2).

Source: Authors' calculations based on WIOD.

6.2. Econometric evidence

The determinants of wage inequality fall within the 5 broad categories identified in the literature review. The first is offshoring which is the key variable of interest and which is proxied by the degree of backward or forward participation in GVCs. The following control variables are also added; i) levels of development and economic size; ii) financial flows – captured through stocks of FDI; iii) measures of technology – as control variables for skill-biased technological change; and iv) variables that reflect domestic policies such as employment rigidities. Different permutations of the following baseline specification are estimated:

$$Gini_{it} = \beta_0 + \beta_1 Backward + \beta_2 lnGDPcap + \beta_3 (lnGDPcap)^2 + \beta_4 lnGDP + \beta_5 FDIstocks + \beta_6 R\&Dexp + \beta_7 DomesticPolicies + e_t + v_i + u_{it} \quad (1)$$

where e_t and v_i represent different time and country fixed effects and u_{it} is a random error term with the usual properties.

Milanovic and Squire's (2007) discussion of possible problems arising from estimating the impact of trade liberalisation on wage inequality helps guide the empirical approach (see the Annex for a more detailed discussion). The key problems that arise relate to biases caused by i) omitted variable bias or ii) unobserved heterogeneity. Different estimation techniques and measures of inequality are used to control for these (results reported in the Annex). Another potential concern relates to sample selection. The WIOD database is heavily biased towards developed countries and since there appear to be big differences between developed and emerging economy levels and changes in wage inequality it is possible that the results mostly reflect effects relevant to developed countries. To reduce such biases, results separating developed and emerging economies are presented. Later, robustness checks are carried out using a more inclusive sample in terms of country coverage although this comes at the cost of granularity related to the loss of information on the nature of the participation in GVCs (whether low or high-skilled).

6.2.1. Aggregate participation and wage inequality

The results from the econometric model (Table 3) confirm the negative relationship between backward GVC participation and wage inequality which holds for both developed and emerging countries.[49] The role of FDI is hard to identify since it is likely to have a double impact. First, inward FDI stocks correlate with backward participation (as documented in OECD, 2015a), second it also affects the technology and therefore its effects can have a skill-bias which can then lead to changes in wage inequality.[50] Nevertheless, in developed countries higher inward stocks of FDI correlate with lower wage inequality whilst in emerging countries the relationship is insignificant. Figini and Gorg (2007) suggest that the inequality-reducing effects of FDI may arise from the technology transfer nature of FDI making technologies more ubiquitous thereby also benefiting low skilled workers (and not just high-skilled workers as it is commonly thought).

The negative coefficient on the technology measure (column 1), captured through the R&D share of GDP, suggests that higher spending on R&D is associated with lower levels of wage inequality and

49. The estimation is a fixed effect panel specification which means that both the within and the between variance of the sample is captured.

50. It is important to note that the FDI variable is to be interpreted at given levels of backward participation. That is to say that there is a positive correlation between FDI inflows and GVC activity (as established in the nascent literature, see WIR, 2013 and OECD, 2014b). In fact, the slight fall in the coefficient on the backward linkage measure after the introduction of this variable suggests that this measure was picking up effects related to changes in FDI inward stocks.

this suggests that upgrading through technology could lead to reductions in wage inequality.[51] The share of the population with tertiary education also shows a negative coefficient thereby confirming the view that skill-upgrading could play an active role in reducing inequality or that increasing the relative supply of skilled labour will have a wage inequality reducing impact. Finally, and perhaps surprisingly, the level of unemployment of a country appears to be negatively related to inequality, though the measure of inequality does not comprise people that are unemployed.[52]

Table 3. Determinants of wage inequality

Dep Var: WIODGini	(1)	(2)	(3)
	All	emerging	developed
Backward participation	-0.191***	-0.194***	-0.247***
	(0.0268)	(0.0582)	(0.0289)
lnGDPperCapita	0.102	0.162	-0.325
	(0.102)	(0.167)	(0.275)
lnGDPperCapita (squared)	-0.00912	-0.00937	0.0188
	(0.00566)	(0.00982)	(0.0133)
lnGDP	0.00681**	0.0173**	0.000859
	(0.00274)	(0.00758)	(0.00277)
lnFDI_Inward_Stock	0.00243	0.00211	-0.00913***
	(0.00244)	(0.00670)	(0.00216)
RandD_expenditure_share_GDP	-0.0244***	0.0680***	-0.0297***
	(0.00264)	(0.00884)	(0.00228)
School_enrollment_tertiary_share	-0.000795**	-0.00108**	-0.000671***
	(0.000271)	(0.000381)	(0.000141)
Unemployment_total_share	-0.00525***	-0.00468***	-0.00122
	(0.000919)	(0.00104)	(0.000740)
Constant	0.0973	-0.747	1.810
	(0.478)	(0.697)	(1.426)
Observations	417	153	264
R-squared	0.646	0.648	0.461
Year Fixed Effects	Y	Y	Y

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

51. Higher R&D expenditure also has a multifaceted effect. It appears to increase inequality in emerging economies but decrease that of developed countries which suggests that spending on research and development could have a high-skill-bias in the developing world whilst it is associated with more equitable distributions in developed countries. These results are rather hard to interpret. R&D spending is expected to increase high-skilled worker productivity (i.e. skill-biased technical change) however the measure is correlated with different variables in the specification and it is therefore hard to trace what it is capturing in this instance since we are already controlling for different aspects of technology transfer transpiring through FDI and indeed the measure of GVC participation.

52. It is conjectured that countries with higher unemployment levels should exhibit lower wage bargaining powers and therefore it might be the case that market wage setting is behind changes in inequality in the working population. On the other hand the negative relationship between inequality and unemployment can be explained by the fact that in countries with underperforming labour market unemployment may encompass those in the workforce that have low or inadequate skills and that would be earning very low wages in countries with low unemployment. As the measure of inequality used is based on wages, unemployment thus may absorb those workers that would otherwise contribute to higher inequality with their low wages.

Three sets of robustness checks are undertaken. The first, reported in Table A.4, uses Gini coefficient measures from different sources (World Bank, OECD and EHII) to see whether the aforementioned effects hold where different types of inequality are concerned. The second, shown in Table A.5, uses different model specifications to control for possible, persistence or unobserved heterogeneity problems (GMM and fractional logit). The third, Table A.6, uses measures of income inequality from the EHII database as well as GVC participation indicators calculated from the EORA database to investigate whether the results continue to hold, and in particular if this is the case in a sample that includes a wider coverage of developing and least developed countries.[53]

Across all three robustness checks the negative relationship between offshoring and wage inequality remains. The estimations therefore appear to be robust with respect to i) different measures of inequality and, importantly, those capturing income rather than wage inequality; ii) different specifications controlling for unobserved heterogeneity or omitted variable bias; and iii) a sample comprising more developing countries. However, when running the model in terms of *changes* rather than levels it is found that the backward linkage variable loses significance (Table A.9). One possible explanation for this could be that the role of changes in offshoring on changes in wage inequality depends on whether the offshoring activity engages high or low skilled workers as is suggested in the theoretical literature (Grossman and Rossi-Hansberg, 2008, and Zhu and Trefler, 2005). This suggests that it is necessary to look deeper into the composition of the participation rate in order to better understand the drivers of changes in wage inequality.

Another aspect to consider is the role that receiving an outsourced task plays in determining the level and changes in wage inequality. The results (Table A.8) suggest that there is a positive correlation between forward participation and wage inequality (which holds when considering emerging and developed countries) but this variable again becomes insignificant in the changes specification (the right panel). This might also arise from the lack of distinction between high and low-skilled participation.

6.2.2. Does the type of participation matter?

To test whether the type of offshoring that countries engage in matters the backward linkage is decomposed into its high and low skill components (Table 4). The results show that higher backward linkages composed of foreign high-skill value added are associated with countries with higher levels of wage inequality where the reverse holds for sourcing low and medium skill value added in exports; results which reflect the theoretical predictions of Grossman and Rossi-Hansberg (2008). These results hold for emerging and developed countries although for the latter the coefficient on high-skill offshoring is not significantly different from zero. The remainder of the results are in line with the earlier estimations of Table 3.[54]

In order to identify whether these results remain valid with respect to income rather than wage inequality, the same regressions are ran using the OECD's Gini coefficient. Here it is found that the

53. Although this new database has a wider coverage in terms of countries the measurement of GVC participation is less precise (see OECD,2015a for a discussion of using GVC participation indicators calculated from the EORA database).

54. When looking at whether changes in the type of offshoring correlate with changes in wage inequality in columns 4, 5 and 6, the results for the entire sample (column 4) show that the wage inequality-reducing impact of low-skilled offshoring prevails as does the wage inequality augmenting impact of growing high-skilled offshoring. Looking at these results in light of those in Table A.8 (where no differentiation across the type of backward linkage was made) suggests that this differentiation is important and explains why significant coefficients were not obtained earlier. However, when looking at how this decomposes across emerging and developed countries it is found that there is no statistically significant relationship between the type of backward participation and wage inequality

general results hold (Table A.9), that is to say that income inequality also seems to be affected in a similar fashion as wage inequality (see also Table A.12).[55]

Table 4. Determinants of wage inequality by type of backward linkage

	(1)	(2)	(3)	(4)	(5)	(6)
		Levels			Changes	
VARIABLES	All	Emerging	Developed	All	Emerging	Developed
High-skill backward participation	2.700***	5.320***	0.195	1.058**	1.760	-0.0485
	(0.245)	(0.997)	(0.118)	(0.522)	(1.416)	(0.530)
Low/medium-skill backward participation	-1.873***	-2.792***	-0.853***	-0.479*	-0.850	-0.0758
	(0.0867)	(0.337)	(0.0614)	(0.237)	(0.483)	(0.292)
lnGDPperCapita	0.413***	0.511**	-0.593	0.255	0.893**	-1.125
	(0.0549)	(0.188)	(0.336)	(0.213)	(0.310)	(0.755)
lnGDPperCapita (squared)	-0.0261***	-0.0309**	0.0306*	-0.0221**	-0.0602***	0.0580
	(0.00297)	(0.0113)	(0.0162)	(0.0103)	(0.0112)	(0.0393)
lnGDP	0.00845***	0.0197**	-0.00162	0.142	0.147	0.0201
	(0.00196)	(0.00718)	(0.00279)	(0.115)	(0.206)	(0.175)
lnFDI_Inward_Stock	-0.00621***	-0.0155*	-0.00859***	0.00399	0.00700	0.0163*
	(0.00193)	(0.00737)	(0.00197)	(0.00590)	(0.00624)	(0.00951)
RandD_expenditure_share_GDP	-0.0207***	0.0575***	-0.0284***	0.00795	0.00377	0.00526
	(0.00247)	(0.0159)	(0.00226)	(0.0110)	(0.0275)	(0.00871)
School_enrollment_tertiary_share	-0.000514**	-0.000287	-0.000600***	-0.000349	0.000112	-0.000316
	(0.000186)	(0.000259)	(0.000134)	(0.000277)	(0.000401)	(0.000380)
Unemployment_total_share	-0.00448***	-0.00310***	-0.00140*	0.00105	-0.00137*	0.00278***
	(0.000695)	(0.000987)	(0.000738)	(0.000983)	(0.000713)	(0.000914)
Constant	-1.264***	-2.054**	3.382*	-3.912*	-6.667*	4.938
	(0.251)	(0.779)	(1.749)	(2.055)	(3.512)	(5.405)
Observations	417	153	264	417	153	264
R-squared	0.717	0.737	0.487	0.242	0.446	0.302
Number of time	14	14	14			
Number of rep				37	13	24

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Finally, the role of different types of forward and backward engagement in determining wage inequality are investigated in an all-encompassing framework (Table 5).[56] For the entire sample (column 1) the results show that both high skilled forward and backward linkages are associated with

55. One possible concern is that the measures of high and low skill backward participation are collinear and therefore the interpretation of the sign might be complicated. To determine that this is not driving the results a robustness check using the shares that each linkage occupy in the total linkage is undertaken. Similar results are found (see Table A.10).

56. Standardised coefficients are used in Table A.9 so as to be able to compare the different coefficients across the different measures of participation. Here the low-skilled backward coefficient is seen to be larger than the high-skilled backward coefficient and therefore the overall impact is dominated by the inequality reducing effect. However where the forward participation coefficients are concerned, the high-skilled coefficient is higher than the low-skill one by quite a bit and this is what drives the positive effects.

higher levels of wage inequality whereas both low skilled linkages are associated with lower levels of wage inequality although were changes in these measures are concerned there are some variables that are not significant. Two robustness tests to verify the validity of these results are undertaken. First, one that considers whether the results hold when using different measures of inequality (Table A.13). Second, one that uses added controls for relative skill intensities as well as offshoring involving capital value added (Table A.14). The results continue to hold thereby lending further support to the idea that it is the type of engagement in GVCs which is important when considering the link with respect to inequality.

Table 5. Determinants of wage inequality across different types of participation

	(1)	(2)	(3)	(4)	(5)	(6)
		Levels			Changes	
VARIABLES	All	Emerging	Developed	All	Emerging	Developed
High-skill backward participation	2.976***	3.261***	0.176	1.207**	2.089	0.179
	(0.268)	(0.794)	(0.184)	(0.569)	(1.535)	(0.606)
Low/medium-skill backward participation	-1.881***	-1.886***	-0.809***	-0.505**	-1.005*	-0.0623
	(0.0925)	(0.362)	(0.0603)	(0.235)	(0.473)	(0.284)
High-skill forward participation	0.900***	3.068***	0.121	0.654**	1.073*	0.392
	(0.0976)	(0.538)	(0.0867)	(0.294)	(0.581)	(0.317)
Low/medium-skill forward participation	-0.131*	-1.015***	-0.135*	-0.0714	-0.111	0.259
	(0.0739)	(0.143)	(0.0748)	(0.188)	(0.233)	(0.408)
lnGDPperCapita	0.482***	1.383***	-0.456	0.342*	0.840**	-1.049
	(0.0568)	(0.220)	(0.376)	(0.199)	(0.302)	(0.911)
lnGDPperCapita (squared)	-0.0302***	-0.0822***	0.0237	-0.0267**	-0.0599***	0.0562
	(0.00305)	(0.0131)	(0.0181)	(0.00986)	(0.0110)	(0.0483)
lnGDP	0.0118***	0.0376***	-0.000261	0.136	0.189	-0.00705
	(0.00234)	(0.0105)	(0.00281)	(0.107)	(0.201)	(0.157)
lnFDI_Inward_Stock	-0.00870***	-0.00714	-0.00937***	0.00436	0.00484	0.0147
	(0.00225)	(0.00754)	(0.00190)	(0.00616)	(0.00898)	(0.00918)
RandD_expenditure_share_GDP	-0.0230***	0.0292	-0.0277***	0.00715	0.00222	0.00425
	(0.00248)	(0.0207)	(0.00268)	(0.0111)	(0.0268)	(0.00916)
School_enrollment_tertiary_share	-0.000676***	0.000406	-0.000627***	-0.000275	0.000142	-0.000359
	(0.000200)	(0.000467)	(0.000140)	(0.000277)	(0.000410)	(0.000390)
Unemployment_total_share	-0.00479***	-0.00402***	-0.00159**	0.00106	-0.00166**	0.00293***
	(0.000638)	(0.000954)	(0.000727)	(0.00103)	(0.000703)	(0.000921)
Constant	-1.634***	-6.275***	2.678	-4.179**	-7.281*	5.053
	(0.255)	(1.021)	(1.962)	(1.933)	(3.445)	(5.925)
Observations	417	153	264	417	153	264
R-squared	0.731	0.796	0.491	0.261	0.470	0.324
Year FE	Y	Y	Y	Y	Y	Y
Number of rep	N	N	N	Y	Y	Y

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In order to compare the relative magnitudes of the different types of participation standardised coefficients are used (reported in Table A.11). The results suggests that, where the backward linkage is concerned, the coefficient on the low-skilled backward participation is larger than the coefficient on high-skilled backward coefficient and therefore that the overall impact is dominated by the inequality reducing effect. However where forward participation is concerned, the coefficient on high-skilled participation is higher than the coefficient on low-skilled one suggesting that the inequality increasing effect dominates.

7. Conclusions and implications for policy

Income inequality has been on the rise in several countries since the beginning of the 1990s (OECD, 2011, 2014 and 2015b) even at a time where global inequality appears to have fallen (Milanovic, 2012). Changes in the distribution of income are not only an important economic phenomenon but also a formidable social and political challenge, and globalisation and trade are seen as potential culprits. Economic research on its own cannot substitute for the political process in deciding whether, and if so how, income inequality should be reduced, but it can help by disentangling the different determinants as well as shedding light on the underlying mechanisms thereby informing the political process.

Factors that contribute to income inequality are multifaceted; they include, for example, unequal returns to factors of production (e.g. factor scarcity), exposure to competition, taxation, access to education, skill-biased technological change and employment or welfare policies (i.e. public transfers, income tax policies and the like, see OECD, 2011). But with the concurrent wave of globalisation, evidenced through the growing participation in global value chains as shown in OECD (2013), questions related to how these processes are linked are increasingly coming to the fore.

The objective of this paper was therefore to contribute to a better understanding of the relationship between inequality and trade by revisiting the links between one important component of income inequality—wage inequality—and the proliferation of global value chains.

This paper shows that changes in country-specific inequality have been mixed, but certain common features emerge. For example, although the level of development appears to be a strong determinant of inequality, with emerging countries exhibiting higher average levels of inequality, it also seems to be the case that these have managed to reduce their levels of inequality and are therefore converged towards the lower developed country levels of wage inequality. However developed countries have, in general, experienced increases in their wage inequality.

There is evidence that although GVCs can play a role in determining wage inequality this role is relatively small and at times it can even be positive: countries which have a higher backward GVC participation tend to have lower wage inequality. However, the type of engagement in GVCs matters. The results suggest that offshoring low-skilled tasks is associated with reductions in wage inequality but also that offshoring high-skill tasks leads to increases in wage inequality as wages for higher skilled workers rise. These effects are in line with the theoretical predictions of Grossman and Rossi-Hansberg (2008).

From a policy stand-point, and in the context of the emerging empirical results showing the aggregate benefits of GVC participation in terms of productivity, product sophistication and diversification (OECD, 2015a), the results of this study suggest that the equity-efficiency trade off—or the potential tension between equity and the aggregate economic outcomes of GVC participation—may hold only in certain cases. GVC participation is estimated to have a small effect on the distribution of wages and, when it has, it can sometimes reduce wage inequality, particularly when it concerns GVC participation of low-skilled segments of the labour force. Low-skilled labour is, according to the data at hand, traded within value chains more intensely than high-skilled labour, hence the recent overall positive effect of GVC participation on wage inequality.

For policy-makers seeking to maximise the benefits of GVC participation, questions of a more equitable distribution of returns to workers might therefore focus in particular on skill-upgrading of low-skilled labour by promoting further tertiary education and development of skills since this is found to reduce inequality both in developed and emerging economies. This latter result is consistent with the more general finding from the literature on inequality which finds that diffusion of knowledge and investment in training and skills are the main forces that can reduce income inequality (e.g. Piketty, 2014).

Bibliography

Amador, J. and S. Cabral (2009), "Vertical Specialization Across the World: A Relative Measure", *The North American Journal of Economics and Finance*, Vol. 20(3), pp. 267-80.

Autor, D., F. Levy and R. Murnane (2003), "The Skill Content of Recent Technological Change: An Empirical Exploration", *Quarterly Journal of Economics*, Vol. 118(4), pp. 1279-1333.

Baldwin R.E. (2008), *The Development and Testing of Heckscher-Ohlin Trade Models*, MIT Press, Cambridge.

Baldwin, R. (2012), "Trade and Industrialisation after Globalisation's Second Unbundling: How Building and Joining a Supply Chain are Different and Why it Matters", in *Globalization in an Age of Crisis: Multilateral Economic Cooperation in the Twenty-First Century*, R. Feenstra and A. Taylor (eds.), University of Chicago Press, Chicago.

Baldwin, R.E. and J. Lopez-Gonzalez (2013), "Supply-Chain Trade: A Portrait of Global Patterns and Several Testable Hypotheses", *NBER Working Paper Series*, No. 18957, National Bureau of Economic Research, http://www.nber.org/papers/w18957.

Baldwin, R. and F. Robert-Nicoud (2010), "Trade-in-Goods and Trade-in-Tasks: An Integrating Framework", *NBER Working Paper Series*, No. 15882, National Bureau of Economic Research, http://www.nber.org/papers/w15882.

Barro, R.J. (2000), "Inequality and Growth in a Panel of Countries", *Journal of Economic Growth*, Vol. 5(1), pp. 5-32.

Bartelsman, E.J, R. Caballero and R.K. Lyons (1994), "Customer- and Supplier-Driven Externalities", *American Economic Review*, American Economic Association, Vol. 84(4), pp. 1075-84.

Bartels, B.L. (2008), "Beyond "Fixed Effects Versus Random Effects: A Framework for Improving Substantive and Statistical Analysis of Panel, Time-Series Cross-Sectional and Multilevel Data", unpublished manuscript available at: http://polmeth.wustl.edu/media/Paper/Polmeth2008paper-Bartels.pdf

Blinder, A.S. (2009), "How Many US Jobs Might be Offshorable?", *World Economics*, World Economics, Economic & Financial Publishing, London, Vol. 10(2), pp.41-78.

Blinder, A.S. (2006), "Offshoring: The Next Industrial Revolution", *Foreign Affairs*, Vol. 85, 113.

Bourguignon, F. and C. Morrison (2002), "Inequality Among World Citizens: 1820-1992", *American Economic Review*, American Economic Association, Vol. 92(4), pp. 727-744.

Costinot, A., J. Vogel and S. Wang (2012), "Global Supply Chains and Wage Inequality", *American Economic Review*, American Economic Association, Vol. 102(3), pp. 396-401.

Costinot, A., J. Vogel and S. Wang (2011), "An Elementary Theory of Global Supply Chains", *NBER Working Paper Series*, No. 16936, National Bureau of Economic Research. http://www.nber.org/papers/w16936.

Daudin, G., C. Rifflart and D. Schweisguth (2011), "Who Produces for Whom in the World Economy?", *Canadian Journal of Economics/Revue Canadienne d'Économie*, Vol. 44(4), pp. 1403-37.

Deardorff, A.V. (2001), "Fragmentation in Simple Trade Models", *The North American Journal of Economics and Finance*, Vol. 12(2), pp. 121-37.

K. Deininger and L. Squire (1996), "A New Data Set Measuring Income Inequality", *The World Bank Economic Review*, Vol.10(3), pp. 565-91.

Dollar, D., T. Kleinberg and A. Kraay (2013), "Growth Still Is Good for the Poor", *Policy Research Working Paper* No. 6568, The World Bank, Washington D.C.

Feenstra, R.C. and G.H. Hanson (1999), "The Impact of Outsourcing and High Technology Capital on Wages: Estimates for the United States, 1979-1990", *Quarterly Journal of Economics*, Vol. 114 (3), pp. 907-40.

Feenstra, R.C. and G.H. Hanson (1996), "Globalization, Outsourcing, and Wage Inequality", *American Economic Review*, American Economic Association, Vol. 86(2), pp. 240-45.

Figini, P. and H. Gorg (2006), "Does Foreign Direct Investment affect wage inequality? An empirical investigation", *IZA discussion Paper Series*, IZA DP No. 2336, September.

Forbes, K.J. (2000), "A Reassessment of the Relationship Between Inequality and Growth", *American Economic Review.* American Economic Association, Vol. 90(4), pp. 869 - 887.

Frazer, G. (2006), "Inequality and Development Across and Within Countries", *World Development*, Elsevier, Vol. 34(9), pp. 1459-1481.

Galbraith, J. and H. Kum (2004), "Inequality and Economic Growth: A Global View Based on Measures of Pay", *CESifo Economic Studies*, Vol. 49(4), pp. 527-556.

Grossman, G.M. and E. Rossi-Hansberg (2008), "Trading Tasks: A Simple Theory of Offshoring", *American Economic Review*, Vol. 98(5), pp. 1978-97.

Helpman, E., O. Itskhoki and S.J. Redding (2011), "Trade and Labor Market Outcomes", *CEPR Discussion Papers* No. 8191, Centre for Economic Policy Research. www.cepr.org/active/publications/discussion_papers/dp.php?dpno=8191 .

Hummels, D., J. Ishii and K-M. Yi (2001), "The Nature and Growth of Vertical Specialization in World Trade", *Journal of international Economics*, Vol. 54(1), pp. 75-96.

Johnson, R.C. and G. Noguera (2012a), "Fragmentation and Trade in Value Added over Four Decades", *NBER Working Paper Series*, No. 18186, National Bureau of Economic Research. http://www.nber.org/papers/w18186.

Jones, R.W. and H. Kierzkowski (1990), "The Role of Services in Production and International Trade: A Theoretical Framework", in R.W. Jones and A.O. Krueger (eds.), *The Political Economy of International Trade*, Oxford: Blackwell.

Kaplinsky R. and M. Morris (2001), *A Handbook for Value Chain Research*, Vol. 113, International Development Research Centre, Ottawa, http://www.ids.ac.uk/ids/global/pdfs/ValuechainHBRKMMNov2001.pdf

Knight, J. (2013), "Inequality in China; An Overview", *Policy Research Working Paper* 6482, The World Bank, Washington D.C.

Koopman, R., W. Powers, Z. Wang and S-J. Wei (2010), "Give Credit Where Credit Is Due: Tracing Value Added in Global Production Chains", *NBER Working Paper Series*, No. 16426. National Bureau of Economic Research. http://www.nber.org/papers/w16426.

Koopman, R., Z. Wang and S-J. Wei (2008), "How Much of Chinese Exports Is Really Made in China? Assessing Domestic Value-Added When Processing Trade Is Pervasive", *NBER Working Paper Series*, No. 14109. National Bureau of Economic Research. http://www.nber.org/papers/w14109.

Krugman, P (2007), "Trade and Inequality, Revisited", *VOX EU*, 15 June.

Kuznet, S. (1955), "Economic Growth and Income Inequality", *American Economic Review*, American Economic Association, Vol. 65, pp. 1-28.

Lanz, R., S. Miroudot and H.K. Nordås (2011), "Trade in Tasks", *OECD Trade Policy Papers*, No. 117, OECD Publishing, Paris.
DOI: http://dx.doi.org/10.1787/5kg6v2hkvmmw-en.

Leamer, E. and M. Storper (2001), "The Economic Geography of the Internet Age", *NBER Working Paper Series*, No. 8450, National Bureau of Economic Research.
http://www.nber.org/papers/w8450.

López-González, J. (2012), *Vertical Specialisation and New Regionalism*, Doctoral thesis (PhD), University of Sussex. http://sro.sussex.ac.uk/43255/.

Mankiw, N.G. (2013), "Defending the One Percent", *Journal of Economic Perspectives*, Vol. 27(3), pp. 21-34, Summer.

Meschi, E. and M. Vivarelli (2009), "Trade and Income Inequality in Developing Countries", *World Development* Vol. 37(2), pp. 287-302.

Michaels, G., A. Natraj and J. Van Reenen (2010), "Has ICT Polarized Skill Demand? Evidence from Eleven Countries Over 25 years", mimeo, London School of Economics.

Milanovic, B. (2012), "Global Income Inequality by the Numbers: In History and Now – An Overview", *Policy Research Working Paper Series* 6259, The World Bank.

Milanovic, B. and L. Squire (2007), Does Tariff Liberalization Increase Wage Inequality? Some Empirical Evidence, *NBER Chapters*, in: *Globalization and Poverty*, pp. 143-182 National Bureau of Economic Research, Inc.

OECD (2015a), "Developing Countries Participation in Global Value Chains and its Implications for Trade and Trade Related Policies", *OECD Trade Policy Paper* No. 179, OECD Publishing.
DOI: http://dx.doi.org/10.1787/5js33lfw0xxn-en

OECD (2015b), *In It Together: Why Less Inequality Benefits All*, OECD Publishing.
DOI: http://dx.doi.org/10.1787/9789264235120-en.

OECD (2014), *All on Board, Making Inclusive Growth Happen*, OECD Publishing.
DOI: http://dx.doi.org/10.1787/9789264218512-en.

OECD (2013), *Interconnected Economies – Benefiting from Global Value Chains*, OECD Publishing.
DOI: http://dx.doi.org/10.1787/9789264189560-en

OECD (2011), *Divided We Stand: Why Inequality Keeps Rising*, OECD Publishing, Paris.
DOI: http://dx.doi.org/10.1787/9789264119536-en.

OECD (2009), *Globalisation and Emerging Economies: Brazil, Russia, India, Indonesia, China and South Africa*, OECD Publishing, Paris.
DOI: http://dx.doi.org/10.1787/9789264044814-en.

Offer, V. (2013), "Narrow banking, real estate, and financial stability in the UK, c.1870-2010", Oxford University Economic and Social History Series 116, Economics Group, Nuffield College, University of Oxford.

PEW (2014), *Faith and Skepticism about Trade, Foreign Investment*, Pew Research Centre, September.

Piketty, T. (2013), *Le capital au XXIème siècle*, Broché.

Subramanian, A. and M. Kessler (2013), "The Hyperglobalization of Trade and its Future", Peterson Institute of International Economics *Working Papers Series*, No. 13-6, July.

Sicular, T. (2013), "The Challenge of High Inequality in China", *Inequality in Focus*, The World Bank Poverty and Equity Department, Vol. 2, No. 2, August.

WIR (2013) *World Investment report 2013: Global Value Chains: Investment and Trade for Development*, United Nations Conference on Trade and Development, *United Nations Publication* ISBN 978-92-1-112868-0.

Wolf, M. (2013) "Globalisation in a Time of Transition", *Financial Times,* 16 July.

WTO (2008), *World Trade Report 2008; Trade in a Globalizing World*, World Trade Organisation, Geneva.

Yeats, A. (1998), "Just How Big Is Global Production Sharing?", *World Bank Policy Research Working Paper*, (1871).

Zhu, S. and D. Trefler (2005), "Trade and Inequality in Developing Countries: A General Equilibrium Analysis", *Journal of International Economics*, Vol. 65(1), pp. 21-48, January.

Annex

GVCs and inequality; the Ricardian approach

The literature review in Section 2 focused on implications of offshoring for inequality from a factor endowment and factor intensity perspective. However, the idea of offshoring costs driving GVC activity and inequality has also been explored in the so-called Ricardian framework where labour skills are normally assumed to be homogenous across countries and where trade is driven by technology differences. With such an approach, predictions related to within-country inequality are complicated.[1] Nevertheless, a series of papers by Costinot, Vogel and Wang (Costinot, Vogel and Wang 2011 and 2012) explore how the emergence of global supply chains may affect inequality both across and within countries. In their approach, production is sequential - meaning that the production of one unit of intermediates requires a unit of labour and a unit of a preceding intermediate product. Mistakes in production, which in this context mean zero output at this production stage and stages that follows downstream, occur at a constant and country-specific failure rate which determines how countries allocate along the value chain or, in other words, determines their comparative advantage within the value chain. Since mistakes imply the loss of all the preceding intermediate stages of production, more productive countries, which have a lower mistake rate, locate at the later stages of production.

Costinot et al. (2011) assume away within-country heterogeneity to focus on global inequality and disentangle the effects of increasing i) the complexity (the number of sequences a product has to undergo); and ii) the standardisation of production (a uniform decrease in failure rates worldwide). They argue that increases in both of these measures allow countries to move up the value chain but that these have opposite effects on inequality between nations. Increases in complexity make the gap between poor and rich (less and more productive countries) grow as complexity favours those higher up the value chain. However, increases in standardisation reduce global inequality since these increase the productivity (reduce the mistake rate) of the poor countries proportionally more. The impact of the proliferation of GVCs on world inequality therefore depends on changes in complexity and in standardisation.

In a more targeted extension of the sequential production model, Costinot et al. (2012) assume the world economy to be composed of two countries, the North and the South, where the North is assumed to be relatively skill abundant. They show that a transition from autarky, where supply chains are purely local, to complete goods market integration, where supply chains are both local and global, leads all workers in developing countries to move into earlier stages of production (their definition of downgrading) and all workers in developed countries to move into later stages (upgrading). They also show that in the South, wage inequality decreases for low-skilled Southern workers (i.e. those employed at the bottom of the chain). This is because with global trade low-skilled workers become relatively less abundant which leads to their higher relative wages, thereby diminishing the differences between the least and most paid workers of this type. By a mirror image of the same mechanism, wage inequality among high-skilled developing country workers increases.

Costinot at al. (2012) attribute this non-monotonic effect of globalisation on inequality to the sequential nature of the production process: “In a perfectly competitive model without sequential production, changes in wages reflect changes in the prices of the goods produced by different workers. If free trade makes the prices of the goods produced by high-skill workers relatively cheaper in South compared to autarky, then inequality must go down in South. In a perfectly competitive model with

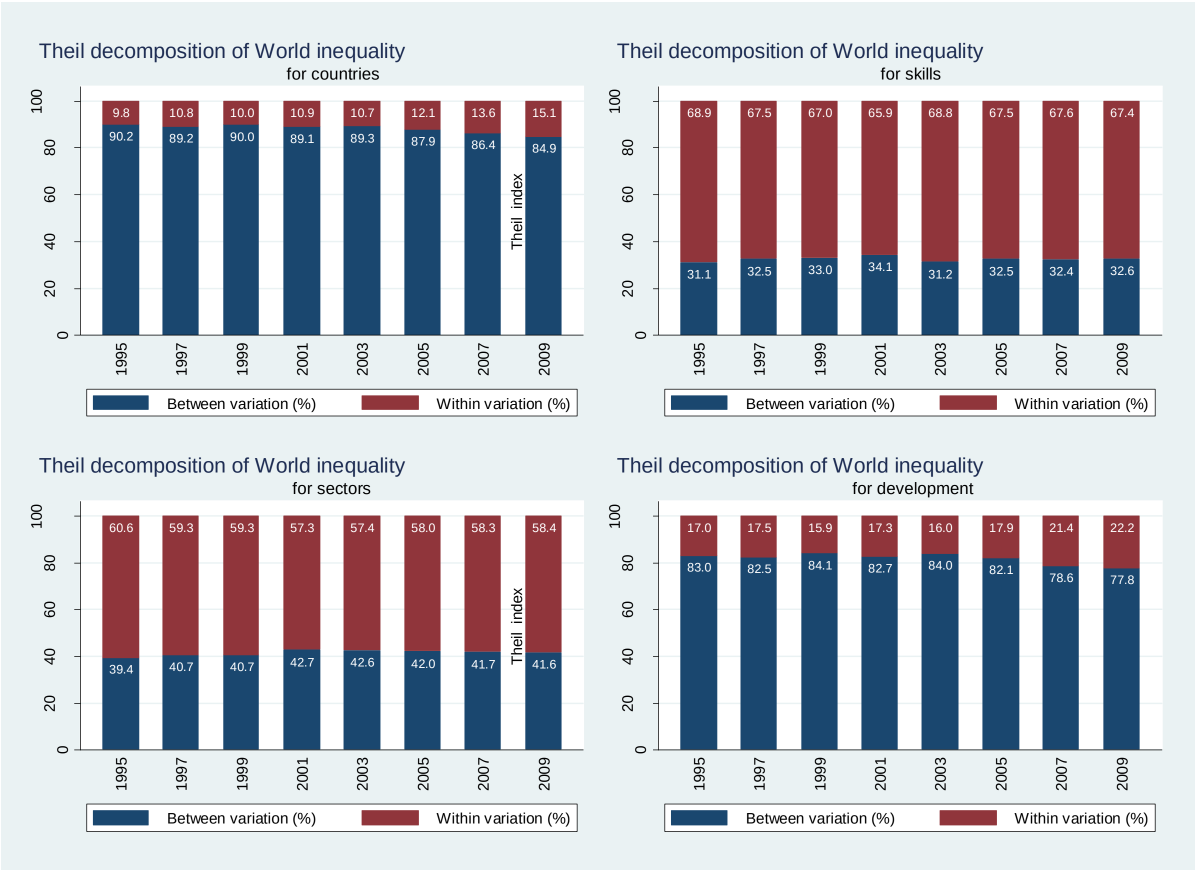
1. Predictions on global inequality using the HOS model will depend on how Factor Prize Equalisation (FPE) evolves. Deardorff (2001) argues that fragmentation may lead to increased FPE and therefore that GVCs will lead to a reduction in global inequality.

sequential production, by contrast, changes in wages also reflect changes in the prices of the intermediate goods used by these workers. In this environment, if free trade makes the prices of the intermediate goods used by high-skill workers relatively cheaper in South compared to autarky, then this tends to increase inequality."

Global wage inequality

The Theil index lends itself to decomposing the determinants of global wage inequality along different dimensions. For example, the top left panel of Figure A.1 shows how within and between country differences help explain inequality. The between country element of inequality clearly dominates; levels of global inequality are predominantly driven by differences across countries rather than within countries (i.e. differences between, for example, the US and Brazil rather than differences in wages within the US)—a finding similar to that of Bourguignon and Morrison (2002).

Figure A.1. Decomposition of drivers of world inequality across categories (Theil index) 1995-2009



Note: Global inequality is calculated using a Theil Index on pooled country-sector-year wage data from the WIOD database (4 200 observations per year, 40 countries, 35 sectors and three skill categories).

Source: Authors' calculations from WIOD.

The top right panel presents the decomposition of the Theil index according to skill variation. *Within* skill variation dominates, suggesting that it is inequality arising from differences in, for example, payments to low-skilled labour that dominate over those arising from differences between the wages of low-skilled and medium-skilled workers. This is corroborated later where little by way of differences in changes within high and low skilled wages in developed and emerging economies are seen (Figure A.2). Similarly, the decomposition across sectors (bottom left panel) suggests that it is the within sector rather than the between sector element which is most important as a determinant of global inequality. The bottom right panel then shows that global inequality is strongly determined by differences between developed and emerging economies rather than by differences within them.[2]

Country-specific wage inequality

Table A.1. Levels and growth rates of Gini coefficients between the period 1995-2009

	WIOD GINI1			WDI GINI			OECD GINI			EHII Gini		
	Cons	β		Cons	β		Cons	β		Cons	β	
AUS	0.21	0.15%	***				0.42	-0.01%		0.36	0.04%	
AUT	0.17	0.24%	***				0.39	0.17%		0.35	0.04%	*
BEL	0.19	-0.07%	**				0.46	-0.37%	**	0.37	0.22%	***
BGR	0.27	0.06%		0.30	-0.05%					0.40	0.04%	
BRA	0.59	-0.61%	***	0.62	-0.43%	***				0.49	-0.03%	
CAN	0.21	0.07%	***	0.37	0.46%	***	0.41	0.02%		0.38	0.06%	***
CHN	0.40	0.57%	***							0.48	-0.76%	***
CYP[1, 2]	0.24	0.38%	***							0.40	-0.26%	***
CZE	0.16	0.07%					0.39	0.07%		0.29	0.10%	**
DEU	0.20	0.30%	***				0.39	0.17%				
DNK	0.14	0.14%	***				0.37	-0.02%		0.30	0.26%	***
ESP	0.26	-0.51%	***				0.30	0.79%	*	0.40	-0.16%	***
EST	0.27	-0.29%	**	0.33	0.50%		0.52	-0.87%		0.36	-0.11%	**
FIN	0.12	0.26%	***				0.44	-0.22%	*	0.32	0.15%	***
FRA	0.21	-0.34%	***				0.43	0.02%		0.36	0.10%	***
GBR	0.17	0.00%					0.44	0.13%		0.35	0.20%	***
GRC	0.29	-0.66%	***				0.32	0.92%	**	0.43	0.01%	
HUN	0.28	0.19%	***	0.23	0.61%	***				0.40	0.00%	
IDN	0.43	0.26%		0.29	0.35%					0.49	-0.16%	
IND	0.46	0.49%	***							0.50	0.13%	***
IRL	0.19	0.16%	***				0.26	1.69%	**	0.36	-0.02%	
ITA	0.20	-0.11%	**				0.42	0.02%		0.37	-0.02%	
JPN	0.24	0.13%	***				0.37	0.23%	*	0.39	0.33%	***
KOR	0.32	0.02%					0.28	0.30%		0.37	0.20%	***
LTU	0.31	-0.69%	***	0.29	0.56%	**				0.40	-0.05%	
LUX	0.23	0.11%	*				0.34	0.60%	*	0.33	0.33%	***
LVA	0.29	-0.34%	***	0.32	0.37%	***				0.39	-0.29%	**
MEX	0.46	-0.02%		0.50	-0.08%					0.46	0.15%	
MLT	0.27	0.43%	***							0.34	0.35%	***
NLD	0.19	0.17%	***				0.43	-0.35%	**	0.35	0.15%	**

continued

2. Looking at changes in time by tracking the evolution of the shares we are able to qualify that although the between country element is the largest determinant of global inequality, it is in fact the within element that is growing and therefore driving reductions in global inequality. For example, although the difference in inequality between Brazil and the US is the biggest determinant of global inequality, it is changes in inequality within Brazil and the US which are driving the reductions in inequality (tentatively implying that there is some convergence taking place). Similarly, although to a lesser extent, we also find that in terms of skills, the within variation is dominant but the between variation is the one that is driving the reductions.

Table A.1. Levels and growth rates of Gini coefficients between the period 1995-2009 (*cont.*)

	WIOD GINI1			WDI GINI			OECD GINI			EHII Gini		
	Cons	β		Cons	β		Cons	β		Cons	β	
POL	0.26	-0.41%	***	0.32	0.15%	**	0.67	-1.64%	***	0.38	0.21%	
PRT	0.28	-0.01%					0.42	0.29%		0.37	0.23%	***
ROM	0.24	-0.26%	*	0.30	0.12%					0.35	0.41%	***
RUS	0.46	-0.11%	*	0.40	-0.01%					0.41	-0.07%	
SVK	0.16	0.24%	***	0.27	0.07%		0.48	-0.79%		0.36	0.19%	***
SVN	0.21	-0.09%	**	0.26	0.46%	*	0.45	-0.48%		0.32	0.15%	**
SWE	0.13	-0.06%	**				0.37	0.01%		0.30	-0.02%	
TUR	0.34	-0.05%		0.50	-0.7%	***				0.49	-0.14%	*
TWN	0.33	0.01%								0.32	0.10%	
USA	0.23	0.34%					0.44	0.13%	**	0.38	0.20%	***
Average												
TOTAL	0.27	0.00%		0.35	0.16%		0.41	0.03%		0.38	0.06%	
Emerging	0.36	-0.09%		0.37	0.11%		0.59	-1.26%		0.43	-0.05%	
Developed	0.21	0.05%		0.30	0.33%		0.39	0.14%		0.35	0.12%	
Average (only for significant)												
TOTAL	0.27	-0.02%		0.35	0.18%		0.41	0.18%		0.38	0.08%	
Emerging	0.36	-0.13%		0.37	0.09%		0.59	-1.64%		0.43	-0.13%	
Developed	0.21	0.05%		0.30	0.46%		0.39	0.35%		0.35	0.15%	

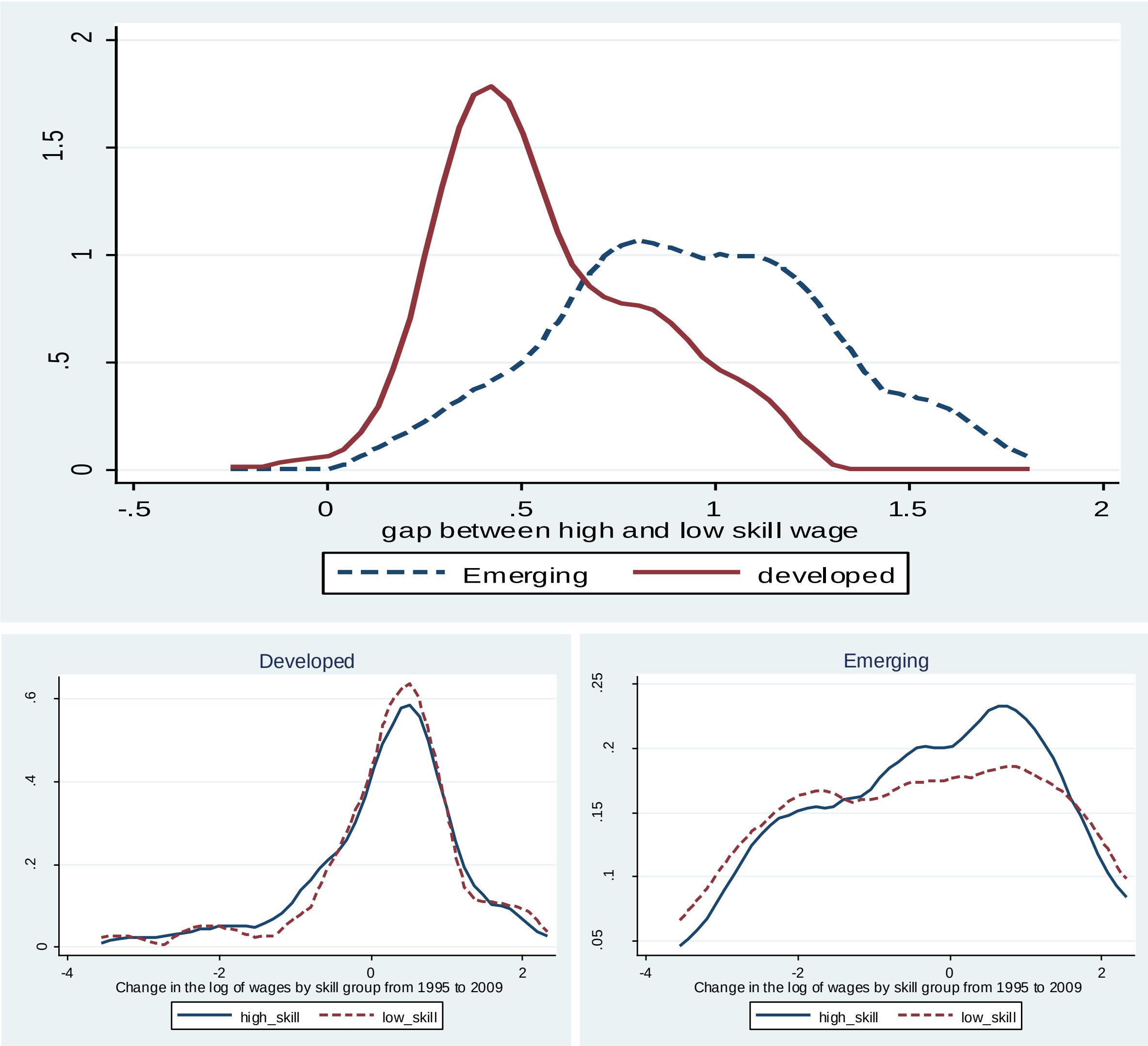
1. Footnote by Turkey: The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of United Nations, Turkey shall preserve its position concerning the "Cyprus" issue

2. Footnote by all the European Union Member States of the OECD and the European Union: The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

Note: β identifies the gradient of the time trend and therefore the growth in inequality, the constant then shows where the regression line meets the axis and therefore gives us an indication of the starting levels of inequality in a country. Number of observations across the different indicators varies and data has not been deflated. ***1%, **5% and *10% confidence levels.

The top panel of Figure A.2, showing the density of the wage gap between high and low skilled workers in developed and emerging economies, gives further evidence to the reported differences between emerging and developed country wage inequality. Indeed the wage gap in emerging countries is, on average, larger and also has a higher variance. However, when we look at how changes in low and high skill wages distribute across developed (bottom left panel) and emerging (bottom right panel) economies, we perceive no discernible differences. Developed country high and low skill wages appear to follow a similar evolution. Emerging country changes seem more volatile with the spread of the low-skill changes being larger (note that we observe instances where low skill wages grow both faster and slower than the high-skill wages). This then suggests that variance in the wage inequality measure is likely to be dominated by differences across rather than within countries.

Figure A.2. Wage differences in levels and changes across developed and emerging countries



Note: Diagrams show kernel densities. Changes calculated as log differences between 1995 and 2009.
Source: Authors' calculation based on WIOD SEA data.

Trends in percentile based measures of inequality

Table A.2 shows the results of looking at percentile based measures of inequality derived from the WIOD database. This allows facilitates an investigation into differences in changes in inequality across different parts of the wage distribution (which the Gini measures does not allow). The first column shows the evolution of the ratio of the 90th percentile to that of the 10th – a broad measure of inequality across the whole distribution.[3] The evolution of the ratio of the 90th to that of the 50th percentiles captures changes at top end of the distribution and the 50th and the 10th percentiles at the bottom end of the distribution.[4]

The HOS effect where inequality falls in developing but rises in developed countries is no longer discernible; in fact rising inequality for both emerging and developed economies is perceived. At the top end of the distribution (r90t50) inequality is falling for emerging economies and rising for developed countries. In contrast, inequality seems to be falling at the bottom end of the distribution (r50t10) for developed countries but rising for emerging economies. In the context of the theoretical literature there appears to be a combination of effects. The unskilled-labour augmenting changes (predicted by Grossman and Rossi-Hansberg, 2008) may be pushing up wages of unskilled workers in developed countries therefore driving reductions in inequality at the bottom end of the distribution. In contrast, the increase in inequality at the bottom end of the distribution witnessed in emerging economies may be explained through the lens of Zhu and Trefler (2005). They suggest that the tasks that are being offshored to emerging economies could be relatively high skill intensive from the perspective of emerging economies that perform them and therefore driving increases in inequality at the bottom end of the distribution.

Looking at country-specific developments can help illustrate some of the mechanisms that explain differences in changes in inequality at the top and bottom ends of the distribution. In China the gap between the top and bottom earners has increased sharply but not as much as at the bottom end of the distribution where inequality is rising at a much faster pace.[5] China has witnessed an important increase in its backward GVC participation and this may have altered wage structures. The Zhu and Trefler (2005) effect suggests that the low-skilled tasks offshored from developed countries, say the assembly of mobile phones, are actually relatively skill-intensive in China compared to, for example, agricultural production. This implies that the workers engaged in the assembly of mobile phones are likely to command higher wages than those that are still employed in agricultural activities and therefore GVC participation can drive an increase in inequality at the bottom end of the distribution.

In contrast, Hungary has also witnessed an increase in inequality but this is due to rising disparities at the top end of the distribution with a fall of inequality at the bottom end. Here we can think of GVC engagement in the production of cars soaking up the remaining workers that were engaged in agricultural activities and therefore reducing inequality at the bottom of the distribution. Increases at the top may then be driven by higher salaries being paid to the managers that oversee these new activities. Although these are hypothetical illustrations they help us relate the observed trends to the ideas put forward by the theoretical literature.

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3. These are ratios of wages of individuals at different parts of the distribution. See Box 2 for a more in depth definition.

4. It is important to note that different inequality measures capture different forms of inequality (see also Box 2). Percentile based measures are easy to understand but they do not necessarily take into consideration the distribution of workers across the wage spectrum as do the weighted Gini coefficients used in the paper.

5. Similar important increases in inequality are also noted by Knight (2013) and Sicular (2013) although since these use different underlying data the results are not completely comparable. However Sicular (2013) suggests that: "Inequality in China is not the result of stagnant or declining incomes among poorer groups, but of more rapid growth in incomes of richer groups." Much of this is led by changes in income from private property which are not captured in the measures used.

Table A.2. Levels and growth rates of percentile based measures of inequality between the period 1995-2009

	r90t10			t90t50			r50t10		
	Cons	**Β**		**Cons**	**β**		**Cons**	**Β**	
AUS	2.77	3.52%	***	1.52	1.36%	***	1.83	0.62%	***
AUT	2.29	1.07%	***	1.64	-0.17%		1.39	0.81%	***
BEL	2.51	-2.13%	***	1.68	-1.16%	***	1.50	-0.26%	
BGR	3.13	-0.53%		2.39	0.08%		1.32	-0.30%	
BRA				5.29	-10.89%	***			
CAN	2.82	-1.50%		1.36	0.34%		2.06	-1.53%	*
CHN	5.75	78.92%	***	4.15	4.49%		1.38	17.08%	***
CYP[1, 2]	2.83	4.46%	***	1.56	3.50%	***	1.81	-0.81%	
CZE	2.16	0.53%		1.39	2.60%	***	1.54	-1.97%	***
DEU	2.41	2.27%	***	1.57	0.50%	***	1.54	0.90%	***
DNK	1.83	1.71%	***	1.32	0.44%	*	1.39	0.80%	***
ESP	3.66	-9.43%	***	1.92	-3.02%	***	1.91	-2.40%	***
EST	3.53	-6.11%	***	1.94	-0.92%		1.82	-2.43%	***
FIN	1.63	3.95%	***	1.21	2.04%	***	1.36	0.74%	***
FRA	2.68	-2.45%	**	1.70	-1.18%	***	1.57	-0.40%	
GBR	2.06	-0.11%		1.65	-0.70%	**	1.25	0.50%	*
GRC	4.21	-12.03%	***	1.82	-0.11%		2.35	-6.82%	***
HUN	3.08	7.02%	***	1.76	5.79%	***	1.72	-1.04%	*
IDN	3.71	12.28%	**	3.51	-2.33%		1.04	4.77%	***
IND	5.24	10.16%	***	4.95	1.61%		1.06	1.63%	***
IRL	2.24	3.76%	***	1.32	0.98%	**	1.70	1.41%	***
ITA	2.47	-0.90%		1.76	-1.54%	***	1.40	0.85%	**
JPN	2.99	4.34%	***	1.57	0.33%		1.91	2.31%	***
KOR	5.06	-3.48%		2.05	-0.20%		2.47	-1.47%	
LTU	3.48	-5.52%		1.92	-1.97%	**	1.81	-1.12%	
LUX	3.06	1.91%		1.92	0.04%		1.59	0.96%	
LVA	3.36	-0.27%		1.84	0.77%		1.82	-0.70%	
MEX	8.63	12.86%	***	3.37	-2.60%	***	2.54	6.58%	***
MLT	2.93	13.03%	***	2.02	4.08%	***	1.48	2.49%	***
NLD	2.36	1.77%	***	1.24	1.81%	***	1.89	-1.09%	**
POL	4.19	-14.05%	***	1.84	-1.62%		2.28	-6.22%	***
PRT	3.52	-0.24%		2.34	0.77%		1.51	-0.60%	
ROM	2.46	2.60%		1.85	-1.99%		1.37	3.38%	
RUS	7.90	-11.28%	**	3.42	-11.37%	***	2.21	8.26%	***
SVK	1.68	6.09%	***	1.11	5.48%	***	1.49	-0.93%	
SVN	2.81	-1.76%	**	1.91	0.26%		1.47	-1.11%	***
SWE	1.70	0.04%		1.24	0.96%	***	1.37	-0.92%	**
TUR	3.52	9.36%	**	2.72	-1.51%		1.29	4.72%	**
TWN	3.57	0.49%		1.88	1.40%	***	1.89	-1.00%	
USA	3.24	5.17%	***	1.67	1.83%	**	1.94	0.81%	
Average									
TOTAL	3.32	2.96%		2.08	-0.05%		1.67	0.68%	
Emerging	4.46	7.34%		2.93	-1.60%		1.67	2.66%	
Developed	2.75	0.77%		1.63	0.79%		1.68	-0.31%	
Average (only for significant)									
TOTAL	3.32	4.71%		2.08	-0.07%		1.67	1.07%	
Emerging	4.46	11.02%		2.93	-4.21%		1.67	3.70%	
Developed	2.65	1.37%		1.57	1.11%		1.68	-0.26%	

1. Footnote by Turkey: The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of United Nations, Turkey shall preserve its position concerning the "Cyprus" issue

2. Footnote by all the European Union Member States of the OECD and the European Union: The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

Note: β identifies the gradient of the time trend and therefore the growth in inequality, the constant then shows where the regression line meets the axis and therefore gives us an indication of the starting levels of inequality in a country. Number of observations across the different indicators varies and there is no need to deflate data in this analysis since inflation at top and bottom end are likely to be the same and therefore percentile measures will not suffer from biases due to changes in relative prices. ***1%, **5% and *10% confidence levels.

Figure A.3. Backward and forward participation in value chains by type

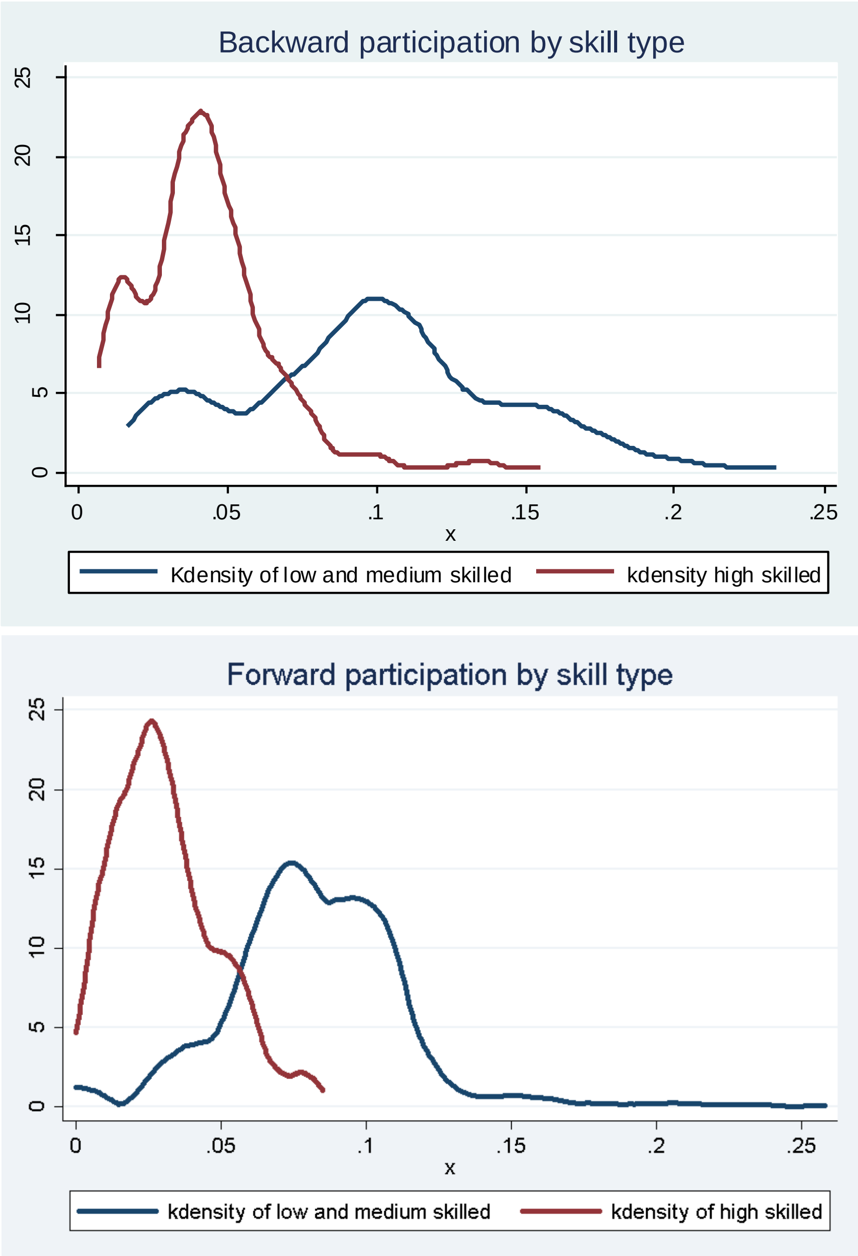

Figure A.4. Global flows of value added in exports by type

		1995		2009	
		Developed	Emerging	Developed	Emerging
Developed	High skill	3%	0%	3%	1%
	Low -medium skill	7%	1%	5%	1%
	Capital	6%	1%	5%	1%
Emerging	High-Skill	0%	0%	0%	0%
	Low -medium skill	1%	0%	2%	0%
	Capital	1%	0%	3%	0%
Domestic	High skill	12%	1%	13%	2%
	Low -medium skill	34%	4%	22%	7%
	Capital	25%	5%	21%	12%

		1995		2009	
		Developed	Emerging	Developed	Emerging
Developed	High skill	14%	1%	15%	3%
	Low -medium skill	38%	3%	23%	5%
	Capital	30%	3%	24%	5%
Emerging	High-Skill	1%	0%	2%	0%
	Low -medium skill	3%	0%	7%	1%
	Capital	5%	1%	13%	2%

Note: Left panel shows the share that each column country type represents in global exports of the indicated year. For example, in 1995 12% of global value added in exports came from developed country high-skilled labour. The right panel shows the same figures but as a ratio of global value added in exports flows so that in 2009 24% of traded value added in exports came from capital value added in developed countries.

Source: Authors' calculations from WIOD.

Discussion of the empirical complications associated with capturing the impact of globalisation on wage inequality

Milanovic and Squire's (2007) discussion on possible problems arising from estimating the impact of trade liberalisation on wage inequality helps guide our empirical approach. They suggests that two key complications arise in this type of exercise. The first relates to the *domain* dimension which is that the sample or choice of measures, be it of liberalisation (globalisation) or inequality, matters. Indeed the selection of countries in the sample may not be random and if this selection is correlated with determinants of the inequality measure then there can be a selection problem. Our sample is largely composed of developed and emerging economies (biased towards the former) and includes no least developed countries. If there is a strong development element to cross-sectional differences in inequality then the biases in our sample imply that our results are not likely to hold for LDCs. There is little that can be done about this since data restrictions constrain the number of countries for which reliable measures of both GVC participation and wage inequality can be obtained. Robustness checks are however undertaken using different sources of data both for inequality (EHIIGini) as well as GVC participation (derived from the EORA database) which allow a broadening of the sample although at the cost of precision (the precision of the EORA database in capturing GVC participation is debatable – see OECD, 2015a).

The second problem that arises in these estimations relates to the *specification* dimension which is whether one chooses to estimate the relationship in levels or in changes. The key problem here is that estimating in levels may suffer from omitted variable bias or indeed unobserved heterogeneity. But estimating in changes can also be problematic if changes have different impacts across different levels (i.e. the impact of a 1 percentage point increase in GVC participation on wage inequality from a starting level of zero might be different to that of a 1 percentage point increase in GVC participation in a country which has a participation rate of 20%).

The more recent empirical literature has moved towards estimations which rely on specifications that capture changes in variables but the results have been mixed. If variables of interest do not vary much in time (i.e. changes in backward participation for some countries are slow) then it will be harder to find a statistically significant relationship between the variables of interest. Additionally, not looking at levels implies abstracting from the large variance that is seen between developing and emerging economies in Figure 5 or that between levels of participation in GVCs and wage inequality in Figure 6.

Another potential concern with the specification used is that of potentially unobserved determinants that may simultaneously determine the degree of offshoring as well as the levels of inequality within a country.[6] These are likely to be technological changes that not only facilitate the process of offshoring but also affect the distribution of income through skilled biased technological change. An example is the adoption of the internet as a means of communication. To correct for these biases time fixed effects are introduced under the assumption that the source for unobserved heterogeneity does not vary across countries. This may not be a strong assumption in the case of adoption of ICT technologies which indeed can be thought of a positive technology shock affecting all economies in a similar way.[7]

Other possible sources of bias in the estimation can arise from persistence of within country inequality driven by sluggish adjustment in wages as noted by Meschi and Vivarelli (2009). They propose the use of a dynamic specification using a Least Squares Dummy Variable Corrected (LSDVC) estimator to account for this. Additionally complications in the estimation can also arise from the truncated nature of the dependent variable. The Gini coefficient which is used as dependent variable lies in the 0-1 interval and this may require the use of a logistic estimation. The problem then becomes one of introducing fixed effects into such specifications and avoiding the 'incidental parameters problem' (see Neyman and Scott, 1948). To control for this a robustness check using different conditional or fractional logit specifications is done.

Table A.3. Summary of independent variables

Determinant	Variable	Observations	Mean	Std. Dev	Min	Max
Offshorability	Backward participation	615	0.28	0.11	0.05	0.62
Levels of development	GDPperCapita	580	21 726.28	12 373.64	1 420.00	74 000.00
Financial flows	FDI inward stock	554	206 435.20	439 018.80	303.36	3 551 307.00
Technology	R&Dexpenditure	495	1.42	0.91	0.05	4.13
Domestic policies	Tax_revenue_shareGDP	497	19.79	8.73	4.70	65.90
	School_enrollment_tertiary_share	529	49.67	22.00	4.51	102.00
	Unemployment, total share	526	7.77	3.76	1.80	22.70

6. Consider the following model of inequality where Inequality (G) is determined by a set of explanatory variables (X) and an error component v so that Git = Xit β+ vit and vit=ct+uit. The error structure in this model is one where vit is formed of an unobservable component ct which is time-specific and a random error disturbance uit which is IID. If the unobservable term is uncorrelated with the covariates then there are no problems with estimating this specification using OLS. However, if the unobservable terms are correlated with some of the explanatory variables then the estimates of the β coefficient will be biased.

7. It is however important to note that if the impact of the ICT revolution differs across countries, and therefore the structure of the error term in the estimation is one where the term ct becomes cit (implying country time-specific disturbances), then the correction method used can still yield biased estimates of the β coefficient.

Table A.4. Determinants of wage inequality across different measures (pooled model)

	(1)	(2)	(3)	(4)
Dep Var:	WDI_Gini	OECD_Gini	WIOD_Gini1	EHII_Gini
backward	-0.166**	-0.146***	-0.188***	-0.0655**
	(0.0710)	(0.0313)	(0.0369)	(0.0288)
ln_GDPcapPPP	0.403	-1.310***	-0.0297	-0.340***
	(0.281)	(0.456)	(0.148)	(0.0727)
ln_GDPcapPPP2	-0.0224	0.0651***	-0.00211	0.0168***
	(0.0153)	(0.0219)	(0.00807)	(0.00380)
lnUNCTAD_stock_inward	0.0107**	0.00213	0.00472**	0.00638***
	(0.00496)	(0.00241)	(0.00227)	(0.00197)
_RandD_expenditure_share_GDP	-0.0192	-0.0130***	-0.0226***	-0.0224***
	(0.0157)	(0.00460)	(0.00327)	(0.00429)
_Tax_revenueshareGDP	-0.00364*	0.00127**	-0.000132	-7.75e-05
	(0.00210)	(0.000588)	(0.000510)	(0.000325)
_School_enrollment_ter_share	0.000458	4.92e-05	-0.000850***	0.000119
	(0.000561)	(0.000183)	(0.000253)	(0.000217)
_Unemployment_total_share	-0.00139	0.00309**	-0.00438***	0.000625
	(0.00132)	(0.00145)	(0.000934)	(0.000488)
Constant	-1.459	6.973***	0.829	2.061***
	(1.270)	(2.364)	(0.677)	(0.329)
Observations	87	117	358	277
R-squared	0.466	0.391	0.658	0.505
Year FE	Y	Y	Y	Y

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.5. Determinants of inequality using different specifications

	(1)	(2)	(3)
VARIABLES	GMM	FLogit marginal	OLS
backward	-0.173***	-0.189*	-0.188***
	(0.0625)	(0.103)	(0.0369)
ln_GDPcapPPP	-0.0156	0.0916	-0.0297
	(0.132)	(0.306)	(0.148)
ln_GDPcapPPP2	-0.00275	-0.00780	-0.00211
	(0.00725)	(0.0168)	(0.00807)
lnUNCTAD_stock_inward	0.00903***	0.00399	0.00472**
	(0.00257)	(0.00500)	(0.00227)
_RandD_expenditure_sha	-0.0306***	-0.0266***	-0.0226***
	(0.00637)	(0.00868)	(0.00327)
_Tax_revenueshareGDP	-0.000868	-0.000247	-0.000132
	(0.000975)	(0.00117)	(0.000510)
_School_enrollment_ter	-0.000502	-0.000852	-0.000850***
	(0.000370)	(0.000567)	(0.000253)
_Unemployment_total_sh	-0.00559***	-0.00410**	-0.00438***
	(0.00103)	(0.00184)	(0.000934)
Constant	0.748		0.829
	(0.594)		(0.677)
Observations	357	357	357
R-squared			0.689

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.6. Backward participation and inequality using EHII and EORA

VARIABLES: EHII_Gini	(1) All	(2) Lower-Middle Income	(3) Upper-Middle Income	(4) High Income
backward	-0.174***	-0.218***	-0.316***	-0.0903*
	(0.0207)	(0.0597)	(0.0525)	(0.0416)
ln_GDPcapPPP	0.0320	-0.219	-0.892**	-0.325***
	(0.0581)	(0.455)	(0.316)	(0.0817)
ln_GDPcapPPP2	-0.00418	0.00925	0.0500**	0.0155***
	(0.00324)	(0.0265)	(0.0181)	(0.00423)
ln_GDP_PPP	-0.0113***	-0.0232**	-0.0247***	0.00398
	(0.00244)	(0.0101)	(0.00605)	(0.00355)
lnUNCTAD_stock_inward	0.0149***	0.0222*	0.0311***	-0.000799
	(0.00282)	(0.0119)	(0.00615)	(0.00283)
_RandD_expenditure_share_GDP	0.00253	-0.0343***	-0.0552***	0.00207
	(0.00287)	(0.00676)	(0.0169)	(0.00265)
_School_enrollment_ter_share	-0.000698***	-0.000592	-0.00101***	-0.000638***
	(9.87e-05)	(0.000584)	(0.000223)	(0.000162)
_Unemployment_total_share	0.00121***	0.00118	0.00198***	0.00168***
	(0.000255)	(0.00107)	(0.000389)	(0.000200)
Constant	0.687**	2.113	4.861***	2.023***
	(0.259)	(2.086)	(1.340)	(0.377)
Observations	494	41	125	322
R-squared	0.578	0.883	0.668	0.238
Year FE	13	13	13	13

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Within estimation of impact of backward participation on wage inequality

The results presented in the text draw on regressions combining cross-country and in-time variation which are likely to reflect long-run equilibrium effects.[8] However it is also important to focus on what is happening within countries so that we may understand the determinants of *changes* in wage inequality and how these relate to *changes* in the variables of interest.[9] This can be accomplished by introducing country-specific fixed effects into the above specifications allowing to control for the characteristics of countries such as geographical location or broad institutional quality and also

8. This is because there is a greater cross-sectional rather than temporal variance of the inequality measure. Since the pooled regressions take into account both these elements but the cross-sectional dimension dominates the regressions are more likely to be capturing the long run equilibrium effects.

9. This is likely to reflect short-run adjustments towards the longer run equilibrium that should be captured by the pooled model. This distinction between long run equilibrium effects and short-run effects is derived from Bartelsman et al. (1994) who suggest that including cross-sectional elements is likely to reflect equilibrium values once various factors have adjusted. In contrast, within country changes are likely to be more representative of the short-term adjustments.

reducing possible biases caused by omitted variables which do not change much in time.[10] This allows us to identify what is driving within country *changes* in wage inequality.

The results, presented in Table A.7, suggest that the relationship between changes in inequality and changes in backward GVC participation cannot be firmly established (i.e. it is not statistically significant). One possibility is that this arises from there being a differential impact on wage inequality according to whether the offshoring activity engages high or low skilled workers as is predicted in the theoretical models (Grossman and Rossi-Hansberg, 2008).

Table A.7. Determinants of changes in wage inequality – Within developed and emerging economies

Dep Var: WIODGini	(1)	(2)	(3)
	All	emerging	developed
Backward participation	0.0245	-0.00392	-0.116
	(0.0698)	(0.0780)	(0.111)
lnGDPperCapita	0.183	1.021***	-0.960
	(0.234)	(0.265)	(0.765)
lnGDPperCapita2	-0.0172	-0.0599***	0.0517
	(0.0107)	(0.0115)	(0.0391)
lnGDP	0.136	-0.00273	-0.0235
	(0.122)	(0.177)	(0.172)
lnFDI_Inward_Stock	0.00508	0.00377	0.0162
	(0.00616)	(0.00666)	(0.00967)
RandD_expenditure_share_GDP	0.00913	0.0180	0.00681
	(0.0111)	(0.0295)	(0.00911)
School_enrollment_tertiary_share	-0.000395	-0.000186	-0.000320
	(0.000293)	(0.000483)	(0.000394)
Unemployment_total_share	0.00129	-0.00129	0.00279***
	(0.000970)	(0.000813)	(0.000801)
Constant	-3.526	-3.950	5.082
	(2.115)	(3.247)	(5.098)
Observations	417	153	264
R-squared	0.215	0.409	0.316
Reporter Fixed Effects	Y	Y	Y

Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

10. This also allows controlling for both unobserved heterogeneity arising from time invariant country-specific factors as well as omitted variable biases which could be biasing the coefficients.

Table A.8. Forward participation and wage inequality

Dep Var: WIODGini	(1)	(2)	(3)	(4)	(5)	(6)
	All	Emerging	Developed	All	Emerging	Developed
		Pooled model			Within	
Forward	0.240***	0.289***	0.00104	-0.0159	0.0726	0.0409
	(0.0441)	(0.0733)	(0.0710)	(0.0569)	(0.0685)	(0.121)
ln_GDPcapPPP	-0.0120	-0.0252	0.515*	0.204	1.020***	-1.139
	(0.0933)	(0.186)	(0.260)	(0.213)	(0.267)	(0.732)
ln_GDPcapPPP2	-0.00279	0.00129	-0.0216	-0.0183*	-0.0594***	0.0586
	(0.00521)	(0.0111)	(0.0124)	(0.00996)	(0.0107)	(0.0384)
ln_GDP_PPP	0.0171***	0.0251***	0.0197***	0.131	-0.0188	0.0256
	(0.00185)	(0.00526)	(0.00136)	(0.118)	(0.181)	(0.165)
lnUNCTAD_stock_inward	-0.00377	-0.00569	-0.0202***	0.00511	0.00128	0.0163
	(0.00227)	(0.00665)	(0.00247)	(0.00635)	(0.00809)	(0.00983)
_RandD_expenditure_share_GDP	-0.0288***	0.0504***	-0.0306***	0.00931	0.0221	0.00425
	(0.00256)	(0.00863)	(0.00162)	(0.0113)	(0.0295)	(0.00872)
_School_enrollment_ter_share	-0.000790**	-0.00172**	-0.000586**	-0.000383	-0.000207	-0.000334
	(0.000315)	(0.000658)	(0.000198)	(0.000296)	(0.000489)	(0.000360)
_Unemployment_total_share	-0.00580***	-0.00448***	-0.00176**	0.00129	-0.00137	0.00276***
	(0.00103)	(0.00126)	(0.000768)	(0.000970)	(0.000803)	(0.000891)
Constant	0.298	-0.140	-2.992**	-3.518	-3.556	4.864
	(0.452)	(0.753)	(1.338)	(2.112)	(3.233)	(5.224)
Observations	417	153	264	417	153	264
R-squared	0.646	0.658	0.385	0.214	0.415	0.301
Year FE	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	Y	Y	Y

Table A.9. Backward participation by type and OECD inequality measure

	(1)	(2)	(3)	(4)	(5)	(6)
		Pooled			Within	
VARIABLES: OECDGini	All	Emerging	Developed	All	Emerging	Developed
hsbackward	1.681***	1.653	1.658***	0.838**	3.981*	0.745
	(0.288)	(1.086)	(0.184)	(0.361)	(1.821)	(0.440)
lmbackward	-1.634***	-1.988***	-1.556***	0.142	-1.476	0.171
	(0.140)	(0.579)	(0.166)	(0.188)	(1.375)	(0.340)
ln_GDPcapPPP	-1.551***	-2.493	-2.215***	-1.375***	8.129	-1.395**
	(0.177)	(3.724)	(0.320)	(0.355)	(4.260)	(0.515)
ln_GDPcapPPP2	0.0724***	0.120	0.104***	0.0618***	-0.451	0.0606**
	(0.00872)	(0.191)	(0.0152)	(0.0181)	(0.227)	(0.0242)
ln_GDP_PPP	0.00729	-0.0523**	0.0114**	0.138	0.726	0.171
	(0.00427)	(0.0197)	(0.00507)	(0.0947)	(0.352)	(0.177)
lnUNCTAD_stock_inward	0.000587	0.0524*	-0.000130	-0.000709	-0.0710**	0.000687
	(0.00232)	(0.0238)	(0.00293)	(0.00491)	(0.0242)	(0.00771)
_RandD_expenditure_share_GDP	-0.0185***	-0.0344	-0.0186***	-0.00682	0.0157	-0.00745
	(0.00410)	(0.0549)	(0.00352)	(0.0117)	(0.0431)	(0.0128)
_School_enrollment_ter_share	0.000432**	-0.00118	0.000634***	-4.50e-05	0.00222	-0.000113
	(0.000163)	(0.00102)	(0.000104)	(0.000165)	(0.00132)	(0.000172)
_Unemployment_total_share	-0.00235**	-0.00266	-0.00141	0.00146***	0.00187	0.00131*
	(0.000893)	(0.00282)	(0.000885)	(0.000490)	(0.00193)	(0.000758)
Constant	8.492***	14.26	11.80***	4.121	-54.38*	3.539
	(0.928)	(18.35)	(1.750)	(2.667)	(25.47)	(4.130)
Observations	159	27	132	159	27	132
R-squared	0.831	0.958	0.836	0.433	0.951	0.407
Year FE	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	Y	Y	Y

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A.10. Backward participation by type and wage inequality (shares of shares)

	(1)	(2)	(3)	(4)	(5)	(6)
		Pooled			Within	
VARIABLES: WIODGini1	All	Emerging	All	Emerging	All	Emerging
hsbackwardshare	0.503***	-0.127	-0.770***	-0.0980	0.270	-0.320
	(0.103)	(0.247)	(0.0795)	(0.305)	(0.628)	(0.221)
lmbackwardshare	-0.837***	-1.554***	-0.970***	-0.384**	-0.580**	-0.144
	(0.0844)	(0.135)	(0.109)	(0.169)	(0.237)	(0.247)
hsforwardshare	0.174***	0.530***	0.178***	0.236**	0.288	0.193*
	(0.0410)	(0.115)	(0.0210)	(0.0969)	(0.179)	(0.107)
lmforwardshare	-0.0775***	-0.306***	0.0940***	-0.00620	-0.0438	0.102
	(0.0137)	(0.0238)	(0.0172)	(0.0521)	(0.0642)	(0.0874)
ln_GDPcapPPP	0.297***	1.162***	0.729**	0.295	0.739*	-0.928
	(0.0611)	(0.207)	(0.330)	(0.224)	(0.341)	(0.894)
ln_GDPcapPPP2	-0.0199***	-0.0692***	-0.0340*	-0.0232**	-0.0517***	0.0490
	(0.00342)	(0.0121)	(0.0158)	(0.00956)	(0.0144)	(0.0471)
ln_GDP_PPP	0.0260***	0.0476***	0.00714***	0.129	0.120	0.0139
	(0.00196)	(0.00554)	(0.00175)	(0.116)	(0.164)	(0.146)
lnUNCTAD_stock_inward	-0.0165***	-0.00783	-0.0149***	0.00654	0.00421	0.0144
	(0.00186)	(0.00723)	(0.00257)	(0.00576)	(0.00868)	(0.00840)
_RandD_expenditure_share_GDP	-0.0302***	0.0280**	-0.0376***	0.00660	0.0144	0.00599
	(0.00339)	(0.0104)	(0.00223)	(0.0112)	(0.0303)	(0.00842)
_School_enrollment_ter_share	-0.000260	0.00124***	-0.000544***	-0.000205	0.000154	-0.000226
	(0.000210)	(0.000173)	(0.000154)	(0.000263)	(0.000453)	(0.000313)
_Unemployment_total_share	-0.00539***	-0.00455***	-0.00120*	0.00106	-0.00242**	0.00297***
	(0.000823)	(0.00110)	(0.000673)	(0.00107)	(0.000900)	(0.000923)
Constant	-0.879**	-4.958***	-3.133*	-3.704*	-5.053*	4.077
	(0.295)	(0.841)	(1.692)	(1.890)	(2.577)	(5.901)
Observations	417	153	264	417	153	264
R-squared	0.712	0.877	0.533	0.270	0.485	0.358
Year FE	14	14	14			
Country FE				37	13	24

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A.11. Participation by type and wage inequality (standardised coefficients)

	(1)	(2)	(3)	(4)	(5)	(6)
		Pooled model			Within	
VARIABLES	All	Emerging	Developed	All	Emerging	Developed
stdhsbackward	0.586***	0.711***	0.0425	0.264**	0.677*	0.00644
	(0.0590)	(0.192)	(0.0409)	(0.125)	(0.373)	(0.126)
stdlmbackward	-0.694***	-0.911***	-0.328***	-0.184*	-0.540**	-0.0180
	(0.0305)	(0.174)	(0.0203)	(0.101)	(0.224)	(0.125)
stdhsforward	0.137***	0.276***	0.0270	0.0848	0.207**	0.107*
	(0.0183)	(0.0767)	(0.0157)	(0.0517)	(0.0944)	(0.0556)
stdlmforward	-0.0141	-0.198***	-0.0504**	-0.00477	-0.0198	0.0412
	(0.0202)	(0.0475)	(0.0202)	(0.0581)	(0.0632)	(0.111)
stdln_GDPcapPPP2	-0.557***	-0.0795	0.215***	-1.392*	-3.115**	0.444
	(0.0422)	(0.0692)	(0.0545)	(0.798)	(1.104)	(1.248)
ln_GDP_PPP	0.153***	0.314***	0.0131	1.947*	4.250**	-0.0754
	(0.0244)	(0.0880)	(0.0304)	(0.999)	(1.524)	(1.632)
stdlnUNCTAD_stock_inward	-0.237***	-0.283**	-0.193***	0.0932	0.0954	0.203
	(0.0299)	(0.113)	(0.0503)	(0.113)	(0.181)	(0.171)
_RandD_expenditure_share_GDP	-0.305***	0.418	-0.267***	0.0710	-0.117	0.0758
	(0.0300)	(0.246)	(0.0259)	(0.0991)	(0.264)	(0.0943)
std_School_enrollment_ter_share	-0.107**	-0.109	-0.152***	-0.0770	-0.0163	-0.0914
	(0.0446)	(0.103)	(0.0316)	(0.0652)	(0.119)	(0.0851)
_Unemployment_total_share	-0.0400***	-0.0220	-0.0137**	0.0139	-0.00787	0.0281***
	(0.00793)	(0.0136)	(0.00508)	(0.0104)	(0.00955)	(0.00979)
Constant	-3.431***	-7.772***	-0.380	-51.58*	-112.6**	0.918
	(0.633)	(2.364)	(0.763)	(26.26)	(40.31)	(42.60)
Observations	417	153	264	417	153	264
R-squared	0.714	0.758	0.488	0.243	0.414	0.308
Year FE	Y	Y	Y	Y	Y	Y
Country FE	N	N	N	Y	Y	Y

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A.12. Participation by type and income inequality (using OECD measure)

	(1)	(2)	(3)	(4)	(5)
	X1	X2	X3	X5	X6
VARIABLES: OECDGINIpt	OECDGINI	OECDGINI	OECDGINI	OECDGINI	OECDGINI
hsbackward	1.473***	-1.055	1.771***	0.963***	0.953**
	(0.257)	(0.737)	(0.204)	(0.328)	(0.398)
lmbackward	-1.542***	-1.143*	-1.585***	0.126	0.0205
	(0.133)	(0.526)	(0.183)	(0.184)	(0.289)
hsforward	0.184	4.543*	0.0379	-0.558	-0.921**
	(0.138)	(2.465)	(0.158)	(0.386)	(0.370)
lmforward	-0.241**	-3.487***	0.0929	0.273	0.382**
	(0.107)	(0.648)	(0.169)	(0.241)	(0.184)
ln_GDPcapPPP	-1.372***	4.853*	-2.198***	-1.618***	-2.055***
	(0.220)	(2.615)	(0.369)	(0.424)	(0.631)
ln_GDPcapPPP2	0.0636***	-0.246*	0.104***	0.0749***	0.0955***
	(0.0109)	(0.133)	(0.0178)	(0.0216)	(0.0303)
ln_GDP_PPP	0.00727	0.0210	0.0117**	0.130	0.139
	(0.00428)	(0.0168)	(0.00470)	(0.0907)	(0.138)
lnUNCTAD_stock_inward	-6.00e-05	0.0207**	-0.000563	-0.00262	-0.00220
	(0.00286)	(0.00936)	(0.00315)	(0.00536)	(0.00686)
_RandD_expenditure_share_GDP	-0.0177***	0.0143	-0.0197***	-0.0100	-0.0112
	(0.00453)	(0.0298)	(0.00447)	(0.0103)	(0.0111)
_School_enrollment_ter_share	0.000311	-0.000929**	0.000665***	-0.000120	-0.000241
	(0.000180)	(0.000415)	(0.000141)	(0.000180)	(0.000187)
_Unemployment_total_share	-0.00239***	0.00423***	-0.00123	0.00159***	0.00173**
	(0.000780)	(0.00114)	(0.000908)	(0.000558)	(0.000698)
Constant	7.601***	-23.97*	11.68***	5.487*	7.559*
	(1.149)	(12.60)	(1.956)	(2.696)	(3.800)
Observations	159	27	132	159	132
R-squared	0.838	0.996	0.837	0.453	0.461
Year FE	Y	Y	Y	Y	Y
Country FE	N	N	N	Y	Y

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A.13. Participation by type using different measures of income inequality

	(1)	(2)	(3)	(4)	(5)
VARIABLES	WIODGini	EHIIGini	OECDGINI	WDI_Gini	UNIDOGini
hsbackward	2.976***	0.253**	1.473***	2.106***	0.116
	(0.268)	(0.104)	(0.257)	(0.380)	(0.0864)
lmbackward	-1.881***	-0.365***	-1.542***	-1.928***	-0.0180
	(0.0925)	(0.0496)	(0.133)	(0.173)	(0.0324)
hsforward	0.900***	0.108*	0.184	1.436***	-0.0869*
	(0.0976)	(0.0587)	(0.138)	(0.463)	(0.0448)
lmforward	-0.131*	-0.413***	-0.241**	-0.879***	-0.103***
	(0.0739)	(0.0677)	(0.107)	(0.104)	(0.0280)
ln_GDPcapPPP	0.482***	-0.0777	-1.372***	0.828***	0.0270
	(0.0568)	(0.0459)	(0.220)	(0.260)	(0.0398)
ln_GDPcapPPP2	-0.0302***	0.00351	0.0636***	-0.0449***	-0.00183
	(0.00305)	(0.00249)	(0.0109)	(0.0142)	(0.00207)
ln_GDP_PPP	0.0118***	0.0175***	0.00727	0.0128	0.0139***
	(0.00234)	(0.00277)	(0.00428)	(0.0123)	(0.00183)
lnUNCTAD_stock_inward	-0.00870***	-0.00986***	-6.00e-05	-0.00382	-0.0111***
	(0.00225)	(0.00291)	(0.00286)	(0.0121)	(0.00178)
_RandD_expenditure_share_GDP	-0.0230***	-0.0175***	-0.0177***	-0.0267***	-0.00147*
	(0.00248)	(0.00174)	(0.00453)	(0.00848)	(0.000789)
_School_enrollment_ter_share	-0.000676***	-3.36e-05	0.000311	8.75e-05	4.88e-05
	(0.000200)	(6.63e-05)	(0.000180)	(0.000461)	(6.09e-05)
_Unemployment_total_share	-0.00479***	0.000689	-0.00239***	-0.00206**	-2.64e-05
	(0.000638)	(0.000416)	(0.000780)	(0.000728)	(0.000202)
Constant	-1.634***	0.526*	7.601***	-3.565***	-0.298
	(0.255)	(0.248)	(1.149)	(1.055)	(0.207)
Observations	417	320	159	110	326
R-squared	0.731	0.589	0.838	0.767	0.512
Number of time	14	13	14	14	13

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table A.14. Introducing other control variables

	(1)	(2)	(3)	(4)	(5)	(6)
		Pooled model			Within	
VARIABLES	All	Emerging	Developed	All	Emerging	Developed
hsbackward	2.319***	3.157***	-0.123	0.768	1.993	-0.260
	(0.279)	(0.524)	(0.238)	(0.701)	(1.521)	(0.382)
lmbackward	-1.565***	-2.673***	-0.873***	-0.669**	-1.353**	-0.109
	(0.199)	(0.162)	(0.113)	(0.266)	(0.459)	(0.311)
capbackward	0.299*	1.746***	0.120	0.495*	0.642*	0.303
	(0.162)	(0.225)	(0.182)	(0.278)	(0.334)	(0.335)
hsforward	0.959***	2.273***	0.0430	0.759***	1.094**	0.295
	(0.0895)	(0.690)	(0.108)	(0.271)	(0.501)	(0.286)
lmforward	-0.222***	-0.796***	-0.282***	-0.0182	-0.0463	0.375
	(0.0509)	(0.146)	(0.0813)	(0.182)	(0.204)	(0.403)
capforward	0.519***	1.134***	-0.345***	0.0468	0.175	-0.144
	(0.0632)	(0.110)	(0.0815)	(0.113)	(0.144)	(0.199)
relskillint	-0.000664***	-0.000311	-0.000110	7.40e-05	-9.27e-05	-0.000510
	(8.34e-05)	(0.000571)	(6.81e-05)	(0.000312)	(0.000680)	(0.000303)
ln_GDPcapPPP	0.392***	0.641**	-1.088***	0.387*	0.811**	-0.526
	(0.0566)	(0.274)	(0.327)	(0.203)	(0.300)	(0.856)
ln_GDPcapPPP2	-0.0247***	-0.0386**	0.0539***	-0.0296***	-0.0603***	0.0308
	(0.00312)	(0.0162)	(0.0157)	(0.0101)	(0.0127)	(0.0449)
ln_GDP_PPP	0.0126***	0.0352***	9.47e-05	0.142	0.227	0.00665
	(0.00245)	(0.00584)	(0.00279)	(0.102)	(0.175)	(0.154)
lnUNCTAD_stock_inward	-0.00702***	-0.0112*	-0.00819***	0.00429	0.00737	0.0170*
	(0.00222)	(0.00606)	(0.00234)	(0.00573)	(0.00959)	(0.00856)
_RandD_expenditure_share_GDP	-0.0189***	0.0430**	-0.0239***	0.00744	0.0103	0.00613
	(0.00326)	(0.0159)	(0.00260)	(0.0108)	(0.0284)	(0.00905)
_School_enrollment_ter_share	-0.000773***	-0.000665*	-0.000547***	-0.000321	9.28e-05	-0.000455
	(0.000213)	(0.000374)	(0.000152)	(0.000253)	(0.000325)	(0.000366)
_Unemployment_total_share	-0.00490***	-0.00266**	-0.00179**	0.000865	-0.00193**	0.00332***
	(0.000751)	(0.00108)	(0.000789)	(0.00105)	(0.000677)	(0.000908)
Constant	-1.375***	-3.218**	6.012***	-4.504**	-8.039**	1.974
	(0.249)	(1.146)	(1.692)	(1.845)	(3.017)	(5.543)
Observations	417	153	264	417	153	264
R-squared	0.753	0.887	0.514	0.277	0.495	0.356
Number of time	14	14	14			
Number of rep				37	13	24

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Measures of GVC participation

Backward and forward participation indicators are calculated from first principles using the WIOD database. To decompose the value added content of export (which is shortened to VAE in the following) the product of the following equation is taken:

$$VAE = \hat{V}[I - A]^{-1}X \qquad (1)$$

Where V is a diagonalised $ni\ x\ ni$ matrix of n countries (n={1,2… 41}) and i sectors of activity (i={1,2… 35}) with elements $v_{ni} = {V_{ni}}/{Y_{ni}}$ capturing the direct value added (V) share of sector i in country n in the output (Y) of the industry. The $[I - A]^{-1}$ is the Leontief inverse matrix which represents the interlinkages that arise within and between countries. The elements of the A matrix capture the input share of output better known as the technical coefficients ($a_{ni} = {I_{ni,j}}/{Y_{ni}}$ where I is the gross use of intermediate inputs of industry *i* from industry *j* in country *n*). X is then a vector of gross exports with elements x_{ni} (the gross exports of industry *i* in country *n*). The product of this equation gives an *ni x ni* matrix decomposing the value added embodied in exports according where it ultimately originates. By summing the non-diagonal elements of this matrix across column nations a metric of the foreign value added of exports can be obtained. Presenting this value as a share of gross exports then gives the measure of backward participation.

The forward participation indicator is calculated from the same baseline VAE matrix but, rather than summing across column nations, summing across the non-diagonal elements of the row nation. Similarly, dividing the value obtained by total gross exports of the row nation yields the forward participation indicator which is the value added content of gross exports that is used by foreign nations to produce their exports as a share of the reporting country's gross exports.

Table A.15. Socio-Economic Accounts

Values	***Description***
GO	Gross output by industry at current basic prices (in millions of national currency)
II	Intermediate inputs at current purchasers' prices (in millions of national currency)
VA	Gross value added at current basic prices (in millions of national currency)
COMP	Compensation of employees (in millions of national currency)
LAB	Labour compensation (in millions of national currency)
CAP	Capital compensation (in millions of national currency)
GFCF	Nominal gross fixed capital formation (in millions of national currency)
EMP	Number of persons engaged (thousands)
EMPE	Number of employees (thousands)
H_EMP	Total hours worked by persons engaged (millions)
H_EMPE	Total hours worked by employees (millions)
Prices	
GO_P	Price levels gross output, 1995=100
II_P	Price levels of intermediate inputs, 1995=100
VA_P	Price levels of gross value added, 1995=100
GFCF_P	Price levels of gross fixed capital formation, 1995=100

Values	***Description***
Volumes	
GO_QI	Gross output, volume indices, 1995 = 100
II_QI	Intermediate inputs, volume indices, 1995 = 100
VA_QI	Gross value added, volume indices, 1995 = 100
K_GFCF	Real fixed capital stock, 1995 prices
Additional variables	
LABHS	High-skilled labour compensation (share in total labour compensation)
LABMS	Medium-skilled labour compensation (share in total labour compensation)
LABLS	Low-skilled labour compensation (share in total labour compensation)
H_HS	Hours worked by high-skilled persons engaged (share in total hours)
H_MS	Hours worked by medium-skilled persons engaged (share in total hours)
H_LS	Hours worked by low-skilled persons engaged (share in total hours)

Table A.16. WIOD Country Coverage

European Union			**North America**	**Asia and Pacific**
Austria	Germany	Netherlands	Canada	China
Belgium	Greece	Poland	United States	India
Bulgaria	Hungary	Portugal		Japan
Cyprus [1, 2]	Ireland	Romania	**Latin America**	Korea
Czech Republic	Italy	Slovak Republic	Brazil	Australia
Denmark	Latvia	Slovenia	Mexico	Chinese Taipei
Estonia	Lithuania	Spain		Turkey
Finland	Luxembourg	Sweden		Indonesia
France	Malta	United Kingdom		Russia

1. Footnote by Turkey: The information in this document with reference to “Cyprus” relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of United Nations, Turkey shall preserve its position concerning the “Cyprus” issue

2. Footnote by all the European Union Member States of the OECD and the European Union: The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.