Losers of globalisation: The effect of trade with developing countries on low-skilled individuals in the Netherlands

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Abstract

Economic theory and empirical research suggest that economic globalisation can be harmful for some groups within countries. This paper tests this prediction by measuring the effect of increased trade exposure between the Netherlands and developing countries on the labour market position of low-skilled individuals in the Netherlands using regional data. It also aims to correct for the newest academic insights concerning the effect of technological development on the labour market, i.e. task biased technological change and the Frey & Osborne prediction. It finds that increased trade exposure has a positive effect on the labour market position of low-skilled individuals in the aggregate, but not for everyone.

Keywords: import competition, export opportunities, trade exposure, low-skilled labour, computerisation, task biased technological change

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1. Introduction

The presidential campaign of Donald Trump relied heavily on his firm criticism of US trade policy which – according to him - has cost the United States (US) millions of jobs. In fact, Trump even accused Chinese traders of "raping the United States" and called the trade deal with China "the biggest theft in the history of the world" (BBC, 2016). Trade with Mexico was not considered much better: "Our politicians have aggressively pursued a policy of globalisation, moving our jobs, our wealth and our factories to Mexico and overseas" (Time, 2016).

Trump's narrative is to a certain extent supported by economic theory and empirical research. For instance, Nobel Prize winner Paul Krugman advocated for the support of the "losers of globalisation" in the US – workers with less formal education - when the current president was still a business man (2007). Besides, Autor, Dorn and Hanson concluded that trade with China caused 1.5 million job losses in the US manufacturing industry within only 17 years (2013). However, other academics claim that globalisation is not to blame for the job displacements. They argue that automation and computerisation are the key drivers of job losses in the low-skilled labour segment the US (Cocco, 2016; Feenstra & Hanson, 1999; Frey & Osborne, 2017). Thus, there exists disagreement in the academic world and in the political arena[1] as to the drivers of low-skilled job displacements in developed countries like the US.

In the Netherlands, the potential negative impact of trade with the third world on low-skilled individuals has gone largely unnoticed in politics. Instead, the fear of the consequences of computerisation on the labour market attracts much attention in political and academic circles. Despite this, there are theoretical reasons (and empirical examples from other countries) to believe that trade with the developing world could also be harmful for certain groups within the Netherlands. In order to narrow this gap in the literature, this paper studies the effect of economic globalisation – defined as increased import and export exposure with low and middle-income countries– on the labour market position of low-skilled individuals in the Netherlands whilst correcting for the most recently identified channels through which technological development can affect the labour market – task biased technological change model and the Frey & Osborne prediction.[2] Import exposure is defined as the extent to which a certain region has employment in import competing industries – for example the

[1] Several republicans plead Trump not to halt globalisation by breaking down trade deals (Steinhauer, 2017)
[2] Task biased technological change: Technological change replaces certain tasks within jobs differently rather than complete jobs. Frey and Osborne estimate the probability of computerisation for numerous jobs based on combining knowledge from fields of research: economics and computer sciences.

manufacturing industry in developed countries which faces competition from developing countries.[3]

The empirical strategy used to tackle this question is very similar to those of Autor et al. (2013) and Dauth, Findeisen & Suedekum (2014) who studied the effect of increased exposure to import competition on regional labour markets, whilst correcting for task biased technological change in the US and Germany respectively. Yet, this paper contributes considerably to the economic literature as it aims to extend the methodology with the newest academic insights concerning the predictions of the potential effects of computerisation on the labour market identified by Frey and Osborne (2017). The data period also differs as it covers regional data from 2008 up till and including 2014. Finally, this paper fixates entirely on the labour market position of the low-skilled individual, which is defined as the following group of measures: employment in the manufacturing sector, overall employment, wages, poverty and unemployment benefits. For Dutch policy makers, this paper is very relevant: if trade were to harm certain groups in society, these groups have economic reasons to rise against globalisation. If policy makers want to prevent this from happening, measures should be taken to support the economic inclusion of these "losers of globalisation".

This paper unravels a positive causal relation of increased trade exposure with low and middle-income countries on the labour market position of low-skilled Dutch citizens in the aggregate. However, it also finds that, in cases of severe import competition and few export opportunities, the labour market position can indeed be harmed by increased trade with low and middle-income countries. The positive effect – on the low-skilled individual - is roughly 15 times bigger than the negative effect.

The remainder of this paper is structured as follows: Chapter 2 will review the relevant contemporary literature on the effect of economic globalisation on the labour market and identifies the channels through which technological development affects the labour market. Chapter 3 follows with an elaboration of the theoretical framework, empirical strategy and data. After this, chapter 4 will present the results and discuss them in the relevant context to get a deeper understanding of the magnitudes and implications. Chapter 5 will then explain the limitations of this research. Finally, chapter 6 will draw conclusions and suggest new angles for future research.

[3] Export exposure is the other side of the medal: the extent to which a certain region has employment in industries that experience new export opportunities towards developing countries.

2. Literature review

This chapter reviews the relevant theoretical and empirical developments in the academic literature on the effect of international trade and technological development on the labour market and in particular on the mechanisms through which the position of the low-skilled individual is affected. First, the literature on the impact of increased international trade on a broad scope of measures will be discussed. The studies that assess the impact of technological development on the labour market in developed economies will then be reviewed. Thereupon, the scope will be narrowed down as the focus shifts to academic research that pertains to the Dutch labour market. Finally, the contributions of this study will be discussed.

2.1 The globalising world and the impact on low-skilled individuals

Our world is getting increasingly globalised; relative distances are shrinking, cultures are blending and there is even trade between the Netherlands and the most remote places on earth.[4] Although globalisation covers numerous elements, this study focusses only on economic globalisation: “The integration of economies around the world, particularly through the movement of goods, services and capital across borders” (International Monetary Fund, 2008). The impact of economic globalisation on our daily lives has been widely discussed throughout history. In fact, it was already a central topic in Adam Smith's monumental work - and the corner stone of classical economic literature - *The Wealth of Nations* in which he theorised the impact of the division of labour (and specialisation) on society (1827).

Besides, the hypothesis that trade can have negative consequences for low-skilled individuals in developed countries can be derived from the classical canonical trade models, which date back to 1817 when David Ricardo published his first work on comparative advantages. The theory of comparative advantages is the foundation of later international trade models such as the Heckscher-Ohlin (HO) and Stolper-Samuelson models. Extensions of these models imply that international inter-industry trade decreases the return (wage) on the relative scarce factor of production as countries specialise in the production of the product which uses their relative abundant factor of production intensively. In general, developed economies are relatively abundant in the supply of high-skilled labour and developing countries are relatively abundant in low-skilled labour. This implies that trade between

[4] On the other hand, the increase in regional trade agreements suggests that globalisation is not heading to a world without borders and impediments to trade but perhaps to a world with numerous trade blocs.

developed and developing economies could lower the return (wage) on low-skilled labour (the scarce factor) in developed countries.[5]

Although old trade theories are well suited to explain decreasing wages in some sectors because of the increase in international trade, the models failed to explain contemporary empirical observations. For instance, they are not able to explain the observed rise in intra-industry trade and the North-North trade (Brülhart, 2009). Based on these flaws, Krugman derived his *new trade theory* (1980) which was later extended by Helpman (Helpman & Krugman, 1985) and in the 21st century by the pioneering work of Melitz (2003). One of Melitz´s fundamental contributions is that exporting firms pay higher wages, which implies that these firms' employees benefit relatively more from trade liberalisation than those of non-exporting firms. Furthermore, Mayer and Ottaviano, who studied the characteristics of European exporting firms, find that exporters employ relatively more high-skilled labour (2008). This suggests that globalisation - increased international trade - increases the wage of high-skilled workers more compared to the wage of low-skilled workers.

Whereas the aforementioned authors focused on explaining general stylised empirical facts and patterns in international trade data, later scholars had a different focal point in their analyses: the impact of globalisation on the labour market. In the 1990s and 2000s, the topic caught the attention of politicians and academics in US as researchers sought to find the roots for the increased income inequality that the US had experienced since the 1980s (Ashenfelter & Card, 1999; Feenstra & Hanson, 1999; Krugman, 2008; Leamer, 1994). One of the most prominent studies was conducted by Feenstra and Hanson who found that North-South trade was one of the causes of the augmented income inequality in the US (1999).

In 2013, a highly influential study undertaken by Autor, Dorn and Hanson changed all perspectives thanks to both their innovative methodology - the extensive use of regional microdata and a convincing Instrumental Variable (IV) strategy – and the strength of their results. They discovered that US regions specialised in industries which face severe import

[5] Imagine a simple HO-model with two factors of production (low-skilled and high-skilled labour) and two countries (a developed and developing country). When the countries start to trade, each country will (specialise and) export the product which uses the relative abundant factor intensively in the production process and it will import the good which uses the scarce factor intensively. The developed country has high-skilled workers as the abundant factor of production relative to developing countries. Thus, the developed country exports the product which requires intensive use of high-skilled labour which increases the demand for high-skilled labour in this country. Therefore, the return on high skilled labour (wages) increases. However, as the developed country specialises in the industry which requires higher-skilled labour, demand for low-skilled labour falls. Therefore, the return on this factor of production decreases and the wage for low-skilled workers decreases in the developed country.

competition from China are substantially harmed (i.e. lower wages, lower employment and higher dependency on transfer payments) by the growing imports of low-skilled labour intensive (intermediate) products from China. Moreover, they show that these results are not only applicable to the manufacturing sector - which is characterised by a higher than average fraction of low-skilled workers (Notowidigdo, 2011) - but on other sectors as well.

In the contemporary literature, the views of Autor et al. are widely shared. In 2016 for example, Pierce and Schott concluded that employment in the US manufacturing industry has declined since the US granted China *permanent normal trade relations*.[6] Besides, Autor and his cowriters extended their research: in 2014, based on further disaggregated data, they found that the decline in wages was even fiercer for individuals with low initial wages (Autor, Dorn & Hanson). This suggests that the negative impact of increased import competition from China is larger for low-skilled workers as they generally earn lower wages. In 2016, the effect of Chinese import competition in the 21st century was quantified. Import competition from China is estimated to have caused the loss of 2 to 2.4 million jobs in the US between 1999 and 2011 (Acemoglu, Autor & Dorn, 2016).

Despite the eminent role in the academic literature of the “losers of trade” in the US, this topic has hardly been studied in a European framework prior to 2009 as income inequality in Europe was far less intense than in the US. Freeman´s sceptical view of trade as a driver of increased income inequality can be seen as the general tendency[7] at that time: “I am not convinced that continued expansion of trade with less-developed countries spells doom for low-skilled westerners.” (1995, p.30)

Inspired by the earlier work of David Autor and different cowriters (Autor, Levy, & Murnane, 2003; Autor & Dorn, 2008; Autor & Handel, 2013; Autor, Katz, & Krueger, 1998; David, Katz, & Kearney, 2006), Goos, Manning and Salomons were among the first authors to publish a prominent study regarding the polarising[8] European labour market and the roles of globalisation and technological development (2009). Yet, in in contrast to Autor et al. (2013), they use the offshorability of products as proxy for economic globalisation. Their main results are in essence similar to the contemporary American literature. However, they regard technological development as a more important driver of the changing European labour market than globalisation (i.e. offshorability).

[6] This agreement eradicated the uncertainty of the historical annual renewals of the US import tariffs of Chinese products.
[7] For example: Desjonqueres, Machin, Van Reenen, & Reenen, 1999
[8] Polarisation on the labour market: employment rises in both the upper and lower tail in the income distribution, but decreases in the middle part (Goos et al., 2009).

More recently, several German academics applied the conceptual framework designed by Autor et al. (2013) on German data. They conclude that the framework is well suited for analysing European countries. Yet, the results are slightly different. Although the boost in trade with developing countries generated a decrease in employment in German regions with a high concentration of import-competing industries, the magnitude of job displacement is much lower than in the US and the negative effects are more than offset by positive effects of increased export opportunities in other regions (Dauth, Findeisen, & Suedekum, 2014). Unlike Autor et al. (2013), their research is not limited to trade with the far East (i.e. China); they also consider imports from Eastern Europe. Similar results were found in other novel country studies on Norway and Denmark (Balsvik, Jensen, & Salvanes, 2014; Hummels, Jørgensen, & Munch, 2014).

2.2 Technological development and the impact on low-skilled individuals

The fear of the effect of technological development on the labour market is even more ancient than the fear of globalisation. In fact, Aristotle already referred to the substitution of human labour by machines in an analysis on slavery thousands of years ago. He argued that once technological development and automation become sufficiently advanced, human labour can be replaced by technology (Aristotle, 350 BC). This fear remained persistent throughout history and is still present.[9] This paragraph elaborates on the academic literature that linked technological development to changes in the labour market focusing on the low-skilled segment

As mentioned before, income inequality in the US became one of the most important research fields for economists in the 1990s. In 1993, Juhn, Murphy and Pierce were among the first to point out that income inequality in the US had risen significantly between 1970 and 1990. The primary driver for this phenomenon was the increase in premia on skill (for a given educational level and experience). Later research delved into the origins of these premia and suggested that skill biased technological change (SBTC)[10] could be the underlying source of the increased premia on skill (Berman, Bound, & Machin, 1998). They show that low-skilled employment shrank and that wage inequality increased in the US in the 1980s and attribute this primarily to SBTC. Feenstra and Hanson confirmed this: they argue that SBTC is a more important driver for inequality than the changes in trade patterns (1999). Yet, there

[9] For instance: Rolvink Couzy (2017).

[10] SBTC: Productivity for high-skilled workers increases at a faster rate than productivity for low-skilled workers as production technologies advance. This increases the relative demand for high-skilled labour (with respect to low-skilled labour) (Berman et al., 1998).

was no clear consensus in the academic world regarding this last conclusion (Krugman, 2000). In the 2000s, empirical researchers argued that the detected impact of SBTC on wage inequality was an episodic event as wage inequality had stagnated in the 1990s and the rapid improvements in (computer) technologies continued (Card & Dinardo, 2002; Lemieux, 2006).[11]

Along with his contributions to the trade literature, David Autor is also responsible for unique insights in this segment of economics. In 2003, he and his cowriters shifted the attention from SBTC to *task biased technological change* or the *task model* (Autor, Levy and Murnane). This theory predicts that technological development (i.e. computerisation) replaces routine *tasks* within jobs instead of complete (low-skilled) jobs: "Computer technology substitutes for workers in performing routine tasks that can be readily described with programmed rules, while complementing workers in executing non-routine tasks demanding flexibility, creativity, generalised problem-solving capabilities, and complex communications" (Autor et al., 2003, p. 1322). Moreover, they find that technological development can in fact decrease income inequality in the lower tail of the income distribution (Autor, Levy & Murnane, 2003). More recent studies are in line with this, such as that of Acemoglu et al. (2016).

In 2013, Frey and Osborne predicted that labour markets would change thoroughly due to a new phase of computerisation (2017).[12] The authors draw this conclusion based on extensive interdisciplinary research in which economists and computer scientist engineers were involved to estimate the probability of computerisation for a large set of individual occupations.[13] Frey and Osborne argue that the new phase of technological development – the application of algorithms and robotics - could potentially even replace non-routine jobs. In fact, 47% of all employment in the US faces high risks of being fully automatized soon - ¨Perhaps over the next decade or two¨ (Frey & Osborne, 2017, p. 44). The fundamental difference between the task model and the Frey & Osborne prediction is the scope of technological development. As the boundaries of the tasks which computers can execute are currently much wider and will only become wider in the near future, more jobs are susceptible to computerisation (Brynjolfsson & Mcafee, 2012).

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[11] Card and DiNardo point at the decrease in the minimum wage as the predominant reason of the rise in inequality.

[12] The authors made these predictions back in 2013. Their research was finally published in 2017.

[13] For a detailed description of their method, please consult their paper *The Future of Employment: How susceptible are jobs to computerisation* (Frey & Osborne, 2017).

2.3 The Dutch labour market in perspective

The discrepancies between the findings in the European and US' studies – the results differ in magnitudes and directions - suggest that the effects of economic globalisation and technological development depend critically on country specific trade patterns and local labour markets. This implies that the conclusions drawn from the aforementioned studies are only relevant for the Netherlands to the extent at which these countries have similar trade patterns and comparable labour markets. With respect to trade, the Netherlands differs significantly from the US and Germany: whereas the US runs huge trade deficit vis-à-vis China, the Netherlands runs a much smaller trade with most low and middle-income countries.[14] Besides, the Netherlands is a tiny country compared to the US and Germany (whose economies are 24 and 4.5 times larger than the Dutch respectively) and is thus likely to have considerably different trade patterns (The World Bank, 2017). Moreover, the European labour market differs significantly from the US' equivalent in terms of institutions and regulations which cause distinct labour market patterns in wages, employment, unemployment benefits and labour market rigidities (Atkinson, 2003). Therefore, several Dutch scholars have analysed the impact of economic globalisation and technological development on the Dutch labour market.

In 2015, Van den Berge and Ter Weel found that the current Dutch developments in employment structures are in line with the general European trend of job polarisation. They conclude that jobs in the middle segment are lost due to technological development. Therefore, employees who used to work in the middle segment are increasingly employed in the lower segment which induces lower wages and thus harms the position of the low-skilled worker.

In the same year, two eminent Dutch research institutes joined forces to conduct research on the labour market position of low-educated individuals in the Netherlands based on data until 2009 (de Graaf-Zijl et al., 2015). They find that real wages for low-educated employees remained stable between 1990 and 2005 whereas the hourly real wage for highly-educated employees increased by 29%. Concerning the near future for Dutch employment, the researchers estimate a fall in employment in the lower segment and an increase in income inequality even though the supply of low-educated Dutch employees is expected to decrease significantly. This predication is based on the SBTC theory and on the impact of economic

[14] In 2014, the US imports from China were almost 4 times bigger than the exports towards China. In comparison, the imports from low and middle-income countries in the Netherlands were only 2 times bigger than the exports in the same year (United Nations, 2014).

globalisation on low-educated individuals. To the best of my knowledge, this research is the most relevant for this paper as it pertains to the impact of globalisation and technological development on low-skilled Dutch citizens. Yet, they do not consider the impact of increased trade exposure, nor the new phase of technological development suggested by Frey and Osborne.

2.4 Contributions

The relevant academic work on the topic of economic globalisation, technological development and their effects on the labour market position of low-skilled individuals has been discussed extensively. In has been shown that economic globalisation (through increased trade exposure) harms the position of the low-skilled individual through decreased employment and lower wages in the US in the manufacturing sector and beyond (Autor et al., 2013). On the other hand, in Germany the effects of rising trade with the East is beneficial in the aggregate. However, the gains are distributed unevenly which has led to a deteriorated position of individuals in regions with a high degree of trade integration (Dauth et al., 2014).

Several channels are identified through which technological development can harm the labour market position of low-skilled individuals. In the 1990s, skill biased technological change was considered the key driver behind the deteriorating labour market conditions (Feenstra & Hanson, 1999). In due course, the attention first shifted to the task biased technological change (Autor et al., 2003) and more recently to the new phase of technological development based on the application of algorithms and robotics (Frey & Osborne, 2017). To all appearances, there is no definite answer to the question as to what phenomena has the greatest impact on the labour market position of low-skilled individuals; it is dependent on local conditions and can differ between countries (Dauth et al., 2014).

The conditions in the Netherlands deviate from those in the US and Germany. In earlier research, no significant negative effect of import competition on the Dutch labour market has been identified. Instead, technological development was identified as the driver of the changes in income inequality and labour market patterns. Yet, the newest findings in the academic literature – the effect of trade exposure and the new phase of technological development on the labour market - have not yet been jointly studied in the Netherlands.

This study contributes to the existing literature in various ways. First, it applies the theoretical framework designed by Autor et al. (2013) - and appended by Dauth et al. (2014) - on the Dutch labour market and thus studies the effects of trade with low and middle-income countries on the labour market position of low-skilled individuals in the Netherlands whilst correcting for task biased technological change. Second, unlike Autor et al. and Dauth et al., it incorporates the newest phase of technological development by including the risk of computerisation estimates based on algorithms and robotics in the analysis. Third, it unfolds the effects of trade with low and middle-income countries on the groups which are theorised to be the "losers of globalisation" in developed countries. Fourth, it aims to provide a decent framework for researchers who want to analyse the impact of increased trade integration whilst correcting for technological development on the Dutch labour market.

3. Theoretical framework and empirical strategy

This chapter will elaborate on the empirical strategy. It will start on a rather abstract level by explaining the underlying theoretical model of the impact of trade exposure on labour markets. It will then describe the empirical approach which should enable this paper to measure the key effects of economic globalisation on the labour market position of low-skilled individuals in the Netherlands and to correct for the effect of technological development on this labour market position. Thereupon, it will explain the data sources as well as all necessary changes in the data. The final paragraph will provide the most important descriptive statistics. Both the theoretical as well as the empirical approach are to a large extent in line with Autor, Dorn & Hanson's (2013) approach (therefore labelled as ADH) and Dauth, Findeisen & Suedekum's (2014) approach (therefore labelled as DFS). Whenever deviations are made from this approach, they will be mentioned explicitly.

3.1 The theoretical effect of trade exposure on the labour market

To isolate the effect of economic globalisation, ADH's theoretical monopolistic competition framework is used.[15] Thus, this paper focuses entirely on trade exposure as a measurement of economic globalisation. Whenever (economic) globalisation is used in the rest of this paper, it refers to increased trade exposure.

ADH's micro founded model builds upon the *new trade theory* (Helpman & Krugman, 1985) and the *new new trade theory* (Melitz, 2003). It regards trade in a gravity form, which implies a negative (positive) effect of distance (size) and trade barriers on bilateral trade flow quantities (Tinbergen, 1962). Furthermore, it assumes that firms in each region (i) produce tradeable goods (T) and non-tradeable goods (N) and ignores migration between regions.

[15] This model is described extensively in the online theory appendix in ADH's paper.

When one analyses the Dutch labour market through this theoretical model, each regional Dutch labour market (i) is assumed to be a small open economy. The key advantage of this regional approach is that it allows the effects of increased trade exposure to differ between regions within a country. Thus, it enables one to identify distributional differences of the aggregate effect in the Netherlands. Trade theory suggests that globalisation (and economic development in low and middle-income countries) affects these regional markets (i) through two channels. Firstly, it opens new markets in which to sell Dutch products which induces new export opportunities for Dutch firms in low and middle-income countries ($\hat{E}_j^{Low}$). Secondly, it intensifies competition for Dutch enterprises as the export capabilities of low and middle-income countries are incremented ($\hat{A}_j^{Low}$). The model assumes that both effects generate changes that vary across industries (j). This is formally illustrated by the following labour market equations:

$$(1) \quad \begin{cases} \widehat{W}_i = \sum_j S_{ij} \dfrac{L_{ij}}{L_{Ni}} \left[\dfrac{X_{ij}{}^{Low}}{X_{ij}} \hat{E}_j^{Low} - \sum_k \dfrac{X_{ijk}}{X_{ij}} \dfrac{M_{kj}{}^{Low}}{E_{kj}} \hat{A}_j^{Low} \right] \\ \hat{L}_{Ti} = \rho_i \sum_j S_{ij} \dfrac{L_{ij}}{L_{Ti}} \left[\dfrac{X_{ij}{}^{Low}}{X_{ij}} \hat{E}_j^{Low} - \sum_k \dfrac{X_{ijk}}{X_{ij}} \dfrac{M_{kj}{}^{Low}}{E_{kj}} \hat{A}_j^{Low} \right] \\ \hat{L}_{Ni} = \rho_i \sum_j S_{ij} \dfrac{L_{ij}}{L_{Ni}} \left[-\dfrac{X_{ij}{}^{Low}}{X_{ij}} \hat{E}_j^{Low} + \sum_k \dfrac{X_{ijk}}{X_{ij}} \dfrac{M_{kj}{}^{Low}}{E_{kj}} \hat{A}_j^{Low} \right] \end{cases}$$

Although equation (1) might appear complicated, the equations essentially only represent the effect of both trade exposure channels on labour market variables.[16] Starting with the wage equation, export capabilities ($\hat{E}_j^{Low}$) is weighted by the initial share of sales of region i that is exported to low and middle-income countries ($\frac{X_{ij}{}^{Low}}{X_{ij}}$). The second channel, the change in import competition ($\hat{A}_j^{Low}$), is weighted by the initial share of output by region i that is exported to each market k ($\frac{X_{ijk}}{X_{ij}}$) and by the initial share of imports from low and middle-income countries in total purchases per market ($\frac{M_{kj}{}^{Low}}{E_{kj}}$). To identify the net effect, one must sum across all industries and weight it by the share of initial employment in each industry (j) in total employment in the non-tradeable sector (which is not directly affected by trade

[16] All main variables are in log changes (indicated with a hat) to capture the dynamic effects: $\widehat{W}_i = \Delta \log W_i$. This approximates the change in wages.

exposure). Finally, the equation includes a general-equilibrium scaling factor (S_{ij}) which is greater than zero.[17]

It only takes some minor modifications to get from the wage equation to the employment equations. Concerning employment in the tradeable sector, the key difference is that it is weighted by employment in the tradeable sector (instead of the non-tradeable sector). Moreover, in the non-tradeable sector, signs are different; the rise in employment resulting from increased export exposure in the tradeable goods sector comes at the cost of decreased employment in the non-tradeable sector.

The signs in the equations reveal the theoretical mechanisms described above: a rise in import competition has a negative (positive) effect on wages and employment in the tradeable (non-tradeable) goods sector and a rise in exports from the Netherlands towards low and middle-income countries has a positive (negative) effect on wages and employment in the tradeable (non-tradeable) goods sector. Finally, the employment equations are multiplied by the share of the current account deficit in total expenditure in region i (ρi). This implies that trade imbalance is a necessary condition for any net impact of globalisation on wages and employment. If trade would be balanced, employment losses in one region would be neutralised by an increase in employment in other regions (ADH). Since this paper covers a rather short time span, trade imbalance is considered a trivial assumption; countries usually do not have equal imports and exports in the short run (nor does the Netherlands vis-à-vis low and middle-income countries).

3.2 Empirical strategy – trade exposure

The theoretical model needs to undergo several transformations before it is suitable to isolate the effect of trade exposure on the Dutch labour market. The following simplifications are in line with ADH in the derivation of the empirical effect of import exposure on employment in the tradeable goods sector. First, it is assumed that the general equilibrium scaling factor and the trade imbalance variable are identical across all regions in the Netherlands. Besides, in the absence of data on purchases, it is assumed that the share of Dutch employment in region i in industry j can proxy the share of region i's purchases in total Dutch purchases in industry j ($X_{ijNL}/E_{jNL}=L_{ij}/L_{jNL}$). Lastly, due to the specific nature of ADH's monopolistic model, L_{ij}/X_{ij} can be regarded as a constant. After some algebra (see appendix A) the following model is

[17] S_{ij} captures feedback effects (S_{ij} is a function of the model parameters) related to the elasticity of substitution between industries, comparative advantages and the initial expenditure shares. A detailed explanation is provided in the theoretical appendix of ADH.

derived which estimates the effect of globalisation on employment in the tradeable goods sector:

$$\hat{L}_{Ti} = -\beta \sum_j \frac{L_{ij}}{L_{jNL}} \frac{M_{jNL}^{Low} \hat{A}_j^{Low}}{L_{Ti}} \tag{2}$$

Since the Netherlands also experienced increased export opportunities towards low and middle-income countries, it would be inaccurate not to include the increased export opportunities in the model (following DFS). This leads to the following measures of the effect of the change in trade exposure on employment in the tradeable goods sector in the Netherlands:

$$\hat{L}_{Ti} = \underbrace{\alpha \sum_j \frac{L_{ij}}{L_{jNL}} \frac{X_{ij}^{Low} \hat{E}_j^{Low}}{L_{Ti}}}_{\text{Export exposure}} - \underbrace{\alpha \sum_j \frac{L_{ij}}{L_{jNL}} \frac{M_{jNL}^{Low} \hat{A}_j^{Low}}{L_{Ti}}}_{\text{Import exposure}} \tag{3}$$

In equation (3), employment in the tradeable goods sector depends positively on the increase in exports towards low and middle-income countries through increased export opportunities ($X_{ij}^{Low} \hat{E}_j^{Low}$), scaled by the labour force in region i (L_{Ti}) and weighted by region i's national employment share in industry j ($\frac{L_{ij}}{L_{jNL}}$). It depends negatively on the increase of imports from low income countries through increased export capabilities ($M_{jNL}^{Low} \hat{A}_j^{Low}$), scaled by the labour force (L_{Ti}) and weighted by region i's national employment share in industry j ($\frac{L_{ij}}{L_{jNL}}$).

In line with the theoretical model, wages are positively affected by the increase in export competition and negatively by a higher exposure to import competition. The measures for import and export exposure are constructed following ADH's method. The variables measure the potential increase in import and export exposure for any region i, given the initial employment patterns. This is achieved because the measures allocate the national change in industry imports and exports to the region based on their shares in national industry employment.

$$\Delta IE_{it}^{Low\ in\ NL} = \sum_j \frac{L_{ijt}}{L_{jt}} \frac{\hat{M}_j^{Low\ in\ NL}}{L_{it}} \tag{4}$$

$$\Delta EE_{it}^{NL\ in\ Low} = \sum_j \frac{L_{ijt}}{L_{jt}} \frac{\hat{X}_j^{NL\ in\ Low}}{L_{it}} \tag{5}$$

where $\hat{M}_j^{Low\ in\ NL}$ ($\hat{X}_j^{NL\ in\ Low}$) represents the change in imports (exports) in industry j from (to) low and middle-income countries. Unlike most variables, these variables do not vary across regions. Thus, by construction it is assumed that import and export exposure can differ between industries, but are identical between regions within the Netherlands.[18] $\frac{L_{ijt}}{L_{jt}}$ is the share of regional employment in industry j compared to national employment in that industry.[19]

3.3 Empirical strategy – technological development and the labour market

Throughout the years, different methodologies have been used in empirical studies to identify the channels through which technological development affects the labour market. In prominent contemporary research that acts on the intersect of economic globalisation and technological development, one theory dominated: task biased technological change.[20] However, as explained in paragraph 2.2, other academics believe that the world entered (or will soon enter) a new phase of technological development which broadens the scope of jobs that are susceptible to computerisation (Brynjolfsson & Mcafee, 2012; Frey & Osborne, 2017). This paper takes an extra methodological step by incorporating the Frey & Osborne prediction in the empirical strategy. Since the Frey and Osborne's study is a prediction, this paper can of course not validate their claim. However, it can verify if this new phase of technological development is already affecting the labour market position of low-skilled individuals.

ADH and DFS control for task biased technological change in their analyses by the inclusion of the share of employment in routine jobs per region. This paper can adopt this strategy due to the nature of the Dutch employment data which is categorised into four groups: routine (tasks) employment, non-complex (tasks) employment, complex (tasks) employment and very complex (tasks) employment.[21] Thus, the task biased technological change theory can be easily verified by including the regional share of routine employment in the regressions (following ADH).

The integration of the Frey & Osborne prediction - a large amount of (non-routine) jobs will be lost 'soon' due to the application of robotics and algorithms – is less straightforward as their research uses the American labour market taxonomy. Two adjustments are made to ensure the feasibility of the Frey & Osborne prediction for studies on the Dutch labour market. First, the American employment classification is harmonised with the European equivalent. Second, Dutch employment shares are used to construct correctly

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[18] This must be assumed since the data on import and export is not decomposed into regions.
[19] This study ignores the potential effect of offshorability motivated by the following reasons: (i) Due to the small time span, it is unlikely that important advances are made in the pace of offshorability, (ii) the most contemporary literature focusses on trade exposure instead of offshorability and (iii) the lack of decent data.
[20] For example: ADH, DFS and De Graaf-Zijl et al. (2015)
[21] Equivalent to ISCO 1, ISCO 2, ISCO 3 and ISCO 4 in CBS data.

weighted estimates for the risk of computerisation of the four Dutch employment categories.[22] Details on these adjustments and background information on the Frey & Osborne methodology are discussed in appendix B.

The alignment of the Frey & Osborne prediction with the Dutch labour market statistics already reveals a key difference between the task model and their theory: instead of routine employment, the Frey & Osborne prediction (applied on Dutch data) illustrates that non-complex employment is considered more susceptible to technological development. Based on this observation, this paper proxies the Frey & Osborne prediction by including the share of non-complex employment. Since this is an unconventional step, several sensitivity tests are conducted by using different estimates.

In short, the empirical strategy deviates from the original ADH model in several dimensions. First, this paper uses data on the Netherlands and low and middle-income countries instead of the US and China. Second, the data covers a shorter and more recent time span: 2008-2014. Third, the data contains more data points since this paper considers the change in trade exposure per year instead of ten years (ADH and DFS). Fourth, increased export exposure is taken into account. Fifth, instead of only focussing on the task biased technological change as the channel through which technological development affects individuals on the labour market differently, the Frey & Osborne prediction is included as well.

3.4 Benchmark regression

The empirical adjustments of the theoretical framework evolve in the following regression:

$$(6) \qquad \Delta Y_{it} = \beta_0 + \beta_1 \Delta IE_{it}^{Low\ in\ NL} + \beta_2 \Delta EE_{it}^{NL\ in\ Low} + \beta_3 \Delta Tech_{it} + \beta_4 X_{it} + \varepsilon_{it}$$

where the dependent variable ΔY_{it} is the change in a set of regional labour market variables between year t and t-1. The independent variables include the regional change in import exposure ($\Delta IE_{it}^{Low\ in\ NL}$), the regional change in export exposure ($\Delta EE_{it}^{NL\ in\ Low}$), a set of variables that capture task biased technological change and the Frey & Osborne prediction ($\Delta Tech_t$) and a set of regular regional control variables (X_{it}).[23] In the benchmark model, ΔY_{it}

[22] Note that the changes were *only* made to align the American labour market taxonomy with Dutch labour market data. No other changes were made.

[23] Note that this specification is almost identical to DFS. The only slight difference is the inclusion of the set of technological development parameters as main independent variable.

is the change in the share of manufacturing employment per region and $\Delta Tech_t$ is the share of routine employment (task biased technological change) and the share of non-complex employment (Frey & Osborne prediction). Since low-skilled employees are relatively more prevalent in the manufacturing industry, this is considered a legitimate initial variable to study the effect on low-skilled individuals (DFS). This first difference model is preferred over a fixed effects model as a fixed effects model suffers from severe autocorrelation in which case a first difference model is considered more efficient (Wooldridge, 2012).

Based on previous research, the model controls for the (time variant) composition of the local labour market as this is likely to explain a significant amount of the variation in import and export exposure as well as the dependent variable (ADH). [24] Since women, high-skilled and foreign employees are predominately working in the service sector, they are negatively related to manufacturing employment (DFS).

3.5 Causal interference: endogeneity and simultaneity bias

There are several threats to causal interference in the benchmark estimation. To start with, it is likely to suffer from endogeneity. If unobserved economic shocks affect both import and export exposure as well as regional labour market outcomes, the estimated effects of trade exposure will be biased.[25] An Instrumental Variable (IV) approach – which is in essence very similar to ADH and DFS - is applied to cope with this challenge. Besides endogeneity, another threat to causal interference is the simultaneity bias: labour markets could anticipate the upcoming effects of economic globalisation. For instance, employers could decrease the demand for labour in the tradeable goods sector as they expect future effects of international trade on their business. To minimise this threat, lagged trade exposure variables are used in the IV-approach.[26] The following measures are constructed for the IV-strategy:

(7) $\Delta IE_{it*}^{Low\ in\ IV} = \sum_j \frac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta M_{jt}^{Low\ in\ IV}}{L_{it-1}}$ (8) $\Delta EE_{it*}^{IV\ in\ Low} = \sum_j \frac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta X_{jt}^{IV\ in\ Low}}{L_{it-1}}$

Measures (7) and (8) are only marginally different from (4) and (5). In the superscripts, the Netherlands (^{NL}) is replaced by countries which have comparable trade patterns with low and middle-income countries (^{IV}) and the timing subscript ($_t$) is replaced by its lag ($_{t-1}$). The IV-approach should isolate the causal effect of increased trade exposure with low and middle-countries and should eradicate the unobserved domestic economic shocks affecting both the

[24] As can be observed in the summary statistics figures in table C1 in appendix C.
[25] In case of a positive unobserved demand shock, the labour market variables (employment and wages) and imports could be positively affected by this shock (ADH).
[26] Note that the threat of endogeneity is only minimised. Labour markets could anticipate on the effects of globalisation with more than 1 year.

dependent and independent variables as well as the anticipation of the labour market on increased trade exposure.

The quality of the IV-strategy depends on two conditions: instrumental exogeneity and instrumental relevance (Wooldridge, 2012).[27] For this paper, the first implies that the unobserved economic shocks which potentially affect the Netherlands should not have a high correlation with the trade flows between low and middle-income countries and the IV-countries. Moreover, there should not be any unobserved economic shock through which increased trade between the IV-countries and low and middle-income countries affects the Dutch labour market. The second implies that trade flows between the IV-countries and the low and middle-income countries should be highly correlated with the trade flows between the Netherlands and the low and middle-income countries.

Instrumental endogeneity is a serious caveat for the IV-strategy. Due to the increased international integration, it is likely that economic shocks which affect the Dutch economy as well as trade between the Netherlands and low and middle-income countries also (indirectly) affect the economies and trade patterns of other developed countries. To reduce this threat, two measures are taken to minimise the ties between the IV-countries and the Netherlands: The initial IV-countries (1) cover different continents and (2) do not include neighbouring countries nor Euro countries. The selection methodology of IV-countries is in line with DFS. Yet, the final set of IV-countries is distinctive and include Denmark, Japan, New Zealand, Norway, Sweden, Singapore, South Korea and the United Kingdom. In appendix D the sensitivity of the IV-countries is tested by adding other countries. [28]

The threats to causal interference for trade exposure are arguably equally relevant in the case of technological development: If unobserved economic shocks affect both the (dependent) labour market variables and the technological development variables, the results will be biased. Moreover, the threat of reversed causality is considered even more relevant for technological development than for trade exposure. One cannot exclude the possibility that employers substitute tasks of low-skilled human labour by machines as a result of the

[27] Strong instruments: In equation $y=\beta_1 + \beta_2 x + u$, x and u are correlated (which disables causal interference). For an IV (z) to solve this problem, it must me unrelated to u: $Cov(z,u)=0$ (instrumental exogeneity). Thus, z should not have any other (partial) effect on y but through z and z should be uncorrelated to omitted variables. Moreover, since we are interested in identifying the effect of x on y (through z), z must be a decent proxy of x. Thus, z must be highly correlated to x: $Cov(z,x)\neq 0$ (instrumental relevance). (Wooldridge, 2012)

[28] ADH identifies another threat to identification. Reduced productivity in certain industries could cause an increase in imports in this industry from *all* countries – including the low and middle-income countries. In this case, the increased trade exposure does not evolve from the increased competitiveness from the low and middle-income countries, but from decreased Dutch productivity. However, this paper does not consider this a threat. The identification of the source for increased trade exposure is beyond the scope of this research.

expected technological development (or because of a decrease in the supply of low-skilled employees).

Solving the puzzle concerning endogeneity of technological development in the model in considered beyond the scope of this research. Yet, the threat reversed causality is reduced by using lagged variables for technological development in the identification model. The final identification model is:

$$(8) \qquad \Delta Y_{it} = \beta_0 + \beta_1 \Delta IE_{it*}^{Low\ in\ IV} + \beta_2 \Delta EE_{it*}^{IV\ in\ Low} + \beta_3 \Delta Tech_{it-1} + \beta_4 X_{it} + \varepsilon_{it}$$

and only differs from equation (6) in $\Delta IE_{it*}^{Low\ in\ IV}$ and $\Delta EE_{it*}^{IV\ in\ Low}$ (where ^{NL} is replaced by ^{IV} as the trade exposures of IV-countries are used and where $_{it}$ is replaced by $_{it*}$ to illustrate that the lagged employment statistics were used in the construction of the trade exposures) and in $Tech_{it-1}$ (where $_{it}$ is replaced by $_{it-1}$ to illustrate the inclusion of the first lag).

Finally, the use of regional data generates another challenge to causal identification. If increased trade exposure would cause significant migration between regions, the potential effect on the labour market position of low-skilled individuals cannot be measured correctly. To verify the importance if this threat, the effects on migration are also incorporated in the analysis.

3.6 Data sources

Data for the empirical analysis is gathered using various sources. The international trade statistics are extracted from the *United Nations Comtrade* database.[29] It encompasses the import and export statistics of the Netherlands towards and from the low and middle-income countries[30] , as well as the statistics for the set of IV-countries.

All statistics on the Dutch labour market and all industrial data is retrieved from *Statistics Netherlands* (CBS). The central CBS database used in this paper is the *Regional Key Figures* (CBS, 2017) [31], which contains data on the basic characteristics of citizens such as education, income and unemployment benefits at a neighbourhood level. Yet, this paper uses data on a municipality level rather than a neighbourhood level. This choice is made based on a theoretical and a practical reason. Concerning the first, it is unlikely that neighbourhoods represent local labour markets; citizens living in the same neighbourhood often work in

[29] Which was extracted from the World Bank's World Integrated Trade Solution database (WITS): http://wits.worldbank.org/
[30] World Bank definition of low and middle-income countries (see figure C8 in appendix C)
[31] This data can only be found using the Dutch translation: *Regionale kerncijfers Nederland*.

different neighbourhoods. Therefore, studying the impact on local labour markets requires a level of detail which is more similar to regional labour markets. The practical reason is the availability of high quality data.

The *Regional Key Figures* database does not contain all necessary information to conduct this research and is not sufficiently detailed in some cases. Therefore, the data set is enlarged by merging it with CBS data on the following subjects: migration between municipalities, businesses in municipalities, income, poverty and employment per industry. Moreover, it includes a measurement of the share of routine employment per municipality. This variable does not vary across industries. A detailed overview of the exact data sources per variable is provided in table C9 in appendix C.

After cleaning the data, which is explained in appendix B, the final data panel covers 403 municipalities and 19 different industries (of which 5 contain trade data) between 2008 and 2014.

3.7 Descriptive statistics

The impact of trade exposure on the labour market position of low-skilled individual depends on country specific characteristics such as the particular labour market and trade patterns. As mentioned in paragraph 2.3, the Netherlands deviates notably from the US and Germany with respect to these characteristics. Therefore, it is essential to have a clear understanding of the Dutch labour market and its trade partners. Analysing the data unravels some key developments in the Netherlands.

Even though the data only covers a short period, the variables that represent the state of the Dutch labour market have changed significantly. Table C1 in appendix C displays these advances at a national level. Since the data includes the period during which the global financial and economic crisis struck, it is not surprising that the unemployment rate doubled and both the share of individuals receiving unemployment benefits and the poverty rate[32] increased sharply. With respect to the labour force, increases are observed in the share of highly-educated individuals and in the share of foreign born individuals.

The general tendency in the trade patterns with low and middle-income countries are displayed in figure C1 in appendix C. Imports and exports have an upward sloping trend from which it only deviated during the toughest years of the crisis. Besides, it is shown that the Netherlands runs a trade deficit with the low and middle-income countries. Whereas exports

[32] Poverty is estimated by the share of employees that earned less than 110% of the social minimum income.

in 2014 equalled 50 billion US$, the total value of imports was more than twice that amount: 112 billion US$.[33]

The descriptive statistics also unravel the different patterns between industries (table C2). Although there is a substantial amount of missing data,[34] the amounts of imports in the first three sectors draw attention as sharp rises in the industries *agriculture, forestry and fishing* (A) and *manufacturing* (C) are observed. Yet, exports have also risen in the sample period for *all* tradeable industries for which data was available. The increase in import exposure in some sectors could potentially have serious consequences for regions with high employment shares in importing competing industries. In some regions, around 30% of all employment is in the manufacturing sector (table C3).

The descriptive statistics with respect to technological development and the effects of technological development on the labour market can be found in tables C4 and C5 and figures C2 and C3. The share of high-technology exports in the total exports shows the (growing) importance of sophisticated technology for the Dutch economy compared to the US (where the share has shrunken) and Germany (where the magnitude is smaller even though it grows at a faster rate). This suggests that the effect of technology on the labour market can be different in the Netherlands than in the US and Germany. In terms of labour productivity and the importance of ICT, the Netherlands is placed between the US and Germany: the US (Germany) has a higher (lower) labour productivity and higher investments in ICT.

The changes in routine and non-complex employment shares confirm that the Dutch labour market has polarised: the share of routine tasks jobs and the share of very complex tasks jobs have increased. On the other hand, the employment shares in the middle segments (ISCO 2 and 3) have decreased. Furthermore, the employment group with the highest computed Frey & Osborne risk of computerisation estimate – non-complex employment – already decreased in significance (compared to overall employment) over the sample period.

Finally, figures C4 to C7 provide a visual explanation of the differences concerning the labour market variables between regions by means of geographical maps. They illustrate the variation in the variables between regions – which suggests that different regions are differently affected by trade exposure. These figures clearly show that employment and wages are higher in the urban provinces. Instead, routine employment and jobs with a high risk of

[33] These numbers are based on the trade data after the harmonisation process. The real trade values are higher as not all trade flows could be harmonised. Yet, the ratio imports vs. exports does not differ significantly.

[34] Or the trade data could not be aligned with the particular SBI2008 industry.

computerisation are overrepresented in rural areas in the Southern, the Eastern and the Northern provinces.

4. Results

This chapter will discuss the results of the regressions. It will start with an extensive discussion of the benchmark model which is the estimation of equation (6). The independent variable is the yearly change in manufacturing employment. Thereupon, it will analyse the results of the identification model and of a broader set of regional labour market measures. Finally, it will reveal the results of the task biased technological change and the Frey & Osborne prediction.

4.1 Benchmark estimation and initial robustness test

Table 1 shows the results of the benchmark model (column 4) as well as an initial sensitivity test (column 5). The dependent variable is very similar[35] to the ADH's and DFS' benchmark models: the yearly change in the share of manufacturing employment per region.

In the first two columns, the results of the most elementary regressions are displayed for trade exposure and technological development respectively. The subsequent column, extended the model by adding a set of variables that control for the local labour market composition. The results are only moderately in line with expectations as no statistical significant effect was identified for Δ import exposure. On the other hand, for Δ export exposure the expected positive (and significant) effect was identified. Concerning task biased technological change, a positive (in contrast to expectations) statistical significant relation was unravelled between the share of routine employment and the share of manufacturing employment in regions. None of the regular control variables were shown to have a statistically significant effect on manufacturing employment except the share of women in the labour force.

In column 4, considerable advances were made in correcting for noise in the data. First, the model corrected for time variant (regional invariant) shocks - such as the global financial and economic crisis and its aftermath – and for unobserved time invariant differences between municipalities by introducing yearly and regional dummies respectively. Moreover, standard errors were clustered by municipalities since less variation in the dependent variable was expected within municipalities than across municipalities (and

[35] The only difference is that they use differences of 10 years instead of 1 year.

confirmed by an intra-class correlation of 25.4% within municipalities).[36] This had critical consequences for (the significance) of the variables: Δ Import exposure became significant (P-value=0.036) and the effects of both trade exposure measures increased in magnitude. Concerning the variables that should capture the effect of technological development on the labour market, the positive significant relation between the share of routine employment and the share of manufacturing employment became insignificant. With respect to the local labour

Table 1: Benchmark regression results (import exposure in million US$ per person)

	Dependent Variable: Yearly change in the share of manufacturing employment in total employment				
Explanatory Variables	(1) Trade	(2) Technology	(3) Labour market controls	(4) Year and municipality dummies	(5) Year and labour market dummies
Δ Import exposure	-0.00975		-0.0130	-0.0554**	-0.0259
	(0.00813)		(0.00812)	(0.0263)	(0.0252)
Δ Export exposure	1.330***		1.363***	2.055***	1.663***
	(0.0604)		(0.0606)	(0.576)	(0.530)
% Routine employment		0.000423	0.00345*	0.00777	0.00503
		(0.00197)	(0.00197)	(0.0126)	(0.00701)
% Non-complex employment		-0.000118	0.000857	0.00396	0.000337
		(0.00120)	(0.00165)	(0.0115)	(0.00684)
% Foreign population			0.000245	-0.155*	-0.00203
			(0.000928)	(0.0880)	(0.00327)
% Female			0.0213***	0.0717**	0.0324***
			(0.00201)	(0.0292)	(0.0121)
% High educated			0.00140	-0.0254	-0.00799
			(0.00213)	(0.0226)	(0.0109)
R-squared	0.031	0.000	0.038	0.362	0.119
Time FE	-	-	-	Yes	Yes
Municipalities FE	-	-	-	Yes	-
Labour markets FE	-	-	-	-	Yes

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence

Note: *The number of observations is 16,169 in all columns. Standard errors (in brackets) are robust and clustered by municipalities in column 4 and 5, dealing with the detected autocorrelation and heteroskedasticity. The labour market composition control variables are constructed as percentage of the population (foreign and education) and as percentage of the labour force (female). Constants are not reported.*

[36] In other words, it was expected that the share of manufacturing employment (and other dependent variables) would correlate more over time within a region than across regions in the same year. In case of normal standard errors, this correlation would violate the assumption that standard errors are independently and identically distributed. Clustered robust errors allow for intra-class correlation and are thus required (Wooldridge, 2012).

market control variables, the share of foreign-born individuals in the population became significant because of the inclusion of the time and regional dummies. Yet, the sign of the effect of the share of women in the labour force remained positive (and significant), contrary to expectations.

Column 5 shows the results of the initial sensitivity check. Instead of defining local labour markets as municipalities, the CBS definition of (35) local labour markets was used.[37] The results revealed that the benchmark model is fairly robust in both the trade exposure results and the technological development results. First, Δ import exposure and Δ export exposure have steady magnitudes and directions. Second, both estimations failed to identify a statistically significant effect of either task biased technological change or the Frey & Osborne prediction. However, the effects of trade exposure decreased in significance. A possible explanation for this is that this specification is less qualified to correct for the time invariant differences between regions.

Column 4, the preferred estimation,[38] suggests that – when controlling for the labour market composition, task biased technological change, the Frey & Osborne prediction, time invariant differences between municipalities and regional invariant shocks - an increase of US$ 1,000,000 in import exposure per person is related to a decrease in the share of manufacturing employment of 0.0554 percentage points per year. This result is statistically significant at a 5% significance level. Instead, an increase of US$ 1,000,000 in export exposure per person is related to an increase in the share of manufacturing employment of 2.055 percentage points per year, ceteris paribus. Due to the nature of the independent variables, these results are rather incomprehensible. In paragraph 4.5 the results are placed in perspective to get to the very essence of the implications.

4.2 Causal identification

Paragraph 3.4 elaborated on two threats to causal identification: reversed causality and endogeneity of Dutch trade exposure. Therefore, the benchmark estimation (column 4 in table

[37] It could be argued that municipalities do not truly represent local labour markets. In a small country such as the Netherlands, citizens often live and work in different municipalities. In fact, the average distance between the municipality in which an individual lives and in which it works was 14.6 kilometres in 2014 (CBS, 2016a). Therefore, the CBS definition of local labour markets is used as sensitivity test. The F-statistic of this model is much lower than in the benchmark model. For this reason, this model is considered inferior to the benchmark definition.

[38] This municipality model is preferred since it corrects for more time invariant regional differences to get closer to the true impact of trade exposure and technological development.

1) was advanced by exploring the theoretically supported econometric tools to reduce these threats.

The identification strategy was done in two phases. First, Dutch trade exposure was instrumented by trade exposure of a set of other developed countries aiming to minimise the threat of endogeneity. Second, the IV-strategy was extended by using the first lag of the employment statistics in the construction of the import and export exposure measures and the first lag of the technological development measures to lower the probability of potential reversed causality.[39]

The required postestimations were realised aiming to prove severe endogeneity in the models and to validate the instruments (Wooldridge, 2012). Contrary to expectations, only in the non-lagged regressions was endogeneity identified at strong confidence levels (P-value lower than 0.10). Yet, the IV-estimations are still preferred over OLS as the theoretical arguments are too compelling to ignore and were therefore used in the identification strategy.[40]

Table 2 shows the results of the benchmark model with local labour markets defined as municipalities and both steps to get closer to causal interference (separately). The main difference between the OLS-regression and both IV-regressions is the statistical significance which is slightly lower in both IV-estimations. This is a sound consequence of the IV-strategy being less efficient than OLS. Thus, in the model that reduces the threat of endogeneity, the negative effect of import exposure on the share of manufacturing employment can only be revealed with 90% confidence. Aside from this, the results are very robust in terms of statistical significance, signs and magnitudes. This implies that the findings do not hinge on the exogeneity of trade exposure. Therefore, the IV-models are preferred over OLS and used in paragraph 4.5 for interpretation.

The robustness of the identification results is confirmed by tables D1 – D3 in appendix D. Table D1 shows the results of the initial sensitivity test in case of the IV-estimation (column 3 and 4). Besides, an additional sensitivity test was performed to validate the instruments by changing the set of IV-countries (table D2 and D3). The strong similarities

[39] The threat of reversed causality is reduced but not expelled. If labour markets anticipate changes in trade exposure and technological progress by more than one year ahead, potential reversed causality remains present.
[40] If variables are not endogenous, OLS estimations are preferred since IV estimates are less efficient due to their higher standard errors (Wooldridge, 2012). However, not being able to detect endogeneity (using the Durbin-Wu-Hausman test) does not prove that the variables are exogenous – one only fails to detect endogeneity. Since the non-lagged models are proved to be endogenous and due to the theoretical reasons provided by ADH and DFS which are also very relevant for the Netherlands, the IV estimations are preferred over OLS. Despite, OLS-estimations are disclosed in the appendices and do not show significantly different results.

between the results of the OLS estimation, the initial sensitivity test and the IV-estimations suggest that the results do not critically depend on the chosen IV-countries, endogeneity of trade exposure nor on the definition of local labour markets.

Table 2: Identification results

Explanatory variables	Dependent Variable: Yearly change in the share of manufacturing employment in total employment		
	(1)	(2)	(3)
	Benchmark - OLS	IV	IV with lags
Δ Import exposure****	-0.0554**	-0.0696*	-0.0459*
	(0.0263)	(0.0409)	(0.0266)
Δ Export exposure ****	2.055***	3.188***	2.174***
	(0.576)	(0.579)	(0.678)
% Routine employment ****	0.00777	0.00894	-0.0179
	(0.0126)	(0.0124)	(0.0115)
% Non-complex employment ****	0.00396	0.00444	0.00479
	(0.0115)	(0.0117)	(0.00871)
% Foreign population	-0.155*	-0.150*	-0.145*
	(0.0880)	(0.0861)	(0.0875)
% Female	0.0717**	0.0725**	0.0728**
	(0.0292)	(0.0289)	(0.0296)
% High educated	-0.0254	-0.0251	-0.0274
	(0.0226)	(0.0225)	(0.0210)
R-squared	0.362	0.357	0.348
Time FE	Yes	Yes	Yes
Municipalities FE	Yes	Yes	Yes

* Significantly different from zero at 90% confidence

** Significantly different from zero at 95% confidence

*** Significantly different from zero at 99% confidence

**** In column 3 Δ import and Δ export exposures are constructed with lagged employment data and the shares of routine and non-complex employment are lagged.

Notes: *The number of observations is 16,169 in all columns. Standard errors (in brackets) are robust and clustered by municipalities dealing with the detected autocorrelation and heteroskedasticity. The labour market composition control variables are constructed as percentage of the population (foreign education) and as percentage of the labour force (female). Constants are not reported.*

4.3 Beyond employment in the manufacturing sector

In order to establish conclusions concerning the effects of trade exposure on the labour market position of low-skilled Dutch citizens, it does not suffice to consider manufacturing employment only; other industries can be affected as well.[41] The dependent variable from the benchmark identification model was therefore replaced by several labour market measures:

[41] Theoretical reasons are identified by ADH: if labour markets are not fully geographically integrated and competitive, shocks in employment in one industry or region can influence labour markets in other industries or regions.

the unemployment rate in other industries, average incomes, poverty[42] and the share of the labour force that receives unemployment benefits (and the share of individuals moving in or out of a municipality - migration – for causal interference). The extensive regression results of these variables can be found in appendix D (tables D4-D8).

Table 3 shows the simplified results of the effect of changes in trade exposure on different labour market outcomes. The variables *unemployment rate, the share of individuals whose income is less than 110% of the social minimum* and *the share of individuals receiving unemployment benefits* are of particular interest as these categories specifically assess the impact on the "losers of globalisation". Even though no statistically significant effect of import exposure was identified on the unemployment rate or wages, columns 6 and 7 confirm the existence of "losers of import competition" in the Netherlands: all else equal, an increase in import exposure increased the share of individuals in poverty and the share of individuals receiving unemployment benefits.

The results on migration imply that migration was not a threat to causal identification (as suggested in paragraph 3.5). Concerning import exposure, no statistically significant effect on either form of migration was found. Export exposure does not have a significant effect on migrations to another municipality. The effect on migration into the municipality is only significant at a 10% significance level and should not be interpreted as it contradicts expectations and the literature (regions with more export opportunities attract fewer individuals to move into the region).

Table 3: IV with lag identification results with other labour market variables as dependent variables

	Dependent variables					
Explanatory variables	(1) Δ% Unemployment	(2) Δ Wage	(3) Δ% Poverty	(4) Δ% Move out	(5) Δ% Move in	(6) Δ% Unemployment Benefits
Δ Import exposure	-0.00213	-0.659	0.0202***	-0.000343	0.00483	0.0165*
	(0.00816)	(0.592)	(0.00645)	(0.0117)	(0.00798)	(0.00872)
Δ Export exposure	-0.182**	0.932	-0.258	0.139	-0.494*	-0.544***
	(0.0883)	(12.12)	(0.167)	(0.302)	(0.258)	(0.140)

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence

Note: *The number of observations is between 45,011 and 45,277 in all columns. Standard errors (in brackets) are robust and clustered by region. The results follow from the 2SLS – lagged first difference identification regression (similar to column 3 from table 2). The only changes are the dependent variables. The complete tables can be found in appendix D tables D4-D8.*

[42] Estimated by the share of the population whose income is 110% of the social minimum or lower.

4.4 Technological development

Although all previous models failed to identify a robust statistically significant effect of either task biased technological change or the Frey & Osborne prediction on the share of manufacturing employment, the models do find statistically significant effects on other labour market dependent variables. In contrast to ADH and DFS, this paper discloses the effect of technological development on the other labour market outcomes (tables D4-D9 in appendix D).

The first observation worth noting is that *none* of the models identified a robust statistically significant effect in line with expectations of either the share of routine employment or the share of non-complex employment. Only for the variables *average income* and *poverty* were significant results in line with expectations. However, these results are not robust as they are only (marginally) statistically significant in some of the estimations. For all other dependent variables for which a significant effect was found, the signs were counterintuitive. The results suggest that regions with higher routine and non-complex employment shares are related to less poverty, higher wages and lower shares of individuals with unemployment benefits. Since all these effects are contrary to the (theoretical) expectations, several sensitivity tests were performed in which the technology change variables were altered.

Instead of the shares in employment, dummy variables were used which equalled 1 if a region has an above-average employment share in routine or non-complex employment and 0 if otherwise (see table D9 in appendix D). Besides, the regressions were run with an estimate covering the risk of computerisation for the average job per region per year – based on the Frey & Osborne estimate (explained in appendix B). These adjustments did not lead to considerably different results.

4.5 The results in perspective

Extracting the academic and policy implications from the results does not go without a decent comprehension of the economic consequences of the crude results. Therefore, the results are placed in the economic context and compared with ADH and DFS in this paragraph.

In the interpretation of the regression estimates, a similar strategy as ADH and DFS is used.[43] Applying the estimates on the average size of the labour force and mean import

[43] The difference with ADH and DFS is that this paper does not distinguish between supply (increased productivity in low and middle-income countries) and demand driven import exposure. ADH and DFS do this by

exposure per person suggests that import competition caused a decline in manufacturing employment of 60 jobs at a national level per year.[44] Yet, when the increase of export opportunities is included, the net effect of increased trade exposure with low and middle-income countries was positive: an increase of 1,439 jobs in the manufacturing industry per year between 2008 and 2014.

Along the same line, the estimated effect of import competition on poverty was deducted: increased import exposure caused a yearly rise of 14 individuals earning less than 110% of the social minimum in the Netherlands.[45] Nonetheless, the estimate of the net effect of trade exposure is a yearly decline of 75 individuals living in poverty. Yet, since the effect of export exposure was not statistically significant in the IV-lag model, one cannot exclude potential reversed causality. Therefore, causality of the net effect is not claimed. Furthermore, increased import exposure is related to an increase of 22 individuals that receive unemployment benefits.[46] The net effect however, is a decrease of 338 individuals. Increased import (export) exposure does not seem to lead to migration between labour markets. A potential explanation for this is the definition of local labour markets used in this study: if a municipality is confronted with negative developments on their labour market, individuals do not necessarily have to move to another municipality as other labour markets are within close reach of the residence municipality.

A precise comparison between these findings and ADH's and DFS' findings is precarious due to the differences in time span and in trading partners: whereas this paper covers a short period with an economic crisis, ADH and DFS study a period of 17 and 20 years respectively. In spite of this, a reserved comparison – whilst keeping these differences in mind - is useful for understanding the impact of trade exposure on the labour market in the Netherlands. ADH conclude that increased import competition from China cost 1.5 million jobs in the manufacturing industry in the US between 1990 and 2007. In contrast, between 1988 and 2008, trade exposure with Eastern Europe and China has increased employment in the German manufacturing sector by 305 thousand jobs as the positive effect of new export

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using the subtracting the OLS-estimate from the IV estimate. Yet, since this would cause a negative estimate in this paper and because causal identification is not achieved, this is considered a step too far.

[44] Average labour force (based on 2008 and 2014) * mean imports per person in labour force (in million USD) * regression estimate divided by 100 due to percentage points: (8,571,000+8,677,000)/2*(131,650/8,571,000)* -0.0554/100= -72.93
The overall import and export means are used instead of the aggregates of the sample data.

[45] Average population * mean imports per person*regression estimate divided by 100: (16,405,000+16,829,000)/2*(131,650/8,571,000)* 0.0202/100 = 13.8

[46] Average labour force * mean imports per person* regression estimate divided by 100: (8,571,000+8,677,000)/2*(131,650/8,571,000)* 0.0165/100= 21.7

opportunities was much greater than the negative consequences of import competition (DFS). At first sight, these magnitudes seem much bigger than those found in this paper. However, this puzzle can be solved by correcting for the differences in time and the size of the labour forces. When this is done, the net effect of increased trade exposure on the employment in the manufacturing sector is only approximately 2 times smaller than in Germany.[47] The results are more in line with DFS than with ADH as the effect of the change in export exposure is consistently greater in magnitude than the change in import exposure (for all dependent variables). This implies that, on average, the effects of a rise in trade exposure with low and middle-income countries has a robust and positive effect on low-skilled individuals.

This paper also aimed to control for two of the most eminent and modern theories regarding the channels through which technological development affects individuals on the labour market in different ways. However, no statistically significant effects in accordance with the hypothesised signs were found. Even though a profound analysis on the theoretical and empirical reasons behind this is beyond the scope of this paper, some potential reasons are discussed.

The first can be found in the level of disaggregation of the data. At a regional level, there are only 4 categories of the complexity of employment shares which are all distinctly susceptible to computerisation. Thus, in contrast to the trade data which covers 20 industries, there is very few regional variation in the variables that should capture the channels through which technological development effects the labour market.

Concerning the benchmark model, there is a more fundamental drawback in the methodology. The regression establishes a relation between the share of manufacturing employment per region and the share of routine and non-complex employment. As mentioned in paragraph 2.1, the manufacturing industry is relatively abundant in low-skilled employees (Notowidigdo, 2011). However, if the share of routine employment (and the share of non-complex employment to a smaller extent) estimates the share of low-skilled employment instead of the indirect mechanism of task biased technological change, a positive relation between the share of routine employment would be plausible. It would only confirm that the manufacturing sector is indeed abundant in low-skilled labour and it is therefore questionable

[47] Compare effects: Net effect / number of years / (US or German labour force / Dutch labour force)
US: 1.5 million / 17 / (163/9) = 4872 jobs
Germany: 305,000 / 20 / (43/9) = 3192 jobs
(World Bank labour forces of 2016 were used to correct for the labour market size)
Note that this approach does not correct for trading partner groups (low and middle-income countries vs China (US) and China and Eastern Europe (Germany)).

to what extent employment shares are the correct measures to study the effect of technological development on different individuals.

With respect to income, a fairly robust positively significant effect of the share of non-complex employment on wages is found. However, similar concerns apply; one does not know whether a positive sign of non-complex employment indicates a positive relation between non-complex employment and wages because of the high susceptibility to computerisation or due to other (demand driven) reasons. This is partly due to the definition of income: it does not truly represent income from labour. In fact, it also encompasses income from entrepreneurship and social security payments which generates noise in the regression (income includes unemployment as well). Thus, it is plausible that a higher share in non-complex employment has a positive impact on the average wage as wages are probably higher than in regions with higher routine-employment shares or even higher unemployment rates.

In short, the unexpected results which are supposed to represent the effects (or existence) of task biased technological change and the Frey & Osborne prediction, are probably a consequence of methodological and data matters rather than real economic reasons. It is therefore questionable to what extent this methodology – and in ADH's and DFS's [48]– genuinely captures the effect of (task biased) technological change and the effect on the labour market.

5. Discussion and limitations

This paper aimed to measure the effect of economic globalisation – through increased exposure to import competition and export opportunities from low and middle-income countries – on the labour market position of low-skilled individuals in the Netherlands, whilst correcting for the effect of technological development on the labour market. It unravelled a causal significant negative effect of increased import competition on the labour market position of low-skilled individuals in the Netherlands. The position is worsened in various ways: a decrease in manufacturing employment – which is characterised by a higher than average share of low-skilled employees -, an increase in individuals who earn an income lower than 110% of the social minimum and an increase in individuals who receive unemployment benefits.

[48] This is not necessarily problematic in ADH and DFS. Under the assumption that there IV strategy isolates the causal effect of trade exposure on the labour market, one does not have to control for other variables. Thus, the implications with respect to the effect of trade exposure are not weakened by this methodological flaw. If the suggested methodological flaws of incorporating the task model in the regression are valid, one cannot draw conclusions regarding the effect of task biased technological change (which they do not do).

However, the economic significance of this finding diminishes when the positive effects of increased export opportunities on the position of the low-skilled worker are taken into account. In the aggregate, the positive net effect of increased trade exposure with low and middle-income countries is roughly 15 times bigger than the negative effect of increased import competition - mostly through a decrease in unemployment. The conclusion that regions with increased export opportunities are related to improved labour market positions for low-skilled individuals, is in line with most contemporary research.[49]

Yet, the results do not imply that import competition is beneficial for everyone. In fact, the results suggest that the benefits of increased trade could be unequally distributed across the Netherlands. Low-skilled individuals in regions with few export opportunities but substantial import competition can be harmed by increased trade exposure with low and middle-income countries. These implications have not been revealed before for the Netherlands by studies that use methodologies similar to Autor et al.'s eminent one (2013). Yet, the importance of these regions in the Netherlands remains unclear.

A comparison between this study and previous country studies on the US (Autor et al., 2014) and Germany (Dauth et al, 2014), reveals that the effect of increased trade exposure on the Netherlands is more comparable to Germany than to the US. However, the magnitudes of the effects are bigger in the German case. Although a profound analysis on the underlying mechanisms for the greater magnitudes is beyond the scope of this paper, two potential explanations are discussed. Whereas Germany is a large economy with a huge domestic consuming market, the Netherlands – as a small(er) open economy – is characterised as a transit country: a large share of the imported goods does not remain in the country but is (processed and) re-exported to the European hinterland. Thus, while the import statistics of Germany mainly cover imports that compete with domestic producers on the domestic market, the import statistics for the Netherlands cover a substantial amount of imports that hardly influence the domestic producers since products do not remain on the domestic market. Moreover, the data used in Dauth et al. (2014) includes a crucial historical event: the fall of the iron curtain. The reunification of East and West Germany opened a whole new (low-income) market bordering the domestic market.

Regarding the effect of technological development on the labour market position of low-skilled individuals through task biased technological change and the Frey & Osborne prediction, no robust statistically significant effect in line with the expectations was identified.

[49] For instance, Melitz (2003) identified a positive relation between exporting firms and wages.

Yet, this is presumably a consequence of the methodology and the (variation in the) data rather than a claim that technological development does not unevenly affect individuals with different skill levels.

The results initiate both academic and policy implications. The key academic implication is that the leading methodology designed by Autor et al. (2013) and extended by Dauth et al (2014), is not adequate to study the true mechanism of task biased technological change or the Frey & Osborne prediction. Nevertheless, under the condition that the IV-strategy isolates the causal effect of increased trade exposure on the labour market, this flaw does not harm the implications regarding trade exposure. The main policy implication is that policymakers and politicians who claim to defend the interests of low-skilled Dutch citizens should encourage trade with low and middle-income countries, as the labour market position of the low-skilled individual improves in the aggregate. Regardless, policymakers concerned about the distributions of the benefits could plead for strategies that ensure that the "losers of trade" reap the overall benefits of increased trade as well – even though this group is small.

Without degrading the implications, several flaws in the data and the methodology were identified. Regarding the first, the sample period (2008-2014) caused genuine challenges since it includes the years of the economic crisis. This caused a declining growth in trade compared to previous years. Moreover, the labour market variables behaved unusually. This had significant consequences for the Δ import and Δ export exposure measures as they were negative in certain years. A second concern in the data is the level of disaggregation. The labour market data only allows one to compare industries in municipalities. Thus, all conclusions are based on comparisons between regional averages and regional shares rather than comparisons between individuals. Moreover, most of the labour market data is reported in thousands. This implies that for small municipalities, the labour market variables are less precise and sometimes even wrong as many variables are mistakenly reported as zeros. This also causes less variation in the data for small municipalities.

With respect to the trade data, imperfections are also found. In the harmonisation process, 20% of the overall trade data is lost. Moreover, as the detailed trade data was aggregated in order to be in line with the employment data, a lot of variation in the trade data was lost. The final dataset only contained 20 industries - 5 with trade data, 7 with missing trade data and 8 which are assumed to be non-tradeable.

As for methodological limitations, it is questionable to what extent this methodology enables one to correct for the true effect of task biased technological change or the Frey & Osborne prediction on the labour market position of low-skilled individuals. The share of routine employment (and non-complex employment) in a municipality is likely to contain more information than the (pure) task biased technological change. Moreover, even though the potential endogeneity of trade exposure is minimised trough the IV-estimations, the variables which should measure the mechanisms through which technological development affects the labour market position could also be endogenous, thereby undermining the interpretation of these effects.

6. Concluding remarks

Economic globalisation can engender positive effects for the Dutch economy. However, the social and academic debate shows little consensus on the effect on low-skilled individuals in the Netherlands. This paper investigates the effect of economic globalisation – through increased trade exposure with low and middle-income countries - whilst correcting for the effect of technological development – through the task biased technological change and the Frey & Osborne prediction - on the labour market position of low-skilled individuals in the Netherlands. It does so by applying the latest methodological developments in economics and by aiming to incorporate the latest findings in the field of technology and computerisation. The main implications are twofold. In the aggregate, increased trade exposure with low and middle-income countries improves the labour market position of low-skilled individuals. Although the positive effect of increased export opportunities is approximately a factor 15 bigger than the negative effect of increased import competition, increased trade exposure can harm low-skilled individuals in regions that have predominately employment in industries which face fierce import competition and few export opportunities. Thus, political parties that represent the low-skilled individuals in the Netherlands should plead for inclusive measures to distribute the benefits of globalisation equally.

The findings and limitations open new angles for future research. To start with, It would be insightful to extend this study by applying the methodological framework on more detailed CBS-microdata (which is not publicly available) and a larger time span to overcome the issues which arise from working with aggregated data and crises years. Moreover, the exact size of the group which faces severe import competition and very few export opportunities should be explored as it determines the magnitude of the problem. Lastly, for economists – amongst whom there is still no consensus on the importance of the effects of globalisation and technological development (through automation and computerisation) on the labour market – it would be valuable to narrow the gap between the views of (trade) economists and academics that believe automation has a more sizeable effect on the labour market. To accomplish this, integrated methodologies are required, which capture the effects of globalisation and technological development – such as the Frey & Osborne prediction - on the labour market. Very recently, Dauth, Findeisen, Suedekum and Woessner attempted this by testing the impact of rising robot exposure and trade exposure on the German labour market (2017). Conducting this type of research in the Netherlands could bring us closer in identifying the true impact of both globalisation and technological development on the labour market.

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8. Appendices

8.1 Appendix A: Theoretical derivations

1. Basic model ignoring export exposure:

$$\hat{L}_{Ti} = \rho_i \sum_j C_{ij} \frac{L_{ij}}{L_{Ti}} \left[-\sum_k \theta_{ijk} \emptyset_{jk}^{Low} \hat{A}_j^{Low} \right]$$

2. Assume that the share of trade imbalances and the scaling factor are the same for each region within the Netherlands: $\rho_i C_{ij} = \alpha$

$$\hat{L}_{Ti} = \beta \sum_j \frac{L_{ij}}{L_{Ti}} \left[-\sum_k \theta_{ijk} \emptyset_{jk}^{Low} \hat{A}_j^{Low} \right]$$

3. Substitute for: ${\theta_{ij}}^{Low} = \frac{X_{ij}^{Low}}{X_{ij}}$ $and\ \theta_{ijk} = \frac{X_{ijk}}{X_{ij}}$ $and\ \emptyset_{jk}^{Low} = \frac{M_{kj}^{Low}}{E_{kj}}$

$$\hat{L}_{Ti} = \beta \sum_j \frac{L_{ij}}{L_{Ti}} \left[-\sum_k \frac{X_{ijk}}{X_{ij}} \frac{M_{kj}^{Low}}{E_{kj}} \hat{A}_j^{Low} \right]$$

4. Assume that the share of region i in total Dutch imports from low and middle-income countries in industry j can be estimated by the share of region i employment in Dutch employment in industry j: $\frac{X_{ijNL}}{E_{jNL}} = \frac{L_{ij}}{L_{jNL}}$

   Moreover, following Autor et al.'s monopolistic competition model (2013), $\frac{L_{ij}}{X_{ij}}$ equals a constant.

$$\hat{L}_{Ti} = -\beta \sum_j \frac{L_{ij}}{L_{jNL}} \frac{M_{jNL}^{Low} \hat{A}_j^{Low}}{L_{Ti}}$$

8.2 Appendix B: Data cleaning

Several steps were taken to construct the final dataset. These steps included merging, recoding, renaming and reconstructing datasets. This appendix elaborates on each step in this process.

Trade

The original UN Comtrade data was extracted in 4-digit Standard International Trade Classification (SITC) Rev. 3 format. This data was first converted into the Nomenclature statistique des activités économiques dans la Nace Communauté Européenne (Nace) Rev 1, then into Nace Rev 1.1 and finally into Nace Rev 2, which is identical to SBI 2008 (the CBS format). SITC Rev. 3 was chosen since it is rather harmless convertible into Nace format (compared to more recent versions of SITC and the Harmonized System Codes (HS). The United Nations (UN) – by means of the Reference And Management of Nomenclatures (Ramon) - and WITS provide correspondence tables which are used to match the different types of data.[50] Theoretically, the 5-digit SITC would suit this research better as it is more disaggregated and therefore more easily convertible into the Nace format. However, the 5-digit data is incomplete - it covers only 35% of total trade - and it is unbalanced in the product types. The 4-digit level on the other hand, covers 92% of the total trade in the reference year 2010.

The harmonisation process between SITC and Nace Rev. 1 is done in two stages. First, the official concordance schedule of WITS is used at a 4-digit level – which is in line with the 4-digit SITC data. At this level, the crosswalk is far from complete and only 27.1% of the data is matched. However, since the available labour market data is at a 1-digit level, a similar level of detail in trade data suffices for this research. Therefore, the concordance schedule can be adjusted manually to enable matching at a more aggregate level. To start with, the official 5-digit correspondence schedule and the trade data is transformed into a 3-digit data (by deleting the last (2) digit(s)). Hereafter, an additional matching schedule is constructed which includes only the variables which are completely identical at a 3-digit level. This schedule is then used to harmonise all data which was not matched in the first stage. The second stage increases the matching score to 85.6%.

[50] http://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL & http://wits.worldbank.org/product_concordance.html

The transition from Nace Rev 1. to Nace Rev. 1.1 is much easier: one should only follow the official UN RAMON correspondence table. This step changes only 35 variables in the dataset.

Finally, the 3-digit Nace Rev 1.1 needs to be transposed into 1-digit Nace Rev. 2. The first step in this process is to write the 3-digit Nace Rev. 1.1 in 2 digits by simply deleting the last digit. Secondly, a rule is made in Excel which attaches a 1-digit label on the 2-digit Nace Rev. 2 correspondence table. This is less straightforward; the simple strategy of deleting the last digit cannot be used anymore since the 1-digit Nace Rev. 2 uses (more than 10) letters instead of numbers. Thirdly, it is tested manually which Nace Rev 1.1 2-digit variables can be matched with 1-digit Nace Rev. 2. After the application of this last step, in which minor[51] matching mistakes are ignored, the dataset covers 78.2% of all trade between the Netherlands and low and middle-income countries.

Table B1 shows the trade data coverage of the master dataset. The first row represents the aggregates of the original UN Comtrade data and the last column displays the share of the original data which is covered by the master dataset. Hence, 61% of all exports are covered by the dataset and 80% of all imports.

After the trade data is harmonised with industry codes, it is merged with the labour market statistics. If this had been done without any manual changes in the trade data, it would have resulted in a large number of missing data: 72.1% of the data does not contain information about trade. The reason for this is the inclusion of industries in the non-tradeable goods sector in the dataset (which are recorded as missing data). Therefore, missing trade observations are replaced by zeros in all non-tradeable goods sectors. The process of verifying which industry only contains non-tradeable goods is based on two pillars. First, the disaggregated trade data which could not be used in the final dataset due to matching issues is used to check if trade took place in a certain industry. Second, it is manually verified if sectors without trade data are completely non-tradeable.[52] Missing data is replaced by a zero in the following industries: Electricity, gas steam and air conditioning supply (D), Construction (F), Accommodation and food service activities (I), Real estate activities (L), Public administration and defence (O), Human health and social work activities (Q) and Other

[51] Minor mistakes have a maximum error margin of 10%

[52] Example: In the case of Wholesale and Retail Trade (G) there was no trade data reported. However, since is evident that this is a tradeable sector, it is not replaced by zeros. Instead, it is still considered missing data.

service activities (S). After these changes, the dataset includes 54,793 observations of which 41.2% is in the non-tradeable goods sector and 58.8% in the tradeable goods sector. 47.5% of this data contains information regarding trade, but for the remaining 52.5% trade data is absent.

Table B1: Coverage of trade data in reference year 2008

Data format	Exports	Imports
UN Comtrade Aggregates	60.7	123
%	100%	100%
4-digit SITC Rev 3 data UN Comtrade	50.5	112
%	83%	91%
Final data: SBI2008	37.3	98.6
%	61%	80%

Risk of computerisation

The risk of computerisation variable is based on the risk assessment in Frey and Osborne's famous work *The Future of Employment: How susceptible are jobs to computerisation* (2017). In their appendix, one can find a list with 702 different occupations specified with the US' equivalent of the European job classification system (ISCO): the 6-digit Standard Occupational Classification System. For each individual job, Frey and Osborne derived the probability that a job is computerised within an unspecified number of years. These probabilities hinge on a two-pillar strategy. First, the authors, in cooperation with machine learning researchers, assessed 10% of all occupations and assigned a 1 to each occupation which is potentially fully automatable and a 0 if not. More precisely, they aimed to answer the following question for each occupation: *"Can the task of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?"* Second, they use a more objective approach on all 702 SOC-occupations by analysing the tasks of each occupation using the US' O*NET database. The tasks involved in *perception and manipulation*, *creative intelligence* and *social intelligence* are of particular interest to the researchers since these tasks were defined as the bottlenecks for computerisation.

Finally, they construct an algorithm based on the aforementioned analyses and derive the probability of computerisation for each SOC-occupation. As mentioned before, the authors emphasise that they do not attach a specific time horizon to the probabilities. The most definite estimate is in "…perhaps a decade or two" (Frey & Osborne, 2017, p. 38).

For the Frey & Osborne probabilities to be suitable for this paper, several steps are required. First, the SOC-occupations need to be transposed in the 4-digit ISCO-2008 system. Instead of harmonising the SOC and ISCO codes manually, the correspondence table published by Statistics Norway was used (Pajarinen, Rouvinen, & Ekeland, 2015). This table attains the Frey's and Osborne's risk estimates at each 4-digit ISCO-2008 occupation. Once this is achieved, all the 4-digit ISCO-2008 risk estimates need to be aggregated to the 1-digit ISCO-2008 system since regional occupational data in the Netherlands is only available at a 1-digit level. Yet, for an appropriate aggregation, all 4-digit ISCO-2008 occupations should be weighted by the extent to which each 4-digit ISCO-2008 occupation contributes to the 1-digit ISCO-2008 system using the Dutch labour market statistics.[53]

A trade-off was made in computing the appropriate weight. Whereas the CBS has national time variant data on employment at a 3-digit ISCO-2008 level, the Research Centre for Education and the Labour Market (ROA) and the CBS have a combined publication in which they provide time invariant (2014) national data at a 4-digit ISCO-2008 level (Fouarge & Dijksman, 2014). Although time invariant weights are an important limitation in the construction of Frey and Osborne risk estimates applicable in this research, it is considered less harmful than the first option since that option would cause unconquerable issues in matching the risk estimates with the employment data. This strategy attains a weighted risk of computerisation probability for 88.3% for all (weighted) occupations in the Netherlands in 2014.

The application of the Frey & Osborne prediction on the Netherlands engenders the following probabilities of computerisation: 60% for routine employment, 65% for non-complex employment, 36% for complex employment and 12% for very complex employment. Non-complex employment is thus slightly more vulnerable to computerisation than routine employment.

One last step is performed to generate an estimate that attains a risk of computerisation of the weighted average job per municipality per year:

$$FOrisk^{it} = ShareISCO1^{it} * FOrisk1 + ShareISCO2^{it} * FOrisk2 + ShareISCO3^{it} * FOrisk3 + ShareISCO4^{it} * FOrisk4$$

Weighting example: Employment in the ISCO 1 category in 2014 in the Netherlands was 754,000. The 4-digit ISCO 9111 category is part of ISCO 1 at a 1-digit level and employment in this occupation equalled 77,000 in the same year. Hence, the risk of computerisation (0.69 in this specific case) is multiplied by 77 and divided by 754 in the aggregation process. This strategy has been applied for all variables.

where $FOrisk^{it}$ captures the time variant[54] risk of computerisation estimate for each region i. $ShareISCO1^{it}$ covers the share of ISCO 1 occupations in region i at year t. FOrisk1 is the weighted risk of computerisation probability of ISCO 1 occupation using national employment data for 2014. The subsequent ShareISCO and FOrisk variables are constructed accordingly.

In short, $FOrisk^{it}$ captures the probability of computerisation of the (weighted) average job in region i in year t based on the Frey and Osborne risk of computerisation estimates. Yet, the weights, which are of essential importance in the construction of this variable, are based on national employment statistics of the year 2014.

[54] Calculated with time invariant weights.

Figure C1: Imports and exports from and to low and middle-income countries

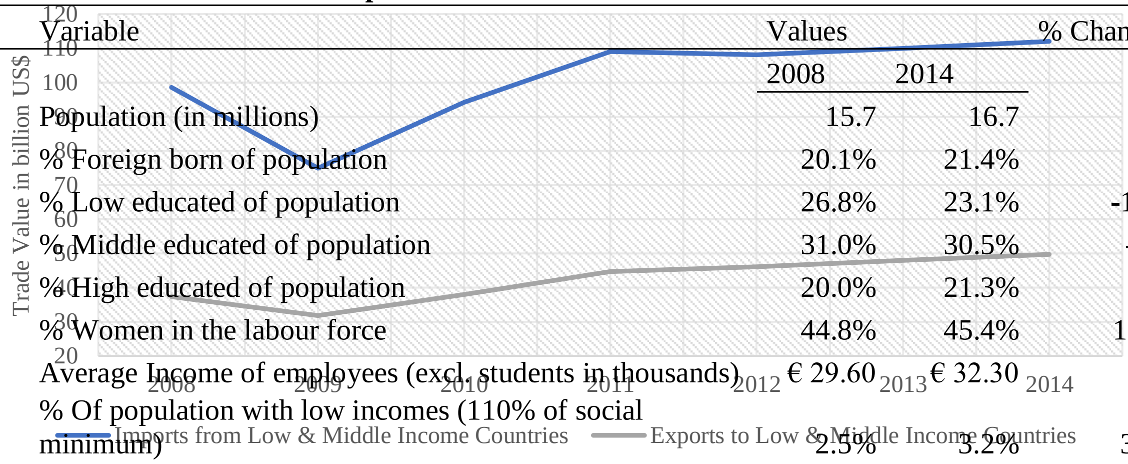


Table C1: National Descriptive Statistics

	Variable	Values 2008	Values 2014	% Change
1	Population (in millions)	15.7	16.7	6%
2	% Foreign born of population	20.1%	21.4%	7%
3	% Low educated of population	26.8%	23.1%	-14%
4	% Middle educated of population	31.0%	30.5%	-2%
5	% High educated of population	20.0%	21.3%	7%
6	% Women in the labour force	44.8%	45.4%	1.3%
7	Average Income of employees (excl. students in thousands)	€ 29.60	€ 32.30	9%
8	% Of population with low incomes (110% of social minimum)	2.5%	3.2%	30%
9	% Of individuals receiving unemployment benefits	1.9 %	2.6%	36%
10	Unemployment Rate	3.7%	7.4%	100%
11	Imports from Low and middle-income countries (in billion US$)	98	112	14%
12	Exports to Low and middle-income countries (in billion US$)	37	49	33%
13	Import exposure	0.01302	0.0160	23%
14	Export exposure	0.00516	0.00762	48%
15	% Of routine employment (ISCO 1)	8.4%	9.0%	6.4%
16	% Of non-complex employment (ISCO 2)	48.7%	45.2%	-7.3%
17	Risk of computerisation average job (Frey & Osborne)	46.0%	43.9%	-4.6%

Note: *This table displays the changes in some key variables within the sample period. With respect to education, a shift towards more highly educated population is detected. The average income has increased. Yet, the share individuals with low incomes, the unemployment rate and unemployment benefits have increased. Concerning trade, imports and exports towards and from low and middle-income countries has increased. In terms of the technological variables and their effect on the labour market, an increase in routine employment is observed. Yet, a decrease is displayed in the risk of computerisation of the average job following the Frey & Osborne definition.*

Table C2: Change in trade per industry (in million USD$)						
	Imports			Exports		
SBI2008	2008	2014	% Change	2008	2014	% Change
A: Agriculture, forestry and fishing	6467	7419	15%	2111	2442	16%
B: Mining and quarrying	28100	27100	-4%	96	336	251%
C: Manufacturing	63600	76700	21%	34600	45800	32%
D: Electricity, gas, steam and air conditioning supply	0	0	0%	0	0	0%
E: Water supply; sewerage, waste management and remediation activities	484	325	-33%	554	1091	97%
F: Construction	0	0	0%	0	0	0%
G: Wholesale and retail trade; repair of motor vehicles and motorcycles						
H: Transportation and storage						
I: Accommodation and food service activities	0	0	0%	0	0	0%
J: Information and communication						
K: Financial and insurance activities						
L: Real estate activities	0	0	0%	0	0	0%
M: Professional, scientific and technical activities	0.113	0.073	-36%	0.474	0.090	-81%
N: Administrative and support service activities						
O: Public administration and defence; compulsory social security	0	0	0%	0	0	0%
P: Education	0	0	0%	0	0	0%
Q: Human health and social work activities	0	0	0%	0	0	0%
R: Arts, entertainment and recreation						
S: Other service activities	0	0	0%	0	0	0%
T: Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use						

Note: *This table discloses the changes in trade with low and middle-income countries per industry following the SBI2008 classification. Whenever an industry is considered non-tradeable, the trade values equal zero. Note also that data is missing for some tradeable industries. It is observed that imports have risen in industry A and C between 2008 and 2014. Yet, exports have also increased in these industries. The sharpest increase in exports is detected in industry B: mining and quarrying.*

Table C3: Top 10 municipalities with the highest share of manufacturing employment

	Municipality	Values 2008		2014
1	Boxtel	28.4%	Bladel	33.7%
2	Bunschoten	27.0%	Boxmeer	25.5%
3	Boxmeer	26.8%	Cuijk	23.1%
4	Meppel	24.3%	Brummen	22.7%
5	Oost Gelre	23.9%	Almelo	22.2%
6	Almelo	22.6%	Etten-Leur	21.1%
7	Hardinxveld-Giessendam	22.4%	Moerdijk	21.1%
8	Sittard-Geleen	22.2%	Sittard-Geleen	20.9%
9	Moerdijk	21.2%	Oost Gelre	20.3%
10	Redmond	21.2%	Redmond	20.3%

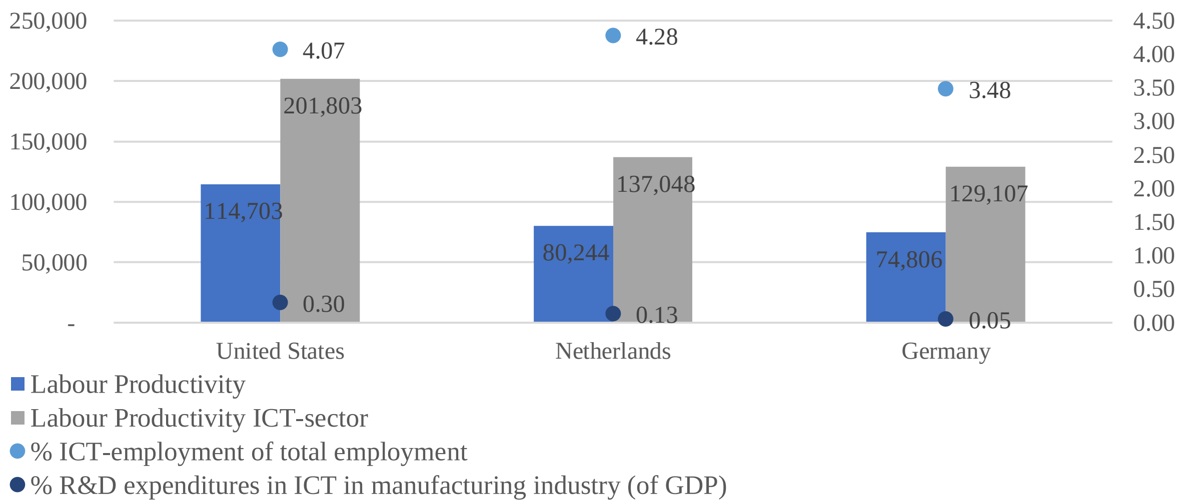
Note: *This table shows the 10 municipalities with the highest share of employment in the sector with the sharpest increase in import exposure: the manufacturing industry*.

Table C4: High-technology in countries

% High-technology exports from total exports	2008	2010	2012	2014
Countries:				
The Netherlands	19.2%	21.3%	20.0%	19.9%
Germany	13.3%	15.3%	16.0%	16.0%
The United States	25.9%	20.0%	17.8%	18.2%

Note: *This table displays the importance high-technology in a country's exports. The share of high-tech exports in total exports for the Netherlands is remarkably stable and even slightly growing over time. In Germany, a positive trend is observed as well whereas the trend is decreasing in the United States.* (World Bank, 2017)

Figure C2: Technology and ICT comparison of the USA, the Netherlands and Germany



Note: *This figure displays the differences between the US, the Netherlands and Germany with respect to labour productivity and the importance of ICT in each country. The labour productivity variables are in 2013 US$ PPP. (OECD, 2015)*

	Table C5: Risk of computerisation in jobs					
	Variable	Year				
		2008	2010	2012	2014	Time invariant
1	% Routine employment (ISCO 1)	8.1%	7.7%	7.6%	9.0%	
2	% Non-complex employment (ISCO 2)	48.7%	47.1%	46.6%	45.4%	
3	% Complex employment (ISCO 3)	17.9%	18.0%	18.2%	17.2%	
4	% Very complex employment (ISCO 4)	23.4%	25.2%	25.4%	25.7%	
5	Risk of computerisation ISCO 1 (Frey & Osborne)					60.1%
6	Risk of computerisation ISCO 2 (Frey & Osborne)					65.4%
7	Risk of computerisation ISCO 3 (Frey & Osborne)					35.5%
8	Risk of computerisation ISCO 4 (Frey & Osborne)					12.2%
9	Risk of computerisation of the average job (Frey & Osborne)	46.0%	44.9%	45.0%	43.9%	

Note: *This table displays the changes in employment related to technological change. One could say that the first four variables confirm the polarisation of the Dutch labour market to some extent: relative employment has increased in both the upper (ISCO 4) and lower (ISCO 1) tale and has decreased in middle (ISCO 2 and 3). Row 5-8 display the computed Frey and Osborne risk of computerisation estimate at an ISCO-level. As one can see, their estimate considers the ISCO 2 group to be the most vulnerable. The last variable discloses the risk of computerisation following Frey and Osborne applied on the employment of those years. It can be observed that employment in high risk jobs has already decreased.*

Figure C3: The development of the employment shares and the computed Frey & Osborne risk of computerisation estimates

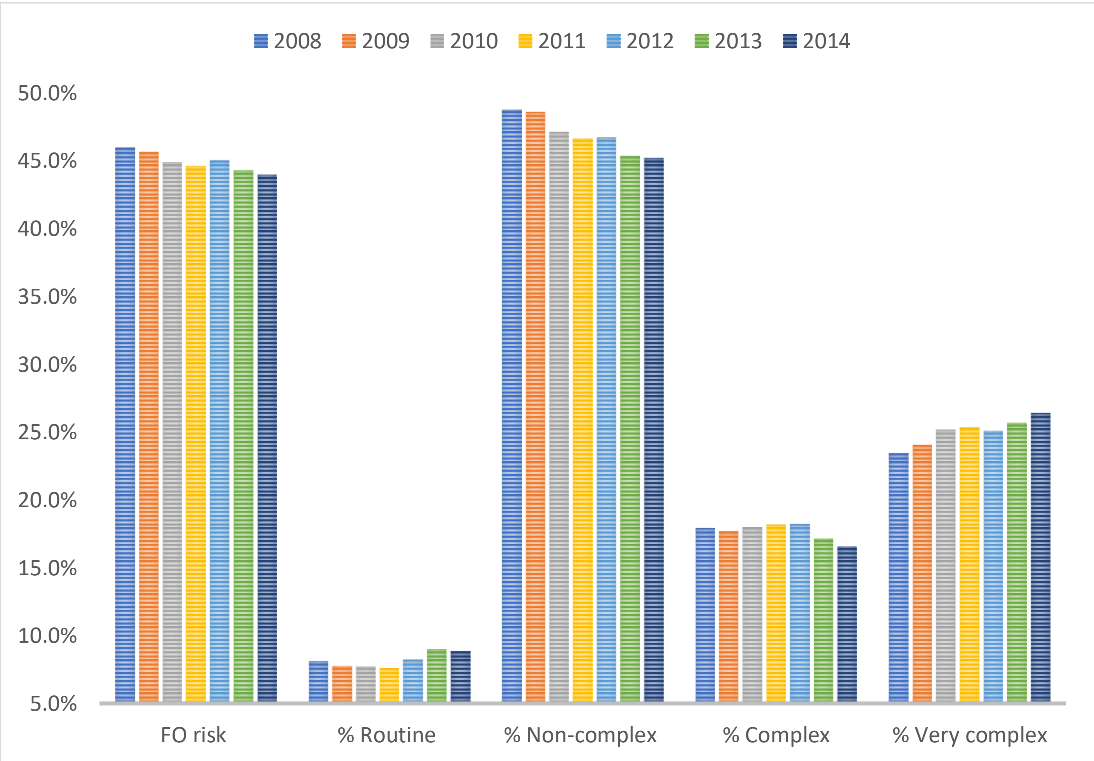


Figure C4: The average income per person per municipality (x €1000)

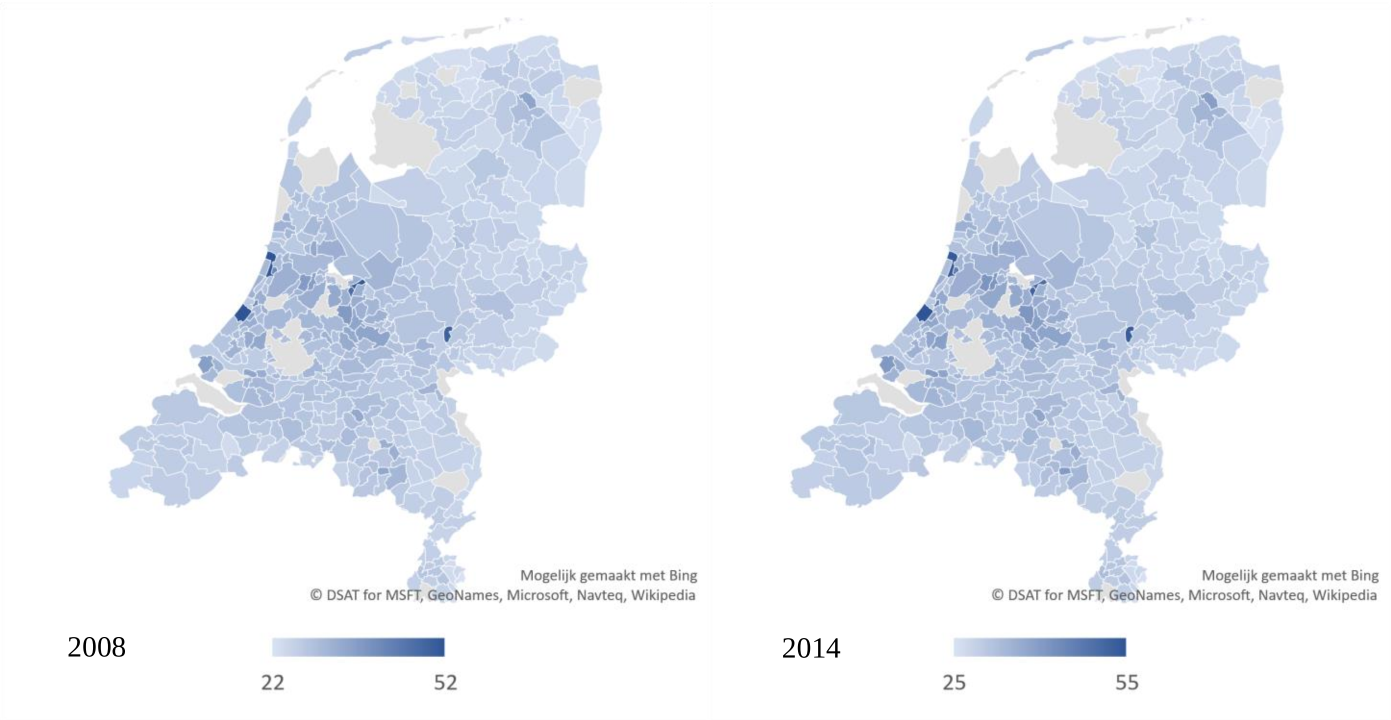


Figure C5: The share of routine (ISCO-2008 1) employment per region

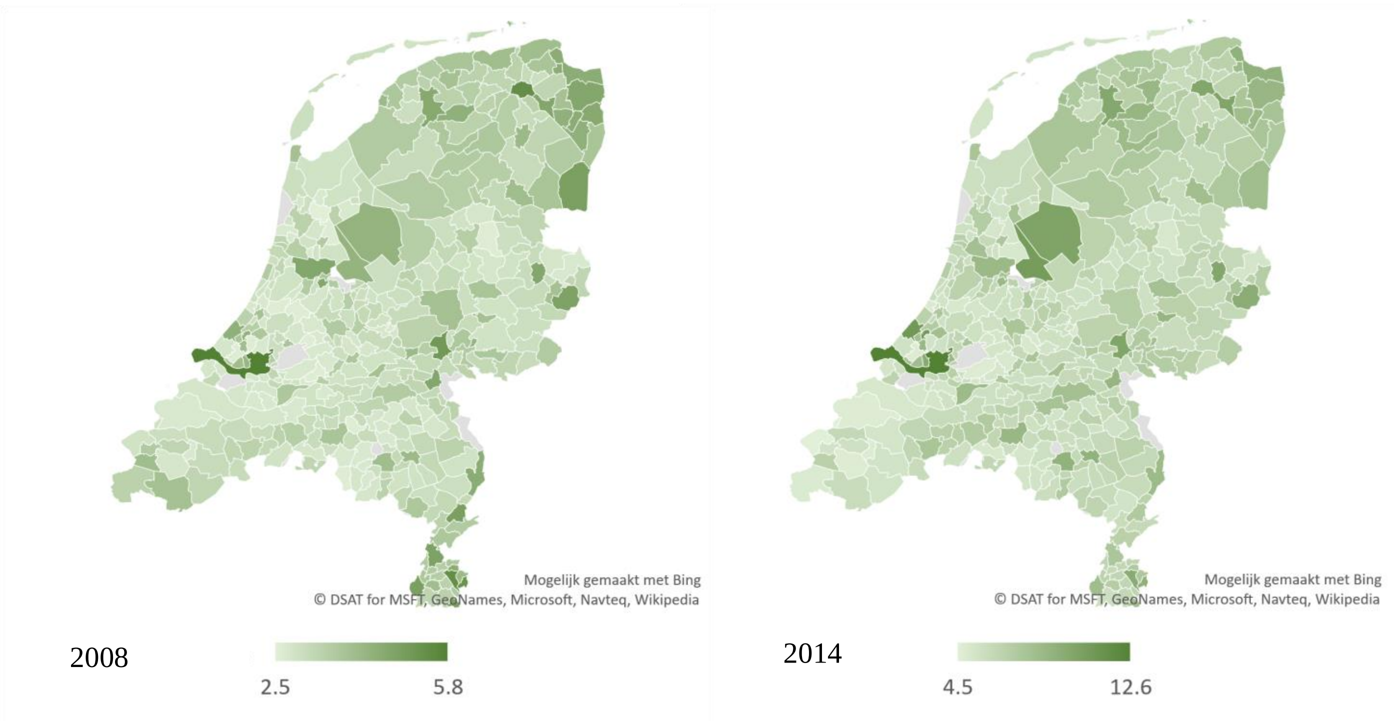


Figure C6: The share of routine (ISCO-2008 1) employment per region

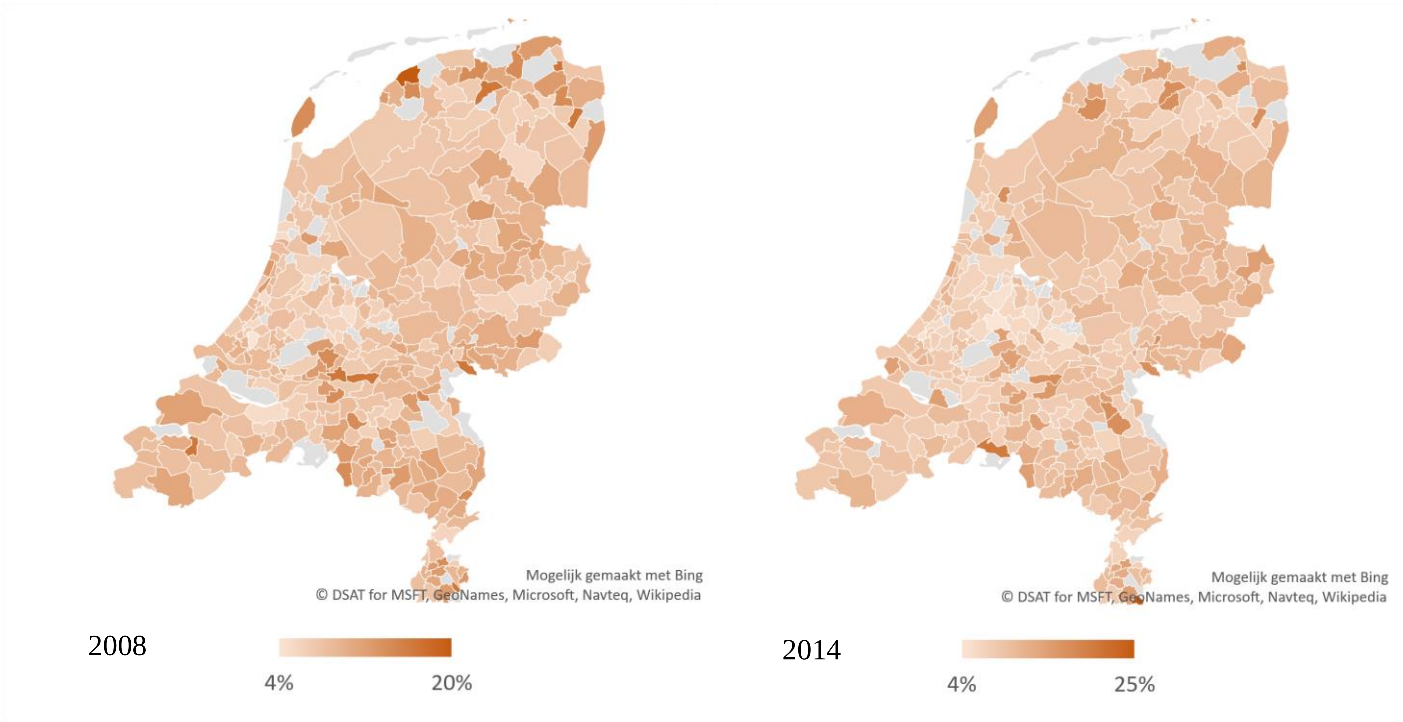


Figure C7: The Frey & Osborne risk of computerisation estimates per region

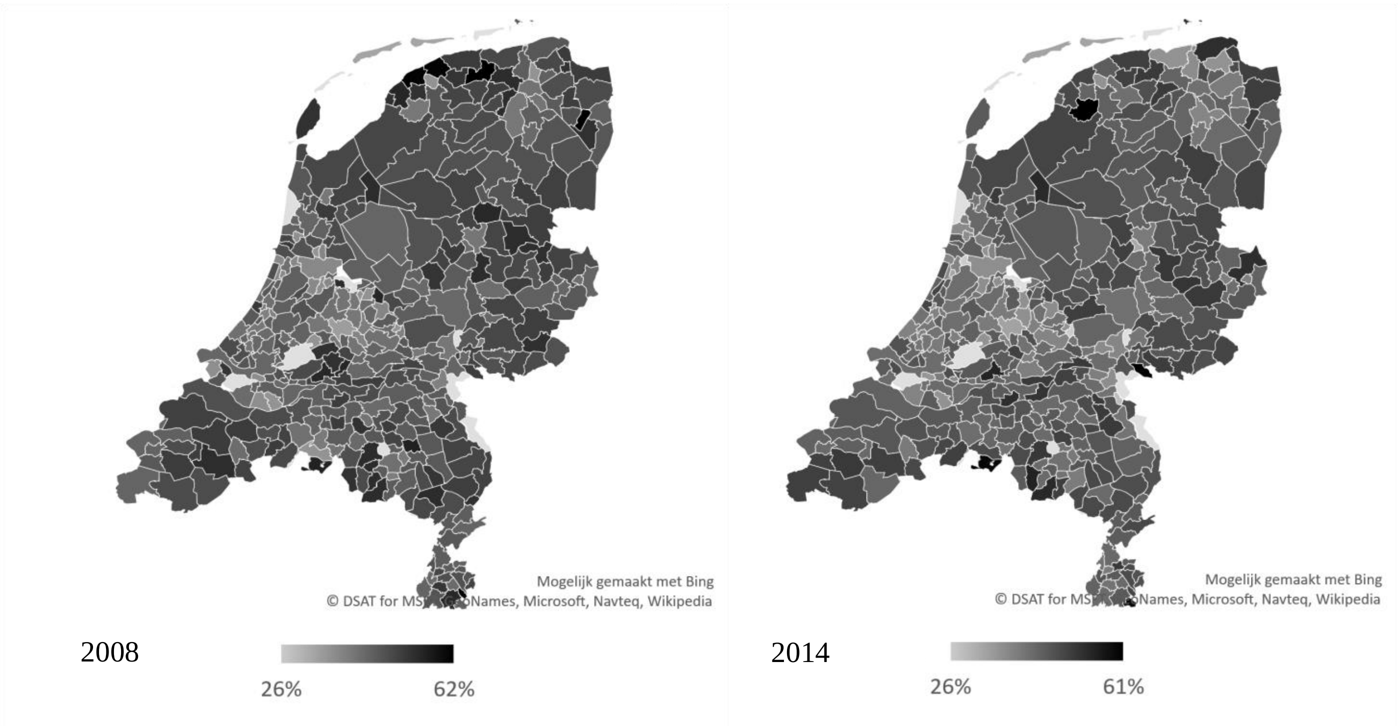


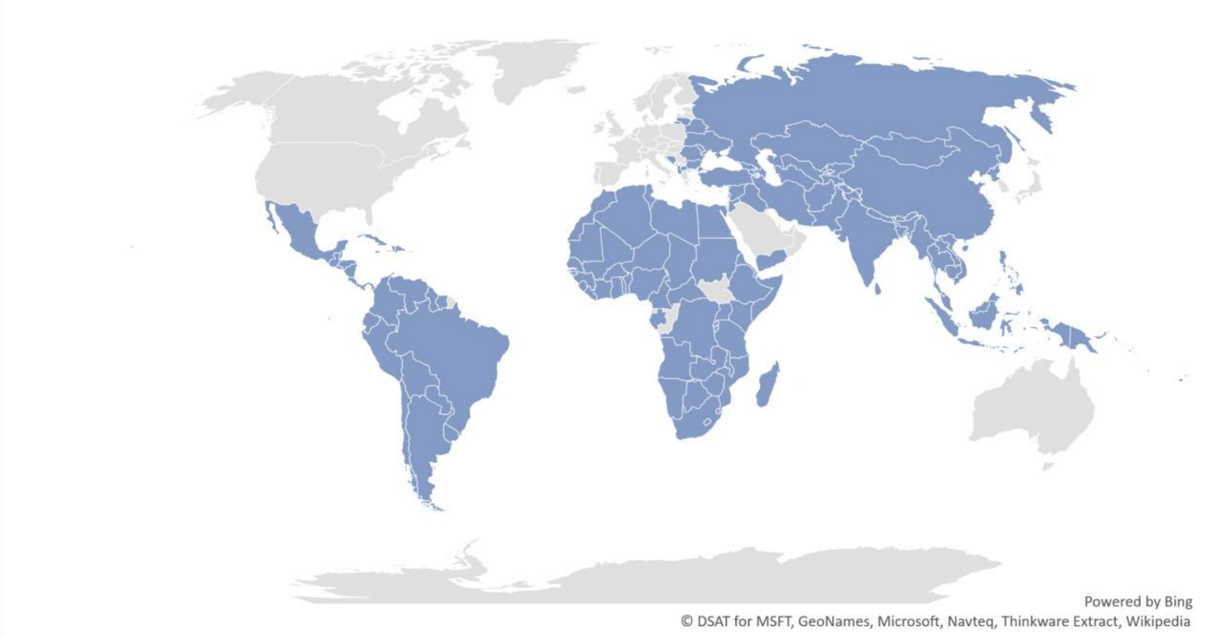
Table C8: Summary Statistics of variables of interest					
	(1)	(2)	(3)	(4)	(5)
Variables	Observations	Mean	Standard Deviation	Min.	Max.
Panel ID: Region x Indsutry$_{ij}$	53,599	3,829	2,210	1	7,657
Time$_{t}$	53,599	2,011	2.000	2,008	2,014
Industry$_{j}$	53,599	10	5.477	1	19
Region (municipality)$_{i}$	53,599	202	116.3	1	403
Imports$_{jt}$	36,673	7,757	18,641	0	76,731
Exports$_{jt}$	36,673	3,246	10,497	0	45,801
Δ Import exposure$_{it}$	53,599	0.000584	0.00848	-0.227	0.195
Δ Export exposure$_{it}$	53,599	0.000300	0.000924	-0.00469	0.00545
Share of routine employment$_{it}$	53,599	0.0819	0.04209	0	0.25
Share of non-complex employment$_{it}$	53,599	0.4690	0.07345	0.25	0.75
Average risk of computerisation	53,466	0.449	0.0577	0	0.615
Employment$_{ijt}$	37,398	1.295	3.741	0	87.07
Unemployment rate$_{it}$	53,599	0.0484	0.0143	0.0250	0.126
Income$_{it}$	52,782	30.76	4.229	23.10	56.40
Share with less than 110% of social minimum$_{it}$	52,801	0.0685	0.0227	0.0190	0.189
Share of moving out$_{it}$	52,782	0.0678	0.0208	0.0175	0.189
Share of moving in$_{it}$	52,782	0.0694	0.0194	0.0203	0.206
Share receiving unemployment benefits$_{it}$	52,782	0.0335	0.0126	0.006	0.08
Labour force$_{it}$	53,599	21.78	33.97	0	456
Total population$_{it}$	52,782	41,038	63,562	932	810,937
Share of foreign population$_{it}$	52,782	0.134	0.0777	0.0247	0.507
Share of high educated$_{it}$	52,782	0.179	0.0536	0	0.482
Share female labour force$_{it}$	53,466	0.454	0.0506	0	0.667

Table C9: Description of all variables of interest and data source

Variable	Description
Panel ID: Region x Industry$_{ij}$	Combined panel data variable for municipalities and industries
Time$_t$	Year
Industry$_j$	Standard Company Classification 2008
Region (municipality)$_i$	Municipalities according CBS 2014 classification
Exports$_{jt}$	Exports to all low middle-income countries x1000 USD (UN Comtrade)
Imports$_{jt}$	Imports from low middle-income countries x1000 USD (UN Comtrade)
Δ Import exposure$_{ijt}$	Change in import exposure between year t and t-1
Δ Export exposure$_{ijt}$	Change in export exposure between year t and t-1
Share of routine employment$_{it}$	Share of routine jobs in total employment - ISCO 1 (CBS***)
Share of non-complex employment$_{it}$	Share of non-complex jobs in total employment - ISCO 2 (CBS***)
Average risk of computerisation	Freu & Osborne risk of computerisation (Frey & Osborne, 2017)
Employment$_{ijt}$	Employment (CBS****)
Unemployment rate$_{it}$	Unemployment rate (CBS**)
Income$_{it}$	Mean income of individuals who had a job during the whole year, students excluded (CBS*****)
Share with less than 110% of social minimum$_{it}$	Individuals whose income is less than 110% of the social minimum (CBS *******)
Share of moving out$_{it}$	Share of population who move to a different municipality (CBS*)
Share receiving unemployment benefits$_{it}$	Share of labour force receiving unemployment benefits (CBS***)
Labour force$_{it}$	Labour force (CBS*)
Total population$_{it}$	Total population (CBS*)
Share of foreign population$_{it}$	Share of foreigners in total population (CBS*)

Note: **Regional Key Figures (CBS, 2017b), ** Labour participation, Regional classification 2014 (CBS, 2015), *** Persons with unemployment benefits; beneficiaries per region (CBS, 2017a), **** Jobs of employees in December; SBI2008 and region(CBS, 2016b), *****Average income by characteristics and region (CBS, 2016c), ****** Growth accounts; National accounts (CBS, 2016d), ******* Low and long-term low incomes by characteristics and region (CBS, 2016e)*

Figure C8: Low and Middle-income countries according to World Bank definition



Note: The map includes almost all low and middle-income countries. The complete group is: Afghanistan, Albania, Algeria, American Samoa, Angola, Antigua and Barbuda, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cote d'Ivoire, Cabo Verde, Cambodia, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo, Cook Islands, Costa Rica, Cuba, Democratic People's Republic of Korea, Democratic Republic of the Congo, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Eritrea, Ethiopia, Fiji, FS Micronesia, Gabon, Gambia, Georgia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Kyrgyzstan, Lao People's Dem. Republic, Lebanon, Lesotho, Liberia, Libya, Lithuania, Madagascar, Malawi, Malaysia, Maldives, Mali, Marshall Islands, Mauritania, Mauritius, Mayotte, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Republic of Moldova, Romania, Russian Federation, Rwanda, Saint Kitts and Nevis, Saint Lucia, Samoa, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Solomon Islands, Somalia, South Africa, Sri Lanka, Sudan, Suriname, Swaziland, Syria, Tajikistan, TFYR of Macedonia, Thailand, Timor-Leste, Togo, Tonga, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, United Republic of Tanzania, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia and Zimbabwe

8.4 Appendix D: Results

Table D1: Preferred IV-estimation

Explanatory variables	Dependent Variable: Yearly change in the share of manufacturing employment in total employment (1) Municipalities	 (2) Municipalities with lag	 (4) Labour markets	 (5) Labour markets - lag
Δ Import exposure****	-0.0696*	-0.0481*	-0.0301	-0.0108
	(0.0409)	(0.0272)	(0.0340)	(0.0204)
Δ Export exposure ****	3.188***	2.221***	2.608***	1.525**
	(0.579)	(0.668)	(0.655)	(0.677)
% Routine employment	-0.150*	-0.142	-0.00193	-0.00208
	(0.0861)	(0.0875)	(0.00333)	(0.00322)
% Non-complex employment	0.0725**	0.0712**	0.0337***	0.0327***
	(0.0289)	(0.0299)	(0.0122)	(0.0123)
% Foreign population	-0.0251	-0.0263	-0.00591	-0.00843
	(0.0225)	(0.0229)	(0.0113)	(0.0113)
% Female	0.00894	0.00790	0.00701	0.00473
	(0.0124)	(0.0130)	(0.00693)	(0.00701)
% High educated	0.00444	0.00248	0.000154	-9.44e-05
	(0.0117)	(0.0116)	(0.00690)	(0.00686)
R-squared	0.357	0.346	0.114	0.106
Time FE	Yes	Yes	Yes	Yes
Municipalities FE	Yes	Yes	-	-
Labour markets FE	-	-	Yes	Yes
	First stage results with import exposure as dependent variable			
Import exposure	0.13598***	0.167***	0.136***	0.163***
Export exposure	-0.0340***	-0.0466***	-0.038***	-0.0478***
R-squared	0.729	0.674	0.767	0.694
F-test	9207.16	9220.52	9502.16	9078.12
	First stage results with export exposure as dependent variable			
Import exposure	0.00106**	0.0030***	0.0009**	0.0035***
Export exposure	0.029***	0.029***	0.0305***	0.0269***
R-squared	0.555	0.543	0.551	0.537
F-test	9207.16	9220.52	9502.16	9078.12

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence
**** In columns 2 and 4 the Δ import and Δ export exposures are constructed with lagged employment data

Note: *The number of observations is 16,169 in all columns. Standard errors (in brackets) are robust and clustered by municipalities dealing with the detected autocorrelation and heteroskedasticity. The labour market composition control variables are constructed as percentage of the population (foreign education) and as percentage of the labour force (female). Constants are not reported. Tests for endogeneity of the trade variables and the quality of the instruments have been executed (Wooldridge, 2012).*

Table D2: IV-estimations sensitivity check (with Germany)				
	Dependent Variable: Yearly change in the share of manufacturing employment in total employment			
Explanatory variables	(1) Municipalities	(2) Municipalities - lag	(3) Labour markets	(4) Labour markets - lag
Δ Import exposure****	-0.0658*	-0.0460**	-0.0283	-0.0129
	(0.0372)	(0.0230)	(0.0310)	(0.0179)
Δ Export exposure ****	3.041***	2.189***	2.509***	1.578**
	(0.515)	(0.602)	(0.590)	(0.621)
% Routine employment	0.00878	0.00789	0.00679	0.00484
	(0.0124)	(0.0130)	(0.00694)	(0.00703)
% Non-complex employment	0.00437	0.00247	0.000176	-0.000109
	(0.0117)	(0.0116)	(0.00690)	(0.00688)
% Foreign population	-0.151*	-0.143	-0.00195	-0.00207
	(0.0863)	(0.0875)	(0.00332)	(0.00323)
% Female	0.0724**	0.0711**	0.0335***	0.0328***
	(0.0290)	(0.0299)	(0.0122)	(0.0123)
% High educated	-0.0251	-0.0263	-0.00610	-0.00834
	(0.0225)	(0.0229)	(0.0112)	(0.0112)
R-squared	0.339	0.343	0.116	0.109
Time FE	Yes	Yes	Yes	Yes
Municipalities FE	Yes	Yes	-	-
Labour markets FE	-	-	Yes	Yes
	First stage results with import exposure as dependent variable			
Import exposure	0.0786***	0.09542***	0.0977***	0.0965***
Export exposure	-0.0024	-0.01746	-0.00084	-0.011*
R-squared	0.712	0.682	0.754	0.705
F-test	11792.1	12612.1	11917.2	11622.5
	First stage results with export exposure as dependent variable			
Import exposure	0.00053***	0.002462	0.00159***	0.00194***
Export exposure	0.0228***	0.0233***	0.0228***	0.023***
R-squared	0.629	0.619	0.611	0.596
F-test	11792.1	12612.1	11917.2	11622.5

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence
**** In columns 2 and 4 the Δ import and Δ export exposures are constructed with lagged employment data

Note: *The number of observations is 16,169 in all columns. Standard errors (in brackets) are robust and clustered by municipalities dealing with the detected autocorrelation and heteroskedasticity. The labour market composition control variables are constructed as percentage of the population (foreign education) and as percentage of the labour force (female). Constants are not reported. Tests for endogeneity of the trade variables and the quality of the instruments have been executed (Wooldridge, 2012).*

Table D3: IV-estimations sensitivity check (with Germany and Canada)				
	Dependent Variable: Yearly change in the share of manufacturing employment in total employment			
Explanatory variables	(1) Municipalities	(2) Municipalities - lag	(3) Labour markets	(4) Labour markets - lag
Δ Import exposure****	-0.0641*	-0.0467**	-0.0287	-0.0156
	(0.0345)	(0.0203)	(0.0286)	(0.0162)
Δ Export exposure ****	3.009***	2.167***	2.484***	1.566**
	(0.512)	(0.599)	(0.588)	(0.619)
% Routine employment	0.00875	0.00785	0.00674	0.00480
	(0.0124)	(0.0130)	(0.00694)	(0.00703)
% Non-complex employment	0.00436	0.00249	0.000180	-8.30e-05
	(0.0117)	(0.0116)	(0.00689)	(0.00687)
% Foreign population	-0.151*	-0.143	-0.00195	-0.00205
	(0.0863)	(0.0875)	(0.00332)	(0.00323)
% Female	0.0723**	0.0711**	0.0335***	0.0328***
	(0.0290)	(0.0299)	(0.0122)	(0.0123)
% High educated	-0.0251	-0.0263	-0.00616	-0.00839
	(0.0225)	(0.0229)	(0.0112)	(0.0112)
R-squared	0.359	0.347	0.115	0.106
Time FE	Yes	Yes	Yes	Yes
Municipalities FE	Yes	Yes	-	-
Labour markets FE	-	-	Yes	Yes
	First stage results with import exposure as dependent variable			
Import exposure	0.06721***	0.08309***	0.0686***	0.08371***
Export exposure	-0.0030	-0.0019	0.0016	-0.0057
R-squared	0.726	0.699	0.760	0.719
F-test	12036.7	12974.9	11974.3	11762.9
	First stage results with export exposure as dependent variable			
Import exposure	0.000426***	0.00127***	0.00040***	0.00156***
Export exposure	0.0225***	0.0225***	0.0233***	0.0232***
R-squared	0.631	0.622	0.612	0.596
F-test	12036.7	12974.9	11974.3	11762.9

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence
**** In columns 2 and 4 the Δ import and Δ export exposures are constructed with lagged employment data

Note: *The number of observations is 16,169 in all columns. Standard errors (in brackets) are robust and clustered by municipalities dealing with the detected autocorrelation and heteroskedasticity. The labour market composition control variables are constructed as percentage of the population (foreign education) and as percentage of the labour force (female). Constants are not reported. Tests for endogeneity of the trade variables and the quality of the instruments have been executed (Wooldridge, 2012).*

Table D4: Regression results other labour market variables I (using identification models)			
	Dependent variable: Δ Unemployment rate		
Explanatory variables	(1)	(2)	(3)
	Benchmark - OLS	IV	IV with lags
Δ Import exposure****	-0.00110	-0.00865	-0.00213
	(0.00671)	(0.00600)	(0.00816)
Δ Export exposure ****	-0.212***	-0.217***	-0.182**
	(0.0760)	(0.0833)	(0.0883)
% Routine employment ****	-0.00239	-0.00238	0.00228
	(0.00249)	(0.00248)	(0.00198)
% Non-complex employment ****	-0.00136	-0.00138	0.00123
	(0.00135)	(0.00134)	(0.00143)
% Foreign population	-0.00278	-0.00282	-0.00224
	(0.00216)	(0.00215)	(0.00215)
% Female	0.00159	0.00161	0.00207
	(0.0149)	(0.0148)	(0.0151)
% High educated	-0.000634	-0.000640	9.51e-05
	(0.00215)	(0.00214)	(0.00211)
R-squared	0.776	0.775	0.775
Time FE	Yes	Yes	Yes
Municipalities FE	Yes	Yes	Yes

* Significantly different from zero at 90% confidence

** Significantly different from zero at 95% confidence

*** Significantly different from zero at 99% confidence

**** In column 3 Δ import and Δ export exposures are constructed with lagged employment data and the shares of routine and non-complex employment are lagged.

Note: *The number of observations is 47,277 in all columns. Standard errors (in brackets) are robust and clustered by municipalities*. *Constants are not reported.*

Table D5: Regression results other labour market variables II (using identification models)			
	Dependent variable: Δ Average income		
Explanatory variables	(1)	(2)	(3)
	Benchmark - OLS	IV	IV with lags
Δ Import exposure****	-0.788*	-0.665**	-0.659
	(0.418)	(0.309)	(0.592)
Δ Export exposure ****	0.409	1.172	0.932
	(9.922)	(11.41)	(12.12)
% Routine employment ****	-0.0110	-0.0111	-0.415*
	(0.287)	(0.286)	(0.229)
% Non-complex employment ****	0.291	0.291	0.107
	(0.236)	(0.235)	(0.185)
% Female	-0.168	-0.167	-0.165
	(0.341)	(0.339)	(0.321)
% Foreign population	-2.069	-2.070	-2.136
	(2.660)	(2.645)	(2.665)
% High educated	0.272	0.272	0.203
	(0.313)	(0.311)	(0.304)
R-squared	0.259	0.259	0.259
Time FE	Yes	Yes	Yes
Municipalities FE	Yes	Yes	Yes

* Significantly different from zero at 90% confidence

** Significantly different from zero at 95% confidence

*** Significantly different from zero at 99% confidence

**** In column 3 Δ import and Δ export exposures are constructed with lagged employment data and the shares of routine and non-complex employment are lagged.

Note: *The number of observations is 45,030 in all columns. Standard errors (in brackets) are robust and clustered by municipalities. Constants are not reported.*

Table D6: Regression results other labour market variables III (using identification models)			
	Dependent variable: Δ Share of individuals with an income lower than 110% of the social minimum		
Explanatory variables	(1)	(2)	(3)
	Benchmark - OLS	IV	IV with lags
Δ Import exposure****	0.0185***	0.0212*	0.0202***
	(0.00617)	(0.0111)	(0.00645)
Δ Export exposure ****	-0.285**	-0.298*	-0.258
	(0.132)	(0.169)	(0.167)
% Routine employment ****	0.00622	0.00621	0.00681*
	(0.00390)	(0.00387)	(0.00382)
% Non-complex employment ****	-0.0155	-0.0155	-0.0135
	(0.0189)	(0.0188)	(0.0190)
% Female	0.00231	0.00230	0.00332
	(0.00388)	(0.00386)	(0.00365)
% Foreign population	-0.00157	-0.00157	0.0102***
	(0.00343)	(0.00341)	(0.00306)
% High educated	-0.00221	-0.00220	0.00130
	(0.00237)	(0.00236)	(0.00247)
R-squared	0.296	0.296	0.298
Time FE	Yes	Yes	Yes
Municipalities FE	Yes	Yes	Yes

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence
**** In column 3 Δ import and Δ export exposures are constructed with lagged employment data and the shares of routine and non-complex employment are lagged.
Note: *The number of observations is 45,059 in all columns. Standard errors (in brackets) are robust and clustered by municipalities. Constants are not reported.*

Table D7A: Regression results other labour market variables IV (using identification models)			
	Dependent variable: Δ Share of individuals moving to another municipality		
Explanatory variables	(1)	(2)	(3)
	Benchmark - OLS	IV	IV with lags
Δ Import exposure****	0.00922	0.00870	-0.000343
	(0.00918)	(0.00987)	(0.0117)
Δ Export exposure ****	-0.111	-0.133	0.139
	(0.246)	(0.291)	(0.302)
% Routine employment ****	-0.0228***	-0.0228***	0.0128
	(0.00638)	(0.00634)	(0.00899)
% Non-complex employment ****	-0.00804*	-0.00805*	-0.000826
	(0.00484)	(0.00482)	(0.00674)
% Female	0.0286***	0.0286***	0.0289***
	(0.0109)	(0.0108)	(0.0109)
% Foreign population	-0.130**	-0.130**	-0.119**
	(0.0539)	(0.0536)	(0.0546)
% High educated	-0.00583	-0.00584	-0.00245
	(0.00946)	(0.00940)	(0.00933)
R-squared	0.244	0.244	0.241
Time FE	Yes	Yes	Yes
Municipalities FE	Yes	Yes	Yes

* Significantly different from zero at 90% confidence

** Significantly different from zero at 95% confidence

*** Significantly different from zero at 99% confidence

**** In column 3 Δ import and Δ export exposures are constructed with lagged employment data and the shares of routine and non-complex employment are lagged.

Note: *The number of observations is 45,011 in all columns. Standard errors (in brackets) are robust and clustered by municipalities. Constants are not reported.*

Table D7B: Regression results other labour market variables IV (using identification models)			
	Dependent variable: Δ Share of individuals moving into municipality		
Explanatory variables	(1)	(2)	(3)
	Benchmark - OLS	IV	IV with lags
Δ Import exposure****	-0.00411	-0.00255	0.00483
	(0.00477)	(0.00826)	(0.00798)
Δ Export exposure ****	-0.0968	-0.181	-0.494*
	(0.187)	(0.230)	(0.258)
% Routine employment ****	-0.000635	-0.000645	-0.00611
	(0.00651)	(0.00647)	(0.00667)
% Non-complex employment ****	-0.00192	-0.00192	0.00700
	(0.00598)	(0.00595)	(0.00494)
% Female	0.0379***	0.0378***	0.0396***
	(0.0121)	(0.0121)	(0.0121)
% Foreign population	0.173**	0.173**	0.170**
	(0.0829)	(0.0824)	(0.0828)
% High educated	-0.0201**	-0.0202**	-0.0190**
	(0.00917)	(0.00912)	(0.00903)
R-squared	0.257	0.257	0.258
Time FE	Yes	Yes	Yes
Municipalities FE	Yes	Yes	Yes

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence
**** In column 3 Δ import and Δ export exposures are constructed with lagged employment data and the shares of routine and non-complex employment are lagged.

Note: *The number of observations is 45,011 in all columns. Standard errors (in brackets) are robust and clustered by municipalities. Constants are not reported.*

Table D8: Regression results other labour market variables V (using identification models)			
	Dependent variable: Δ Share of labour force with unemployment benefits		
Explanatory variables	(1) Benchmark - OLS	(2) IV	(3) IV with lags
Δ Import exposure****	0.00132	0.0139***	0.0165*
	(0.00496)	(0.00472)	(0.00872)
Δ Export exposure ****	-0.397***	-0.615***	-0.544***
	(0.0927)	(0.118)	(0.140)
% Routine employment ****	-0.00159	-0.00162	-0.000944
	(0.00237)	(0.00235)	(0.00283)
% Non-complex employment ****	-0.00309	-0.00307	0.00118
	(0.00217)	(0.00217)	(0.00165)
% Female	0.00998**	0.00977**	0.0112***
	(0.00416)	(0.00418)	(0.00413)
% Foreign population	-0.0469**	-0.0468**	-0.0502***
	(0.0192)	(0.0191)	(0.0193)
% High educated	-0.0119***	-0.0119***	-0.0107***
	(0.00345)	(0.00343)	(0.00338)
R-squared	0.720	0.718	0.716
Time FE	Yes	Yes	Yes
Municipalities FE	Yes	Yes	Yes

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence
**** In column 3 Δ import and Δ export exposures are constructed with lagged employment data and the shares of routine and non-complex employment are lagged.
Note: *The number of observations is 45,011 in all columns. Standard errors (in brackets) are robust and clustered by municipalities. Constants are not reported.*

Table D9: Sensitivity tests of technological development variables (all regressions are 2SLS)

Explanatory variables	Dependent variables: (1) Unemployment	(2) Unemployment - lag	(3) Wage	(4) Wage - lag	(5) Poverty	(6) Poverty - lag
% Routine employment	-0.00238	0.00228	-0.0111	-0.415*	0.00621	0.00681*
	(0.00248)	(0.00198)	(0.286)	(0.229)	(0.00387)	(0.00382)
% Non-complex employment	-0.00138	0.00123	0.291	0.107	-0.0155	-0.0135
	(0.00134)	(0.00143)	(0.235)	(0.185)	(0.0188)	(0.0190)
Dummy routine employment	-0.000143	-0.000155	-0.0187	-0.0195	-0.000234	-0.000227
	(0.000239)	(0.000241)	(0.0249)	(0.0249)	(0.000299)	(0.000303)
Dummy non-complex empl.	-0.000266	-0.000266	0.0507**	0.0509**	-0.000279	-0.000284
	(0.000185)	(0.000186)	(0.0218)	(0.0219)	(0.000255)	(0.000256)
Frey & Osborne risk estimates	-0.00272	-0.00258	0.236	0.236	-0.00135	-0.00120
	(0.00191)	(0.00192)	(0.300)	(0.299)	(0.00294)	(0.00294)

* Significantly different from zero at 90% confidence
** Significantly different from zero at 95% confidence
*** Significantly different from zero at 99% confidence

Note: This table shows the results of the 2SLS regressions including the control variables and the trade exposure measures. These variables are not displayed as the objective is to show the differences and similarities between the different technological development variables. The dummy variable routine (non-complex) employment equals 1 in case a municipality has an above-mean routine (non-complex) employment and equals zero otherwise.

Table D9 (continued)

Explanatory variables	Dependent variables: (7) Move out	(8) Move out – lag	(9) Move in	(10) Move in – lag	(11) Unemployment benefits	(12) Unemployment benefits - lag
% Routine employment	-0.0228***	0.0128	-0.000645	-0.00611	-0.00162	-0.000944
	(0.00634)	(0.00899)	(0.00647)	(0.00667)	(0.00235)	(0.00283)
% Non-complex employment	-0.00805*	-0.000826	-0.00192	0.00700	-0.00307	0.00118
	(0.00482)	(0.00674)	(0.00595)	(0.00494)	(0.00217)	(0.00165)
Dummy routine employment	-0.00171***	-0.00169***	-0.000385	-0.000419	-8.06e-05	5.91e-05
	(0.000576)	(0.000578)	(0.000539)	(0.000542)	(0.000225)	(0.000251)
Dummy non-complex empl.	-0.000691	-0.000690	-0.000332	-0.000332	-0.000246	0.000183
	(0.000503)	(0.000505)	(0.000558)	(0.000558)	(0.000200)	(0.000180)
Frey & Osborne risk estimates	-0.0209***	-0.0209***	-0.00132	-0.00108	-0.00420*	-0.00384
	(0.00613)	(0.00614)	(0.00716)	(0.00716)	(0.00240)	(0.00239)