Evaluating the impact of automation on labour markets in England and Wales

Submitted in partial fulfilment
of the requirements for the degree of the
Master of Philosophy in Economics

by

Anil Prashar
Candidate no. 1014125

St Cross College,
University of Oxford.

Word count: 23,593

Supervisors:
Dr. Abigail Adams and Dr. Carl Benedikt Frey

Acknowledgements

Above all, I must thank my supervisors, Dr. Abigail Adams and Dr. Carl Frey, who have been of immense help in providing ideas and guidance throughout my research. I have been fortunate to have had supervisors who are not only endowed with brilliant minds, but also thoroughly engaged with my area of research. It has been a privilege to work with both of them.

The time and the opportunities provided by my supervisors has been invaluable. Dr. Adams provided me with the benefits of her experience through frequent discussions. I can only hope that my research output is able to reflect the time that she has spent supporting me and that she does not feel as if her time would have achieved a higher marginal benefit from other activities.

Dr. Frey provided me with guidance and direction that I do not believe I would have been able to receive anywhere else. His subject knowledge has been of great use. In addition, through his involvement, I was given the opportunity to present the preliminary results of this research at the Institute for New Economic Thinking at the Oxford Martin School. I am grateful to those who attended the presentation. The feedback I received was enormously valuable.

I must also acknowledge the funding for the International Federation of Robotics (IFR) data which was facilitated by Dr. Frey and generously provided by the Oxford Martin School. Before the data was procured, I had already started imagining tenuous strategies that I could employ to proxy automation. It is by the generosity of the Oxford Martin School and Dr. Frey that I have been able to present empirical research that aligns meaningfully with the existing literature.

Finally, I must acknowledge my peers who have provided moral support throughout this process. Like a soldier returning to peaceful idylls after facing the heavy shelling of war, I am left with a feeling of emptiness. It saddens me that I am to no longer feel that sense of camaraderie that fills one as they awake to the thought of a day that, though it will be testing, is to be served in pursuit of a greater purpose amongst like-minded individuals. With them, I have enjoyed and suffered all times greatly.

Beyond this, “the usual caveats” apply, and it is certainly not my wish to implicate any others in the inadequacies of my research. Nonetheless, it is no exaggeration that this research has only been made possible by the kindness and generosity of many others; I am indebted to them for all their support.

Abstract

Robots are now able to complete many tasks with greater efficiency than humans. This is leading employers to demand different skills from their workforces. Simultaneously, there has been a notable decline in manufacturing employment in the UK. Using data at a local authority level, this thesis shows that industrial robot technology in the transportation manufacturing industry, an empirical proxy for automation, had a negative and statistically significant effect on employment across England and Wales between 1991 and 2001; a period of increasing industrial robot usage in the UK. Using structural parameter estimates for the UK economy, the empirical results suggest that one industrial robot in the transportation manufacturing industry reduced employment by 4.2 workers between 1991 and 2001. This is equivalent to approximately 21,000 job losses over the decade. Upon establishing the result for automation, the empirical analysis is extended to disentangle the impact of automation from trade. It is found that Chinese import exposure had a larger effect than automation between 1991-2001, accounting for approximately 27% of the decline in UK manufacturing employment over the period.

Contents

List of Figures .... **iv**
List of Tables .... **iv**
List of Notation .... **v**

1. Introduction **1**
1.1 Motivation 1
1.2 Contribution 3
1.3 Outline 6
2. Literature Review **7**
2.1 Context 7
2.2 Contribution 9
3. Theoretical Model **11**
3.1 Motivating Literature 11
3.2 Model 11
3.3 Empirical Specification 19
4. Data **22**
4.1 Exposure to Robots 22
4.2 Dependent Variable 24
4.3 Trade 26
4.4 Other Controls 28
5. Summary Statistics and First Stage **30**
5.1 Summary Statistics 30
5.2 First Stage 33
6. Results **34**
6.1 Results for Employment 34
6.2 Alternative Empirical Specifications and Wage Results 44
6.3 Local Interpretation of Results 45
6.4 Aggregate Interpretation of Results 45
7. Disentangling the Impact of Trade **48**
7.1 The Role of Trade 48
7.2 UK Trading Partners 49
7.3 Results for Employment 55
7.4 Alternative Empirical Specifications 57
7.5 Interpreting the Results 58
8. Conclusion **60**
Appendices: Additional Results **63**
References **72**

List of Figures

Figure 1: UK manufacturing jobs (1981-2016) 2
Figure 2a: UK robot adoption rate and manufacturing employment (1993-2015) 4
Figure 2b: Robot adoption rate across Europe (1993-2015) 4
Figure 3: Change in UK operational stock of industrial robots (1993-2011) 5
Figure 4: Robot adoption rate for UK and 10th percentile of European countries 24
Figure 5: Density of automation and trade variables (1991-2011) 32
Figure 6: Density of automation and trade (removing top percentile) (1991-2011) 32
Figure 7: Density of exposure to robots in England and Wales (1991-2011) 32
Figure 8: Evolution of UK net imports (1993-2011) 49

List of Tables

Table 1: Summary statistics of key variables (1991-2011) 30
Table 2: Long differences using all industries (1991-2011) 34
Table 3: Long differences with transportation manufacturing (1991-2011) 36
Table 4: Stacked differences with transportation manufacturing (1991-2011) 37
Table 5a: Automation in all industries on employment (1991-2001) 39
Table 5b: Transportation manufacturing automation on employment (1991-2001) 40
Table 5c: Impact on manufacturing employment only (1991-2001) 41
Table 6: Summary of AIC results for different models (1991-2001) 43
Table 7: 2SLS results using AIC and LASSO (1991-2001) 44
Table 8a: Stacked differences for Chinese trade (1991-2011) 50
Table 8b: Stacked differences for German trade (1991-2011) 51
Table 8c: Stacked differences for Dutch trade (1991-2011) 51
Table 9a: Chinese imports on employment, including Netherlands (1991-2001) 52
Table 9b: German imports on employment, including Netherlands (1991-2001) 53
Table 9c: Dutch imports on employment (1991-2001) 54
Table 10a: Chinese imports on employment, excluding Netherlands (1991-2001) 55
Table 10b: German imports on employment, excluding Netherlands (1991-2001) 56
Table 11: Chinese imports on manufacturing employment (1991-2001) 57
Table 12: Means and standard deviations for interpreting trade results (1991-2011) 58

List of Notation

$L^{UK}_{c,t}$ = Total number of UK full time employees in local authority c at time t

$L^{UK}_{i,t}$ = Total number of UK full time employees in industry i at time t

$R^{UK}_{i,t}$ = Total number of industrial robots in the UK in industry i at time t

$P^{UK}_{c,t}$ = Total number of UK residents in local authority c at time t

ℓ^{t}_{ci} = UK employees working in industry i and local authority c as a proportion of total employees

$p_{10}\left(\frac{R_{i,t}}{L_{i,s}}\right)$ = 10^{th} percentile of robots (at t) per thousand workers (at s) in industry i across 8 countries (Denmark, Finland, France, Germany, Italy, Norway, Spain and Sweden)

$X_{c,t}$ = Level controls for local authority c at time t

$\Delta Y_{c,t+1\,-\,t}$ = Difference between level controls for $t+1$ and t for local authority c

Note $\Delta Y_{c,t+1\,-\,t} \subseteq \Delta X_{c,t+1\,-\,t}$. That is, the difference controls are a subset of the differences of the levels. In some cases, difference controls are not included based on the construction of the level control or the empirical specification.

$\hat{\pi}$ denotes that π has been fitted from a first-stage regression in a 2SLS specification.

1. Introduction

1.1 Motivation

When it comes to automation, economists have a history of kicking the can down the road. In 1821, an essay published by David Ricardo considered the 'machine question'. Notably, Ricardo wrote about the 'influence of machinery on the interests of the different classes of society' and stated that it was 'a subject of great importance … which appears never to have been investigated in a manner to lead to any certain or satisfactory results'. In 1930, John Maynard Keynes coined the phrase 'technological unemployment', defined as 'unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour'. Robert Solow in 1968 stated that, 'perhaps the question, "Does automation create or destroy more jobs?" is answerable in principle … What is perfectly clear is that the question is simply unanswerable in fact'.

Economists have tended to stop short of providing a formal analysis of automation due to the sheer scale of technology. Or, to take another quote from Robert Solow, 'I doubt that anyone could make a good estimate of the net number of jobs created or destroyed merely by the invention of the zipper or of sliced bread'. The implication being that the demands of such a task are too great. The omnipresence of technology means that the data required for analysis is immense and the mechanisms through which automation may affect jobs, both directly and indirectly, are difficult to disentangle.

Yet, in the face of recent innovation, the potential impacts of automation are being questioned once more. These past few decades have resulted in breakthroughs in artificial intelligence and industrial technologies which mean that many historically useful skillsets are being automated, raising speculation about the possible impact on labour forces across the world. Various tasks are being performed by robots that can work more efficiently than humans. The ability to recall information, to calculate and to speak languages are within the scope of robots that are capable of perceiving and responding to their environments. These robots are also not limited by the working week and can complete tasks in extreme environments without endangering lives.

Furthermore, within the UK, there has been a pronounced decline in manufacturing employment over the past few decades. In 1981, there were 5.6 million manufacturing jobs in the UK and by 2015 there were only 2.6 million (see Figure 1). This decline is not unique to the UK, and the fall in manufacturing employment has been explored in a US context. Explanations for this phenomenon have included trade liberalisation, routinisation, offshoring and automation. The possible role of automation has resulted in a renewed attempt to quantify its effects. This time there is hope for a more comprehensive framework as economists are armed with datasets which are available due to rapid developments that have occurred in storage and sharing technologies.

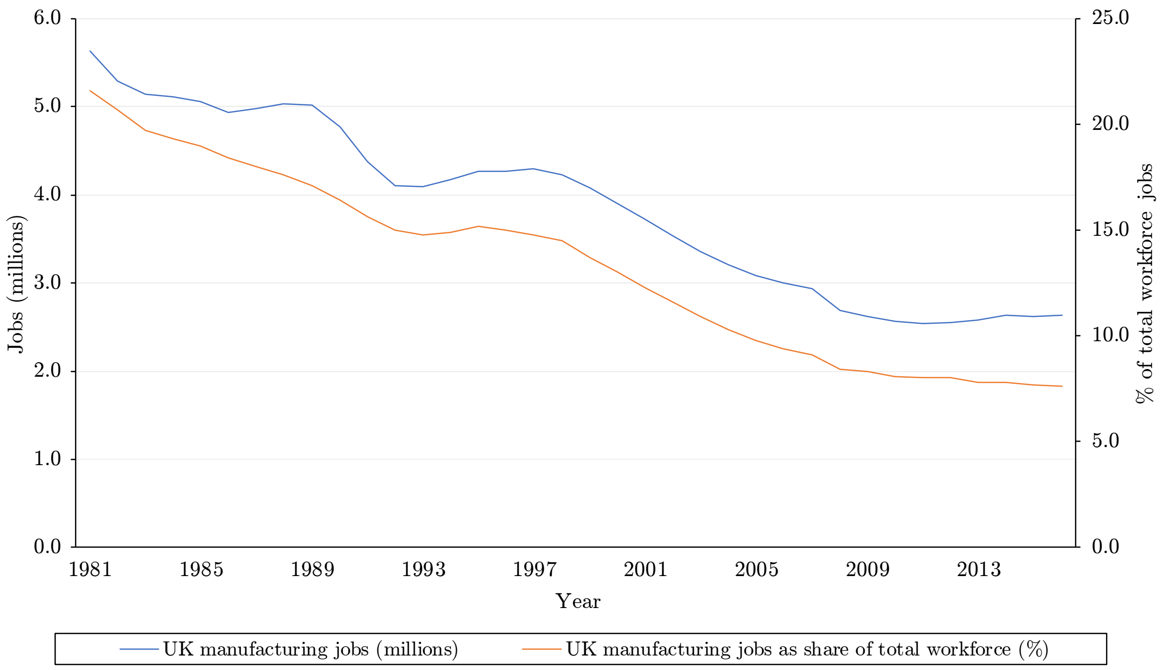

Figure 1: UK manufacturing jobs (1981-2016)

Note: Total manufacturing jobs in millions (left scale) and manufacturing jobs as percentage of workforce (right scale). Data is from Nomis (Source: Office of National Statistics) and represents December workforce jobs by industry (SIC 2007) - seasonally adjusted.

Automation can be defined as an expansion of the set of tasks where capital can substitute for labour (Acemoglu and Restrepo, 2018). This differs from traditional production analysis where the focus is on capital that complements the efforts of labour. Automation focuses on capital replacing labour. Automation is also not limited to routine tasks. Routine is a label that can be used to characterise a task and refers to tasks that can be accomplished by following explicit rules. Automation is a process whereby the set of tasks that can be carried out by machines is increasing. Using the definition of automation, the argument linking automation and the loss in manufacturing jobs is intuitive;

technological improvements result in more tasks being carried out by capital, reducing the need for human workers in manufacturing processes.

The counter-argument also follows from the definition. Sophisticated technologies result in the creation of new tasks for humans to do that machines cannot. Automated processes require human oversight, resulting in the creation of jobs[1] which offset losses. Additionally, if there is an increase in output due to cost-effective automation, then more workers are needed to produce the higher levels of output. As such, the explanation for the decline in manufacturing jobs may not be due to automation and may instead be driven by alternate factors. On an aggregate level, manufacturing job losses may also result in a shift towards service sector jobs. It is with these phenomena in mind that this thesis is written. This thesis evaluates the magnitude of the local and aggregate impacts of automation on the labour markets of England and Wales.

1.2 Contribution

This thesis seeks to contribute to the literature by evaluating the impact of industrial robots on employment in labour markets in England and Wales in equilibrium. The theoretical framework underlying the evaluation follows Acemoglu and Restrepo (2017) and uses local authorities as the UK unit of analysis. The use of local authorities has previously been pursued in the empirical literature, although this is the first known use of the data to assess the effects of automation on employment. Local authorities provide more detailed datasets with which to estimate the impact of factors on labour market outcomes. As such, local authority analysis goes beyond nationwide or standard region summaries. The theoretical framework also allows for a broader interpretation of local impacts, estimated with regressions, and aggregate impacts, estimated with regression coefficients and UK structural parameters.

The UK is interesting for economic and political reasons. As the UK has a relatively low robot adoption rate (see Figures 2a and 2b), it offers insights into the impact of robots at the lower end of the adoption distribution. Existing approaches have considered nations with higher or mid-level adoption rates, such as Germany and the US, which may have

[1]Given that a job can be viewed as a set of tasks.

cultural forces driving their relationship with automation. Germany, for example, is a heavy user and engineer of robots.

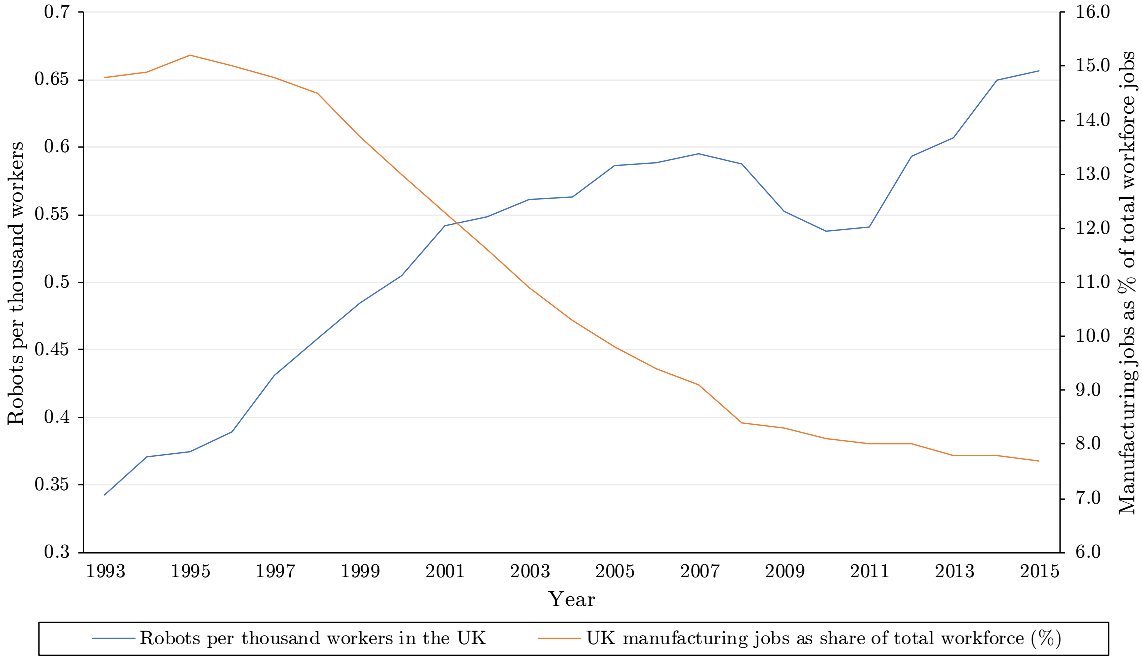

Figure 2a: UK robot adoption rate and manufacturing employment (1993-2015)

Note: Robots per thousand workers in UK (left scale) and manufacturing jobs as percentage of workforce (right scale).

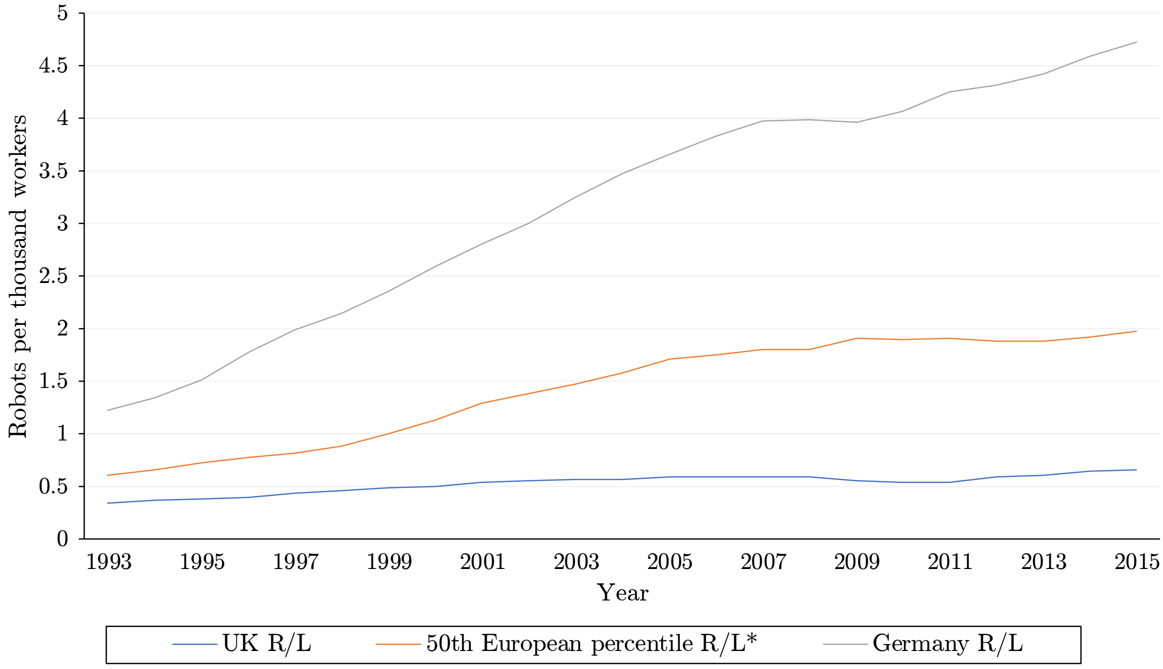

Figure 2b: Robot adoption rate across Europe (1993-2015)

Note: R/L denotes robots per thousand workers. Industrial robot data is from International Federation of Robotics (IFR) and worker data is from EU KLEMS. *Countries used for 50th percentile are: Denmark, Finland, France, Germany, Italy, Norway, Spain and Sweden.

Using industrial robot data and UK Census data, this thesis estimates a statistically significant and negative relationship between exposure to robots in transportation manufacturing[2] – the largest industry user of robots (see Figure 3) – and employment at a local authority level between 1991 and 2001.[3] This relationship remains after controlling for: demographics; industry shares; routinisation; offshoring; and trade.

The main specification in this thesis considers the change in the full-time employment to population ratio as the dependent variable and starts by considering employment outcomes between 1991 and 2011. Robot adoption heterogeneity across industries leads to a focus on the transportation manufacturing industry. Also, the significant reduction in the adoption of robots between 2001-2011 in the UK (see Figure 3) motivates a stacked analysis, resulting in a focus on 1991-2001. In addition to controls, further robustness checks are used, including Akaike Information Criteria (AIC) minimisation and Least Absolute Shrinkage and Selection Operator (LASSO), which validate the main result. The use of total employment, as opposed to full-time employment only, also does not change the result (see Appendices). These robustness checks demonstrate the importance of automation in the transportation manufacturing industry for explaining UK employment outcomes between 1991 and 2001.

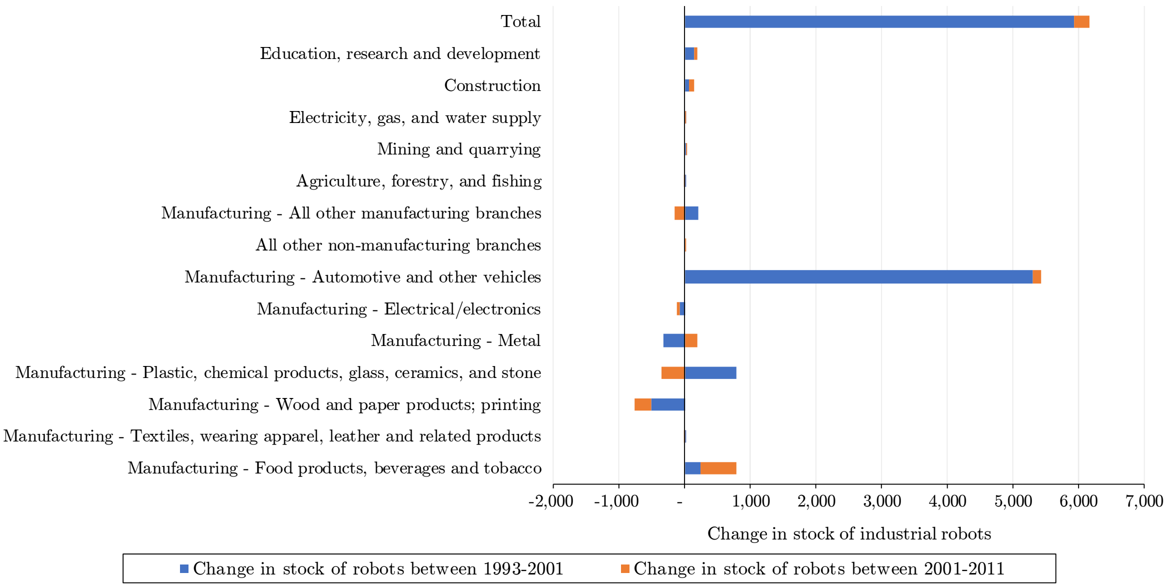

Figure 3: Change in UK operational stock of industrial robots (1993-2011)

Note: Data from International Federation of Robotics (IFR).

[2]Primarily made up of automotive manufacturers.

[3]IFR robot data is only available from 1993 onwards (see Chapter Four for discussion).

As the automation analysis involves controlling for trade, this thesis also extends the results to consider an empirical analysis of the impact of imports from China and Germany on labour markets in England and Wales. The impact of trade on UK employment outcomes has previously been considered for the period between 1998 and 2011 (Bilici, 2016). To show that the impact of robots is quantitatively and qualitatively different from Chinese and German import competition, this thesis considers the period between 1991 to 2011. It is found that there is no evidence of a significant impact of Chinese or German import exposure on employment outcomes between 2001-2011, consistent with Bilici (2016). Although, evidence is found of Chinese import exposure having a statistically significant and negative effect on manufacturing employment between 1991-2001. As with automation, this result is robust to the addition of controls.

1.3 Outline

This thesis proceeds as follows. Chapter Two summarises the background to the automation literature. It summarises the recent work that has been done to formalise the impact of technology on labour markets and considers the existing empirical studies for Europe and the US. Chapter Three outlines the theoretical model used in this analysis which is taken from Acemoglu and Restrepo (2017). This provides the basis for an empirical specification. The necessity of an instrumental variable strategy to account for endogeneity is explained in greater detail, as is the use of local authorities for UK labour market analysis. Chapter Four outlines the data sources that have been used. Chapter Five discusses the summary statistics and the variation that is exploited for the regressions. Chapter Six presents the results and discusses their interpretations. Chapter Seven disentangles the impact of trade from automation and Chapter Eight concludes. Additional results referenced in this thesis are contained within the Appendices.

2. Literature Review

2.1 Context

At a broad level, the economic analysis of automation is related to other strands of empirical literature that have considered the impact of technology on labour markets. The literature on technology can be traced back to wage inequality discussions which observed an increasing proportion of low-wage jobs (Bluestone and Harrison, 1988). The effects of technology on wage inequality followed (Katz and Murphy, 1992). Increasing discussion around the importance of wage inequality led to the rise of empirical literature on employment polarisation (Autor, Levy and Murnane, 2003; Goos and Manning, 2007; Michaels, Natraj and Van Reenen, 2014). Autor, Levy and Murnane (2003) linked job polarisation to rapid improvements in the productivity of information and communications technologies and, more broadly, symbolic processors. By arguing that computer capital substitutes for workers in performing cognitive and manual tasks that can be accomplished by following explicit rules, an approach was developed that modelled automation as a function of the task contents of different occupations. Goos and Manning (2007) also showed that the UK, since 1975, has exhibited a pattern of job polarisation with increases in employment shares in the highest- and lowest-wage occupations.

Graetz and Michaels (2015) brought to light the lack of a systematic approach for analysing the economic effects of robots. To begin analysis, a simple two sector model was used to motivate an empirical analysis; the two sectors can be interpreted as a robot-using sector and a non-robot-using sector. This approach modelled automation as a capital-augmenting technology, whereby capital improves through automation, becomes cheaper and is more readily adopted. Simultaneously, relative wages rise as it becomes more expensive to take on workers relative to capital. An empirical analysis followed this approach that considered the economic impact of industrial robots across 17 countries. It was estimated that the increased use of robots raised countries' average growth rates by about 0.37% and that robots increased wages and total factor productivity. Robots were found not to have had a significant effect on total hours worked, but there was evidence that robots had reduced the hours of low-skilled and middle-skilled workers. It has also been argued that automation may be a labour-augmenting technology (Bessen, 2017).

More recently, it was noted that the factor-augmenting approach is lacking in its ability to model the displacement effect on workers. The displacement effect reflects how, if we keep prices and output constant, then automation results in robots carrying out tasks previously done by humans and reduces the demand for labour (Acemoglu and Restrepo, 2018). As such, an alternative model has been proposed that considers a task-based framework, as opposed to a factor-augmenting approach (Acemoglu and Restrepo, 2016a). The key benefit of a task-based framework is the ability to explicitly model the displacement effect of machines. In this way, the task-based approach captures a distinctive feature of automation that factor-augmenting approaches miss: the use of machines to substitute for human labour in a widening range of tasks (Acemoglu and Restrepo, 2018).

An empirical task-based local labour market framework was developed to move beyond cross-country and cross-industry comparisons (Acemoglu and Restrepo, 2017). This framework considered the equilibrium impact of industrial robots on local labour markets by using a full general equilibrium model (see Chapter Three) and, using this model, it was found that robots had large and robust negative effects on employment and wages across the United States between 1990 and 2007.

The local labour market framework was then used in a separate context to analyse Germany (Dauth et al., 2017). For Germany, the framework was extended to consider a more detailed analysis at the individual worker level which was made possible by the availability of German individual employee data. The empirical analysis found no evidence that robots caused aggregate job losses in Germany, but automation had contributed to a change in the composition of aggregate employment, shifting manufacturing jobs to service jobs. There is also interest in understanding the impact of automation on manufacturing employment in developing and recently developed countries, such as India (Mani, 2017).

Other narratives have been offered for the decline of manufacturing employment and employment polarisation. The impact of routinisation and international trade on employment have been considered in a US local labour market context. Notably, it was found that import competition had a negative and significant impact on US employment, particularly amongst manufacturing and non-college workers (Autor, Dorn, and Hanson, 2015). The impact of Chinese imports on UK employment has also been considered with a negative, but not significant, result being determined for 1998 to 2013 (Bilici, 2016).

2.2 Contribution

This thesis extends the empirical evidence of the impact of automation in the context of the UK. The approach pursued in this thesis follows the literature by focusing on a specific type of technology: industrial robots. An industrial robot is defined by the International Federation of Robotics (IFR) as 'an automatically controlled, reprogrammable, multipurpose [machine] programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications' (IFR, 2017).

One of the advantages of using industrial robots as an empirical measure of automation is that these machines do not require human operators, as they are 'automatically controlled'. Industrial robots can perform manual tasks and, therefore, can be viewed as substitutes – rather than complements – for labour in production tasks (Acemoglu and Restrepo, 2016b). Industrial robot data is also available from 1993 onwards due to a data gathering effort from IFR. The ability of industrial robots to substitute for humans lends the data to a task-based modelling approach, as opposed to a factor-augmenting approach.

The UK is an interesting case to consider since it has a lower adoption rate of robots relative to other advanced European economies (see Figures 2a and 2b). The heterogeneity of this adoption rate is of interest to social scientists as it offers an opportunity to analyse the impact that robots can have at the lower end of the adoption distribution. The UK is also interesting, relative to the US, as a longer dataset is available. In the case of the US, meaningful industry-level data is only available from 2004 onwards, whereas the UK has industry-level IFR data available from 1993.

The local labour market measure for the UK is taken at the most granular level available which, for the years of interest, are only available for England and Wales. Local authority data at a district level is readily available from Nomis (Source: Office of National Statistics). As in Faggio and Overman (2014), this thesis focuses on local authorities, rather than broader labour market areas, due to data availability. Other units of analysis, such as Travel to Work Areas (TTWAs), are not publicly available across as broad a range of datasets as local authorities. As such, standard errors for the results are clustered at the standard region level to account for potential spatial correlations that may exist across local authorities, and regressions are weighted by the working-age population of each local authority to account for differences in size (see Section 3.3 for further discussion).

After analysing automation, this thesis explores how the effects of automation differ from the effects of trade. This thesis extends the existing empirical evidence by considering three additional areas of interest in relation to UK trade: the impact of trade on UK employment from a period prior to Bilici (2016); an explicit consideration of other large UK trading partners; and the use of an automation regressor for robustness, made possible by the availability of the IFR data.

The ability to provide a meaningful analysis of wages and inequality is limited due to insufficient publicly available wage data at a local authority level. Some progress is made by using data from the Annual Survey of Hours and Earnings (ASHE) which is available from 1997 onwards, although there are still gaps in the reporting of wages across local authorities. Using this data, automation does not appear to have had a statistically significant impact on median wages (either hourly or weekly), although there is some evidence of automation negatively affecting 25th percentile earners. Wage results are contained within Appendix A.2.

3. Theoretical Model

3.1 Motivating Literature

The model used to provide the empirical specification is based on Acemoglu and Restrepo (2016a) which has been used previously to motivate empirical automation analysis (Acemoglu and Restrepo, 2017; Dauth et al., 2017). The model is task-based, and robots compete against human labour in the production of different tasks. As with Acemoglu and Restrepo (2017), the model is first presented as ignoring interactions between local labour markets (autarky) to build intuition of the key effects. The key effects are the productivity effect (robots increasing the output that each worker can produce) and the displacement effect (robots reducing the number of workers needed to produce a given amount of output).

After building intuition, trade is introduced between labour markets; local authorities in the case of the UK. The trade model combines the frameworks of Armington (1969) and Anderson (1979) with robot modelling. The Armington (1969) framework accounts for the simplifying elasticity assumptions to allow for demand function estimation. Namely, assuming that the elasticities of substitution between competing products in any market are constant and the elasticity of substitution between two products competing in a market is the same as that between any other pair of products competing in the same market.

3.2 Model

Autarky

The model in this thesis is identical to Acemoglu and Restrepo (2017) with the main difference being the use of local authorities, instead of commuting zones. The autarky equilibrium provides the intuition of the model. We assume an economy is made up of $|\boldsymbol{C}|$ local authorities and each local authority $c \in \boldsymbol{C}$ has preferences defined over an aggregate of consumption of the output of $|\boldsymbol{I}|$ industries. Preferences are of the constant elasticity of substitution form, such that consumption is:

$$Y_c = \left(\sum_{i \in \boldsymbol{I}} \alpha_i Y_{ci}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

$\sigma > 0$ (in the autarky setting) denotes the elasticity of substitution across goods produced in different industries, whereas α_i denotes the relative importance of industry i in the consumption aggregate, such that $\sum_{i \in \boldsymbol{I}} \alpha_i = 1$. In autarky, each local authority can only consume the production of its own good and X_{ci} denotes the output of industry i in local authority c. Hence in autarky, $\forall c \in \boldsymbol{C}$ and $\forall i \in \boldsymbol{I}$ we have:

$$Y_{ci} = X_{ci}$$

We take the consumption aggregate in each local authority as the numeraire and denote the price of output in industry i in local authority c as $P_{X_{ci}}$. We assume each industry produces output by combining a continuum of tasks, s, with tasks indexed by $s \in [0, S]$. As such, we can denote the quantity of task s that is needed to produce X_{ci} as $x_{ci}(s)$. Assuming tasks are combined in fixed proportions, we can write:

$$X_{ci} = A_{ci} \min_{s \in [0,S]} \{x_{ci}(s)\}$$

A_{ci} denotes the productivity of industry i. Under the assumptions so far, it follows that differences in productivity across industries (A) and the relative importance of industries in the consumption aggregate (α) result in differing shares of industry employment across local authorities. To introduce automation, a simplifying assumption is made about the industrial technology such that industrial robots are assumed to perform some of the tasks that were previously performed by labour. As such, all tasks can be separated into one of two categories: those that robots can do; and those that robots cannot do. For industry i, we say that tasks $[0, M_i]$ can be performed by robots. This means that $M_i \in [0, S]$ tasks are automated. Technological opportunities are assumed to be common across local authorities, which means that the ability to automate production tasks in the automotive industry are identical in York and the City of London.

As noted, one of the key advantages of using this task-based framework, as opposed to a factor-augmenting approach, is that there is an explicit modelling of a displacement effect. By construction, this allows robots to substitute for labour. The issue with this approach, though, is that it creates an aggressive framework through which robots impact jobs. In the task-based framework, it is only possible for robots to create jobs if the magnitude of the productivity effect is large enough to overcome the displacement effect. Yet, this does not fully capture the channels through which automation may be countervailed. These channels include: capital accumulation; deepening of automation; and the introduction of new tasks (Acemoglu and Restrepo, 2018).

A key channel is the introduction of new tasks (Acemoglu and Restrepo, 2016b). M_i represents the tasks that robots can perform in industry i, thus automation is an increase in M_i (if $M_i = S$ for all i then all tasks have been automated). A comprehensive model would endogenise the response of new tasks to automation (an increase in S). Yet, this is troublesome as 'the creation of new tasks is not an autonomous process advancing at a predetermined rate, but one whose speed and nature are shaped by the decisions of firms, workers and other actors in society, and which might be fuelled by new automation technologies' (Acemoglu and Restrepo, 2018).

This is a potential area within which future research may be promising. One way of empirically achieving this would involve aligning the tasks that industrial robots can perform (using IFR data) with the set of tasks that humans are doing (using, for example, O*NET data). As detailed data becomes available over a longer timeframe, such an alignment may yield useful insights into the endogenous response of automation. One theoretical approach to modelling the endogenous response of tasks to automation is also provided in Acemoglu and Restrepo (2016a). The approach assumes that intellectual property rights are held by a technology monopolist. This process assumes there are scientists who are dedicated to working on automation and explicit assumptions are made about the supply of these scientists. This offers a potential starting point for modelling the endogeneity of automation and would involve using cross-country data on patents and scientists. Although, one difficulty of this approach would be determining the number of scientists dedicated to automation. In consideration of these points, this thesis assumes that the set of tasks that can be automated is exogenous.

By normalising the productivity of robots in every task to 1, and making the simplifying assumption that the relative productivity of labour in each task is constant and equal to $\gamma > 0$, we can write the production function for task s in industry i in local authority c as:

$$x_{ci}(s) = \begin{cases} r_{ci}(s) + \gamma l_{ci}(s) & if\ s \leq M_i \\ \gamma l_{ci}(s) & if\ s > M_i \end{cases}$$

Where $l_{ci}(s)$ denotes labour used in the production of task s in industry i in local authority c, and $r_{ci}(s)$ denotes the number of robots used in the production of this task.

As such, tasks $s \in (M_i, S]$ have not been automated and so the use of robots in the production of these tasks is assumed to be impossible. This is important to note as a simplifying assumption for our empirical analysis will be that $M_i \approx 0$ at the beginning of the period being considered and, therefore, approximately zero tasks have been automated at the start of the period. We also assume the supply of labour and robots in each local authority is:

$$W_c = \boldsymbol{\mathcal{W}}_c Y_c L_c^{\varepsilon}$$

$$Q_c = \boldsymbol{\mathcal{Q}}_c \left(\frac{R_c}{Y_c}\right)^{\eta}$$

Where $\varepsilon \geq 0$ and $\eta \geq 0$. R_c is total number of robots, L_c is total amount of labour, Q_c is the price of robots and W_c is the wage rate in local authority c. It follows from the supply equations that $1/\varepsilon$ is the Frisch elasticity of labour supply and $1/\eta$ is the elasticity of supply of robots. Using these assumptions, we define an equilibrium as a set of quantities $\{L_c, R_c\}_{c \in \boldsymbol{C}}$ and prices $\{W_c, Q_c\}_{c \in \boldsymbol{C}}$ such that, in all local authorities, firms maximise profits and the robot and labour markets clear:

$$\sum_{i \in \boldsymbol{I}} \int_0^1 l_{ci}(s) = L_c$$

$$\sum_{i \in \boldsymbol{I}} \int_0^1 r_{ci}(s) = R_c$$

Under these assumptions, it can be shown that an equilibrium exists and is unique (Acemoglu and Restrepo, 2017). A further simplifying assumption is made that it is profitable for firms to use robots in all tasks that are technologically automated. If we let $\pi_c = 1 - (Q_c\gamma/W_c)$ denote the cost-saving gains from using robots rather than labour in a task, then we can simplify this profitability assumption by saying $\pi_c > 0$, $\forall c \in \boldsymbol{C}$. This is equivalent to assuming that there are only positive cost-saving gains associated with using robots. Hence, if there is a task that robots or humans could do, then robots are more cost-effective than human labour. This assumption is necessary for us to focus on the case where improvements in automation (increases in M_i) are binding and affect employment.

Using this assumption, it is possible to derive a partial equilibrium expression for labour demand, L_c^d (Acemoglu and Restrepo, 2017). It can be shown, under the assumptions so far, that demand for labour (L_c^d) in local authority c satisfies:

$$d\ln L_c^d = -\sum_{i\in \boldsymbol{I}} \ell_{ci} \frac{dM_i}{1-M_i} - \sigma \sum_{i\in \boldsymbol{I}} \ell_{ci} d\ln P_{X_{ci}} + d\ln Y_c$$

Where ℓ_{ci} denotes the share of baseline total employment in local authority c in industry i. This is a partial equilibrium expression showing how changes in prices and output depend on the prices and quantities of robots and labour in each local authority, as well as changes in M_i. The intuition behind this expression is that there are three different forces that are shaping labour demand in each local authority.

The first effect is the displacement effect $(-\sum_{i\in \boldsymbol{I}} \ell_{ci} dM_i/[1-M_i])$. Holding prices and output constant, robots displace workers and reduce demand for labour, because with robots it takes fewer workers to produce a given amount of output. As expected, the displacement effect is directly related to the number of tasks that can be automated (M_i).

The second effect is the price-productivity effect $(-\sigma \sum_{i\in \boldsymbol{I}} \ell_{ci} d\ln P_{X_{ci}})$. As the deployment of robots lowers the cost of production in an industry, that industry expands and increases demand for labour. This expansion is greater when the elasticity of substitution between different industries, σ, is higher. The third effect is the scale-productivity effect $(d\ln Y_c)$. The reduction in costs results in an expansion of total output, which also raises the demand for labour in all industries (as we have assumed that an increase in the output of one industry leads to an increase in the marginal value of the output of all other industries; industries are q-complements). The second and third effects can be considered together as the total productivity effect.

Intuitively, it is important to understand that we can distinguish the price-productivity effect from the scale-productivity effect by thinking about the industries being affected. The price-productivity effect is being driven by an expansion of the output of industry i. The scale-productivity effect is being driven by an expansion of all industries (and hence is an expansion of Y_c). In general equilibrium (in autarky), the impact of robots on employment is given by:

$$d\ln L_c = -\frac{1+\eta}{1+\varepsilon} \sum_{i\in \boldsymbol{I}} \ell_{ci} \frac{dM_i}{1-M_i} + \frac{1+\eta}{1+\varepsilon} \pi_c \sum_{i\in \boldsymbol{I}} \ell_{ci} \frac{s_{icL}}{s_{cL}} \frac{dM_i}{1-M_i}$$

Where s_{cL} denotes the share of labour in total output in local authority c and s_{icL} denotes the share of labour in the output of industry i in local authority c. The intuition for this expression follows closely from the partial equilibrium setting. The first term is the general equilibrium version of the displacement effect and the second term is a combination of the price-productivity and scale-productivity effects. These general equilibrium implications are derived by expressing changes in quantities and prices of output and robots in terms of changes in M_i's. This explains why we have local supply elasticities, $1/\varepsilon$ and $1/\eta$, and cost-shares parameters, s_{icL} and s_{cL}, in our expression.

One notable change in the general equilibrium expression is that the productivity effect is expressed as a function of the cost-effectiveness of robots (π_c). As with partial equilibrium, the impact on employment in general equilibrium could be negative because of the displacement effect or positive because of the productivity effect. Although, as noted, the only way for a change in employment to be positive is if the productivity effect is large enough to overcome the displacement effect. In general equilibrium, the productivity effects depend on how cost-effective robots are relative to humans (π_c) which is reflective of technological progress. If π_c is close to 0, then there are hardly any cost-saving gains from replacing humans with robots and the productivity effect of automation is limited.

For the purposes of empirical analysis, we consider the response of employment to changes in the adoption of robots. When $M_i \approx 0$ (the number of tasks that can be automated is close to 0), it can be shown that:

$$\sum_{i \in \boldsymbol{I}} \ell_{ci} \frac{s_{icL}}{s_{cL}} \frac{dM_i}{1 - M_i} \approx \sum_{i \in \boldsymbol{I}} \ell_{ci} \frac{dM_i}{1 - M_i} \approx \frac{1}{\gamma} \sum_{i \in \boldsymbol{I}} \ell_{ci} \frac{dR_i}{L_i} \approx \textit{Exposure to robots}_c$$

The first approximation follows as, when $M_i \approx 0$, then $s_{icL} \approx s_{cL}$, reflecting the fact that the share of labour is the primary driver of the output in industry i. The second approximation follows from a cost minimisation argument. The formula shows that the full impact of robots on a local authority, c, can be summarised with the empirical measure of UK exposure to robots, which is computed from the change in the use of robots in each UK industry divided by that industry's employment. These changes can then be summed using employment shares as weights. The phrase 'exposure to robots' indicates that we are interested in understanding how exposed to robots a local authority is as a proportion of its employment shares in different industries (the ℓ_{ci}'s) and changes in robot adoption across industries (the dR_i's). It follows that breakthroughs in cost-effective industrial robot technology will disproportionately impact local authorities that have a higher share of employment in industries where robots are being more readily adopted.

Trade Between Local Authorities

To extend the model to a more realistic setting, we need to consider interactions across local authorities. Once again, this model with interactions is identical to Acemoglu and Restrepo (2017). Intuitively, if a local authority adopts more robots, then it should be able to decrease its costs and sell more to other local authorities. These interactions change the aggregate impact as we expect lower costs, due to robots, to reduce the cost of living.

To incorporate trade, we assume that the output for local authority i, X_{ci}, is consumed locally and exported to all local authorities. We assume that there are no trade costs in this setting, which is a reasonable assumption when considering interactions across local authorities in England and Wales. The absence of trade costs allows us to assume that the price of the product of industry i from local authority c is the same across England and Wales. This price is denoted by $P_{X_{ci}}$. If X_{cdi} denotes the amount of good i exported to destination d from local authority c, we can then say, using a simple market clearing argument, that for all c and i, we have:

$$X_{ci} = \sum_{d \in \boldsymbol{C}} X_{cdi}$$

As in Armington (1969), each Y_c is a differentiated good traded across local authorities. As such, preferences in a local authority are defined by the same aggregate over consumption goods as in autarky, with the only difference being that consumption of industry i for local authority c is an aggregate of the differentiated varieties sourced from all local authorities. Therefore, consumption can be expressed as:

$$Y_{ci} = \left(\sum_{s \in \boldsymbol{C}} \theta_{si} X_{sci}^{\frac{\lambda - 1}{\lambda}} \right)^{\frac{\lambda}{\lambda - 1}}$$

λ is the elasticity of substitution between varieties sourced from different local authorities. The share parameters, θ_{si}, reflect the desirability of varieties from different sources. Levels of desirability are assumed to be scaled such that $\forall i \in \boldsymbol{I}$, $\sum_{s \in \boldsymbol{C}} \theta_{si} = 1$. We would expect varieties of the same good from different local authorities to be more substitutable than different products in the consumption aggregator, so we assume that $\lambda > \sigma$. It is also assumed that $\sigma \geq 1$ in this trade setting, which implies a preference for variety in traded goods. Based on our assumptions that technological opportunities are common across local authorities and that there are no trade costs across local authorities, it follows that all local authorities will also have the same prices of the consumption aggregates of different industries, P_{Y_i}. Equilibrium is then defined as being equivalent to the autarky equilibrium with the added condition that trade is balanced for all local authorities $c \in \boldsymbol{C}$, such that:

$$Y_c = \sum_{i \in \boldsymbol{I}} X_{ci} \, P_{X_{ci}}$$

It can be shown that an equilibrium in this model with trade exists, and moreover, is unique provided that the M_i's are sufficiently small, which is the case that we are empirically focused on (Acemoglu and Restrepo, 2017). Under these assumptions, it can be shown that demand for labour L_c^d in local authority c in the trading equilibrium satisfies:

$$d\ln L_c^d = -\sum_{i \in \boldsymbol{I}} \ell_{ci} \frac{dM_i}{1 - M_i} - \lambda \sum_{i \in \boldsymbol{I}} \ell_{ci} d\ln P_{X_{ci}} + (\lambda - \sigma) \sum_{i \in \boldsymbol{I}} \ell_{ci} d\ln P_{Y_i} + d\ln Y$$

The displacement effect with trade is identical to the partial equilibrium case under the assumption of autarky. The difference is in the productivity effect. The productivity effect is now made up of three terms. $\lambda \sum_{i \in \boldsymbol{I}} \ell_{ci} d\ln P_{X_{ci}}$ is the price-productivity effect, and because $\lambda > \sigma$, the effect is greater than in the autarky equilibrium. Intuitively, the price-productivity effect reflects robots lowering the cost of production in an industry, resulting in an increase in labour demand to accommodate expansion of that industry. In autarky, an industry is only able to expand relative to other industries in its own local authority, but in the trade setting an industry can gain market share from producers of the same good in other local authorities, resulting in an even greater increase in labour demand. This is the rationale for the more aggressive price-productivity effect with trade.

The price-productivity effect is dampened, however, by $(\lambda - \sigma) \sum_{i \in \boldsymbol{I}} \ell_{ci} d\ln P_{Y_i}$. This term reflects how greater use of robots in industry i reduces production costs in local authority c *and* all other local authorities due to the ability to trade. This lower cost of production in all local authorities results in a reduction in labour demand. The final term, $d\ln Y$, is the equivalent of the scale-productivity effect. The only difference for the scale-productivity effect is that the total output increase is not just at a local authority level. In the trade setting, the effect is an expansion of total output for the whole economy. The general equilibrium counterpart is also outlined in Acemoglu and Restrepo (2017).

3.3 Empirical Specification

Model

The empirical specification for the UK follows directly from the model. If the number of tasks that can be technologically automated (M_i) are sufficiently small, then simple equations can be derived. When $M_i \approx 0$, a reasonable assumption for the UK in 1991, then the model implies that the effect on employment can be estimated from:

$$d\ln L_c^{UK} = \beta_c^L \sum_{i \in \boldsymbol{I}} \ell_{ci} \frac{dR_i^{UK}}{L_i^{UK}} + \varepsilon_c^L$$

ε_c^L denotes an unobserved shock and β_c^L is a random (heterogeneous) coefficient. With trading, if we assume $\pi_c \approx \pi$, we derive the following approximation:

$$\beta_c^L \approx \left(\frac{1+\eta}{1+\varepsilon} (s_{cL}\lambda + (1 - s_{cL})\sigma)\pi_c - \frac{1+\eta}{1+\varepsilon} \frac{s_{cL}\lambda + 1 - s_{cL}}{s_{cL}} \right) \frac{v_c}{\gamma}$$

Where $v_c = \frac{(1+\varepsilon)s_{cL}}{(1+\varepsilon)s_{cL}\lambda \,+\, (1+\eta)(1-s_{cL})}$

Simply running a regression and estimating β^L will not yield a meaningful aggregate interpretation of the effect of robots on employment as the regression is run at a local level. The above approximation for β_c^L means we can combine it with macroeconomic estimates of labour supply ($1/\varepsilon$) and trade (σ and λ) elasticities to recover estimates of other parameters. The key result to note, therefore, is that the regression coefficient in our empirical specification can be interpreted as a function of structural macroeconomic parameters which enables us to back out γ (the productivity of humans relative to robots).

Endogeneity Concerns

$d\ln L_c^{UK} = \beta_c^L \sum_{i \in \boldsymbol{I}} \ell_{ci} [dR_i^{UK}/L_i^{UK}] + \varepsilon_c^L$ could be estimated using Ordinary Least Squares (OLS) with some measure of exposure to robots. Yet, there are plausible explanations as to why the error, ε_c^L, may be correlated with the regressor. After all, a shock to labour demand in a local authority is likely to affect the decision of whether or not to adopt robots within that local authority. To address this endogeneity, an instrument is constructed using the adoption of robots among industries in 8 other European economies[4], in line with Acemoglu

[4]Denmark, Finland, France, Germany, Italy, Norway, Spain and Sweden. Norway data is missing from EU KLEMS, so distribution of employment in the remaining Scandinavian countries (Denmark, Finland and Sweden) is used to impute Norwegian distribution.

and Restrepo (2017) and Dauth et al. (2017). With this instrument we can calculate Two-Stage Least Squares (2SLS) estimates (see Chapter Four for construction).

The use of robot adoption in European economies may not overcome all sources of endogeneity, though. Due to multinational firm linkages, it could be argued that labour demand in local authorities is correlated with the decision to adopt robots in European markets. One could envisage a slowdown that causes labour demand to drop across Europe with multinational firms responding by investing in robots. This would mean robot adoption across Europe is negatively correlated with the error term, as a negative shock to labour demand results in higher robot adoption. This would bias coefficient estimates downwards. Despite this, the instrument does provide protection against labour market shocks concentrated in the UK and can be interpreted as a European technological frontier.

Unit of Analysis

Due to data availability, the unit of analysis used is local authorities, which has previously been used in the empirical literature (Faggio and Overman, 2014). The main disadvantage of local authorities as a measure of local labour markets is that they do not capture 'minimal gross movement across the boundary'. This is what allows an enclosed area to approximate to a perfect market model as it is self-sufficient in labour supply and employment (Goodman, 1970). Travel to Work Areas (TTWAs) attempt to provide a UK local labour market measure, but this has proved to be a challenging task. Between 1991 and 2011, the number of TTWAs decreased from 308 to 228, due to more complex working patterns and changes in travel to work methods (Office of National Statistics, 2015).[5]

Using local authorities means that errors may not be independent of each other: $E(\varepsilon_c^L \varepsilon_d^L) \neq 0$ where $c \neq d$. To make progress in the face of this concern, standard errors for the regression results for local authorities are clustered at the standard region level. By clustering at a standard region level, this allows for correlations within standard regions, but not between standard regions.[6] As such, clustering accounts for spatial correlations that may exist in employment outcomes across England and Wales.[7] In addition, regressions are

[5]It is not possible to map local authorities to TTWAs, or vice versa, as there is overlap. TTWAs contain parts of multiple local authorities and local authorities contain parts of multiple TTWAs.

[6]10 clusters: 9 standard regions of England (North East, North West, Yorkshire and The Humber, East Midlands, West Midlands, East of England, London, South East and South West) and Wales.

[7]Standard errors are cluster-robust and also robust against heteroskedasticity.

weighted by the working-age population of each local authority. This approach also allows us to derive aggregate effects from a granular level using structural parameters.

Additional Controls

The empirical specification provides a framework within which to interpret the coefficient of the regressor for exposure to robots; β_c^L can be viewed as a function of structural parameters. Empirically, there are other confounding factors that we might reasonably expect to affect the dependent variable. The labour market is, after all, millions of people making decisions for several reasons. Therefore, to mitigate omitted variable bias, and to allow for a robust interpretation of β_c^L, sensible controls need to be added.

Formally, ε_c^L may include other determinants of the labour market hiring process. Demographic factors, for example, may be driving the change in employment levels. The share of a population that are of working age, the share of individuals with a university degree and the share of minorities may contribute to different employment outcomes. We would expect these demographics to satisfy the exclusion restriction as changes in the share of working-age individuals and minorities may impact the employees that may be hired, but we would not expect a reverse causality, where employment levels change the share of working-age individuals and minorities. Also, as employment is the dependent variable (not wages), we would not expect an ability bias to result in a reverse causality for employment.

Additional controls are added for broad industry shares which consider the share of employment in manufacturing, the share of employment in construction and the share of female employment in manufacturing. These controls account for potential trending declines. These would not be expected to violate the exclusion restriction as these are shares. These controls capture employment composition and are not directly impacted by employment levels. We might also expect other explanations from the literature to affect labour market outcomes. As such, controls are considered for: offshorability; routinisation; and trade. Trade may violate the exclusion restriction; hence instruments are constructed.

Furthermore, if these controls are correlated with the decision to adopt robots, then an OLS regression may prove problematic. The use of 2SLS mitigates this concern and allows for a more robust interpretation of β_c^L in the presence of these controls. The construction of all variables is discussed in Chapter Four.

4. Data

4.1 Exposure to Robots

Following Chapter Three, we can construct the regressors that will be used for this thesis. The automation regressors of interest are:

$$UK\ exposure\ to\ robots_{c,t} = \sum_{i\in \boldsymbol{I}} \ell_{ci} \frac{dR_i}{L_i} = \sum_{i\in I} \ell_{ci}^{t} \left(\frac{R_{i,t+1}^{UK}}{L_{i,t}^{UK}} - \frac{R_{i,t}^{UK}}{L_{i,t}^{UK}} \right)$$

$$Instrument\ for\ exposure\ to\ robots_{c,t} = \sum_{i\in I} \ell_{ci}^{t-1} \left(p_{10} \left(\frac{R_{i,t+1}}{L_{i,t}} \right) - p_{10} \left(\frac{R_{i,t}}{L_{i,t}} \right) \right)$$

The main data source for robots ($R_{i,t}^{UK}$ and $R_{i,t}$) is the International Federation of Robotics (IFR) which provides operational industrial robot counts by industry, geography and year from 1993 onwards. These counts are based on consolidated data provided by nearly all industrial robot suppliers worldwide to IFR.[8] Access to the IFR data was obtained for this thesis, and this is the first known economic study to be carried out for the UK using the data. When calculating the operational stock, IFR assumes that the average service life is 12 years and there is an immediate withdrawal of robots after 12 years.[9]

Industrial robot data offers the current gold standard for assessing automation based on its usage in the literature (Graetz and Michaels, 2015; Acemoglu and Restrepo, 2017; Dauth et al. 2017), though it should be noted that there are limitations. The definition of automation considered in this thesis is broad, yet there are types of capital that meet the definition of automation that are not captured in the industrial robot data as they are not reprogrammable or multipurpose.

$R_{i,t}^{UK}$ denotes the stock of robots in industry i in year t in the UK (including Scotland and Northern Ireland). Industry data is roughly available at a two-digit level, with

[8]Where countries do surveys of the robot stock, or have their own calculation of operational stock, for instance in Japan, then IFR uses those figures as the operational stock of robots.

[9]This assumption was investigated in a study and it was found that the 12 years' average service life might be too conservative (the indication was that average service life was closer to 15 years).

manufacturing data available at roughly a three-digit level. There are a greater proportion of unspecified robots in the earlier years and, as such, unspecified robots are assigned to the existing total in proportion directly to the proportions that they accounted for in each year between 1993-2011.[10] $L_{i,t}^{UK}$ denotes full-time UK employees in industry i at time t. To ensure UK robot data is weighted by UK employment, the data for $L_{i,t}^{UK}$ is taken from EU KLEMS aggregate estimates (see Jäger, 2016).[11]

The data for the proportion of employees in each industry in each local authority (ℓ_{ci}^{t} and ℓ_{ci}^{t-1}) is taken from 1981 and 1991 Census data for England and Wales, available on Nomis (Source: Office for National Statistics). For 1981 and 1991, the data is from the Census Special Workplace Statistics[12] which is available at a 10% sample level and provides granularity at a three-digit industry level.[13] The 10% sample is a stratified sample covering one in ten enumerated households and one person in ten enumerated in communal establishments. Evaluation of Census data has shown that grossing-up sample counts by the simple factor of 10 is expected to be a reliable estimate of the enumerated population (OPCS, 1992). Industry proportions for 2001 are from the Annual Business Inquiry for Employment (ABI) which provides granularity at a three-digit industry level, which is not directly available from 2001 Census data.[14]

The instrument is constructed using the 10$^{\text{th}}$ percentile of robot exposure in eight European countries[15] due to the endogeneity concerns explored in Section 3.3. The IFR and EU KLEMS data are combined to produce $p_{10}(R_{i,t}/L_{i,t})$ which denotes the 10$^{\text{th}}$ percentile of the robot to employment ratio across the 8 European countries. The 10$^{\text{th}}$ percentile is used due to the low rate of UK robot adoption relative to other European countries. As

[10]Robots for Denmark between 1993-1996 are manually allocated using the 1996 industry compositions to deflate industry allocations from 1996 going backwards.

[11]STAN (OECD.STAT) is used for Norway figures (not available from EU KLEMS).

[12]Set B (Persons with workplace in each zone).

[13]Industry proportions use total employment, rather than full-time employment (due to industry data availability). Employees with industry inadequately described are removed from dataset.

[14]2001 ABI data is from an employer survey with jobs recorded at location of employee workplace. For comparability, 1991 Census Special Workplace Statistics used are from Set B which are based on area of workplace for employees (built up from enumeration districts).

[15]Denmark; Finland; France; Germany; Italy; Spain; Sweden; and Norway. Norway is imputed using average employment rates across industries for Finland, Denmark and Sweden (these are then combined with Norway total employment figures from OECD.STAT).

seen in Figure 4, the 10th percentile for the European countries does a reasonable job of tracking the UK robot adoption rate.

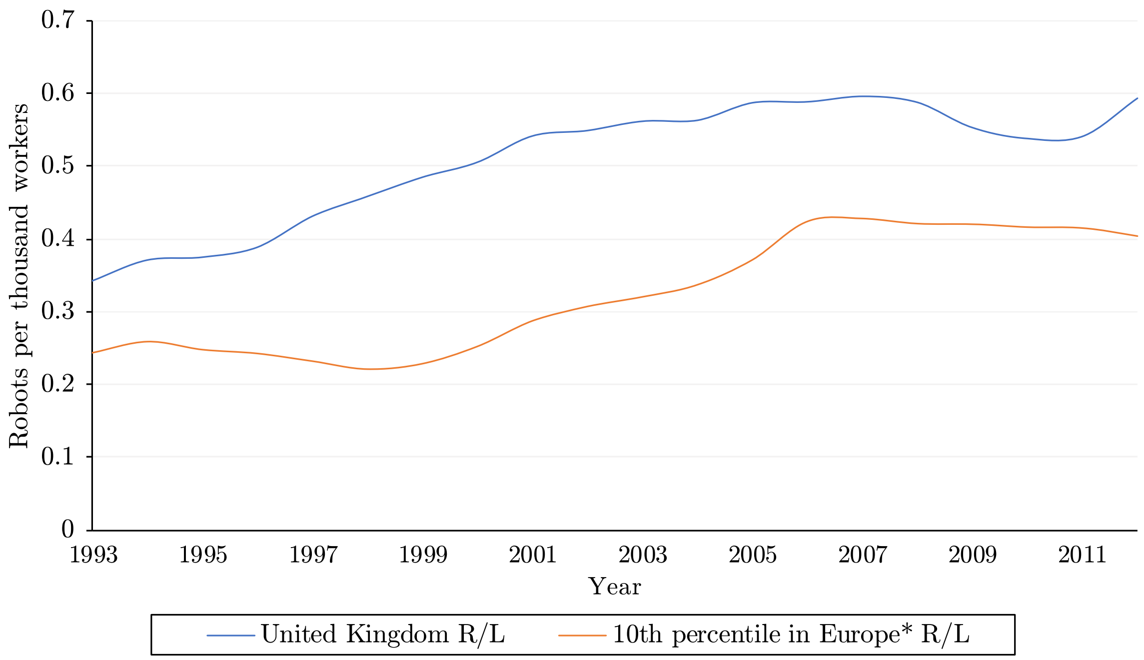

Figure 4: Robot adoption rate for UK and 10th percentile of European countries

Note: R/L denotes robots per thousand workers. Data from IFR and EU KLEMS. *Countries used for 10th percentile are: Denmark, Finland, France, Germany, Italy, Norway, Spain and Sweden.

In addition, the instrument uses the lagged proportion of employees in each industry (ℓ_{ci}^{t-1}) to mitigate a potential simultaneity bias that may occur from using contemporaneous employment. The intuition is that there may be a bias due to employers anticipating automation and acting pre-emptively. If there is a contemporaneous effect on employment due to anticipated automation, then lagged employment should help to protect against this as it reflects a time prior to which the impact of automation could have been known.

4.2 Dependent Variable

$$Dependent\ variable_{c,t} = \frac{L_{c,t+1}^{UK}}{P_{c,t+1}^{UK}} - \frac{L_{c,t}^{UK}}{P_{c,t}^{UK}}$$

In line with the empirical literature, the dependent variable used is the change in the employment to population ratio. The main data sources used for the employment ($L_{c,t}^{UK}$ and $L_{c,t+1}^{UK}$) and population counts ($P_{c,t}^{UK}$ and $P_{c,t+1}^{UK}$) are the 1991, 2001 and 2011 UK Censuses which provide data for local authorities at a district level for England and Wales

(Source: Office for National Statistics).[16] Local authorities have previously been used in the empirical literature as a unit of analysis for the UK (Faggio and Overman, 2014), as discussed in Section 3.3.

For 1991, Census Local Base Statistics (LBS) are used to provide a 100% sample, with the population base being total persons, and employment being full-time employees. For 2011, detailed characteristics datasets are used to provide population and full-time employment counts at a 100% sample level for each local authority. In the case of stacked regressions, variables are also used from the 2001 Census which provides 100% univariate statistics for the purposes of dependent variable construction.

$$Manufacturing\ dependent\ variable_{c,t} = \frac{L_{M,c,t+1}^{UK,TOT}}{P_{c,t+1}^{UK}} - \frac{L_{M,c,t}^{UK,TOT}}{P_{c,t}^{UK}}$$

An alternative dependent variable specification is considered which uses the change in the manufacturing employment to population ratio. This is closer to the dependent variable used in Autor, Dorn and Hanson (2013) and focuses only on the change in manufacturing employment, as opposed to employment across all industries. This, therefore, does not consider spillover effects, such as productivity effects for other industries and the taking up of jobs in non-manufacturing industries by those who have lost manufacturing jobs. To construct the dependent variable, manufacturing employment figures are available for local authorities from the Census datasets at a total employment level (including part-time and self-employed).[17] For completeness, total employment equivalents of all variables are considered in the Appendices. The main results are unchanged using either full-time employment or total employment.

Wage analysis is restricted due to the nature of wage data that is publicly available. Limited wage data is available from the Annual Survey of Hours and Earnings, but public versions of these surveys are only available from 1997 onwards, and the surveys do not provide sufficiently detailed data to allow for analysis across individuals with similar

[16] Definitions in use prior to April 2015.

[17] In the case of 1991, industry employment is a 10% statistic, therefore the value for each local authority is grossed-up by 10. Grossing-up sample counts by the simple factor of 10 is expected to be a reliable estimate of the enumerated population (OPCS, 1992).

characteristics. In particular, it is not possible to consider wage differences across various demographic characteristics, including age, education and race.

4.3 Trade

As will be explained in Chapter Seven, trade controls are added for China and Germany. The theory of the trade controls follows Autor, Dorn and Hanson (2013) who develop a model of trade based on monopolistic competition (Helpman and Krugman, 1987) and variation in industry labour productivities across countries. In this model, each local authority is treated as a small open economy. Assuming trade has a gravity structure, it is possible to map changes in trade quantities into labour-market outcomes.

The main data source for import data is the UN Comtrade database which provides import and export data at a six-digit level across geographies and years. Sufficient data is only available from 1993 onwards, therefore this is the first year used (as opposed to 1991). Commodities are mapped to industries using an off-the-shelf mapping solution that enables commodity codes to be mapped to three-digit SIC industries (Autor et al., 2013). A mapping is created to enable the 1990 industries to be aligned with the Census data industry definitions. If an industry has not been assigned, a manual mapping is assigned by using the definitions from the 1990 Standard Industry Classification codes.

As with automation, the trade covariate is also subject to endogeneity, as import decisions may be impacted by local labour market shocks. Letting X denote China or Germany, the regressor for the change in UK import exposure can be written as:

$$\Delta IPW_{c,t} = \sum_i \frac{L^{UK}_{c,i,t}}{L^{UK}_{i,t}} \frac{\Delta Imports_{X\ to\ UK,i,t+1}/1{,}000}{L^{UK}_{c,t} \times 100}$$

The original Autor, Dorn and Hanson (2013) specification regressed import exposure on the change in percentage points of the share in manufacturing employment. As such, manufacturing employment is considered in the results.[18] One variation on the original specification is that, as this thesis uses shares rather than percentages when constructing variables, the import exposure variable is divided by 100 for comparability with other

[18]Autor, Dorn and Hanson (2013) use working-age population as the denominator in the dependent variable and weight regressions by total population. This thesis uses total population as the denominator in the dependent variable and weights regressions by working-age population, in line with Acemoglu and Restrepo (2017).

variables reported in shares. Intuitively, the coefficient can be thought of as directly relating to a percentage point change in the dependent variable. For example, a coefficient of -1 on the import exposure covariate means that a $1,000 increase in import exposure per worker for a local authority reduced the employment to population ratio by 1%.

To overcome the endogeneity, an instrument is again constructed using imports from China and Germany to other high-income countries. This is in line with Autor, Dorn and Hanson (2013). In the case of China (less so for Germany[19]), this instrument proxies the rising competitiveness of Chinese manufacturers, which can be thought of as a supply shock from a UK producer perspective. Consistent with the approach used by Autor et al. (2013), data has been used for Chinese and German imports in Australia, Denmark, Finland, Japan, New Zealand, Spain and Switzerland. The instrument is defined as:

$$\Delta Instrument\ IPW_{c,t} = \sum_i \frac{L^{UK}_{c,i,t-1}}{L^{UK}_{i,t-1}} \frac{\Delta Imports_{From\ X\ to\ Y,i,t+1}/1{,}000}{L^{UK}_{c,t-1} \times 100}$$

Where X denotes China or Germany and Y denotes Australia, Denmark, Finland, Japan, New Zealand, Spain and Switzerland. The employment level is lagged to mitigate the potential simultaneity bias. Intuitively, if there is a contemporaneous effect on employment due to anticipated trade, lagged employment should not be affected as it reflects employment decisions before the trading impact could have been known.

The employment datasets used for the automation regressor are used to construct the employment components of the trade variables. Total employees in an industry in a local authority ($L^{UK}_{c,i,t}$ and $L^{UK}_{c,i,t-1}$) are from Census Special Workplace Statistics and ABI. EU KLEMS provides UK industry employment ($L^{UK}_{i,t-1}$ and $L^{UK}_{i,t}$), ensuring UK trade is weighted by UK employment. Local authority employment ($L^{UK}_{c,t-1}$ and $L^{UK}_{c,t}$) is from 1981, 1991 and 2001 UK Censuses[20] and total employment equivalents are considered in the Appendices.

[19]Nonetheless, the first-stage for the German import exposure instrument is strong and the F-statistic is comfortably above 10 for the instrumented regressor in 2SLS results.

[20]1981 uses Small Area Statistics and 1991 uses Local Base Statistics (LBS). LBS is not available for 1981. This is not considered to be an issue as the main difference is the threshold for release. Small Area Statistics (SAS) are not released for areas with fewer than 50 usually resident persons and 16 resident households, whereas LBS are issued as abstracts for wards or sub-divisions of wards with both 1,000 or more residents and 320 or more resident households (OPCS, 1992).

4.4 Other Controls

Demographic controls are included for: education; proportion of ethnic minorities; and share of population that are of working-age (16-64). The demographic controls are taken at a local authority level from the 1991, 2001 and 2011 Census datasets where many demographic features are available with a 100% sample size. The education control is the proportion of individuals in each local authority with a first degree.[21] Level and difference demographics controls are used in the empirical specification.

Broad industry share controls are included for manufacturing, construction and female employment in manufacturing by using the proportion of total employment in each local authority in these categories. These broad industry classifications are available from Census datasets. For 1991, industry employee estimates are available at a 10% sample level and grossed up by 10. For 2001 and 2011, these industry shares are available at a 100% sample level. Level and difference controls are added for broad industry shares, unless explicitly stated otherwise.

A routinisation control is added using an off-the-shelf solution, available for US professions (Autor and Dorn, 2013). In this approach, job task requirements for professions are merged with occupational classifications. Tasks are assigned manual, routine and abstract scores on a 0-10 scale based on the Dictionary of Occupational Titles 1977. The average score is then used to calculate Routine Task-Intensity by occupation:

$$RTI_k = \ln(T_k^R) - \ln(T_k^M) - \ln(T_k^A)$$

T_k^R, $T_{k,}^M$ and T_k^A denote routine, manual and abstract task inputs in an occupation (k). For this thesis, US 1990 Occupational Classifications are mapped to UK occupations which allows for use of the routine scores for each UK profession. The share of routine jobs in a local authority is then estimated using occupational data for local authorities from 1991, 2001 and 2011 Censuses.[22] Where multiple US occupations are mapped to a UK occupation, an arithmetic average is used across manual, routine, and abstract scores. This means routine shares may not be evenly allocated across UK professions.[23] Using the average routinisation score for each profession, a cut-off is applied. An occupation is routine if the

[21]In the 1991 Census, Local Base Statistics are used and education is a 10% sample variable.

[22]Unspecified jobs are removed as there is no information to determine routine components.

[23]Ideally, more detailed UK occupation data would be available to generate this covariate.

routinisation score for the profession is greater than the 66th percentile of scores across all professions. As such, the routine employment share can be expressed as:

$$RSH_{c,t} = \left(\sum_{k=1}^{K} L_{k,c,t}^{UK} \times 1[RTI_k > RTI^{P66}]\right)\left(\sum_{k=1}^{K} L_{k,c,t}^{UK}\right)^{-1}$$

Where $L_{k,c,t}^{UK}$ denotes employees working in occupation k in local authority c at time t. $1[.]$ is an indicator function which takes the value 1 if the occupation is routine-intensive (in the top employment-weighted third of routine task-intensity).[24] Level and difference controls are added for the routine share of employment in each local authority.

The offshoring approach uses a similar off-the-shelf solution to routinisation (Autor and Dorn, 2013). It is noted that other offshoring approaches could have been used, including: using a coders' assessment of the ease with which an occupation could be offshored (Blinder and Krueger, 2009); and constructing an offshoring measure based on the share of intermediate inputs imported by each industry (Feenstra and Hanson, 1999; Wright, 2014). Autor and Dorn (2013) assign US professions an offshorability score based on O*NET data which averages two aggregate variables: face-to-face contact; and whether a job is on-site.

Using the same occupational mapping as routinisation, the offshorability of each UK profession can be estimated using the offshorability scores for US professions. As with routinisation, an arithmetic average is used across offshorability scores, as multiple US occupations are mapped to each UK occupation. As such, US professions with extreme offshorability scores may impact UK scores. Therefore, the offshore index is:

$$Offshorability_{c,t} = \sum\nolimits_{k \in K} (l_{k,c,t} \times Offshore\ score_k)$$

$l_{k,c,t}$ is the proportion of employees in occupation k in local authority c at time t. Level and difference offshoring controls are added.

[24] Routine occupations identified are: clerical occupations; secretarial occupations; other skilled trades; buyers, brokers and sales representatives; other sales occupations; industrial plant and machine operators, assemblers; and other elementary occupations.

5. Summary Statistics and First Stage

5.1 Summary Statistics

Table 1: Summary statistics of key variables (1991-2011)

	ALL LOCAL AUTHORITIES	QUARTILES OF THE CHANGE IN UK EXPOSURE TO ROBOTS			
		Q1	Q2	Q3	Q4
	N = 348	N = 111	N = 108	N = 73	N = 56
		Panel A. Outcomes			
Census FTEs to total population ratio in 1991	**0.303** **(0.038)**	0.302 (0.043)	0.302 (0.037)	0.307 (0.033)	0.303 (0.032)
Change in Census FTEs to total population ratio from 1991 to 2011 (in p.p.)	**-1.850** **(1.910)**	-1.580 (2.110)	-1.850 (1.620)	-2.040 (1.830)	-2.190 (2.100)
Change in Census FTEs to total working age population ratio from 1991 to 2011 (in p.p.)	**-2.850** **(2.260)**	-2.300 (2.450)	-2.980 (2.010)	-3.130 (2.120)	-3.390 (2.340)
Change in Census log employment from 1991 to 2011 (in p.p.)	**5.760** **(10.400)**	8.950 (12.100)	5.080 (9.770)	4.030 (8.440)	2.790 (8.190)
		Panel B. Covariates			
Share of employment in manufacturing in 1991	**0.176** **(0.065)**	0.141 (0.058)	0.184 (0.063)	0.194 (0.064)	0.212 (0.048)
Share of employment in construction in 1991	**0.073** **(0.014)**	0.072 (0.018)	0.075 (0.012)	0.070 (0.010)	0.071 (0.011)
Exposure to Chinese imports from 1993 to 2011	**0.049** **(0.031)**	0.045 (0.041)	0.048 (0.026)	0.052 (0.025)	0.057 (0.021)
Share of employment in routine jobs in 1991	**0.448** **(0.047)**	0.424 (0.046)	0.454 (0.045)	0.458 (0.043)	0.469 (0.037)
Offshorability index of jobs in 1991	**0.032** **(0.076)**	0.040 (0.092)	0.018 (0.069)	0.035 (0.068)	0.043 (0.056)
Exposure to German imports from 1993 to 2011	**0.038** **(0.028)**	0.026 (0.030)	0.032 (0.011)	0.042 (0.016)	0.073 (0.033)
Share of population with first degrees in 1991	**0.049** **(0.027)**	0.062 (0.034)	0.043 (0.019)	0.047 (0.020)	0.039 (0.020)

Notes: Sample means and standard deviations (in brackets) for the entire sample of local authorities and by (population-weighted) quartiles of the distribution for exposure to robots.

Table 1 outlines the variation that is used for the regressions in this thesis; it shows the means and standard deviations by quartiles of the UK exposure to robots covariate. Panel A of Table 1 focuses on dependent variables. These focus on the changes in employment in England and Wales between 1991 and 2011. All four quartiles saw a reduction in the employment to population ratio between 1991 and 2011. More relevant to this analysis, local authorities with a higher exposure to robots saw a larger decrease in their employment to population ratio relative to local authorities with a lower exposure to robots. This is directionally consistent with the hypothesis that robots reduce employment; the displacement effect outweighs the productivity effect.

It can also be seen that the share of employment in manufacturing is greater in local authorities where exposure to robots is higher. This is, to some extent, by construction as there are more industrial robots in the manufacturing sectors (Figure 3) and the exposure to robots regressor has been constructed by making use of the proportion of employment across industries. This makes it necessary to control for share of manufacturing when performing regressions to ensure that results are not driven by the declining trend in manufacturing employment (see Figure 1).

Exposure to Chinese and German imports is also greater in local authorities with greater exposure to robots. As such, the instrumented versions of Chinese and German import exposure are included within the empirical specifications to account for increased import competition. An explicit trade-based approach for the UK is considered in Chapter Seven. The share of jobs defined as routine is also increasing with exposure to robots, consistent with the hypothesis that routine jobs are more readily automated. The positive relationship with routinisation supports the view that automation can be interpreted as a function of the task contents of occupations and justifies the inclusion of a routinisation control. There does not appear to be a clear directional relationship between automation and offshoring. Nonetheless, offshoring controls are considered in the results for robustness.

To give a sense of the geographical dispersion of the automation and trade variables, choropleths are included in Figures 5 and 6. Figure 6 shows the distribution of robot and import exposure when removing local authorities within the top percentile for each variable. Removing the top percentile allows for a clearer view of the geographical variation. The more affected areas for automation and trade appear to be within the West Midlands, the North West and Wales. This is due to local authorities in these regions having higher proportions of employment in transportation manufacturing and import competing industries. The dispersion of exposure to robots is also shown in the histogram in Figure 7.

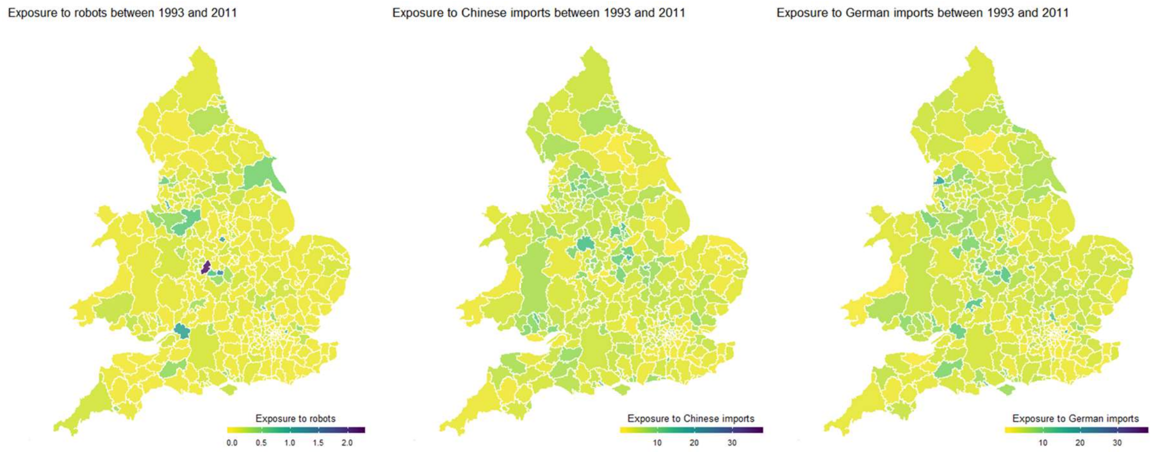

Figure 5: Density of automation and trade variables (1991-2011)

Note: Created in R. Contain OS data © Crown copyright and database right (2018).

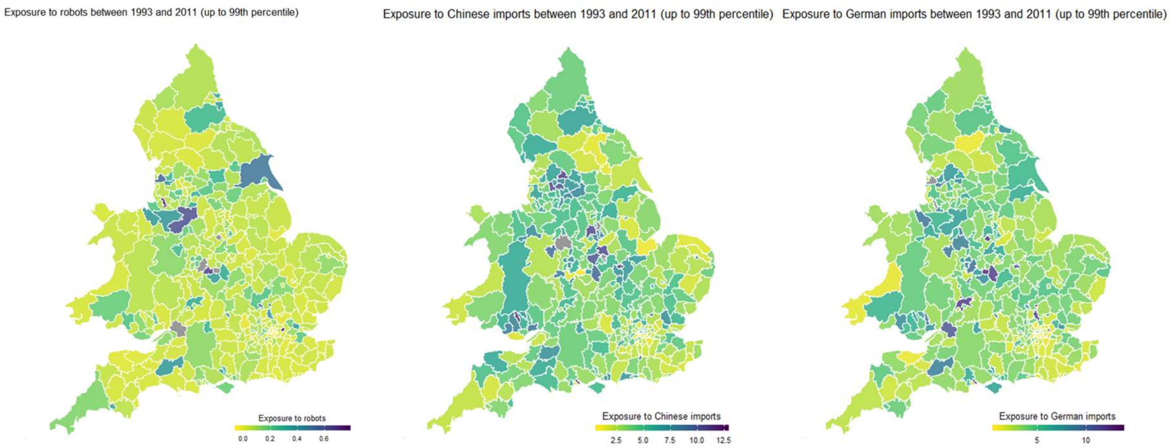

Figure 6: Density of automation and trade (removing top percentile) (1991-2011)

Note: Created in R. Contain OS data © Crown copyright and database right (2018).

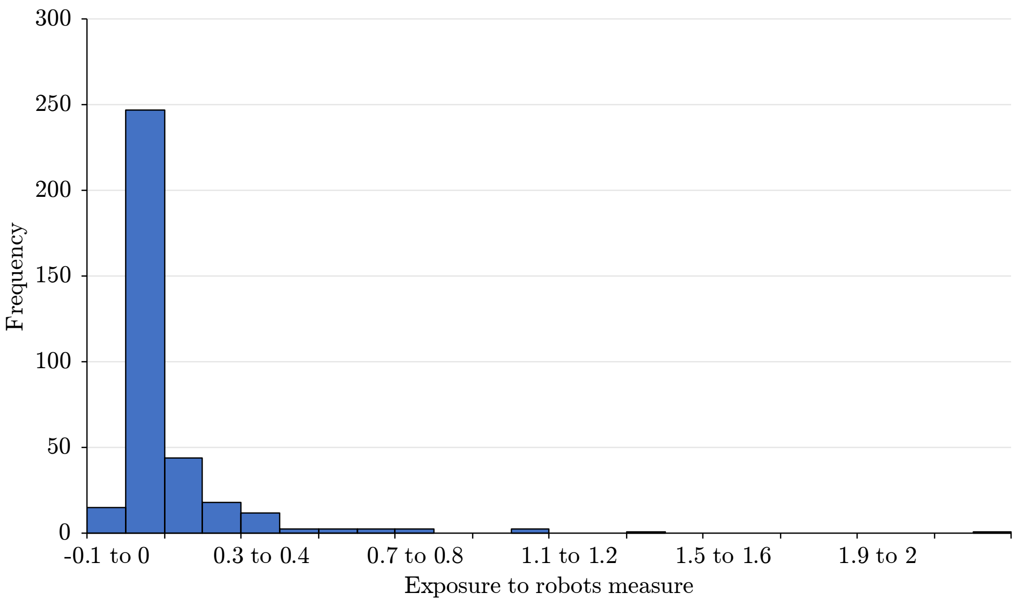

Figure 7: Density of exposure to robots in England and Wales (1991-2011)

Note: Data from IFR, EU KLEMS and Nomis.

5.2 First Stage

Due to the endogeneity concerns explored in Section 3.3, the first stage regression uses the 10th percentile of robot adoption across a basket of European countries as an instrument for UK exposure to robots. The first stage regression can, therefore, be expressed as:

$$\sum_{i \in I} \ell_{ci}^{t} \left(\frac{R_{i,t+1}^{UK}}{L_{i,t}^{UK}} - \frac{R_{i,t}^{UK}}{L_{i,t}^{UK}} \right) = \pi \sum_{i \in I} \ell_{ci}^{t-1} \left(p_{10} \left(\frac{R_{i,t+1}}{L_{i,t}} \right) - p_{10} \left(\frac{R_{i,t}}{L_{i,t}} \right) \right) + \mathit{\Gamma} X_{c,t} + \mathit{\Omega} \Delta Y_{c,t+1-t} + v_c$$

$X_{c,t}$ and $\Delta Y_{c,t+1-t}$ denote the level and difference controls, respectively, added for robustness. These local authority covariates consist of: demographic characteristics[25]; share of employment in manufacturing; share of employment in construction; female share of employment in manufacturing; exposure to Chinese imports; exposure to German imports; offshorability of jobs; and share of routine jobs. Except for Chinese and German imports, level and difference controls are added for all controls, unless stated otherwise.[26] These controls are not viewed as undermining the exclusion restriction (see Section 3.3).

For most specifications considered in this thesis, the instruments have a strong explanatory power, demonstrated by high F statistics. This relationship was also shown in Figure 4 with the similar movement between the 10th percentile of European countries' exposure to robots and UK exposure to robots. Nonetheless, the instrument should not be viewed as a perfect solution as it is subject to theoretical and empirical concerns. As noted, international linkages across multinational firms may lead to theoretical endogeneity issues.

Empirically, the instrument also has an issue which is made apparent when conducting stacked difference regressions (see Chapter Six). In the long difference specification, the instrument performs well as demonstrated by the F statistics. When using a stacked analysis, however, there is evidence that the size of the relationship between the instrument and the endogenous variable changes over time. The coefficient on the instrument in the first stage is significantly lower between 2001-2011 than it is between 1991-2001, and the corresponding F statistic is also lower for the period between 2001-2011. This reflects the fall in the UK robot adoption rate after 2001 (see Figure 3).

[25] Share of working-age population, share of population with a university degree, and share of minority ethnic groups (Black, Asian and Other) in a local authority.

[26] Import exposure covariates are constructed as differences.

6. Results

6.1 Results for Employment

The main result observed is that automation in transportation manufacturing had a negative and statistically significant effect on employment in England and Wales between 1991-2001. This result is determined by starting with a broad empirical specification and then narrowing the analysis. The empirical investigation assesses regressions using Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS or IV).

Table 2: Long differences using all industries (1991-2011)

	Long difference estimates of impact of change in automation across all industries on change in full-time employment between 1991-2011			
	OLS Estimates (β)		2SLS Estimates (β)	
	Automation only (1)	Baseline covariates (2)	Automation only (1)	Baseline covariates (2)
(Δ Robots in UK)/worker	-1.344*** (0.163)	-0.331 (0.229)	-1.372*** (0.302)	-0.213 (0.139)
Number of observations	348	348	348	348
R^2	0.05	0.74	0.05	0.74
First-stage analysis (included where applicable)				
(Δ Robots in EUR countries)/ worker			0.872*** (0.044)	0.857*** (0.064)
F-statistic			395.0	1,265.3

*Notes: Specification (1) regresses the change in full-time employment to population ratio on the relevant automation regressor: for OLS, the automation regressor is the change in UK exposure to robots; and for 2SLS, the automation regressor is the instrumented exposure to robots. Specification (2) is specification (1) plus additional covariates that control for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; routinisation; instrumented exposure to German imports; and instrumented exposure to Chinese imports. All regressions are weighted by the working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. Coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

For Table 2, the OLS specification is:

$$\frac{L_{c,2011}^{UK}}{P_{c,2011}^{UK}} - \frac{L_{c,1991}^{UK}}{P_{c,1991}^{UK}} = \beta \sum_{i \in I} \ell_{ci}^{1991} \left(\frac{R_{i,2011}^{UK}}{L_{i,1991}^{UK}} - \frac{R_{i,1993}^{UK}}{L_{i,1991}^{UK}} \right) + \mathit{\Gamma} X_{c,91} + \mathit{\Omega} \Delta Y_{c,11-91} + \varepsilon_c$$

The second stage for the 2SLS specification in Table 2 can be expressed as:

$$\frac{L^{UK}_{c,2011}}{P^{UK}_{c,2011}} - \frac{L^{UK}_{c,1991}}{P^{UK}_{c,1991}} = \beta\left(\hat{\pi}\sum_{i\in I}\ell^{1981}_{ci}\left(p_{10}\left(\frac{R_{i,2011}}{L_{i,1991}}\right) - p_{10}\left(\frac{R_{i,1993}}{L_{i,1991}}\right)\right)\right) + \varGamma X_{c,91} + \varOmega\Delta Y_{c,11-91} + \varepsilon_c$$

Table 2 begins with a broad analysis. A simple long difference is taken using Census data from 1991 and 2011 to assess the impact of the automation regressor over these years. As IFR data begins in 1993, this is the starting year for robots. In the OLS and 2SLS long difference specifications, there is evidence of a negative relationship between automation and employment, but the effect is not robust to the addition of controls.

To explore this effect further, we consider industry heterogeneity. As noted, the increase in industrial robot adoption has been driven by robots in the transportation manufacturing industry (see Figure 3). To tackle this, the automation regressor is decomposed into two parts: automation in transportation manufacturing; and automation in all other industries. Table 3 contains the output from this approach and shows that the negative relationship between automation and employment is driven by exposure to robots in the transportation manufacturing industry. Once again, the long difference result is not robust to the addition of controls. Table 3 demonstrates the importance of automation in the transportation manufacturing industry and the impact that it has had on employment.

Letting T denote the transportation manufacturing industry, the OLS specification for Table 3 is:

$$\frac{L^{UK}_{c,2011}}{P^{UK}_{c,2011}} - \frac{L^{UK}_{c,1991}}{P^{UK}_{c,1991}} = (\beta \quad \delta)\begin{pmatrix} \ell^{1991}_{cT}\left(\frac{R^{UK}_{T,2011}}{L^{UK}_{T,1991}} - \frac{R^{UK}_{T,1993}}{L^{UK}_{T,1991}}\right) \\ \sum_{\substack{i\in I \\ i\neq T}}\ell^{1991}_{ci}\left(\frac{R^{UK}_{i,2011}}{L^{UK}_{i,1991}} - \frac{R^{UK}_{i,1993}}{L^{UK}_{i,1991}}\right)\end{pmatrix} + \varGamma X_{c,91} + \varOmega\Delta Y_{c,11-91} + \varepsilon_c$$

The second stage for the 2SLS specification for Table 3 can be expressed as:

$$\frac{L^{UK}_{c,2011}}{P^{UK}_{c,2011}} - \frac{L^{UK}_{c,1991}}{P^{UK}_{c,1991}} = (\beta \quad \delta)\begin{pmatrix} \hat{\pi}\ell^{1981}_{cT}\left(p_{10}\left(\frac{R_{T,2011}}{L_{T,1991}}\right) - p_{10}\left(\frac{R_{T,1993}}{L_{T,1991}}\right)\right) \\ \hat{\mu}\sum_{\substack{i\in I \\ i\neq T}}\ell^{1981}_{ci}\left(p_{10}\left(\frac{R_{i,2011}}{L_{i,1991}}\right) - p_{10}\left(\frac{R_{i,1993}}{L_{i,1991}}\right)\right)\end{pmatrix} + \varGamma X_{c,91} + \varOmega\Delta Y_{c,11-91} + \varepsilon_c$$

Table 3: Long differences with transportation manufacturing (1991-2011)

	Long difference estimates of impact of change in automation on change in full-time employment to population ratio between 1991-2011			
	OLS Estimates (β)		2SLS Estimates (β)	
	Automation only (1)	Baseline covariates (2)	Automation only (1)	Baseline covariates (2)
(Δ Robots in UK transportation manufacturing industry)/worker	-1.391*** (0.393)	-0.298 (0.284)	-1.105** (0.438)	-0.379 (0.319)
(Δ Robots in all other UK industries)/worker	0.413 (16.647)	-1.886 (4.456)	-8.889 (19.369)	3.810 (6.893)
Number of observations	348	348	348	348
R^2	0.05	0.74	0.04	0.74
First-stage analysis (included where applicable)				
(Δ Robots in EUR transportation manufacturing industry)/worker			1.480*** (0.042)	1.577*** (0.039)
(Δ Robots in all other EUR industries)/worker			0.073*** (0.009)	0.084*** (0.009)
F-statistic - transportation			1,294.8	1,687.4
F-statistic - all other industries			77.0	87.3

*Notes: Specification (1) regresses the change in full-time employment to population ratio on the relevant automation regressors: for OLS, the automation regressors are the change in exposure to robots for transportation manufacturing and the change in exposure to robots for all other industries; and for 2SLS, the automation regressors are the instrumented equivalents of the OLS automation regressors. Specification (2) is specification (1) plus additional covariates that control for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); share of employment in manufacturing; share of employment in construction; share of female employment in manufacturing; offshoring; routinisation; instrumented exposure to German imports; and instrumented exposure to Chinese imports. All regressions are weighted by the working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. Coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

We can then consider parameter constancy using a stacked analysis. As seen in Figure 3, 1993-2001 saw a larger increase in robot adoption relative to 2001-2011. In total, the stock of industrial robots increased by 5,935 between 1993-2001, but only by 230 between 2001-2011. As such, employment outcomes from 1991-2011 are split into two stacks and an analysis is undertaken focusing on automation in the transportation manufacturing industry. This approach is in Table 4. The stacked differences strategy also involves adding decadal controls which allows for consideration of other potential differential trends.

Table 4: Stacked differences with transportation manufacturing (1991-2011)

	Stacked difference estimates of impact of change in automation in the transportation manufacturing industry on change in full-time employment to population ratio between 1991-2011					
	OLS Estimates (β)			2SLS Estimates (β)		
	1991-2001 (1)	2001-2011 (2)	1991-2011 (3)	1991-2001 (1)	2001-2011 (2)	1991-2011 (3)
(Δ Robots in UK transportation manufacturing industry)/worker	-0.411* (0.215)	-37.300 (27.874)	-0.318 (0.271)	-0.502*** (0.150)	-24.477 (19.512)	4.448 (5.589)
Number of observations	348	348	696	348	348	696
R^2	0.52	0.72	0.56	0.52	0.72	0.21
First-stage analysis (included where applicable)						
(Δ Robots in EUR transportation manufacturing industry)/worker				23.522*** (0.475)	0.036*** (0.002)	-0.286 (0.211)
F-statistic				1,619.4	293.3	8.7

*Notes: The dependent variable for all specifications is the change in full-time employment to population ratio for the relevant period. For OLS, the automation regressor is the change in exposure to robots in the transportation manufacturing industry; and for 2SLS, the automation regressor is the instrumented exposure to robots in the transportation manufacturing industry. All specifications include stack controls for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authority population); industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; routinisation; instrumented exposure to German imports; and instrumented exposure to Chinese imports. Specification (3) includes a time dummy. All regressions are weighted by the working-age population at the start of each stack. Robust standard errors in parentheses are clustered at the standard region level. Coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

The empirical specifications for the OLS and 2SLS estimates in Table 4 are consistent with the approaches used for Tables 2 and 3, with a time dummy also added for the longer stacked analysis (1991-2011, or specification 3). Table 4 shows a negative and statistically significant effect of the transportation automation regressor in the first stack (1991-2001), but not in the second stack (2001-2011). The discussion points from Section 5.2 regarding the first-stage for the second stack become more apparent. The coefficient for the first stage in 1991-2001 (23.522) is much higher than the coefficient for the first stage in 2001-2011 (0.036), reflecting the drop in UK robot adoption between 2001-2011. The UK keeps pace with European countries until 2001, but then starts to lag. This further demonstrates the situation portrayed in Figure 3.

The adoption rate of robots in the UK for 2001-2011 does not provide a meaningful enough variation with which to conduct empirical analysis and this is clearly demonstrated by the inflated coefficients for the OLS and 2SLS regressions on the second stack (2001-2011) and the wide standard errors. In short, Table 4 demonstrates the importance of focusing on a period of time in which there has been a meaningful increase in industrial robot adoption within the UK: 1991-2001.

Tables 5a-5c combine the insights from Tables 3 and 4: the importance of industry heterogeneity; and the relatively meaningful change in UK robot adoption between 1993-2001. As such, Tables 5a-5c focus on stack 1 (1991-2001). Column 4 of these Tables represents the preferred specification for this thesis as it incorporates all the controls and all available information.[27] Three tables are used to consider varying approaches for the main result. The different approaches demonstrate the robustness of the result to different definitions and provide insights into the effects taking place.

Table 5a begins by considering the impact that automation across all industries had on full-time employment outcomes between 1991-2001. The result is negative and statistically significant in the preferred specification, with a coefficient of -0.457 and supports the conclusion that the displacement effect of each new robot outweighed the productivity effect between 1991-2001. As noted, however, this does not consider the fact that the transportation manufacturing industry is responsible for most of the increase in the industrial robot stock over this period (transportation manufacturing robots accounted for 86% of the increase between 1993-2001).

Table 5b demonstrates the main result of this thesis by considering industry heterogeneity and focusing on automation in the transportation manufacturing industry. Column 4 shows that the coefficient of interest is -0.502 and this is the main effect of interest. This is slightly larger than the coefficient from Table 5a, suggesting that each additional robot in the transportation manufacturing industry had a greater effect on employment than robots across all industries. Although, it is noted that, based on the size of the standard errors, we cannot reject the null hypothesis that the two coefficients are equal.

[27] German import exposure is added for completeness. German import exposure covariate is not statistically significant when considered in conjunction with other covariates (as discussed in Chapter Seven), but its inclusion is supported by a bias-adjusted AIC minimisation. The main result is unchanged when the German import exposure covariate is removed.

Table 5a: Automation in all industries on employment (1991-2001)

	STACK 1 ESTIMATES USING 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. First-stage for exposure to robots in the UK from 1993 to 2001					
Exposure to robots in all industries (π)	3.904*** (0.738)	4.058*** (0.732)	3.856*** (0.704)	3.538*** (0.602)	3.097*** (0.577)	1.166*** (0.165)
Observations	348	348	348	348	348	344
R^2	0.68	0.70	0.72	0.86	0.73	0.69
	B. Change in Census FTE to total population ratio (1991-2001)					
Instrumented exposure to robots in all industries (β)	-1.292*** (0.184)	-0.879*** (0.243)	-0.724*** (0.228)	-0.457** (0.186)	-0.543 (0.548)	-1.009 (1.407)
First-stage F statistic	*28.0*	*30.7*	*30.0*	*90.8*	*103.3*	*16.7*
Observations	348	348	348	348	348	344
R^2	0.08	0.35	0.41	0.52	0.44	0.48
Covariates & sample restrictions:						
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓	✓
Unweighted					✓	
Removing highly exposed areas						✓

*Notes: Panel A is the first stage. For Panel B, the dependent variable is change in full-time employment to population ratio between 1991-2001. The automation regressor is the instrumented change in exposure to robots in all industries between 1991-2001. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Level controls only are added for instrumented Chinese import exposure and instrumented German import exposure. Construction of these controls is discussed in Chapter Four. All regressions (except Column 5) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. Coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

The second stage for the 2SLS specification for Table 5a can be expressed as:

$$\frac{L^{UK}_{c,2001}}{P^{UK}_{c,2001}} - \frac{L^{UK}_{c,1991}}{P^{UK}_{c,1991}} = \beta\hat{\pi}\sum_{i\in I}\ell^{1981}_{ci}\left(p_{10}\left(\frac{R_{i,2001}}{L_{i,1991}}\right) - p_{10}\left(\frac{R_{i,1993}}{L_{i,1991}}\right)\right) + \mathit{\Gamma} X_{c,91} + \mathit{\Omega}\Delta Y_{c,01-91} + \varepsilon_c$$

Table 5b: Transportation manufacturing automation on employment (1991-2001)

	STACK 1 ESTIMATES USING 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. First-stage for exposure to robots in the UK from 1993 to 2001					
Exposure to robots in transportation manufacturing (π)	22.134*** (0.625)	22.033*** (0.627)	21.930*** (0.634)	23.522*** (0.475)	22.576*** (0.870)	21.573*** (2.884)
Observations	348	348	348	348	348	344
R^2	0.97	0.97	0.97	0.96	0.89	0.75
	B. Change in Census FTE to total population ratio (1991-2001)					
Inst. exposure to robots in transportation manufacturing (β)	-1.024*** (0.086)	-0.650*** (0.116)	-0.403*** (0.144)	-0.502*** (0.150)	-0.891** (0.433)	-0.832 (1.001)
First-stage F statistic	*1,255.0*	*1,235.3*	*1,194.9*	*1,619.4*	*166.2*	*174.9*
Observations	348	348	348	348	348	344
R^2	0.08	0.35	0.42	0.52	0.44	0.48
Covariates & sample restrictions:						
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓	✓
Unweighted					✓	
Removing highly exposed areas						✓

*Notes: Panel A is the first stage. For Panel B, the dependent variable is change in full-time employment to population ratio between 1991-2001. The automation regressor is the instrumented change in exposure to robots in the transportation manufacturing industry between 1991-2001. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Level controls only are added for instrumented Chinese import exposure and instrumented German import exposure. Construction of these controls is discussed in Chapter Four. All regressions (except Column 5) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. Coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Letting T denote the transportation manufacturing industry, the second stage for the 2SLS specification for Table 5b can be expressed as:

$$\frac{L^{UK}_{c,2001}}{P^{UK}_{c,2001}} - \frac{L^{UK}_{c,1991}}{P^{UK}_{c,1991}} = \beta\hat{\pi}\ell^{1981}_{cT}\left(p_{10}\left(\frac{R_{T,2001}}{L_{T,1991}}\right) - p_{10}\left(\frac{R_{T,1993}}{L_{T,1991}}\right)\right) + \Gamma X_{c,91} + \Omega\Delta Y_{c,01-91} + \varepsilon_c$$

Table 5c: Impact on manufacturing employment only (1991-2001)

	MANUFACTURING EMPLOYMENT STACK 1 ESTIMATES USING 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. First-stage for exposure to robots in the UK from 1993 to 2001					
Exposure to robots in transportation manufacturing (π)	22.134*** (0.625)	22.033*** (0.627)	21.950*** (0.646)	23.446*** (0.459)	22.330*** (0.954)	20.960*** (2.776)
Observations	348	348	348	348	348	344
R^2	0.97	0.97	0.97	0.96	0.90	0.76
	B. Change in manufacturing employment to total population ratio (1991-2001)					
Inst. exposure to robots in transportation manufacturing (β)	-1.295*** (0.172)	-1.004*** (0.260)	-0.240* (0.130)	-0.595** (0.259)	-1.371** (0.666)	-2.992** (1.387)
First-stage F statistic	*1,255.0*	*1,235.3*	*1,153.6*	*2,210.2*	*145.1*	*162.4*
Observations	348	348	348	348	348	344
R^2	0.09	0.22	0.54	0.63	0.58	0.60
Covariates & sample restrictions:						
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓	✓
Unweighted					✓	
Removing highly exposed areas						✓

*Notes: Panel A is the first stage. For Panel B, the dependent variable is change in the total manufacturing employment to population ratio between 1991-2001. The automation regressor is the instrumented change in exposure to robots in the transportation manufacturing industry between 1991-2001. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); share of employment in construction; offshoring; and routinisation. Level controls only are added for: share of employment in manufacturing; share of female employment in manufacturing; instrumented Chinese import exposure; and instrumented German import exposure. Construction of these controls is discussed in Chapter Four. All regressions (except Column 5) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Letting T denote the transportation manufacturing industry and M denote all manufacturing industries, the second stage for Table 5c can be expressed as:

$$\frac{L^{UK,TOT}_{M,c,2001}}{P^{UK}_{c,2001}} - \frac{L^{UK,TOT}_{M,c,1991}}{P^{UK}_{c,1991}} = \beta\hat{\pi}\ell^{1981}_{cT}\left(p_{10}\left(\frac{R_{T,2001}}{L_{T,1991}}\right) - p_{10}\left(\frac{R_{T,1993}}{L_{T,1991}}\right)\right) + \Gamma X_{c,91} + \Omega\Delta Y_{c,01-91} + \varepsilon_c$$

Table 5c focuses on the impact of automation within the manufacturing sector. To do this, the dependent variable used is the change in the manufacturing employment to total population ratio. For this specification, the exclusion restriction needs to be considered for the industry share controls. As we are considering the change in manufacturing employment as a share of the total population, the addition of difference controls for the share of manufacturing employment and the share of female employment in manufacturing are unlikely to yield beneficial insights. Intuitively, this is equivalent to explaining the change in manufacturing employment with the change in manufacturing employment.[28] Due to this, these difference controls are dropped. Nonetheless, level controls for the share of manufacturing employment and share of female employment in manufacturing are retained.

The coefficient of interest in Table 5c is -0.595 and this is slightly larger than the results in Tables 5a and 5b. This intuitively suggests that automation in transportation manufacturing leads to larger job losses in the manufacturing sector. The lower coefficient in Table 5b potentially reflects positive spillovers from individuals switching industries and taking up jobs in other sectors upon losing manufacturing jobs. Nonetheless, due to the size of the standard errors, we cannot reject the hypothesis that the impact of automation on employment in the manufacturing sector and the impact of automation on employment in the whole economy were the same between 1991-2001. Also, the conclusion that there is an offsetting effect is not robust to the breadth of the employment definition (Appendix A.1).

Additional robustness checks are conducted in Columns 5 and 6 of Tables 5a-5c. Column 5 considers the full empirical specification but no longer weights the regression by the working-age population. In this case, the result remains negative and statistically significant when using automation in transportation manufacturing, but not automation in all industries. Column 6 removes local authorities in the top percentile of robot exposure (see Figure 7). The resulting coefficients are negative but no longer significant in Tables 5a and 5b. The standard error also widens in Table 5c. This result is partially by construction, as the local authorities in the top 1% for exposure to robots had higher proportions of transportation manufacturing employment in 1981 and 1991.[29]

Further robustness checks are carried out, taking a cue from the literature on model selection. The Akaike Information Criteria (AIC) is calculated for a set of models and the AIC results compared. The AIC calculations are run on the reduced form likelihood. This

[28]This intuition is supported by a regression of the manufacturing dependent variable on the difference control for the manufacturing share of employment only (with no constant). The resulting coefficient is highly significant, the regression has an R^2 of 0.97 and intuitively has told us nothing about what has caused the change in manufacturing employment.

[29]Birmingham, Coventry, Derby and South Gloucestershire.

means that when endogenous covariates are considered (import exposure), the likelihood is calculated using instruments.[30] The AIC comparisons are in Table 6.

Table 6: Summary of AIC results for different models (1991-2001)

Model	df	AIC	AIC_c	$\Delta AIC_c = AIC_c - AIC_{c(min)}$
lm0	3	-2,123.96	-2,123.89	173.67
lm1	12	-2,140.19	-2,139.26	158.30
lm2	18	-2,223.83	-2,221.75	75.81
lm3	24	-2,239.16	-2,235.44	62.12
lm4	26	-2,272.50	-2,268.12	29.44
lm5	28	-2,300.88	-2,295.79	1.77
lm6	29	-2,302.32	-2,296.85	0.71
lm7	**30**	**-2,303.43**	**-2,297.56**	**0.00**
lm8	185	-2,303.76	-1,878.94	418.62

Notes: df denotes degrees of freedom. Each model nests all preceding models, except for lm8, and all controls are added as levels and differences except for import exposure covariates (defined as differences). lm0 only includes the regressor for automation in transportation manufacturing, lm1 includes dummies for all standard regions in England and a dummy for Wales, lm2 includes demographic controls, lm3 includes industry controls, lm4 includes routinisation controls, lm5 includes offshoring controls, lm6 includes a trade control for China, and lm7 includes a trade control for Germany. lm8 uses a different approach and includes interactions between the controls (levels and differences) with the dummies for the standard regions and Wales. In this sense, lm8 allows for the impact of the controls to vary across regions.

The AIC values are negative, but this is not an issue as it is not the absolute size of the AIC values that we are interested in for model selection. Our focus is on the relative AIC values over the set of models considered (Burnham and Anderson, 2002).[31] A finite sample adjustment is also considered (AIC_c) which accounts for the bias that may occur due to the size of the finite sample (Burnham and Anderson, 2002). The model with the lowest finite sample adjusted AIC is equivalent to the preferred specification in Tables 5a-5c (Column 4) plus dummies for Wales and England standard regions.

Furthermore, LASSO is used with a larger set of covariates. The starting set of covariates includes: dummies for all standard regions in England and for Wales; and interactions between the dummies with the reduced form controls in levels and differences. λ is chosen via cross validation, covariates that are statistically significant for the dependent variable are identified, and 2SLS is run on the set of identified covariates. The 2SLS estimates from the bias-adjusted AIC methodology and LASSO are in Table 7. The main result is unchanged after considering these model selection methods.

[30] Transportation manufacturing automation regressor is forced based on Chapter Three theory and Chapter Six results.

[31] Intuitively, a negative AIC is perfectly plausible: $AIC = 2(K - \ln(Likelihood))$ where K denotes degrees of freedom.

Table 7: 2SLS results using AIC and LASSO (1991-2001)

	2SLS estimates of impact of change in automation in transportation manufacturing on change in full-time employment to population ratio between 1991-2001	
	AIC (1)	LASSO (2)
(Δ Robots in UK transportation manufacturing industry)/worker	-0.730*** (0.136)	-0.599** (0.236)
Number of observations	348	348
R^2	0.56	0.61
First-stage analysis		
(Δ Robots in EUR transportation manufacturing industry)/worker	23.042*** 0.969	21.329*** 0.980
F-statistic	1,629.1	696.5

*Notes: Specification (1) shows the 2SLS estimate for the transportation manufacturing automation coefficient when using lm7 from Table 6 (i.e. the specification that minimises the bias-adjusted AIC). Specification (2) shows the 2SLS estimate when using the variables that were selected from running LASSO (selecting λ by cross validation). The regressions are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

6.2 Alternative Empirical Specifications and Wage Results

The main specification used full-time employment to construct the dependent variable and automation regressors. One concern is that industry employment figures are only available for total employment (including part-time and self-employed workers) and, therefore, there may be a mismatch. Therefore, separate regressions are run using only total employment figures (including part-time and self-employed) to construct all variables. The results are in Appendix A.1 and the main result is unchanged.

Appendix A.2 contains the results for automation and wages. As noted, the wage data is limited due to public ASHE data only starting from 1997 and not being available for all local authorities. Median wages are considered (hourly and weekly) and no robust relationship is determined. Although, more comprehensive data would be required to confirm this conclusion. As a result, the remaining analysis focuses on employment.

One notable observation from considering different wage percentiles is that there is some evidence of a negative relationship between automation and wages at the 25th percentile, although this effect dissipates with the addition of controls. This suggests that automation may impact lower income earners and merits further investigation due to the theoretical relationship between automation and inequality. The generalised version of the model in this thesis (Chapter Three) predicts that inequality increases during transitions, driven by faster automation and the creation of new tasks (Acemoglu and Restrepo, 2016a).

6.3 Local Interpretation of Results

The 2SLS results allow for a straightforward understanding of the quantitative implications for employment in an autarky setting: the local interpretation. Local refers to the difference between a local authority with high exposure to robots and a local authority with low exposure to robots. Column 4 of Table 5a implies that, between 1991 and 2001, one more robot per thousand workers (in a local authority with exposure to robots equal to the UK average) reduced the employment to population ratio by 0.457 percentage points relative to a local authority with no exposure to robots. Column 4 of Table 5b implies that, between 1991 and 2001, one more robot per thousand workers in the transportation manufacturing industry (in a local authority with exposure to robots equal to the UK average) reduced the employment to population ratio by 0.502 percentage points relative to a local authority with no exposure to robots.

6.4 Aggregate Interpretation of Results

If we assume local authorities are unable to trade, then the local interpretation is equivalent to the aggregate. This would mean one more robot per thousand workers reduced the aggregate employment to population ratio by 0.457%. This is, of course, not reflective of our reality where local authorities trade regularly. As such, assumptions need to be made about structural parameters to account for interactions. As discussed in Section 3.3, if we assume M_i (the number of tasks robots can do) is close to 0 and $\pi_c \approx \pi$ for all local authorities, the automation coefficient can be written as:

$$\beta_c^L \approx \left(\frac{1+\eta}{1+\varepsilon} (s_{cL}\lambda + (1 - s_{cL})\sigma)\pi_c - \frac{1+\eta}{1+\varepsilon} \frac{s_{cL}\lambda + 1 - s_{cL}}{s_{cL}} \right) \frac{v_c}{\gamma}$$

Where $v_c = \frac{(1+\varepsilon)s_{cL}}{(1+\varepsilon)s_{cL}\lambda + (1+\eta)(1-s_{cL})}$

Therefore, the structural macro parameters required to estimate this are: the Frisch elasticity of labour supply ($1/\varepsilon$); the trade elasticities (σ and λ); the cost saving gains from using robots (π); and the elasticity of local supply of robots ($1/\eta$). The physical productivity of labour relative to robots (γ) can then be backed out using coefficient estimates.[32] In Acemoglu and Restrepo (2017), the elasticity of local supply of robots is also estimated using comprehensive US wage data. Due to data availability, the empirical approach pursued in this thesis is limited to employment outcomes. As such, the elasticity of supply of robots is from Acemoglu and Restrepo (2017) and this thesis assumes that $\eta = 1.5$, in line with the US. This is a reasonable assumption given that industrial robot suppliers are likely to have similar production and sales constraints for the UK and the US.

The relevant literature relating to the elasticity of labour supply ($1/\varepsilon$) for the UK is from Card (1994) and Faccini et al. (2011). Faccini et al. observe that the posterior mean of the inverse of the Frisch elasticity of labour supply is estimated to be equal to 1.6. This is in line with microeconomic estimates as surveyed by Card (1994). Therefore, the inverse of 1.64 is c. 0.61. The estimate for the cost saving gains from using robots rather than labour in a task is taken from a BCG report (2015) which was used in Acemoglu and Restrepo (2017). BCG estimate that adopting robots increases profits by about 30% relative to using labour. In line with this, it is assumed that $\pi = 0.3$.

The trade elasticity of substitution between industries is subject to debate. UK firm-level evidence from Barnes et al. (2008) estimates the elasticity of substitution between capital and labour is c. 0.4. Yet some researchers believe that the elasticity is around unity (the value in the Cobb-Douglas production function).[33] To align with the model assumptions in Chapter Three, we assume $\sigma = 1$. The elasticity of substitution between traded varieties (the Armington elasticity) is taken from Simonovska and Waugh (2014) and is estimated to be $\lambda = 6$ for the UK. The share of labour in total output is assumed to be in line with the US standard assumption, such that $s_{cL} = 0.66$.

Using these estimates and the expression for β_c^L, we can back out the physical productivity of labour relative to robots (γ). From Table 5a, the coefficient of interest is -0.457 which implies γ is approximately 261. This suggests that one industrial robot performs work equivalent to $1{,}000/\gamma = 3.8$ workers. This is below the estimate of the productivity

[32] An alternative approach would involve assuming the value of γ and backing out estimates of π or η. The approach here is to estimate γ as it is of greater economic interest to determine the relative productivity of humans relative to robots in a UK context.

[33] There is no meaningful difference to the estimate of γ when using $\sigma = 0.4$ or $\sigma = 1$.

rate of robots in the US, where it is estimated that one robot performs work equivalent to 6.5 workers (Acemoglu and Restrepo, 2017). A potential reason for the higher productivity of humans relative to robots in the UK may be due to the limited adoption of robots in the UK and, hence, the limited role that they play in production processes. Between 1993-2001, the UK industrial robot stock increased by 5,935 robots. Over the same period, the US industrial robot stock increased by 53,803 robots.[34]

As we are interested in the equilibrium impact on employment, the heavily automated sectors are of greater interest. As such, we are interested in the impact of automation in the transportation manufacturing industry, as this is the most heavily automated industry. If we focus on robots in the transportation manufacturing industry, we derive a slightly higher estimate of job losses. From Table 5b, the coefficient of interest is -0.502 which implies γ is 238. This suggests that one robot in the transportation manufacturing industry performed the work of $1{,}000/\gamma = 4.2$ workers between 1991-2001; automation had a greater impact in the industry in which it was being more heavily adopted.

If we assume all job losses incurred by automation in transportation manufacturing were concentrated within the manufacturing sector, then we can separate the impact on the manufacturing sector from the impact on aggregate employment using Table 5c. In Table 5c, the coefficient of interest is -0.595. This implies γ is 201, suggesting one robot in the transportation manufacturing industry performed work equivalent to $1{,}000/\gamma = 5.0$ workers in the manufacturing sector between 1991-2001. This is 0.8 workers greater than the effect on aggregate employment, suggesting that, for every five workers who lost their jobs in the manufacturing sector due to a robot in the transportation manufacturing industry, just under one reintegrated into the broader economy between 1991-2001.[35]

The main result can also be stated in terms of total jobs. If we use the result that one robot in the transportation manufacturing industry was equivalent to 4.2 workers between 1991-2001 and combine this with the observation that there was an increase of 5,087 transportation manufacturing robots over the period, then the total number of jobs lost due to robots in the transportation manufacturing industry is estimated to be 21,000.

[34]The industrial robot stock of Germany rose by 57,780 over the same period.

[35]As noted, this conclusion is not robust to the breadth of the employment definition (Appendix A.1). Using total employment, the coefficient for manufacturing sector employment is closer to, and slightly smaller than, the coefficient using employment in all industries.

7. Disentangling the Impact of Trade

7.1 The Role of Trade

While addressing the impact of trade on UK employment is beyond the scope of this thesis, the availability of IFR data provides an opportunity for the analysis to be extended to quantitatively understand another prominent issue: how the impact of automation differs from the impact of trade. As noted in the Introduction, there is a debate surrounding the respective impacts of trade and automation on manufacturing employment. Some argue that increasing trade liberalisation has pressured employees in import-competing industries, thus it is important to understand how the impact on industries affected by trade differs from industries impacted by automation.

The impact of Chinese imports on UK employment has been considered previously (Bilici, 2016), where it was found that, although there was some evidence of a negative effect of Chinese imports on UK employment between 1998-2013, the effect was not robust to the addition of various controls.[36] This thesis confirms the conclusion of Bilici (2016) for 2001-2011 and considers three further areas of interest in relation to UK trade: the impact of trade using an earlier period (starting from 1991); an explicit consideration of other large UK trading partners (Germany and the Netherlands); and the inclusion of an automation control as a robustness check for trade results.

Between 1993 and 2011, the total value of imports reported by the UK increased from $US196 billion to $US718 billion, whereas the value of exports increased from $US167 billion to $US517 billion.[37] This means that net imports[38] for the UK increased from $US28 billion in 1993 to $US200 billion in 2011 (see Figure 8). In the trade literature, the primary country of empirical interest when it comes to understanding the impact of imports has been China. As explored by Autor et al. (2013), there is a clear and persistent impact of Chinese imports on US manufacturing employment.

[36]Bilici (2016) uses Travel to Work Areas as the unit of analysis. Consistent with the automation analysis, this Chapter uses local authorities due to data availability.

[37]All trade values are from UN Comtrade and are in current dollar values.

[38]Defined as imports minus exports.

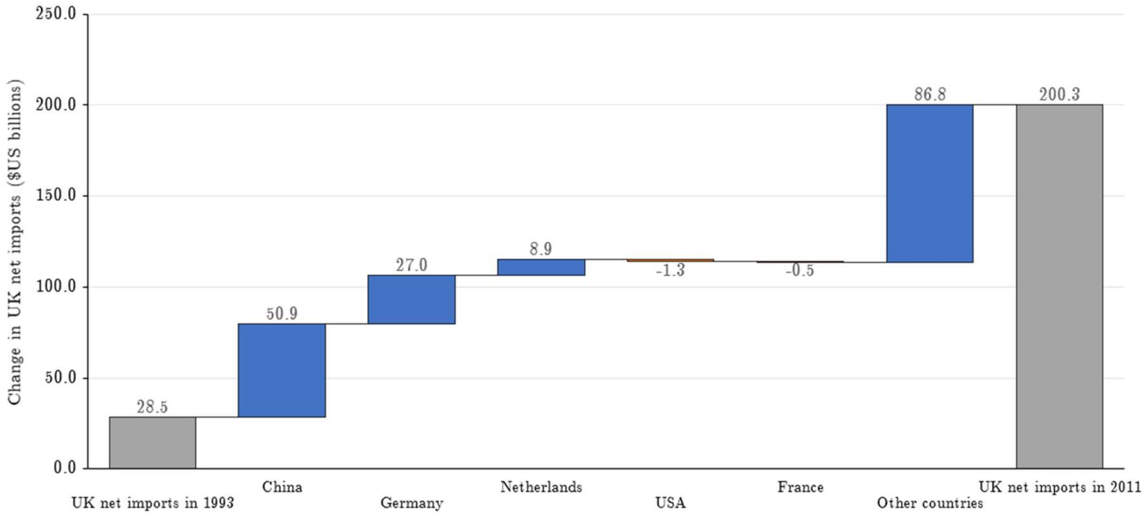

Figure 8: Evolution of UK net imports (1993-2011)

Note: Data from UN Comtrade.

China is also of interest from a UK perspective. Between 1991 and 2011, the value of UK net imports from China increased from $1 billion to $52 billion. China represented 26% of net imports in 2011. A cocktail of factors combined to increase Chinese exports so drastically: China transitioning to a market-oriented economy through a rural-to-urban migration policy for over 150 million workers (Chen et al., 2010); China gaining access to previously banned foreign technologies (Hsieh and Klenow, 2009); and China creating special economic zones allowing foreign companies to set up factories that imported inputs and exported final outputs (Yu M, 2012). These factors were compounded by the accession of China to the World Trade Organization (WTO) in 2001, which gave China most-favoured nation status amongst WTO members. Following the result for automation in the transportation manufacturing industry, this Chapter disentangles the impact of Chinese imports over the same period.

7.2 UK Trading Partners

The importance of China for this analysis cannot be understated. China accounted for 30% of the increase in net imports for the UK between 1993-2011. Yet, other countries have also increased their trading volume with the UK. Between 1993 and 2011, net imports from Germany rose from $US7 billion to $US34 billion. As such, Germany represented 16% of the increase in UK net imports. Similarly, UK net imports from the Netherlands rose from $US1 billion to $US10 billion, representing 5% of the increase in net imports. In total, China, Germany and the Netherlands accounted for 51% of the increase in UK net imports between 1991-2011. Other large trading partners, such as France and the US, saw a reduction in UK net imports over this period (see Figure 8).

The methodology for constructing the import exposure covariates is described in Chapter Four. To determine if there is heterogeneity in the effect across countries, Tables 8a-8c consider the stacked analysis between 1991-2011 for China, Germany and the Netherlands individually.[39] Due to the endogeneity concerns described in Chapter Four, we focus on the 2SLS estimates.

Table 8a shows Chinese import exposure is negative in the second stack (between 2001 and 2011) but not statistically significant. This is consistent with Bilici (2016). More interestingly, and more relevant to this thesis, there is evidence of a negative impact on employment between 1991-2001 for China in Table 8a and Germany in Table 8b. There is also evidence of significance for the Netherlands in in the first stack in Table 8c. 2SLS estimates for the second stack (between 2001-2011) are not significant for any of the three countries. Therefore, the next step is to focus on 1991-2001.

Table 8a: Stacked differences for Chinese trade (1991-2011)

	Stacked differences estimates of impact of Chinese import exposure on change in full-time employment to population ratio between 1991-2011					
	OLS Estimates (β)			2SLS Estimates (β)		
	1991-2001 (1)	2001-2011 (2)	1991-2011 (3)	1991-2001 (1)	2001-2011 (2)	1991-2011 (3)
(Δ UK imports from China)/worker	-0.356** (0.153)	-0.005 (0.006)	0.004 (0.002)	-0.545*** (0.148)	-0.007 (0.012)	-0.005 (0.008)
Number of observations	348	348	696	348	348	696
First-stage analysis (included where applicable)						
(Δ OTH imports from China)/worker				0.216*** (0.021)	1.307*** (0.184)	1.547*** (0.218)
F-statistic				102.0	50.3	50.2

*Notes: Dependent variable for all specifications is change in full-time employment to population ratio for the relevant period. For OLS, regressor is change in Chinese import exposure for each local authority; and for 2SLS, regressor is instrumented Chinese import exposure for each local authority. All specifications include stack controls for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); industry shares (shares of employment in: manufacturing; construction; and female employment in manufacturing); offshoring; and routinisation. Specification (3) includes a time dummy. All regressions are weighted by working-age population at the start of the period. Robust standard errors are clustered at standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

[39]For Tables 8a-8c, transportation manufacturing automation is excluded as a control to determine if there is evidence of an effect independent of automation.

Table 8b: Stacked differences for German trade (1991-2011)

	Stacked differences estimates of impact of German import exposure on change in full-time employment to population ratio between 1991-2011					
	OLS Estimates (β)			2SLS Estimates (β)		
	1991-2001 (1)	2001-2011 (2)	1991-2011 (3)	1991-2001 (1)	2001-2011 (2)	1991-2011 (3)
(Δ UK imports from Germany)/worker	-0.110 (0.121)	0.006* (0.003)	0.006** (0.002)	-0.266*** (0.099)	0.007 (0.006)	0.005 (0.006)
Number of observations	348	348	696	348	348	696
First-stage analysis (included where applicable)						
(Δ OTH imports from Germany)/worker				0.668*** (0.055)	3.099*** (0.604)	3.413*** (0.472)
F-statistic				145.6	26.3	52.3

*Notes: Dependent variable for all specifications is change in full-time employment to population ratio for the relevant period. For OLS, regressor is change in German import exposure for each local authority; and for 2SLS, regressor is instrumented German import exposure for each local authority. All specifications include stack controls for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); industry shares (shares of employment in: manufacturing; construction; and female employment in manufacturing); offshoring; and routinisation. Specification (3) includes a time dummy. All regressions are weighted by working-age population at the start of the period. Robust standard errors are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Table 8c: Stacked differences for Dutch trade (1991-2011)

	Stacked differences estimates of impact of Dutch import exposure on change in full-time employment to population ratio between 1991-2011					
	OLS Estimates (β)			2SLS Estimates (β)		
	1991-2001 (1)	2001-2011 (2)	1991-2011 (3)	1991-2001 (1)	2001-2011 (2)	1991-2011 (3)
(Δ UK imports from Netherlands)/worker	-0.425* (0.203)	0.019*** (0.005)	0.026*** (0.005)	-0.325* (0.197)	-0.005 (0.024)	0.009 (0.021)
Number of observations	348	348	696	348	348	696
First-stage analysis (included where applicable)						
(Δ OTH imports from Netherlands)/worker				0.987*** (0.050)	3.952** (1.452)	4.480*** (0.876)
F-statistic				392.6	7.4	26.2

*Notes: Dependent variable for all specifications is change in full-time employment to population ratio for the relevant period. For OLS, regressor is change in Dutch import exposure for each local authority; and for 2SLS, regressor is instrumented Dutch import exposure for each local authority. All specifications include stack controls for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); industry shares (shares of employment in: manufacturing; construction; and female employment in manufacturing); offshoring; and routinisation. Specification (3) includes a time dummy. All regressions are weighted by working-age population at the start of the period. Robust standard errors are clustered at standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Table 9a: Chinese imports on employment, including Netherlands (1991-2001)

	STACK 1 ESTIMATES USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to Chinese imports in the UK from 1993 to 2001						
Exposure to Chinese imports (π)	0.289*** (0.020)	0.284*** (0.021)	0.222*** (0.019)	0.215*** (0.020)	0.167*** (0.014)	0.140*** (0.013)	0.178*** (0.011)
Observations	348	348	348	348	348	348	344
R^2	0.69	0.74	0.80	0.81	0.88	0.83	0.91
	B. Change in Census FTE to total population ratio (1991-2001)						
Instrumented exposure to Chinese imports (β)	-0.563*** (0.116)	-0.512*** (0.112)	-0.661*** (0.201)	-0.588*** (0.141)	-1.690*** (0.265)	-1.287*** (0.226)	-1.804*** (0.313)
First-stage F statistic	*209.6*	*184.0*	*136.0*	*62.1*	*33.3*	*108.0*	*732.2*
Observations	348	348	348	348	348	348	344
R^2	0.04	0.37	0.43	0.52	0.45	0.39	0.45
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
German and Dutch trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Panel A shows the first stage for the Chinese trade instrument. Panel B shows the coefficients from regressing instrumented Chinese import exposure on the change in full-time employment to population ratio between 1991-2001. Level and difference controls are added for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Instrumented level controls are added for: automation in the transportation manufacturing industry; German import exposure; and Dutch import exposure. The construction of these covariates is discussed in Chapter Four. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. Coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Tables 9a-9c focus on the results for 1991-2001 for China, Germany and the Netherlands. In the preferred specification of Table 9a (Column 4), which includes a control for transportation manufacturing automation, there is evidence of a negative effect of Chinese imports on employment in England and Wales between 1991-2001. This effect is robust to additional checks, including: the addition of other trading partners; not weighting the regression; and removing the local authorities in the top percentile of Chinese import exposure. As such, further analysis is conducted for China. Also, the inclusion of the instrumented Chinese import exposure covariate in the automation analysis in Chapter Six is justified by these results.

Table 9b: German imports on employment, including Netherlands (1991-2001)

	STACK 1 ESTIMATES USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to German imports in the UK from 1993 to 2001						
Exposure to German imports (π)	0.732*** (0.048)	0.741*** (0.058)	0.679*** (0.056)	0.576*** (0.045)	0.790*** (0.081)	0.692*** (0.133)	0.669*** (0.096)
Observations	348	348	348	348	348	348	344
R^2	0.70	0.72	0.75	0.82	0.77	0.87	0.79
	B. Change in Census FTE to total population ratio (1991-2001)						
Instrumented exposure to German imports (β)	-0.465*** (0.126)	-0.375*** (0.081)	-0.297** (0.138)	-0.268*** (0.091)	-0.728*** (0.204)	-0.643** (0.263)	-1.177*** (0.396)
First-stage F statistic	*234.3*	*164.6*	*145.4*	*92.3*	*110.3*	*878.3*	*106.6*
Observations	348	348	348	348	348	348	344
R^2	0.02	0.35	0.40	0.50	0.45	0.39	0.41
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
Chinese and Dutch trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Panel A shows the first stage for the German trade instrument. Panel B shows the coefficients from regressing instrumented German import exposure on the change in full-time employment to population ratio between 1991-2001. Level and difference controls are added for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Instrumented level controls are added for: automation in the transportation manufacturing industry; Chinese import exposure; and Dutch import exposure. Construction of these covariates is discussed in Chapter Four. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. Coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Table 9b explores the negative effect of German imports on employment in England and Wales observed in the first stack. The effect is persistently negative. For completeness, therefore, and to account for the possibility of a confounding trend due to German imports, further analysis is conducted for Germany. Also, this supports the inclusion of the instrumented covariate for German imports in the automation analysis.[40]

From Tables 9a and 9b, it can be seen that the coefficients on the trade covariates widen in the presence of other trade controls, suggesting multicollinearity. This becomes much more evident in Table 9c as the coefficient for Dutch import exposure changes from negative to positive when adding the Chinese and German covariates.

[40]Exclusion of German import exposure covariate does not change the main automation result.

Table 9c: Dutch imports on employment (1991-2001)

	STACK 1 ESTIMATES USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to Dutch imports in the UK from 1993 to 2001						
Exposure to Dutch imports (π)	1.161*** (0.050)	1.121*** (0.058)	1.023*** (0.047)	0.988*** (0.046)	0.642*** (0.075)	0.555*** (0.092)	0.662*** (0.081)
Observations	348	348	348	348	348	348	344
R^2	0.68	0.72	0.79	0.81	0.89	0.94	0.89
	B. Change in Census FTE to total population ratio (1991-2001)						
Instrumented exposure to Dutch imports (β)	-0.647** (0.266)	-0.644*** (0.234)	-0.519* (0.289)	-0.256* (0.155)	2.622*** (0.414)	2.189*** (0.555)	2.536*** (0.426)
First-stage F statistic	*545.9*	*378.5*	*474.3*	*194.7*	*360.0*	*602.0*	*726.6*
Observations	348	348	348	348	348	348	344
R^2	0.03	0.37	0.43	0.52	0.45	0.39	0.44
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
Chinese and German trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Panel A shows the first stage for the Dutch trade instrument. Panel B shows the coefficients from regressing instrumented Dutch import exposure on the change in full-time employment to population ratio between 1991-2001. Level and difference controls are added for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Instrumented level controls are added for: automation in the transportation manufacturing industry; Chinese import exposure; and German import exposure. Construction of these covariates is discussed in Chapter Four. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. Coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Exploring the multicollinearity formally, it is found that there is a large correlation between UK exposure to Dutch imports and UK exposure to Chinese and German imports (c. 0.85). Also, the Variance Inflation Factor (VIF) for Dutch import exposure is estimated to be 5.7. When considering the instruments, the issue worsens and the instrument for Dutch import exposure has higher correlations with the Chinese and German instruments (c. 0.95) and a VIF of 12.9. This exceeds the rule of thumb that the VIF not exceed 5 to avoid multicollinearity (O'Brien, 2007). As such, the Dutch import exposure covariate is excluded from analysis. For completeness, it is noted that the decision to exclude the Dutch covariate has been considered holistically. Further reasons for exclusion include: the change in coefficients when considering Germany, China and the Netherlands simultaneously; and the relatively lower contribution of the Netherlands to UK net imports (see Figure 8).

7.3 Results for Employment

As noted, due to the limitations of wage data, this thesis focuses on employment and a detailed analysis is carried out for Chinese and German imports. The previous automation regressions are run from a trade-first perspective. Tables 10a and 10b contain the results.

Table 10a: Chinese imports on employment, excluding Netherlands (1991-2001)

	STACK 1 ESTIMATES USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to Chinese imports in the UK from 1993 to 2001						
Exposure to Chinese imports (π)	0.289*** (0.020)	0.284*** (0.021)	0.222*** (0.019)	0.215*** (0.020)	0.199*** (0.019)	0.138*** (0.010)	0.225*** (0.009)
Observations	348	348	348	348	348	348	344
R^2	0.69	0.74	0.80	0.81	0.82	0.83	0.85
	B. Change in Census FTE to total population ratio (1991-2001)						
Instrumented exposure to Chinese imports (β)	-0.563*** (0.116)	-0.512*** (0.112)	-0.661*** (0.201)	-0.588*** (0.141)	-0.618*** (0.161)	-0.376** (0.170)	-0.795*** (0.236)
First-stage F statistic	*209.6*	*184.0*	*136.0*	*62.1*	*45.8*	*70.1*	*271.3*
Observations	348	348	348	348	348	348	344
R^2	0.04	0.37	0.43	0.52	0.52	0.44	0.51
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
German trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Panel A shows the first stage for the Chinese trade instrument. Panel B shows the coefficients from regressing instrumented Chinese import exposure on the change in full-time employment to population ratio between 1991-2001. Level and difference controls are added for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Instrumented level controls are added for: automation in the transportation manufacturing industry; and German import exposure. The construction of these covariates is discussed in Chapter Four. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Table 10a shows that, between 1991-2001, Chinese import exposure had a negative and significant impact on employment. The result is robust to: including German import exposure; unweighting; and removing areas with higher exposure to Chinese imports. Column 5 of Table 10a has the same specification as Column 4 of Table 5b, where the main automation result is determined. As automation and Chinese imports remain significant in the presence of each other, this suggests they are quantitatively different phenomena.

Table 10b: German imports on employment, excluding Netherlands (1991-2001)

	STACK 1 ESTIMATES USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to German imports in the UK from 1993 to 2001						
Exposure to German imports (π)	0.732***	0.741***	0.679***	0.576***	0.706***	0.703***	0.598***
	(0.048)	(0.058)	(0.056)	(0.045)	(0.074)	(0.097)	(0.058)
Observations	348	348	348	348	348	348	344
R^2	0.70	0.72	0.75	0.82	0.79	0.87	0.81
	B. Change in Census FTE to total population ratio (1991-2001)						
Instrumented exposure to German imports (β)	-0.465***	-0.375***	-0.297**	-0.268***	0.051	0.130	-0.009
	(0.126)	(0.081)	(0.138)	(0.091)	(0.090)	(0.111)	(0.137)
First-stage F statistic	*234.3*	*164.6*	*145.4*	*92.3*	*78.9*	*884.2*	*123.2*
Observations	348	348	348	348	348	348	344
R^2	0.02	0.35	0.40	0.50	0.52	0.44	0.52
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
Chinese trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Panel A shows the first stage for the German trade instrument. Panel B shows the coefficients from regressing instrumented German import exposure on the change in full-time employment to population ratio between 1991-2001. Level and difference controls are added for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Instrumented level controls are added for: automation in the transportation manufacturing industry; and Chinese import exposure. The construction of these covariates is discussed in Chapter Four. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Table 10b shows that the addition of further controls results in a dissipation of the impact of German import exposure on employment. Notably, the addition of the Chinese import exposure variable results in the impact of German import exposure losing statistical significance. Once again, Column 5 of Table 10b has the same specification as Column 4 of Table 5b, where the main automation result is determined. Despite not being statistically significant, the German import exposure variable is included in the automation empirical specification for completeness. The decision to include the German import exposure covariate is also supported by the AIC minimisation carried out in Chapter Six, as the empirical specification with the lowest bias-adjusted AIC includes German import exposure.

Table 11: Chinese imports on manufacturing employment (1991-2001)

	STACK 1 ESTIMATES FOR MANUFACTURING EMPLOYMENT USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to Chinese imports in the UK from 1993 to 2001						
Exposure to Chinese imports (π)	0.289*** (0.020)	0.284*** (0.021)	0.219*** (0.019)	0.212*** (0.019)	0.195*** (0.018)	0.137*** (0.010)	0.218*** (0.009)
Observations	348	348	348	348	348	348	344
R^2	0.69	0.74	0.80	0.81	0.82	0.83	0.84
	B. Change in manufacturing employment to total population ratio (1991-2001)						
Instrumented exposure to Chinese imports (β)	-1.120*** (0.194)	-1.046*** (0.118)	-0.576*** (0.180)	-0.397** (0.177)	-0.565*** (0.211)	-0.529 (0.347)	-0.605*** (0.232)
First-stage F statistic	*209.6*	*184.0*	*131.5*	*69.5*	*57.4*	*78.8*	*195.9*
Observations	348	348	348	348	348	348	344
R^2	0.15	0.31	0.53	0.63	0.63	0.58	0.61
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
German trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Dependent variable is change in the total manufacturing employment to population ratio between 1991-2001. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); share of employment in construction; offshoring; and routinisation. Level controls only are added for: share of employment in manufacturing; share of female employment in manufacturing; instrumented automation in the transportation manufacturing industry; and instrumented German imports. Construction of these controls is discussed in Chapter Four. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Table 11 contains the main trade result of this thesis. To interpret the result in line with the theoretical framework of Autor, Dorn and Hanson (2013), the dependent variable is changed to the manufacturing employment to population ratio. Column 5 of Table 11 has the same specification as Column 4 of Table 5c. Once again, transportation manufacturing automation and Chinese imports are negative and statistically significant in the presence of each other, suggesting they are quantitatively different phenomena.

7.4 Alternative Empirical Specifications

As with automation, the trade empirical specifications use full-time employment to construct the dependent variables and regressors. For robustness, the same regressions are run with all dependent variables and regressors constructed using total employment figures (including part-time employment and self-employment). These results are in Appendix A.3.

The results are broadly the same when using total employment figures. As with full-time employment, Germany has a negative effect that dissipates with the addition of further controls. China also has a negative and statistically significant effect between 1991-2001 that remains robust to the addition of controls. One difference, however, is that the result for Chinese import exposure is not robust to the regression being unweighted when using total employment variables. This is not seen as taking away from the main conclusion, though, as the weighting accounts for differences in the size of the working-age population across local authorities, allowing the regression to be more representative of the population.

7.5 Interpreting the Results

The coefficient of -0.565 in Column 5 of Table 11 indicates that between 1991-2001, a $1,000 exogenous decadal rise in the Chinese import exposure per worker for a local authority reduced the manufacturing employment to population ratio by 0.57%. To interpret this, Table 12 has the levels and decadal equivalent changes for Chinese import analysis.[41] Table 12 is constructed at a local authority level, where Chinese import exposure per worker in a local authority is calculated by apportioning imports to a local authority according to their share of UK industry employment.

Table 12: Means and standard deviations for interpreting trade results (1991-2011)

	I. Levels			II. 10 Year Equivalent Changes	
	1993 (1)	2001 (2)	2011 (3)	1991-2001 (4)	2001-2011 (5)
(Imports from China to UK) / (workers in 1991) (in kUS$)	0.12 (0.07)	0.99 (0.51)	3.47 (1.77)	1.09 (0.56)	2.48 (1.27)
Percentage of population employed in manufacturing	7.69 (2.80)	6.82 (2.38)	4.28 (1.79)	-0.87 (1.31)	-2.54 (0.87)

Notes: Sample means and standard deviations (in brackets) for the entire sample of local authorities for Chinese imports. All columns are weighted by working-age population in 1991.

As noted, a $1,000 per worker increase in Chinese import exposure over a decade is estimated to reduce the manufacturing employment to population ratio by 0.57%. Column 4 of Table 12 includes the decadal equivalent change in Chinese import exposure for 1993-2001. This shows that Chinese import exposure had a decadal equivalent increase of $1,090 per worker between 1993-2001. We can deduce that Chinese import exposure reduced the

[41] Import data is available from 1993. For comparability, trade growth between 1993-2001 is multiplied by 10/8, in line with Autor et al. (2013).

manufacturing employment to population ratio by 0.61% between 1991-2001. In comparison, the manufacturing employment to population ratio fell by 0.87% between 1991-2001. Simple division suggests trade with China was responsible for 71% of the decline in manufacturing employment. This is very large and possibly overstates the contribution of Chinese imports to the decline in manufacturing jobs.

One way this approach may overstate the impact of Chinese imports is considered in Autor, Dorn and Hanson (2013). In short, the 2SLS estimates may overstate the contribution of Chinese imports as the estimates are intended to measure the causal effect of the Chinese supply shock, but the measure that has been constructed uses total change in Chinese imports per worker which is a combination of supply and demand. If there is a demand-driven component of Chinese imports which has a less negative effect on manufacturing employment than the supply-driven component, then the estimate of 0.61% is likely to be an overstatement.

The approach used to isolate supply shocks is the same as Autor, Dorn and Hanson (2013). This involves using the relationship between the 2SLS and OLS estimates to determine the share of the variance in imports per worker driven by supply forces. The remainder of the variance is assumed to be demand driven. As the IV estimator partitions the variation in UK import exposure into an exogenous component and a residual, it is possible to show that the OLS estimate is a weighted average of the IV estimate (supply-driven) and the residual estimate (demand-driven), with the weights corresponding to the share of the variance explained by each.

Using this calculation implies that 39% of the variation in Chinese import exposure can be attributed to supply. This results in a more conservative estimate. Chinese imports reduced the manufacturing employment to population ratio by 0.24%, explaining 27% of the decline in manufacturing employment between 1991-2001. In this time, manufacturing jobs fell by 654,000 suggesting that Chinese import competition resulted in an estimated loss of 177,000 jobs between 1991-2001. This is notably larger than the 21,000 total job losses as a result of automation in the transportation manufacturing industry.[42]

[42]If we assume all job losses are concentrated in the manufacturing sector, then (using the result from Table 5c) the increase of 5,087 transportation manufacturing robots between 1991-2001 resulted in a loss of c. 25,000 manufacturing jobs.

8. Conclusion

Summary

The UK industrial robot adoption rate lags other advanced economies. Despite this low adoption rate, there is evidence that automation has had a negative impact on employment in years where robot adoption has rapidly increased. The framework pursued in this thesis focused on technology that substitutes for tasks that humans currently carry out. As an increasing number of tasks are automated and industrial robot adoption increases, there will be further risk of displacement for employees.

Using a task-based framework, the main finding of this thesis is that automation had a statistically significant and negative impact on employment across England and Wales between 1991 and 2001, driven by the use of industrial robots in transportation manufacturing. This thesis estimates that the productivity of humans relative to robots over the period was $\gamma = 261$, which is the equivalent of one industrial robot reducing employment by 3.8 workers. If instead the analysis focuses on automation in the transportation manufacturing industry – the most heavily automated industry in the UK – then the relative productivity of humans becomes $\gamma = 238$, implying that one robot in the transportation manufacturing industry reduced employment by 4.2 workers between 1991-2001. There is no evidence of a significant effect of industrial robots on wages, although it is caveated that wage data is limited for the purposes of empirical analysis over the period of economic interest. There is, nonetheless, some evidence of a negative effect on lower percentile earners that warrants further investigation.

Other empirical explanations that could explain a decline in manufacturing are also considered in a UK context, the most important being trade. The rise of China, and the associated increase in Chinese import exposure, is shown to have had a negative and statistically significant impact on employment in England and Wales between 1991 and 2001. The effect of Chinese imports is estimated to have been larger than automation. Chinese imports resulted in an estimated loss of 177,000 manufacturing jobs in the UK between 1991 and 2001, whereas automation in the transportation manufacturing industry resulted in a loss of 21,000 total jobs over the same period (or 25,000 manufacturing jobs if we assume job losses were concentrated in the manufacturing sector). These figures are not implausible and the relative differences in magnitude are reasonable given that the number of industrial robots in the UK has only modestly increased, whereas Chinese import exposure has increased significantly.

The results for trade and automation are robust in the presence of each other, suggesting that they quantitatively differ in the channels through which they impact employment outcomes. Although, it could be argued that there is a meaningful difference between automation and trade from a policymaker perspective. The rise of China is a relatively unique economic event, whereas many UK industries are yet to embed the benefits of modern automation technologies in their production processes.

In summary, the main contributions to the literature of this thesis are: a framework that predicts labour market outcomes for England and Wales at a granular level; an estimation of the productivity of UK labour relative to robots; and a separation of the relative magnitudes of automation and trade on UK employment between 1991 and 2001.

Implications

The main implication of these findings is that the decline in manufacturing jobs, that has been ongoing since 1981, can be partially explained by trade and automation. The automation results raise awareness of the potential employment impact of increasing the adoption of human-substituting capital. Going forwards, the UK is expected to increase its stock of industrial robots by c. 4,000 between 2017-2020, which represents an increase in the operational stock of 22% given that the outstanding stock of industrial robots at the end of 2016 was c. 18,500 (IFR, 2017).

Modern innovations are also expected to result in more tasks being automated. Frey and Osborne (2017) predict that 'most workers in transportation and logistics occupations, together with the bulk of office and administrative support workers, and labour in production occupations, are at risk'. More relevant to the UK, employment in service occupations is also highly susceptible to computerisation, driven by the advent of service robots. As more tasks, that were once uniquely in the domain of human endeavour, move into the set of tasks that can be completed by machines, there will be an increasing need for policymakers to consider the areas within which labour force training remains useful and to rethink the value of the skills that humans can bring to economic processes.

This leads directly into a consideration of new tasks. Weavers who gave way to weaving machines would have found it difficult to comprehend the life of a machine learning engineer. New technologies often bring new tasks with them and the creation of new tasks will be of increasing importance in the face of automation. Even though this thesis has not explicitly considered how these new tasks will enter the economic equation, due to the difficulties associated with their prediction, new tasks will likely require retraining of workforces and the transitional effects will require deft approaches from policymakers and managers.

Future Research

The economic theory on automation is in its infancy. The literature is determining the most appropriate way to model automation, and this thesis has pursued an approach that uses a task-based framework. There is a possibility that other theoretical models of automation develop. These models would ideally provide empirical equivalents that better manage the issue of new tasks being created by endogenising the task creation process. Identifying the nature and importance of factors that contribute to the creation of new tasks is a subject for further study.

The empirical extensions of the automation literature are also rich and manifold. Empirical research approaches are likely to be assisted by the data explosion that we are undergoing which may provide new and novel ways to measure automation in an economy. With improved data, a more detailed wage analysis for the UK would be a particularly useful empirical extension. The ability to assess wages would speak directly to the issue of inequality. Inequality is likely to be a key area of future research as we look to address Ricardo's original concerns about the impact of automation on the different classes of society.

Appendices: Additional Results

A.1 Automation Results Using Total Employment

Table A.1.1: Automation in all industries - total employment (1991-2001)

	TOTAL EMPLOYMENT STACK 1 ESTIMATES USING 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. First-stage for exposure to robots in the UK from 1993 to 2001					
Exposure to robots in all industries (π)	3.684*** (0.673)	3.829*** (0.675)	3.637*** (0.653)	3.318*** (0.561)	2.931*** (0.518)	1.069*** (0.177)
Observations	348	348	348	348	348	344
R^2	0.68	0.70	0.72	0.86	0.73	0.69
	B. Change in total employment to total population ratio (1991-2001)					
Instrumented exposure to robots in all industries (β)	-1.497*** (0.241)	-1.259*** (0.356)	-1.057*** (0.340)	-0.699*** (0.241)	-0.898 (0.703)	-1.976 (2.249)
First-stage F statistic	*30.0*	*32.1*	*31.1*	*85.0*	*103.8*	*15.4*
Observations	348	348	348	348	348	344
R^2	0.07	0.27	0.32	0.45	0.39	0.40
Covariates & sample restrictions:						
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓	✓
Unweighted					✓	
Removing highly exposed areas						✓

*Notes: Dependent variable is change in total employment to population ratio between 1991-2001. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Instrumented level controls only are added for Chinese import exposure and German import exposure. All regressions (except Column 5) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Table A.1.1 is equivalent to Table 5a, except that the dependent variable is the change in the total employment to population ratio and all variables are constructed using total employment. As in Table 5a, the negative result identified is not robust to an unweighted regression, or removal of local authorities with the highest exposure to robots. The productivity of humans relative to robots using β = -0.699 (Column 4) is γ = 171, implying one robot replaces 5.9 workers.

Table A.1.2: Transportation manufacturing automation - total employment (1991-2001)

	TOTAL EMPLOYMENT STACK 1 ESTIMATES USING 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. First-stage for exposure to robots in the UK from 1993 to 2001					
Exposure to robots in transportation manufacturing (π)	21.818*** (0.616)	21.719*** (0.618)	21.617*** (0.625)	23.267*** (0.503)	22.422*** (0.884)	21.453*** (2.954)
Observations	348	348	348	348	348	344
R^2	0.97	0.97	0.97	0.96	0.89	0.75
	B. Change in total employment to total population ratio (1991-2001)					
Inst. exposure to robots in transportation manufacturing (β)	-1.219*** (0.098)	-0.977*** (0.207)	-0.628*** (0.206)	-0.662*** (0.199)	-1.166** (0.494)	-1.029 (1.426)
First-stage F statistic	*1,255.0*	*1,235.3*	*1,194.9*	*1,619.8*	*165.9*	*175.7*
Observations	348	348	348	348	348	344
R^2	0.08	0.28	0.33	0.45	0.39	0.40
Covariates & sample restrictions:						
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓	✓
Unweighted					✓	
Removing highly exposed areas						✓

*Notes: Dependent variable is change in total employment to population ratio between 1991-2001. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Level controls only are added for (instrumented) Chinese and German imports. All regressions (except Column 5) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

As with Table A.1.1, Table A.1.2 is equivalent to Table 5b with the dependent variable and regressors using total employment, rather than full-time employment. The negative and persistent effect seen in Table 5b remains. Once again, the result is no longer statistically significant when the local authorities with the highest exposure to robots are removed. The implied productivity of humans using β = -0.662 (Column 4) is γ = 180, implying one robot in the transportation manufacturing industry replaces 5.5 workers. This is higher than the estimate obtained from using full-time figures. Based on the standard errors, we cannot reject the null hypothesis that the automation coefficient using the full-time employment specification and the coefficient using the total employment specification are equivalent.

Table A.1.3: Transportation manufacturing automation - total manufacturing employment (1991-2001)

	MANUFACTURING EMPLOYMENT STACK 1 ESTIMATES USING 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. First-stage for exposure to robots in the UK from 1993 to 2001					
Exposure to robots in transportation manufacturing (π)	21.818*** (0.616)	21.719*** (0.618)	21.637*** (0.637)	23.184*** (0.484)	22.165*** (0.952)	20.815*** (2.837)
Observations	348	348	348	348	348	344
R^2	0.97	0.97	0.97	0.96	0.89	0.76
	B. Change in manufacturing employment to total population ratio (1991-2001)					
Inst. exposure to robots in transportation manufacturing (β)	-1.339*** (0.178)	-1.039*** (0.269)	-0.248* (0.134)	-0.640** (0.284)	-1.513** (0.720)	-3.205** (1.460)
First-stage F statistic	*1,255.0*	*1,235.3*	*1,153.6*	*2,198.9*	*147.0*	*162.8*
Observations	348	348	348	348	348	344
R^2	0.09	0.22	0.54	0.63	0.58	0.60
Covariates & sample restrictions:						
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓	✓
Unweighted					✓	
Removing highly exposed areas						✓

*Notes: Dependent variable is change in the total manufacturing employment to population ratio between 1991-2001. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); share of employment in construction; offshoring; and routinisation. Level controls only are added for: share of employment in manufacturing; share of female employment in manufacturing; (instrumented) Chinese imports; and (instrumented) German imports. All regressions (except Column 5) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

As with Table 5c, Table A.1.3 demonstrates the negative impact of automation in the transportation manufacturing industry on the manufacturing sector. The implied productivity of humans relative to robots using β = -0.640 (Column 4) is γ = 186, implying one robot in the transportation manufacturing industry replaces 5.4 workers in the manufacturing sector. Using total employment, the impact of robots in the transportation manufacturing industry appear to be more clearly contained within the manufacturing sector (relative to the full-time employment specification), and there is no evidence of offsetting effects at an aggregate level.

A.2 Wage Analysis

The first stage for the wage regressions can be expressed as:[43]

$$\sum_{i \in I} \ell_{ci}^{1991} \left(\frac{R_{i,2011}^{UK}}{L_{i,1997}^{UK}} - \frac{R_{i,1997}^{UK}}{L_{i,1997}^{UK}} \right) = \pi \sum_{i \in I} \ell_{ci}^{1981} \left(p_{10} \left(\frac{R_{i,2011}}{L_{i,1997}} \right) - p_{10} \left(\frac{R_{i,1997}}{L_{i,1997}} \right) \right) + \varGamma X_{c,91} + \varOmega \Delta Y_{c,11-91} + v_c$$

The second stage for the wage regressions can be expressed as:

$$\ln W_{c,11} - \ln W_{c,97} = \beta \left(\hat{\pi} \sum_{i \in I} \ell_{ci}^{1981} \left(p_{10} \left(\frac{R_{i,2011}}{L_{i,1997}} \right) - p_{10} \left(\frac{R_{i,1997}}{L_{i,1997}} \right) \right) \right) + \varGamma X_{c,91} + \varOmega \Delta Y_{c,11-91} + \varepsilon_c$$

Table A.2.1: Median wages using automation in all industries (1997-2011)

	2SLS ESTIMATES FOR MEDIAN WAGES				
	(1)	(2)	(3)	(4)	(5)
	A. Change in log weekly wage between 1997 and 2011				
Exposure to robots in all industries (β)	-0.632 (1.856)	0.005 (1.619)	0.611 (1.832)	-0.521 (3.365)	2.146 (4.617)
First-stage F statistic	*439.6*	*725.0*	*1,287.5*	*1,025.1*	*851.4*
Observations	308	308	308	308	308
R^2	0.00	0.05	0.08	0.13	0.17
	B. Change in log hourly wage between 1997 and 2011				
Exposure to robots in all industries (β)	0.164 (2.272)	1.224 (1.796)	0.67 (1.447)	0.629 (2.858)	8.300 (5.779)
First-stage F statistic	*443.9*	*713.0*	*1,316.9*	*1,108.3*	*1,045.2*
Observations	306	306	306	306	306
R^2	.	0.05	0.10	0.14	0.16
Covariates & sample restrictions:					
Demographics		✓	✓	✓	✓
Broad industry shares			✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓
Unweighted					✓

*Notes: Dependent variable is change in the log of median wages for men between 1997-2011 (Panel A is weekly, and Panel B is hourly). Wages are adjusted for inflation using CPI figures from the Office of National Statistics. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Level controls only are added for (instrumented) Chinese and German imports. All regressions are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

[43] Many controls are only available from the Census data, so level controls are used from 1991 rather than 1997 (also wage data is only available for 308 out of 348 local authorities in 1997).

Table A.2.2: 25th percentile wages using automation in all industries (1997-2011)

	2SLS ESTIMATES FOR 25TH PERCENTILE WAGES					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Change in log weekly wage between 1997 and 2011					
Exposure to robots in all industries (β)	-4.306**	-2.555	-0.985	-2.801	-7.374	0.668
	(2.074)	(1.607)	(1.516)	(3.283)	(7.141)	(16.073)
First-stage F statistic	*421.4*	*713.1*	*1,394.4*	*860.5*	*639.1*	*58.1*
Observations	317	317	317	317	317	313
R^2	0.01	0.05	0.09	0.12	0.11	0.14
	B. Change in log hourly wage between 1997 and 2011					
Exposure to robots in all industries (β)	-4.808***	-2.325*	-1.546	-2.053	-2.888	8.831
	(1.747)	(1.326)	(1.967)	(3.058)	(6.229)	(20.018)
First-stage F statistic	*418.9*	*713.5*	*1,382.2*	*880.0*	*633.4*	*56.9*
Observations	318	318	318	318	318	314
R^2	0.02	0.07	0.09	0.14	0.13	0.15
Covariates & sample restrictions:						
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓	✓
Unweighted					✓	
Removing highly exposed areas						✓

*Notes: Dependent variable is change in the log of wages for men earning at the 25th percentile between 1997-2011 (Panel A is weekly, and Panel B is hourly). Wages are adjusted for inflation using CPI figures from the Office of National Statistics. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Level controls only are added for (instrumented) Chinese and German imports. All regressions are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Table A.2.3: 25th percentile wages using automation in transportation manufacturing (1997-2011)

	2SLS ESTIMATES FOR 25TH PERCENTILE WAGES					
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Change in log weekly wage between 1997 and 2011					
Exposure to robots in transportation manufacturing (β)	-3.354* (2.039)	-2.046 (2.084)	-0.372 (1.642)	-3.275 (3.061)	-8.274 (7.287)	-10.608 (11.917)
First-stage F statistic	*1,443.1*	*1,367.9*	*1,244.7*	*859.7*	*212.7*	*111.7*
Observations	317	317	317	317	317	313
R^2	0.01	0.05	0.09	0.12	0.11	0.14
	B. Change in log hourly wage between 1997 and 2011					
Exposure to robots in transportation manufacturing (β)	-4.164** (1.942)	-2.285 (1.957)	-1.351 (1.879)	-2.235 (2.424)	-4.32 (6.864)	-3.407 (12.651)
First-stage F statistic	*1,443.4*	*1,368.9*	*1,248.5*	*855.8*	*213.3*	*110.6*
Observations	318	318	318	318	318	314
R^2	0.01	0.07	0.09	0.14	0.13	0.15
Covariates & sample restrictions:						
Demographics		✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓
Trade, Routinisation and Offshoring				✓	✓	✓
Unweighted					✓	
Removing highly exposed areas						✓

*Notes: Dependent variable is change in the log of wages for men earning at the 25th percentile between 1997-2011 (Panel A is weekly, and Panel B is hourly). Wages are adjusted for inflation using CPI figures from the Office of National Statistics. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Level controls only are added for (instrumented) Chinese and German imports. All regressions are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Tables A.2.1 to A.2.3 document the regressions where automation is regressed on the difference in wages between 1997-2011. There are several limitations of the publicly available wage data that prohibits a meaningful analysis, but there is some evidence of a negative effect on earnings at the 25th percentile that warrants further investigation given the potential impact that automation could be having on lower income earners.

A.3 Trade Results Using Total Employment

Table A.3.1: Chinese imports - total employment (1991-2001)

	STACK 1 ESTIMATES USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to Chinese imports in the UK from 1993 to 2001						
Exposure to Chinese imports (π)	0.276*** (0.023)	0.268*** (0.022)	0.209*** (0.020)	0.202*** (0.020)	0.184*** (0.019)	0.124*** (0.010)	0.211*** (0.009)
Observations	348	348	348	348	348	348	344
R^2	0.71	0.75	0.81	0.83	0.84	0.85	0.86
	B. Change in total employment to total population ratio (1991-2001)						
Instrumented exposure to Chinese imports (β)	-0.762*** (0.193)	-0.832*** (0.207)	-0.917** (0.387)	-0.796*** (0.259)	-0.828*** (0.305)	-0.363 (0.336)	-1.125** (0.441)
First-stage F statistic	*144.4*	*147.6*	*107.5*	*43.5*	*30.0*	*68.5*	*259.5*
Observations	348	348	348	348	348	348	344
R^2	0.03	0.28	0.33	0.45	0.45	0.39	0.43
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
German trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Panel A shows the first stage from regressing the instrument for Chinese import exposure on UK import exposure from China. Panel B shows the coefficients from regressing instrumented Chinese import exposure on the change in total employment to population ratio between 1991-2001. Level and difference controls are added for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Level controls are added for: (instrumented) automation in the transportation manufacturing industry; and (instrumented) German import exposure. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Tables A.3.1 is equivalent to Table 10a with all variables constructed with total employment figures, rather than full-time employment. The main trade result of the thesis persists. That is, Chinese import exposure had a negative and statistically significant impact on employment in England and Wales between 1991-2001, although it is noted that this conclusion is not robust in the unweighted specification.

Table A.3.2: German imports - total employment (1991-2001)

	STACK 1 ESTIMATES USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to German imports in the UK from 1993 to 2001						
Exposure to German imports (π)	0.683*** (0.045)	0.692*** (0.054)	0.634*** (0.051)	0.535*** (0.040)	0.660*** (0.068)	0.645*** (0.092)	0.560*** (0.053)
Observations	348	348	348	348	348	348	344
R^2	0.72	0.74	0.77	0.84	0.81	0.89	0.83
	B. Change in total employment to total population ratio (1991-2001)						
Instrumented exposure to German imports (β)	-0.713*** (0.229)	-0.682*** (0.175)	-0.501* (0.282)	-0.387* (0.218)	0.049 (0.245)	0.151 (0.203)	-0.126 (0.328)
First-stage F statistic	*227.1*	*166.0*	*155.5*	*105.5*	*89.0*	*1,362.1*	*160.6*
Observations	348	348	348	348	348	348	344
R^2	0.03	0.27	0.31	0.43	0.45	0.39	0.45
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
Chinese trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Panel A shows the first stage from regressing the instrument for German import exposure on UK import exposure from Germany. Panel B shows the coefficients from regressing instrumented German import exposure on the change in total employment to population ratio between 1991-2001. Level and difference controls are added for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); broad industry shares (share of employment in manufacturing, share of employment in construction, and share of female employment in manufacturing); offshoring; and routinisation. Level controls are added for: (instrumented) automation in the transportation manufacturing industry; and (instrumented) Chinese import exposure. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Tables A.3.2 is equivalent to Table 10b with all variables constructed with total employment figures, rather than full-time employment. As before, the German import exposure variable is significant initially, but the result is not robust to the addition of controls. Notably, the covariate loses significance in the presence of the Chinese import exposure covariate.

Table A.3.3: Chinese imports - total manufacturing employment (1991-2001)

	STACK 1 ESTIMATES FOR MANUFACTURING EMPLOYMENT USING 2SLS						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. First-stage for exposure to Chinese imports in the UK from 1993 to 2001						
Exposure to Chinese imports (π)	0.276*** (0.023)	0.268*** (0.022)	0.207*** (0.020)	0.199*** (0.020)	0.180*** (0.019)	0.123*** (0.010)	0.206*** (0.009)
Observations	348	348	348	348	348	348	344
R^2	0.71	0.75	0.81	0.82	0.83	0.85	0.85
	B. Change in manufacturing employment to total population ratio (1991-2001)						
Instrumented exposure to Chinese imports (β)	-1.497*** (0.246)	-1.422*** (0.170)	-0.768*** (0.234)	-0.496** (0.232)	-0.780*** (0.296)	-0.819 (0.502)	-0.830*** (0.320)
First-stage F statistic	*144.4*	*147.6*	*107.1*	*46.7*	*34.6*	*71.1*	*187.6*
Observations	348	348	348	348	348	348	344
R^2	0.16	0.32	0.54	0.63	0.63	0.58	0.61
Covariates & sample restrictions:							
Demographics		✓	✓	✓	✓	✓	✓
Broad industry shares			✓	✓	✓	✓	✓
Automation, Routinisation and Offshoring				✓	✓	✓	✓
German trade					✓	✓	✓
Unweighted						✓	
Removing highly exposed areas							✓

*Notes: Dependent variable is change in the total manufacturing employment to population ratio between 1991-2001. Level and difference controls are considered for: demographics (share of working-age population, share of population with a university degree, share of minority ethnic groups in local authorities); share of employment in construction; offshoring; and routinisation. Level controls only are added for: share of employment in manufacturing; share of female employment in manufacturing; (instrumented) automation in the transportation manufacturing industry; and (instrumented) German imports. Construction of these controls is discussed in Chapter Four. All regressions (except Column 6) are weighted by working-age population at the start of the period. Robust standard errors in parentheses are clustered at the standard region level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.*

Tables A.3.3 is equivalent to Table 11 with all variables constructed with total employment figures, rather than full-time employment. Table 11 provides the main result of the thesis in relation to trade and the result is the same. Two points worth noting about the total employment specification are that: the coefficient on Chinese import exposure is slightly larger than it is in the full-time employment specification; and the result is no longer robust in the unweighted specification.

References

Acemoglu, Daron and David H. Autor (2011) “Skills, tasks and technologies: Implications for employment and earnings” Handbook of Labor Economics, 4: 1043–1171.

Acemoglu, Daron and Pascual Restrepo (2016a) “The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment” NBER Working Paper No. 22252.

Acemoglu, Daron and Pascual Restrepo (2016b) “Robots and Jobs: Evidence from US labor markets” World Bank presentation.

Acemoglu, Daron and Pascual Restrepo (2017) “Robots and Jobs: Evidence from US Labor Markets” NBER Working Paper No. 23285.

Acemoglu, Daron and Pascual Restrepo (2018) “Modeling Automation” forthcoming, American Economic Review Papers and Proceedings.

Anderson, James (1979) “A Theoretical Foundation for the Gravity Equation” American Economic Review, 69(1): 106–160.

Armington, Paul S. (1969) “A Theory of Demand for Products Distinguished by Place of Production” Staff Papers International Monetary Fund, 16(1): 159–178.

Autor, David and David Dorn (2013) “The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market” American Economic Review, 103(5), 1553-1597.

Autor, David H., David Dorn and Gordon H. Hanson (2013) “The China Syndrome: Local Labor Market Effects of Import Competition in the United States” American Economic Review 103(6): 2121–68.

Autor, David H., David Dorn and Gordon H. Hanson (2015) “Untangling Trade and Technology: Evidence from Local Labor Markets” Economic Journal, 125(584): 621-646.

Autor, David H., Frank Levy and Richard J. Murnane (2003) “The Skill Content of Recent Technological Change: An Empirical Exploration” Quarterly Journal of Economics, 116(4).

Barnes, Sebastian N., Simon Price and Maria Barriel (2008) “The Elasticity of Substitution: Evidence from a UK Firm-Level Data Set” Bank of England Working Paper No. 348.

Bessen, James (2017) “Automation and Jobs: When Technology Boosts Employment” Boston University Law and Economics Research Paper No. 17-09.

Bilici, Ozgul (2016) “International Trade in a Competitive World: Empirical Evidence from the UK” PhD thesis, University of Essex.

Blinder, Alan and Alan Krueger (2009) "Alternative Measures of Offshorability: A Survey Approach" NBER Working Paper No. 15287, August 2009.

Bluestone, Barry and Bennet Harrison (1988) "The Growth of Low-Wage Employment: 1963-1986" American Economic Review, LXXVIII, 124-128.

Boston Consulting Group (2015) "The Robotics Revolution: The Next Great Leap in Manufacturing".

Burnham, Kenneth P. and David R. Anderson (2002) "Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach" 2nd ed. Springer-Verlag: 63.

Card, David (1994) "Intertemporal labor supply: an assessment" in Sims, C (ed) *Advances in Econometrics*, Cambridge University Press.

Chen, Yuyu, Ginger Zhe Jin and Yang Yue (2010) "Peer Migration in China" National Bureau of Economic Research Working Paper 15671.

Dauth, Wolfgang, Sebastian Findeisen, Jens Südekum and Nicole Woessner (2017) "German Robots – The Impact of Industrial Robots on Workers" IAB Discussion Paper.

Faccini, Renato, Stephen Millard and Francesco Zanetti (2011) "Wage Rigidities in an Estimated DSGE Model of the UK Labour Market" The Bank of England's research paper series.

Faggio, Giulia and Henry Overman (2014) "The effect of public sector employment on local labour markets" Journal of Urban Economics, Elsevier, vol. 79(C), pages 91-107.

Feenstra, Robert C. and Gordon H. Hanson (1999) "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990" The Quarterly Journal of Economics 114(3): 907–940.

Frey, Carl B. and Michael A. Osborne (2017) "The future of employment: How susceptible are jobs to computerisation?" Technological Forecasting and Social Change, Elsevier, vol. 114, pages 254-280.

Goodman, J.F.B. (1970) "The Definition and Analysis of Local Markets: Some Empirical Problems" British Journal of Industrial Relations, 8, pp. 179-196.

Goos, Maarten and Alan Manning (2007) "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain" The Review of Economics and Statistics, 89(1): 118-133.

Graetz, Georg and Guy Michaels (2015) "Robots at Work" CEP Discussion Paper No. 1335.

Gregory, Terry, Anna Salomons and Ulrich Zierahn (2016) "Racing With or Against the Machine? Evidence from Europe" ZEW - Centre for European Economic Research Discussion Paper No. 16-053.

Helpman, Elhanan and Paul Krugman (1987) "Market Structure and Foreign Trade" Cambridge, MA: MIT Press.

Hsieh, Chang-Tai and Peter J. Klenow (2009) "Misallocation and Manufacturing TFP in China and India" Quarterly Journal of Economics 124 (4): 1403–48.

International Federation of Robotics (IFR) (2017) "World Robotics: Industrial Robots".

Jäger, Kirsten (2016) "EU KLEMS Growth and Productivity Accounts 2016 release - Description of Methodology and General Notes".

Katz, Lawrence F. and Kevin M. Murphy (1992) "Changes in Relative Wages, 1963-1987: Supply and Demand Factors" The Quarterly Journal of Economics, 107(1): 35–78.

Keynes, John Maynard (1930) "Economic Possibilities for our Grandchildren" Chapter in *Essays in Persuasion.*

Mani, Sunil (2017) "Robot Apocalypse: Does it matter for India's manufacturing industry?" Working Paper, Centre for Development Studies.

Michaels, Guy, Ashwini Natraj and John Van Reenen (2014) "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years" Review of Economics and Statistics, 96(1): 60–77.

O'Brien, Robert M. (2007) "A Caution Regarding Rules of Thumb for Variance Inflation Factors" R.M. Qual Quant 41: 673.

Office of National Statistics (2015) "Commuting to work, Changes to Travel to Work Areas: 2001 to 2011".

Office of Population Censuses and Surveys (OPCS) (1992) "1991 Census Definitions: Great Britain".

Ricardo, David (1821) "On Machinery" Chapter in *On the Principles of Political Economy and Taxation.*

Simonovska, Ina and Michael E. Waugh (2014) "The elasticity of trade: Estimates and evidence" Journal of International Economics, Elsevier, vol. 92(1), pages 34-50.

Solow, Robert (1968) "Technology and Unemployment" in Bernard J. Frieden and Robert Morris (eds.), *Urban Planning and Social Policy*, New York: Basic Books.

Wright, Greg C. (2014) "Revisiting the Employment Impact of Offshoring" European Economic Review 66:63–83.

Yu M, Tian W. (2012) "China's firm-level processing trade: trends, characteristics, and productivity" Work. Pap. E2012002, China Cent. Econ. Res., Peking Univ., Beijing, China.