Labour Shares and Import Competition: Is Increasing Import Exposure Driving Down Labour Shares?

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Abstract

This paper explores the effect of import exposure of industries, on the industry-level labour shares across a set of countries over the decade 1995-2005. I use World Input Output data to construct various measures to test negative relation between import exposure and the labour share pointed out by Elsby et al. (2013). This relation has seemingly been difficult to replicate in the literature, and requires a more careful examination. In this paper I argue that the failure to replicate is due to the difference between using gross import measures, versus input-output based measures This paper aims to provide a more thorough exploration of this relationship, a larger coverage of countries, and different measures.

Introduction

The aim of this paper is to show the effect of increasing global integration of production processes have on the labour share in industries whose firms participate in these global production processes. The motivation for this research is the, by now, well-documented decline in the labour share in many countries and industries (Dao et al. 2017; Karabarbounis & Neiman 2014). In this paper, I will examine how the increased prevalence of the offshoring movement has affected the labour share of industries over time, across various countries. I use the World Input-Output Database (WIOD) to construct measures of import exposure at the industry level, and relate them to the industry labour shares.

This work primarily builds on Elsby et al. (2013) who find a negative relation between offshoring and the labour share in the United States. However, a several other papers that aim to control for the effects of trade on the labour share, find very little significance (Autor et al. 2017; Karabarbounis & Neiman 2014). This work aims to explore this relationship, being able to take multiple countries into account, rather than the United States view adopted by Elsby et al. (2013). In addition, this paper puts forward a different measure of import exposure, based on the hypothetical extraction method, suggested by Los et al. (2016). This measure allows me to construct a hypothetical world GDP for each global industry, in case some or all imports to any country cease. Comparing this hypothetical to actual GDP for each industry is a good indication of how exposed a particular industry is to imports (Timmer et al. 2016).

This papers starts with documenting the heterogeneity between sectors in terms of the changing labour share. While most follow a downward trend, this trend is not the same across countries or industries. For this reason, I continue by decomposing labour share changes into within and between changes. This is important for the relation of the labour share with the import exposure of industries. Overall, the import exposure seems to be negatively related to the labour share, like the Elbsy et al. (2013) result. However, this result seems to depend crucially on manufacturing sectors. The negative relation disappears when only considering the non-manufacturing sectors. Furthermore, econometrically establishing causality between trade and the labour share is not within the bounds of this paper, rather the focus is on exploring the relevance of using input-output import competition measures, rather than simply using gross imports, which seems the be the trend in the literature.

This research is related to a growing literature that seeks to establish the nature and origins of the widely observed decline of the labour share. This literature has put forward various explanations of what could be driving down labour shares. These will be discussed in turn in the next section. Additionally, another related literature deals with the effects of import competition from China, and other places. This literature has found strong effects of trade on various mainly macro, but also micro economic phenomena.

Literature & Theory

This section will feature the arguments put forward in the literature about the various drivers influencing factor shares. Most of the literature is written with the declining labour share(s) in mind; however, the arguments are equally (or, sometimes, more) valid in explaining the developments of other factor shares. This section features three broad drivers of factor shares, and arguments put forward in the literature. There is evidence in the literature to suggest that all of the drivers might be important; however, not all drivers are equally vital for all industries. Therefore, this section also discusses expectations about which drivers are vital for which industries.

Biased technological change (BTC) and Automation

The biased technological change (BTC) argument is common in the literature of changing factor shares. BTC is most often assumed capital augmenting, meaning that capital is becoming more productive. The argument is that, as capital becomes more productive, firms use more capital in favour of labour, increasing the capital-labour ratio of production. This can only lead to a decline in the labour share however, if the elasticity of substitution (σ) is greater than one. When this is true, capital and labour are gross complements, and the decline in the relative price of one factor (for example due to BTC) will lead that factor's share in income to increase(Karabarbounis & Neiman 2014; Piketty & Zucman 2014). Both these papers estimate a σ greater than one, and reach similar conclusions about the role of capital in lowering the labour share. Alternatively, Aum et al. (2018) suggest that σ is larger for labour and computer capital, but not necessarily for other types of capital, and link the increase of computer capital (including software) to the decline of the labour share (Aum et al. 2018).

While their argumentation seems to make sense intuitively, their findings of σ greater than one is at odds with other research that estimates σ below (Antràs 2004; Chirinko 2008; Oberfield & Raval 2014). This, and other problems, like the lack of sufficient capital deepening throughout the period of the labour share decline, are pointed out in the literature (Elsby et al. 2013; Rognlie 2015; Bridgman 2017). It is therefore not likely that this argument can fully account for the decline in the labour share and other factor share developments. However, labour share developments in several industries, like some manufacturing industries, high-tech services industries and agriculture especially, might be possible to explain with arguments like this. Many industries within these categories have been most exposed to the price declines of specific types of capital (mainly computer capital), and have experiences capital deepening.

A related literature has developed around similar arguments that do not require assuming σ greater than one. One example that remains close to the conceptual model is Lawrence (2015) who argues that *labour* augmenting technical change is the main river of declining labour shares (in the U.S.A.), rather than capital augmenting technical change. This argument works in the same way as before; however, now we use σ is *less* than one; or capital and labour are gross substitutes. It is the argument above reversed; with labour augmenting technical change, and factors gross substitutes, a decline in the price of labour will actually decrease the share of labour in total value added (Lawrence 2015). He checks this argument for multiple industries in the U.S.A. and finds evidence that it holds for many manufacturing industries, though does not provide evidence for which innovations or technologies are driving this labour augmenting change of workplaces. Similarly, Grossman et al. (2017) also assume σ smaller than one, and endogenise human capital, through educational attainment, into a neoclassical framework. They argue that the labour productivity slowdown starting around the 1980's has led to a decline in the labour share. Their argument is that due to lower productivity, interest rates decline, which boost investments into human capital. These investments in turn reduce the effective capital-labour ratio, because better-educated (and more productive) labour becomes cheaper. As capital and labour are complements, this reduction in the capital-labour ratio leads to a declining share of labour(Grossman 2017).

The literature on automation, more or less avoids the discussion on the elasticity of substitution (Acemoglu & Restrepo 2017; Acemoglu & Restrepo 2016; Acemoglu & Restrepo 2018). They assume a task-based framework where improved technology replaces labour in performing certain tasks. In fact, such advances in automation *always* reduce the labour share. In Acemoglu & Restrepo (2016), this happens because they model the effects of automation on the labour share distinctly from the effects of BTC. In fact, while an increase in automation can increase wages due to a general productivity effect, the overall impact on the labour share is always negative due to a declining number of tasks that labour performs. Acemoglu & Restreppo (2018) therefore also suggest that the 'worst' type of automation, in terms of labour share impact, is automation that is only a little more productive than labour would otherwise have been. This limits the productivity effect, while still reducing the tasks labour performs.

Aghion, Jones & Jones (2017) build a related model to explain changes in the labour share and reach similar conclusions. They develop a model, which uses automation along with the concept of a Baumol cost, to show that even when σ is below one, a declining labour share can be driven by automation of tasks. Their empirical section shows a quick comparison between the capital share changes[1] and the amount of industrial robots in several industries. Interestingly, the correlation between these two is rather low, suggesting other forces are perhaps more important drivers of factor shares of industries. (Aghion et al. 2017)

Intangibles & Market power

Outside the realm of capital and labour, other drivers that can limit the share of labour, and capital for that matter, are the shares of income that are traditionally not explicitly considered. These are the share of the intangible factors of production, and profits of firms.

Koh et al. (2017) hypothesise that the observed decline in the labour share (as well as the decline physical capital share) is due to an increased share of intangible capital (R&D, advertising, brand reputation, etc.). This can explain changing factor shares, because most capital measures do not explicitly consider intangibles. According to the authors, the share of income flowing to intangible capital has been large enough to explain virtually all of the change in the labour share. Haskel & Westlake (2017) who see the intangible economy encroaching on the economy in 'physical' goods also make this argument. They suggest that a small number of very large productive firms drives the shift towards intangible capital. These include high-tech firms that invest a lot in R&D, and other intangibles, like advertising, brand names, etc. This implies lower investments in other types of capital, an observation at the base of a literature on investments (Gutiérrez & Philippon 2016). They, link declining capital investments to intangibles, but also firm concentration, and market power. Increasing market power is a development, which is also considered to be at the root of changing factor shares. A series of papers by various authors all consider the effects of increasing market power and mark-ups of larger firms on the macro-economy (De Loecker & Eeckhout 2017; Barkai 2016; Autor et al. 2017; Kehrig &

[1] Using exhaustive capital and labour incomes, which means the capital share is one , minus the labour share.

Vincent 2017). The timing of this development also coincides with the declining labour share for the United States, making the connection a natural one.

Both the arguments work similarly; the increasing share of either intangibles or profits drives down the shares of labour and/or physical capital. Additionally, these are quite possible related. A firm with a large stock of intangible capital might be at an advantage to its competitors, allowing it increase mark-ups. In fact, some authors suggest that the increasing profit share is mainly due to not registering intangibles as capital (Traina 2018; Görzig & Gornig 2013). Fixing this, they suggest, would considerably reduce the increasing mark-ups. Regardless, across industries, these developments not be the same. Increasing profits is only likely in industries that are conducive to certain factors allowing such profit increases. Similarly, firms in certain industries would not benefit from investments in intangible capital. Industries that are most likely affected are industries that are very R&D heavy (Koh et al. 2015).

Institutional factors

Finally, a third set of drivers are identified in the literature, but are not the focus of the current work. This literature links the decline of the labour share to changes in the institutions affecting the labour market(Bivens & Mishel 2015; Levy & Temin 2007). These papers focus on the United States, and argue that labour market regulations in line with supporting and protecting low- and middle-wage workers before 1980 has provided a boost to the labour share. With the decline of these institutions since the 1980's and 90's, this boost has disappeared and the labour share started its decline. Examples of the policies that facilitated these institutions are the existence and influence of labour unions, or minimum wage regulations.

These institutions likely affect all industries, as institutional forces presumably work economy-wide. However, perhaps there are industry specific regulations that can influence individual industries, in specific countries. That would however require evaluation on an individual country-industry basis, which are difficult to measure.

Trade

Related to the argument that the labour share decline originates from trade rather than capital is Elsby et al. (2013). They suggest that the period of the labour share decline very closely coincides with the latest wave of globalisation, increasing international integration of production. The argument is that due to increasing offshoring of labour-intensive production stages, certain jobs have been shifted abroad, reducing the importance of labour in domestic production. Labour share declines caused by offshoring are by definition more severe in industries heavily exposed to competition from abroad, and those that use value chains that cross multiple countries. Perhaps due to the paper by Elsby et al. (2013), accounting for trade when evaluating drivers of the labour share has become more of less commonplace (Autor et al. 2017). However, many other authors do not seem to find much of a significant relation between trade and the labour share (Karabarbounis & Neiman 2014; Lawrence 2015; Karabarbounis & Neiman 2018; Autor et al. 2017). Either the result of Elsby et al. (2013) is a due to particular sample/data, or their measure based on input-output tables is picking up on more relevant variation, which gross trade based measure (most often used) do not. The reason that this could be, is that import competition can be defined not just as direct competition of imports to the local relevant industry, but to all industries. This is to say that, when goods are imported, they are composed of value added of many different industries in different countries, both directly, and indirectly through the inputs of inputs having different origins. If viewed in this way, the imports of a t-shirt is not just import competition to the textiles industry that could have produced the t-shirt domestically. The import of a t-shirt if in fact competition to all industries that could have potentially added value to the entire process of producing a t-shirt. This is the difference between the input-output measures of import competition, and those that are based on gross imports. This paper will focus on the former, to explore in more detail the relation between trade and the labour share of industries across countries, and over the period 1995-2011.

The next section first presents the labour share data, both from EUKLEMS and WIOD. The derivation of the import exposure measures, and the WIOD input-output data are discussed after that.

Labour share data WIOD & KLEMS

The most detailed factor share data is taken from the EUKLEMS database; specifically the March 2008 release of the analytical EUKLEMS database, which features data from 1970 up to 2005. It contains 32 unique ISIC rev. 3 industries. The next sections delve into more detail, exploring the industry level data. The WIOD data have a more limited availability of years. Starting in 1995, until 2011, but more countries, and similar industry coverage. Therefore, the period I will use for the primary analysis is 1995-2005, yet it is valuable to examine the developments of the labour share before this period.

Labour shares & Self-employment adjustment

The literature strongly argues in favour of correcting the labour share for the income generated by the self-employed[2](Gollin 2017). Currently, the both the WIOD, and EUKLEMS data assign equal hourly wages to self-employed and employed workers. This leads to issues in the distribution of incomes as pointed out by Gollin (2002), Elsby et al (2013), and Karabarbounis & Neiman (2014). In fact, this might lead to an overestimation of the labour share due to the hourly labour-compensation of the self-employed generally being lower than that of employed workers (Elsby et al. 2013). Improving on this assumption is a challenge, as the standard data does not make a distinction between incomes generated by the employed and the self-employed.

An alternative that is popular in the literature is to assume that the capital/labour shares of the employed and self-employed are equal. To introduce this method, data on the value added of the self-employed by industry is required from another source, as the KLEMS database does not suffice here. Unfortunately, such detailed data is not available for many (if any) countries. Another approach, used by Karabarbounis & Neiman (2014), is to only consider the income generated by employed persons, and disregard the income generated by the self-employed. This solution too, is not feasible with the just EUKLEMS or WIOD data, as the mixed income term, which contains all the income generated in the self-employed sector, cannot be distinguished from overall operating surplus.

Other ways of approaching this issue are somewhat cruder. One such approach would be to find and use value added data of the self-employed by industry for some countries. This data could then be applied to industries in other countries, requiring the assumption that industry self-employment shares of value added are equal across countries. Alternatively, the labour share for each industry can be adjusted for self-employment by using data for income generated by the self-employed at the national level for each country. Assuming the national level self-employment for each industry allows

[2] The cost of labour in a particular industry is assumed equal to the income generated by labour, and therefore these terms can be used interchangeably.

me to assign equal capital- and labour shares to the income generated by the employed and self-employed sectors, as suggested above.

To take account for the income of self-employed people therefore, I use the detailed KLEMS data and combine it with data from the OECD on the share of mixed income in total operating surplus. Using this data, the share of mixed income accruing to the self-employed, is applied to each sector's mixed income values (which are derived from KLEMS data on operating surplus). This way for each country, a constant share of gross operating surplus is assigned to self-employed labour income (as well as self-employed capital income). Formally, the gross operating surplus (GOS) of each country-industry (ci) observation in KLEMS is:

$$GOS_{ci} = VA_{ci} - Comp_{ci}^{emp} - Tax_{ci}$$

GOS is value added (VA) minus the compensation of *employees*, minus net taxes (Tax) paid. Additionally, given that the mixed income data for the OECD is only available at the country level, the mixed income assigned to each industry is computed using the number of self-employed persons N^{self} and the wage W^{emp} of employed persons[3]:

$$Mixed_{ci} = Mixed_i * \left(\frac{N_{ci}^{self} * W_{ci}^{emp}}{\sum_i N_{ci}^{self} * W_{ci}^{emp}} \right)$$

Or the national level value of mixed income ($Mixed$) multiplied by the share of self-employed income (using employed persons wages) in the country total of the same measure. This departs from the rigid KLEMS assumption that wage are equal within industries, and merely uses that as a way to divide total mixed income. Following Statistics Netherlands (Cbs & Cpb 2017) I assume that all mixed income is part of the labour income of the self-employed, in favour making any additional (arbitrary) assumptions about the capital share of self-employed income.

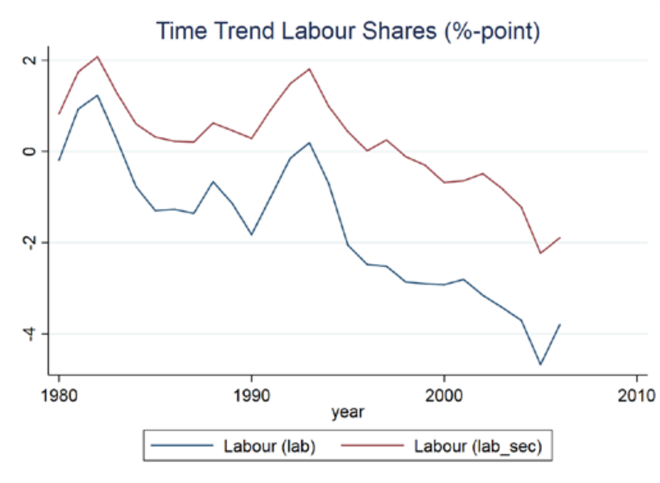
$$Comp_{ci}^{lab} = Comp_{ci}^{emp} + Mixed_{ci}$$

Finally, the labour share is then simply the total labour compensation divided by the industry's value added.

$$Share_{ci}^{lab} = \frac{Comp_{ci}^{lab}}{VA_{ci}}$$

[3] Note that the w^{emp} is computed as compensation of employees divided by total number of employees, for each industry, and for the aggregate. However, this implies that the sum of industry self-employed income ($N_{ci}^{self} * W_{ci}^{emp}$) does necessarily add up to the country aggregate, and thus that $\sum_i Mixed_{ci} \neq Mixed_i$. So to make the self-employed income add up properly, I have rescaled the w^{emp} (only for the self-employed calculation!) for each industry equally, such that self-employed income adds up to the country aggregate.

Figure 1 – time trends of labour shares across all countries in sample.



This adjustment is relevant over time, as Figure 2 shows[4]. The graph clearly shows an increasing gap in the changes of the labour share between the two series during the late 80's and 90's, a gap that narrowed a bit during the 2000's. This means that using our self-employment correction, the decline of labour share since the 80's is less severe than would appear from the basic KLEMS data. This finding is in concurrence with Elsby et al (2013), who find a similar disparity for the United States. In my data, this seem also to hold over a larger set of countries. Yet the decline of the labour share does not disappear, particularly for the post 1995-period, a sizable decline can still be observed. Additionally, both series show virtually the same developments in the post-1995 period.

Industries

To explore the changing labour shares in more detail, in this section I move towards the industry-level, starting with a shift-share analysis, where I decompose the changes in the labour share in within- and between-industry components. The shift-share analysis is based on EUKLEMS data; the WIOD data which will be used below to evaluate the relation between the labour share and import exposure.

Shift-share

Firstly, the shift-share analysis is interesting because it grants additional insight into whether factor changes are due to shifts in factor share within industries themselves, or between industries. This analysis is a useful tool to identify which countries faced labour share changes due to changing industry structure (between) or labour share changes in the industries themselves (within). The Shift-share analysis uses this formula:

$$\Delta Share_c^l = \sum_i \overline{Share_{ci}^{va}} * \Delta Share_{ci}^l + \sum_i \overline{Share_{ci}^l} * \Delta Share_{ci}^{va}$$

Where the change of a variable, indicated by Δ, is between two points in time, the bar over a variable indicates an average value over the same time two points in time. As shown in the equation, the shift-share analysis uses the change in each industries' share of value added in total country value added, and change in labour share in each industry in a country.

The first term on the right is the *within* industry term, it states the part of the total change in country-level labour share that that is due to changes of this factor within industries. The second term on the

[4] These and the subsequent time trend graphs are the year-fixed effects of a regression of the variable displayed versus year, country and industry effects; all series have been set at a starting point of zero in 1970. These graphs therefore depict the average global industry trend in a variable across industries and countries. The y-axis scale indicates percentage points of shares.

right is the *between* industry term; it states the part of variation that is due to changes in value added, or the relative importance of each industry.

Figure 2 – shift share analysis – Only broad industries; countries with less than 2 decades of data excluded.

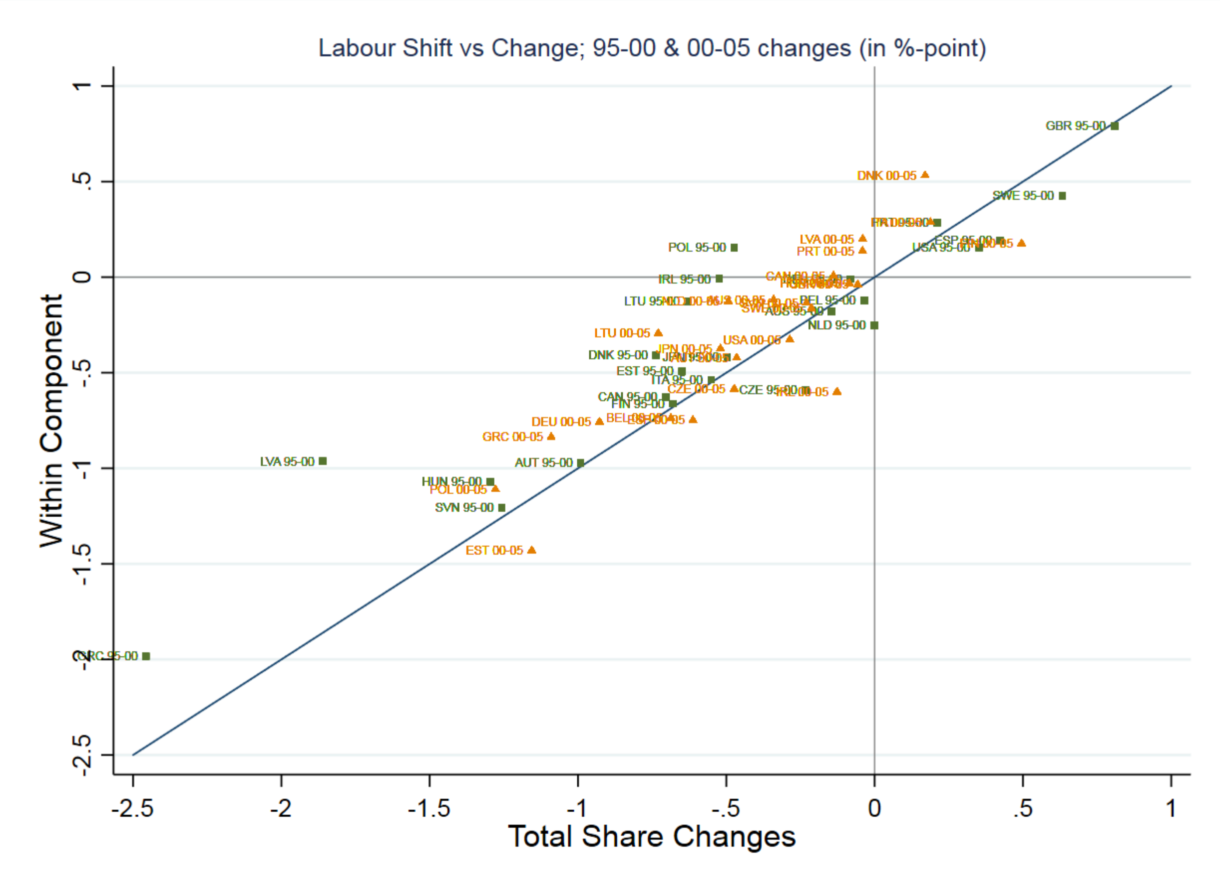


Figure 2 shows the shift share analysis of labour share changes in various countries included in the dataset for the two periods 1995-2000, and 2000-2005. The graph displays the average change to the labour share on the horizontal axis, and the average within industry change on the vertical axis. As such, the between industry effect, is the vertical difference between each point and the diagonal line. For most countries in the graph, the labour share has on average declined in each period, reflecting the declining labour shares. By their proximity to the 45-degree line, for most observations, the within component seems to be the main driver of the total change of the labour share. This is in agreement with pervious literature like Elsby et al (2013), who find that the within component generally accounts for most of the labour share change. In fact, Karabarbounis & Neiman (2014) show a similar shift share analysis, which attributes most of the labour share changes to the within component. They use the standard KLEMS data however, and do not adjust of the self-employed.

The prevalence of within industry changes indicates that aggregate labour changes developments in most countries have not been due to structural reforms of economic activity, shifting value added from high labour share to low labour share industries. Rather, the labour share seems to have been declining in most industries (or at least those that matter), driving down the overall labour share. This is observation is not consistent with drivers that operate at the country level. The pervasive decline of labour shares, coupled with the observation that declines happen within industries suggest some (global) industry specific drivers are likely causing labour share changes. Increasing trade and with it import exposure is a phenomenon that fits this bill, as pointed out by Elsby et al (2013). This idea is further explored in the next sections, where I introduce the import exposure methodology; followed by the WIOD data, and finally the analysis.

Methods Import exposure

To explore one of the potential drivers of changes to the labour share, I examine the relation of import competition to the labour share. Following Elsby et al. (2013), I will use input output tables to construct import competition variables and relate them to labour shares of the industries and countries covered before. Input-output-based measures are superior to using gross imports as measures of inputs competition (this is as in e.g. work by (Autor et al. 2015)). This is because gross imports only take the first order contents of imports into account. Contrary to this, input-output based measures can take all intermediate inputs (direct and indirect) into account. This is important, as the inputs to imported intermediates constitute competition to domestic industries who could have produced these intermediates otherwise.

I use several measures (based on input-output measures) for import competition. First, the measure of Elsby el al. (2013) is based on National Input-output tables. This measure results from the idea of a country being completely self-sufficient. That means that a country would produce all imported input and intermediates itself, or rather that the country would be fully self-sufficient. This is of course a hypothetical case, as almost no country would have the (potential) physical capability to produce all the output required to meet all domestic demand.

Secondly, a different way to examine import competition is from global value chain methods. In fact, this method examines the degree to which value added of value chains ending in each country is generated abroad (Los et al. 2015). The downside of this measure is that it only considers imported intermediates; it does not consider imported final goods. Final goods imports can easily be considered competition to domestic producers of the same goods. The upside of this method is that it does not use any hypothetical constructions of inputs or outputs. It simply uses the actual foreign intermediates used for the production of final output in each industry.

Finally, another import competition measure that I use is based on hypothetical extraction method adapted from Los et al. (2016). This method allows me to generate a hypothetical world in which certain trade links are set to zero. For example, I could generate a counterfactual world GDP in the case that the United States does not import anything (or anything from specific countries). This, compared to the actual world GDP would be the potential increase in GDP of the United States, if it were to produce all its imports itself.

The advantage of the final method is the ability to evaluate the counterfactual situations in which trade links to certain countries are severed, but no others. This reduces the severity of the Elsby et al. (2103) assumption of complete self-sufficiency, by allowing countries to import form certain, but not other countries.

Elsby et al. (2013) use a method to derive their import competition measure based on national input output tables. Compute value added for a country s, in the presence of the rest of the world r, if VA is the value added, v is the vector of value added shares in gross output, $A_{ss}$and A_{rs} are the domestic and imported intermediate input matrixes. Y_s is the vector of final demand for domestically produced output, and Y_{rs} is the vector of imported output for domestic final demand. i is a summation matrix. Equation 1a shows the derivation of the value added

$$VA = \hat{v}(I - A_{ss})^{-1}Y_s i \qquad \text{(1a)}$$

The authors then continue to define the value added of a country without any imports as follows:

$$\widetilde{VA} = \hat{v}\big(I - (A_{ss} + A_{rs})\big)^{-1}(Y_s + Y_{rs})i \qquad \text{(1b)}$$

Equation 1b adds the imported intermediates and final products to the domestic counterparts in an attempt generate counterfactual countries, which are fully self-sufficient (but still engage in exporting). Note that this measure does not just assume that there are no imports, in fact, by adding the imported intermediates and final output to their domestic counterparts, the assumption is made that the country produces domestically all previously imported output, including all of the (indirect) inputs into these imports. This is unrealistic of course, but for an approximation of a situation in which there are no imports, this might be interesting to relate to labour shares.

Alternatively, I can use the structure of the World Input-Output table (WIOT) to derive the measures of import exposure. Particularly, continuing to use the notation introduced above, with domestic country s and the rest of the world r one can think of the different parts of the WIOT as:

$$A = \begin{bmatrix} A_{ss} & A_{sr} \\ A_{rs} & A_{rr} \end{bmatrix}$$

Is the input coefficient matrix where s is the home country, and r is the rest of the world. The matrix A_{ss} contains the domestic input coefficients, and the matrix A_{rs} contains the coefficients for inputs sourced from abroad.

$$Y = \begin{bmatrix} Y_{ss} & Y_{sr} \\ Y_{rs} & Y_{rr} \end{bmatrix}$$

Is the matrix with final demand. Similarly, Y_{ss} lists domestic final demand for domestically produced final goods, and Y_{rs} contains domestic demand for imported final goods.

Then to compute the vector of value added in each country-industry, the following equation, very similar to equation 1a, can be used (Los et al. 2015):

$$VA = \hat{v}(I - A)^{-1}Yi \qquad \text{(2)}$$

In this equation v is the value added coefficient vector (the hat indicates a diagonal matrix), I is the identity matrix of appropriate size, and i is a summation matrix, that sums over different types of final output. In this setup, the vector VA will contain for each industry in each country the amount of value added generated.

For the current purposes, it is interesting to examine the global value added of each industry across countries. To achieve this, I pre-multiply VA with a matrix that sums over industries, across countries.

$$VA^{*} = e\hat{v}(I - A)^{-1}Yi \qquad \text{(3)}$$

Where the matrix e is a matrix of #industry by #country*#industry dimensions, summing the value added of each particular industry across countries. The vector VA^* now contains the value added of each industry globally (no longer making the distinction between countries).

I can manipulate this equation in two ways, to generate a measure of the import exposure that each industry faces. The first method is adapted from Los et al. (2015). This method adjusts the final demand matrix to consider only the demand for the output of a particular industry, or industries. From the example above, this would mean that Y_{ss} and Y_{sr} retain their values, while the rest of the Y matrix is set to zero:

$$Y_s = \begin{bmatrix} Y_{ss} & Y_{sr} \\ 0 & 0 \end{bmatrix}$$

Using this changed final demand matrix in eq. 2, will lead to an estimate of the value added generated globally in each industry, due to final demand for country s's production, i.e.:

$$VA_s^{tva} = e\hat{v}(I - A)^{-1}Y_s i \qquad (4)$$

Which yields a vector with the global value added for each industry associated with final demand in country s.

This result can be used to derive the share of value added for each industry, that is derived abroad; outside country s. To do this, the foreign value added generated by domestic final demand can be computed by having the e matrix only sum over the value added from non-domestic industries, effectively setting domestic value added to zero. Call this new summation matrix e_s, which is therefore different for each country of interest s.

$$VA_s^{fva} = e_s\hat{v}(I - A)^{-1}Y_s i \qquad (5)$$

Then it is a matter of dividing each element i of VA_s^{fva}, the foreign value added vector, by each corresponding element of VA_s^{tva}, the vector with total value added associated with demand for domestic output in a country s,

$$FVAS_s(i) = VA_s^{fva}(i)/VA_s^{tva}(i) \qquad (6)$$

Therefore, each element of the vector $FVAS_s$ is the share of foreign value of each industries output, to meet final demand for domestic output. This measure relies on the actual shares of value that are added abroad, for all the output generated due to domestic final demand. Therefore, it is a straightforward measure of import competition. The downside is, that it does not take the imports of final goods into account, instead only focussing on the value added shares of intermediates.

Finally, an alternative measure of import competition is based the *hypothetical extraction* method (Los et al. 2016). This method removes certain parts of the Input-Output matrix to re-estimate value added, in the hypothetical case that certain (trade) linkages do not exists. It then compares the actual value added to the re-estimated, hypothetical value added.

The estimation of the hypothetical extraction case requires altering both the A and Y matrixes in line with Los et al (2016). However, instead of removing export linkages as they do, I consider the removal of imports linkages. To do this the A and the Y matrixes become:

$$A^{he} = \begin{bmatrix} A_{ss} & A_{sr} \\ 0 & A_{rr} \end{bmatrix}$$

And

$$Y^{he} = \begin{bmatrix} Y_{ss} & Y_{sr} \\ 0 & Y_{rr} \end{bmatrix}$$

Both the imports of intermediate inputs, and imports of final output are set to zero. Using revised matrixes, the calculation of the value added vector then becomes:

$$VA^{he} = e\hat{v}\left(I - A^{he}\right)^{-1} Y^{he} i \qquad (7)$$

Where each industry's global value added is now calculated, without any imports from the rest of the world (r) to country s. The difference between the values of VA_i^{he} and the corresponding values of VA_i^{*} (actual world GDP of each industry) is each global industry's value added that can be traced back to imports of country s.

In this way, this difference can be seen as the potential increase in domestic value added should country s produce all goods domestically.

Therefore, the ratio of the difference to the total value added of each domestic industry in country s, is a measure of the importance of imports in country s.

In the next section, I introduce the WIOD trade data. After that, I will relate these three measures of import exposure to the labour share for the set of countries contained within the WIOD. Subsequently, I will use the labour share data obtained from the KLEMS database, which are of higher quality, but have fewer countries and industries are available. The next section present the analysis and results using these three measures of import competition.

WIOT trade data

This section describes the WIOD data and the changes over time of import exposure measures defined above. First, it serves to look at the degree of imported, compared to domestically produced intermediates in each industry. Figure 3 shows the density of the share of foreign intermediates covering all (unweighted) industries from the WIOD. The blue line shows the 1995 distribution, the red line that from 2007, and green the line in 2011.

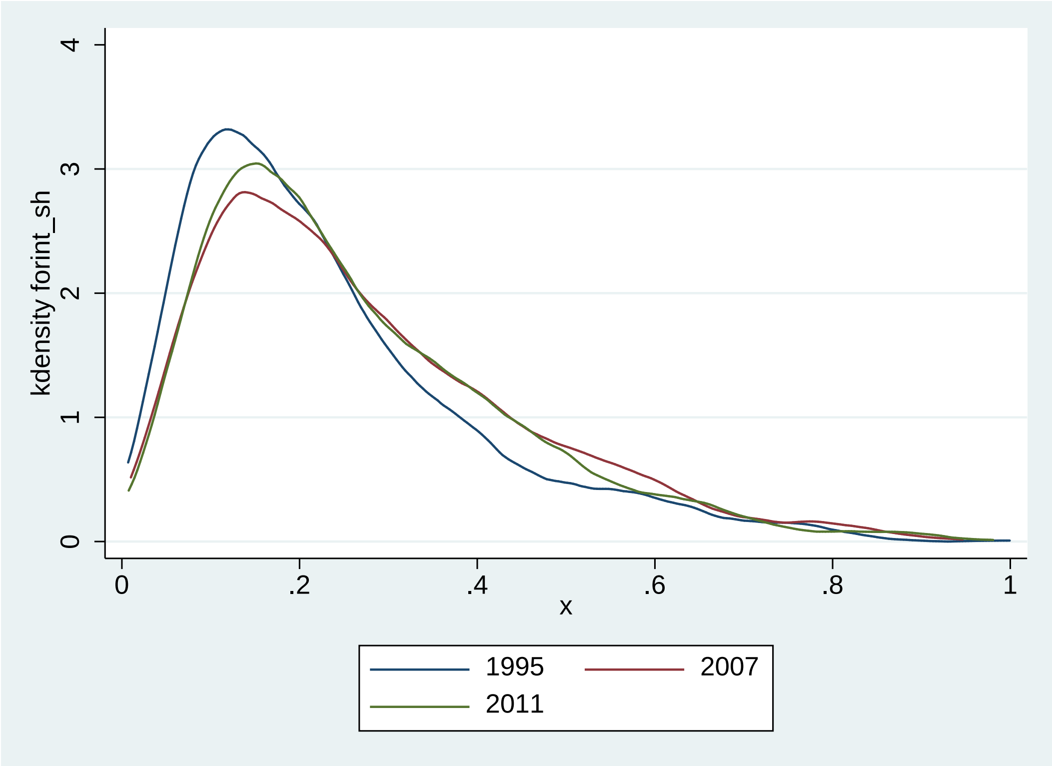


Figure 3 – density foreign intermediate use, 1995, 2007, and 2011

The data presented in figure only capture the first order effects of intermediate inputs, meaning that intermediate inputs into the imported intermediates (which may themselves, be imported) are not taken into account. However, it gives an indication of the increasing degree of foreign value added contained within production. This is especially salient for the 1995-2007 period and slightly offset again after the crisis reflected by the somewhat thinner tail in 2011, compared to 2007. This suggests that gross trade has moved been moving in tandem with the labour share.

The foreign value added share measure introduced above solves this problem, by considering all the indirect intermediates. The density plot changes when considering the total foreign value added share. Figure 4 shows for the same three years as Figure 3 the distribution of the foreign value added share. Again, it is obvious that foreign inputs have grown in importance from 1995 onwards. However, the difference between 2007 and 2011 now largely disappears. This means that while in many industries, the direct imports of foreign inputs declined, the total foreign value added contained with final output did not change much, on average.

Combing the WIOD trade data described above, and the labour share data from KLEMS yields a dataset that runs from 1995 to 2005, contains 25 counties and the WIOD 35 industries that cover the entire economy.

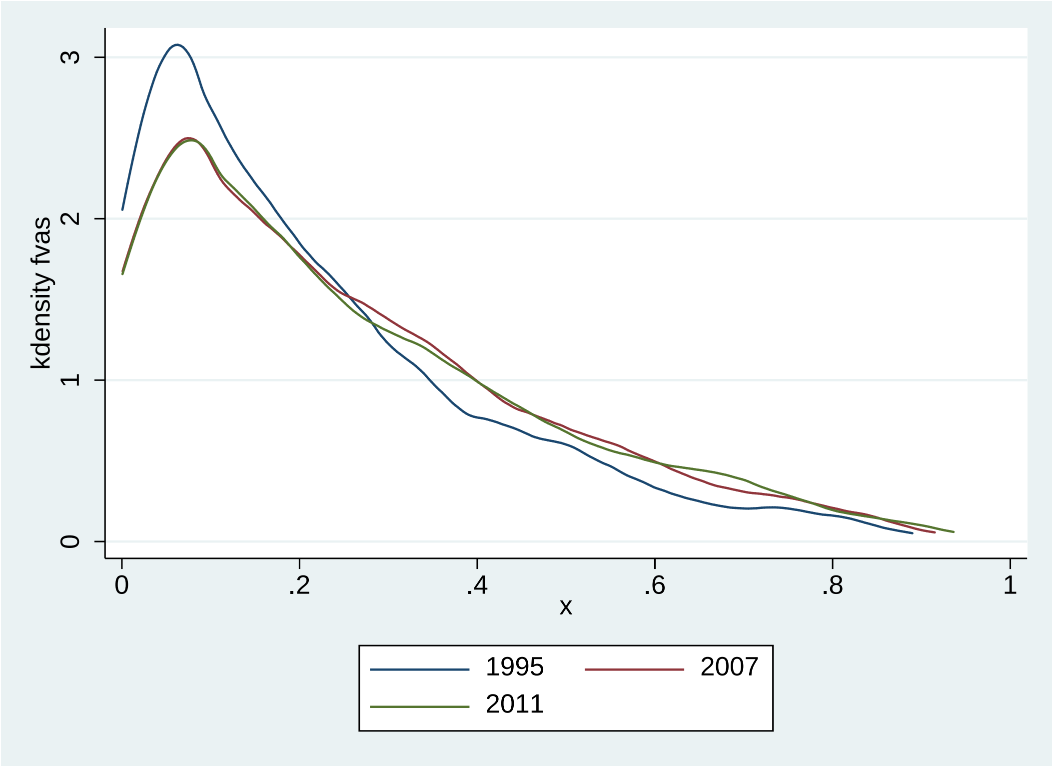


Figure 4 - density foreign value added share, 1995, 2007, and 2011

Results

The regressions to explore the relation between the labour share and the import exposure at the industry level take the form:

$$\Delta Labsh_{ci} = \beta_0 + \beta_{imposure} * \Delta imposure_{ci} + \sum_s \beta_s * \Delta X_{cis} + \eta_c + \mu_i + \epsilon_{ci} \quad ()$$

Where the $\Delta Labsh_{ci}$is the change of the labour share in country c and industry i, and $\Delta imposure_{ci}$ is the change of import exposure in country c and industry i. The vector X_{cis} contains a set of control variables, and finally μ_i and η_c are industry and country dummies to control for the corresponding effects. I specify the variables as stacked 5-year differences, which is convenient to average out effects like for example business cycles. The differences are from 1995-2000 and 2000-2005 in accordance with data availability (KLEMS and WIOD data)[5]. The

Table 5 show the regression results of using equation 8 for the entire sample, which runs from 1995 to 2005. Here the control variable is the change in the investment price of capital goods in the spirit of Karabarbounis & Neiman (2014) (more controls to follow in a future version). The regression results show that for the total sample of industries, both change of the Elbsy et al. (2013) import exposure measure, and the measure based on hypothetical extraction are negatively correlated with the change of the labour share. Interestingly, related to the literature based on the 'China competition', hypothetically extracting imports only from China, is insignificant, and with country-industry controls even positively related to the labour share. This finding is in line with the Elsby et al. (2013) result.

[5] The number of years will be expanded in future versions; using labour share information from WIOD would expand the sample to 2011, however, given the lesser quality of the labour share data from WIOD, and that this period has been the aftermath for the financial crisis, it has not been included.

Table 1 – labour share regressions 5-year differences – all industries (unweighted)

All Industries	(1) Labour share	(2) Labour share	(3) Labour share	(4) Labour share	(5) Labour share	(6) Labour share
Equipment Price	-0.0454*	-0.0637**	-0.0440*	-0.0623**	-0.0457*	-0.0642**
	(0.0262)	(0.0278)	(0.0263)	(0.0279)	(0.0264)	(0.0280)
Import Exposure	-0.0037***	-0.0033***				
	(0.0007)	(0.0007)				
Hypothetical Extr.			-0.0037***	-0.0031***		
			(0.0009)	(0.0009)		
Hypothetical Extr. (China)					-0.0033	0.0021
					(0.0229)	(0.0230)
Constant	-0.0170***	0.0306	-0.0169***	0.0307	-0.0180***	0.0311
	(0.0046)	(0.0347)	(0.0046)	(0.0348)	(0.0047)	(0.0350)
Industry and country FE	NO	YES	NO	YES	NO	YES
Observations	1,700	1,700	1,700	1,700	1,700	1,700
R-squared	0.0188	0.0546	0.0110	0.0474	0.0018	0.0413

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2– labour share regressions 5-year differences – manufacturing industries (unweighted)

Manufacturing	(1) Labour share	(2) Labour share	(3) Labour share	(4) Labour share	(5) Labour share	(6) Labour share
Equipment Price	-0.2396***	-0.3413***	-0.2364***	-0.3379***	-0.2401***	-0.3461***
	(0.0763)	(0.0833)	(0.0765)	(0.0835)	(0.0772)	(0.0842)
Import Exposure	-0.0038***	-0.0035***				
	(0.0010)	(0.0010)				
Hypothetical Extr.			-0.0049***	-0.0043***		
			(0.0015)	(0.0015)		
Hypothetical Extr. (China)					-0.0508	-0.0597
					(0.1100)	(0.1113)
Constant	-0.0194*	0.0046	-0.0195*	0.0051	-0.0202*	0.0073
	(0.0103)	(0.0629)	(0.0103)	(0.0630)	(0.0107)	(0.0635)
Industry and country FE	NO	YES	NO	YES	NO	YES
Observations	698	698	698	698	698	698
R-squared	0.0343	0.0993	0.0289	0.0941	0.0138	0.0832

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The table shows for each specification the staard OLS regression, as well as one with industry and country fixed effects, the different are mostly negligible.

In addition to the full sample, in Table 6 and Table 7 I divide the sample into manufacturing and non-manufacturing industries. This distinction is interesting because the non-manufacturing contain many industries that are usually considered non-traded. Remember, that using the input-output based measures of import competition, also these industries face import competition. The difference between the two sub-samples is striking. All of the negative effects of import exposure seems to be driven by the manufacturing industries, In fact, in the non-manufacturing industries, the correlation is actually positive; suggesting higher import competition facing these industries is related to higher labour shares. Furthermore, a similar situation holds for the equipment price changes variable, which is driven by the manufacturing industries, but insignificant for the non-manufacturing industries.

Table 3– labour share regressions 5-year differences – non-manufacturing industries (unweighted)

	(1)	(2)	(3)	(4)	(5)	(6)
Non-Manufacturing	Labour share	Labour share	Labour share	Labour share	Labour share	Labour share
Equipment Price	0.0188	0.0071	0.0193	0.0086	0.0204	0.0101
	(0.0143)	(0.0150)	(0.0144)	(0.0152)	(0.0144)	(0.0152)
Import Exposure	0.0121***	0.0198***				
	(0.0037)	(0.0040)				
Hypothetical Extr.			0.0022**	0.0031***		
			(0.0011)	(0.0011)		
Hypothetical Extr. (China)					-0.0005	0.0032
					(0.0113)	(0.0112)
Constant	-0.0143***	0.0270	-0.0136***	0.0269	-0.0130***	0.0265
	(0.0029)	(0.0182)	(0.0029)	(0.0184)	(0.0029)	(0.0185)
Industry and country FE	NO	YES	NO	YES	NO	YES
Observations	1,002	1,002	1,002	1,002	1,002	1,002
R-squared	0.0123	0.0969	0.0062	0.0819	0.0020	0.0743

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note however, that for all specification, the R-squared of the regressions is very low. So even though import competition seems to be a significant driver of changes in the labour share, the amount of variation that is actually accounted for is rather small. Note that even with industry and country fixed effects, the total variation of the 5-year labour share changes is limited. This suggests perhaps that there are different factors that operate over time to account for the changes in the labourer share.

Conclusions

I have demonstrated here that using input output measures for calculate import competition measures is relevant to the macro-economic phenomenon of the changing labour share of value added. However, the hypothetical extraction method presented here is applicable in more area's that use indictors of exposure to imports and trade. The results have demonstrated that while trade is not the be-all end-all driver of changing labour shares, selecting the right measure of import exposure is important to identify the relations between the variables.

The current work is a preliminary version of the research, and work is currently being done to expand the number of years available in the WIOD database. This will allow an addition of year to the analysis with which a more longer term view can be established. This will be useful due to the decline of the labour share setting in most countries around the 1980's (Dao et al. 2017; Karabarbounis & Neiman 2014).

Furthermore, the analysis of this draft is (purposefully) left very based to be clear in about what is being done. However, additionally thorough analysis can be performed to ensure that the results presented here are robust findings.

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